End Milling: A Neural Approach for Defining Cutting Conditions

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Abstract. The purpose of this paper is to present a new adaptive solution based on a feed forward neural network (FNN) in order to improve the task of selecting cutting conditions for milling operations. From a set of inputs parameters, such as work material, its mechanical properties, and the type of cutting tool, the system suggests feed rate and cutting speed values. The four main issues related to the neural network-based techniques, namely, the selection of a proper topology of the neural network, the input representation, the training method and the output format are discussed. The proposed network was trained using a set of inputs parameters provided by cutting operations manuals and tool manufacturers catalogues. Some tests and results show that adaptative solution proposed yields performance improvements. Finally, future work and potential applications are outlined.

1 Introduction

Process planning is a function that establishes a set of manufacturing operations and their sequence, and specifies the appropriate resources (machines, cutting tools, fixtures, inspection instruments, etc.) and process parameters in order to convert a blank to a finished component expressed by an engineering drawing and other technical information. The use of computer tools to assist the process plan generation was firstly reported by Niebel [2]. From that work, many other researchers have explored the use of computer systems to obtain a coherent process plan in an automated manner. Recently, the term CAPP (computer aided process planning) appears frequently in the technical literature and can be considered as one of the most active fields of research in manufacturing. In computer integrated manufacturing environments, CAPP can be considered as the link between the CAD phase and CAM. Many researchers have developed solutions to close the gap between the design phase and the generation of manufacturing instructions and/or machine control code. A primer reference in CAPP is Chang [1], who classifies CAPP approaches into two categories, i.e. variant and generative. The variant approach usually incorporates the use of group technology paradigm to recover the most suitable process plan that corresponds to the most similar workpiece to that is being planned. This first approach usually lacks in flexibility and does not consider relationship between features of workpiece. On the other hand, generative process planning generates in an automated manner, a brand new process plan, only based on experience and technical knowledge. According to Chang and Chang [3], most generative CAPP

Duran O., Rodriguez N. and Airton Consalter L. (2008).
End Milling: A Neural Approach for Defining Cutting Conditions.
In *Proceedings of the 4th International Workshop on Artificial Neural Networks and Intelligent Information Processing*, pages 41-50
DOI: 10.5220/0001495400410050

lack in learning ability for environmental changes. Because of that reason, recent researches have being focused on integrating variant and generative CAPP with Expert Systems-based techniques. A number of approaches have been reported in literature to solve the problems occurring in integrating process planning and other computer aided manufacturing applications. Leung [4] published an extensive literature review on CAPP. Other significant number of references was reported by Marri et al. [5]. More recently, Chang and Chang [3] reported artificial intelligence applications for CAPP implementations. In an exploratory examination of the CAPP literature it is easy to conclude that ANN have been intensively used to solve problems such as tool selection, cutting conditions definition, sequencing of operations, etc. Unlike the most published applications of ANN in process planning, where neural networks are used as a means to create optimization models, the proposed approach involves three key differences: neural networks are capable of storing knowledge in a distributed manner, neural networks are capable of learning to recognize relationships between inputs and outputs, while such relationships must be explicitly defined in optimization models, and neural networks are capable of generalizing (i.e., giving a ”closest-fit” answer) when presented with data not used in deriving the relationships learned. This paper presents a proposal of artificial neural network for determining cutting parameters for milling operations. The subsequent content is organized as follows: The second section discusses the process of definition of cutting conditions and the use of Artificial Intelligence techniques for this purpose; the third section presents the suggested approach, specifically it discusses the structure of the developed networks, the training data sets, and the details of the training process. Furthermore, some aspects of the obtained output of the developed networks are presented. Finally, in the last section some conclusions and future works are drawn.

2 Artificial Intelligence and Determination of Cutting Parameters

A workpiece is composed by a set of surfaces or features. These surfaces are obtained by a sequence of machining operations, such as turning, milling, boring and so on. For each one of these features process planners must select adequate tools and optimal cutting parameters. The choice at this stage may be tentative and has to be governed by experience, intuition and based on information gathered in machining handbooks. Mainly, this step of process planning considers the selection of the following parameters:

– The cutting speed (vc) and the rotational speed of the part or of the tool (N).
– The feed rate (fn) or the feed speed in translation of the machine elements (vf).
– The depth of cut (ap) or engagement determining the width of the material to be removed.

Despite the fact that such machining parameters are calculated according to practical values found in handbooks or from experience, they have to be updated or refined to adapt the values to match a specific situation for extracting the best performance of the cutting resources. Influence diagrams have been developed for representing complex decision problems based on incomplete and uncertain information from a variety of sources. Nestler and Shulz [8] presented a simple example of an influence diagram for machining optimizations and discussed their use in optimization of cutting conditions (Fig1).

Data from machining handbooks were separated into different types of machining process, such as turning, drilling, boring, end milling, etc. and classified according to the workpiece material. As it is well known, workpiece materials are classified in various groups covering a wide range of materials according to their hardness: ferrous, non-ferrous, etc. The machining handbooks provide the machining parameters for different tool-work-piece combinations. A comprehensive review of the information obtained from the literature, and from industry, has indicated that the recommended cutting speeds and feed rates for any machining operation may vary considerably [6]. In addition to the proper selection of cutting speeds and feed rates, the optimum condition depends on variables such as part configuration, condition of the machine and fixturing, tolerances and surface quality. Because the effects of these variables on tool life are not always precisely known, it becomes difficult to recommend optimum conditions for a machining operation. Therefore, the recommendations presented in the machining handbooks are nominal ones and should be adjusted by a certain order of processing approach [7].

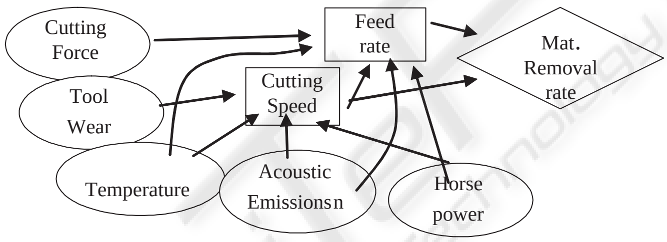

Fig. 1. An influence diagram for determining machining parameters.

Among the applications to determine cutting conditions using an intelligent approach, one must distinguish the systems that perform the task in an off-line mode and the systems that operate in an on-line mode. Off-line calculation of cutting conditions consists in defining all the necessary parameters for execute a workpiece before the process is initiated. According Nestler and Shulz [8], at present, neural networks are especially used to solve sophisticated problems such as determining and modeling correlations between input and output parameters. Hashmi et al. [7] points to other direction to use AI tools for defining cutting conditions, the use of fuzzy logic models for representing knowledge extracted from catalogues or handbooks. According Hashmi et al. [7] fuzzy logic strategy can simulate an operator’s ‘experience and expertise’ in decision-making process to facilitate the operator to select drilling parameters from expert database which can be incorporated in computerized automated systems. On the other hand, the on-line approach corresponds to an automated attempt to adapt and optimize the machining parameters based on sensor information on machining responses in real time. One of the main differences between off-line and on-line determination of cutting conditions is the need of information of temperature and acoustic emissions.

Table 1. Subset of training data.

Operation type	Work Mat Code	Hardness HB	Mill type	Vc m/min	Vf mm/min
1	30,22	90	1	1000	1910,8
2	30,22	90	1	1100	4904,4
3	30,22	90	1	1250	26871,0
4	30,22	90	1	130	4968,1
1	1,10	125	1	155	288,0
2	1,10	125	1	200	891,7
3	1,10	125	1	375	8061,3
4	1,10	125	1	690	26369,4
1	1,10	125	3	145	450,2
2	1,10	125	3	160	1452,2
1	1,20	150	1	135	257,0
1	7,10	150	1	135	257,9

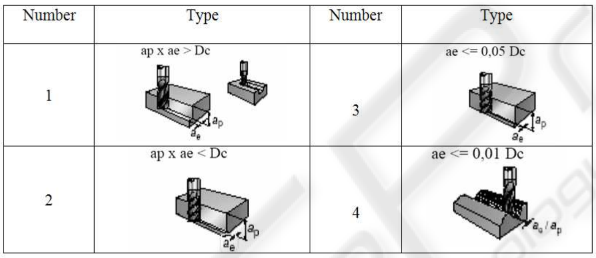

Fig. 2. Types of operations considered in the experiment.

Hence any on-line intelligent system has to be integrated with a sensing device system for extracting in real time conditions of cutting processes. AI techniques allows modeling the information coming from the sensors systems and optimizing machining parameters by learning from machining events such as tool wear, machine breakdowns and other failures.

3 Neural Network Model

Several papers recommend that feed forward multilayer backpropagation nets with one or two hidden layers with 10 to 30 neurons each are appropriate for handling cutting data selection problems [8]. The approach suggested here is to use two neural networks one for the selection of cutting speed and the second one for the selection of the feed speed. Both networks use the same set of inputs. Therefore, the same training and testing sets were used for each one of the nets. There is just one difference between the two training sets: the second network uses the set of training data plus the correspondent cutting speed values. Thus, the propose here is to link both networks to work in an integrated manner to produce cutting parameters from the same set of input data, namely, workpiece material and type of milling operation and cutter. Most of the information used in the preparation of learning and testing data was extracted from a

Table 2. Alternative Configurations tested and their performance indicators.

ID of ANN cfg.	Num.of hidden layers	Num. of layer 1	Num. of layer 2	Num. of layer 3	MAD (mm/min)	GF %
1	3	10	10	10	31,0	100,00
5	2	7	7	0	18,5	90,91
2	3	11	11	11	11,3	85,46
4	3	6	7	8	13,0	83,64
3	2	8	8	0	1,3	83,64
16	2	10	10	0	23,5	80,00
6	2	9	10	0	30,1	78,18
13	2	6	6	0	47,4	74,55
7	2	7	8	0	31,8	74,55
9	3	6	6	6	95,4	72,73
19	2	11	11	0	15,3	72,73
14	3	7	7	7	14,2	72,73
10	3	9	10	11	25,3	69,09
11	3	8	9	10	10,8	69,09
12	3	9	9	9	8,1	69,09
17	2	6	7	0	46,1	67,27
20	2	9	9	0	47,2	65,46
15	2	8	9	0	3,2	63,64
8	3	7	8	9	5,0	60,00
18	3	8	8	8	34,5	58,18

Table 3. Configuration parameters selected for each network.

Network ID	Output parameter	Num. of Inputs	Num. of Hidden Layers	Num. of Neurons Lay.1	Num. of Neurons Lay.2	Num. of Neurons Lay.3
1	Vc	4	3	7 sig	7 sig	7 lin
2	Vf	5	2	8 sig	8 sig	-

Sandvik Coromant Catalog. The collected information is in the form of tables, which show the recommended cutting conditions for different types and geometries of cutters and materials of workpieces depending on factors affecting machinability. As the original information on cutting conditions is given in the form of intervals representations, the midpoints of such intervals were used as the representative values to construct the training and testing data sets. In addition, two machining specialists refined these data. The specialist adapted the data sets assuming a potentially real situation and a given and known machine tool. By doing so, it will be feasible to incorporate empirical knowledge to the training process. It was considered for this experiment four types of operations, as shown in (Fig.2).

The selected input parameters were: milling operation type, workpiece material, workpiece material hardness and type of mill. Table 1 shows a subset of the used training data. As can be noticed in table 2, the desired output data are distributed in a wide interval. This is due to the large number of different types of workpiece materials. This situation may be seen as a rather complex problem to be handled by any neural network. This situation leads the authors to choose the strategy of two networks, the first

Table 4. Percent error according to the operation type.

Operation type	network 1 %	network 2 %
1	1,44	15,11
2	3,27	24,76
3	2,06	1,91
4	0,44	35,34

Table 5. Percent error according to the workpiece material.

Material type	network 1 (%)	network 2 (%)
High Alloy Steel	1,37	8,38
Hardened Steel	3,09	18,26
Titanium alloys	0,91	24,11
Aluminium alloys	0,25	1,92

with a single output to estimate the cutting speed and the second one to estimate the feed speed. The first column represents the operations type, namely, the relation between the depth of cut (ap) and cutting width (ae), as shown in Figure 2. The second and the third columns in table 1 represent workpiece material and its Brinell hardness. Different workpieces materials were represented using the Coromant Material Code. In a similar way, the type of mill was represented as an integer that regards the material and geometrical configuration of the milling tool. In the experiment four types of commercial end mills were considered. As it was commented previously, network designers have to test several configurations, including different numbers of hidden layers and different number of neurons in each one of the hidden layers. There can be any number of hidden layers in a neural network. In common use most neural networks will have only one hidden layer. It is very rare for a neural network to have more than two hidden layers. The number of neurons for the hidden layer(s) depends on the complexity of the problem and should be set empirically. With too few neurons the network may not converge in training, whilst with too many hidden-layer neurons the network starts to lose generalization ability [9]. In this work, we compare the performance of networks with two and three hidden layers and the number of neurons in each layer ranging from 5 to 15. Designer selects the network configuration that presents the minimum error and the fastest rate of convergence. A series of alternative configurations have been tested to determine the proper configuration of both networks. Several tests were conducted varying the number of hidden layers, different numbers of neurons for each layer and different transitions functions. The learning algorithm adopted in all these tests was the backpropagation algorithm with momentum. As it is usual in the approaches using this kind of networks, the set of data was divided into two subsets: the first used as the training data set contains 138 patterns and the second, used as a validation set to evaluate the responses of the net to unseen information, contains 55 patterns. Through the use of these two sets, networks parameters can be adjusted and the generalization ability can be evaluated. To select the most appropriate configuration two traditional performance indicators were used. We refer to the medium absolute deviation (MAD), which was computed in two phases, during the training process and the testing process. The deviations were calculated as the difference between the actual speed and the estimated speed, both for the training and testing sets. The second performance indicator that was used to evaluate the generalization capacity of the tested configurations is the Generalization Factor (GF), defined by Eq. (1).

$$GF = \frac{k}{n} * 100 \tag{1}$$

Where n is the number of patterns that compose the validation set and k is the number of such patterns estimated with an error less than 2 % (this value having been fixed as a threshold level). Table 2 summarizes the results obtained from an alternative configuration of neural networks for estimating feed speed (network number two). It is quite evident that the configuration number 1 (with three hidden layers) showed better generalization performance since GF is 100%. However, the MAD seemed to be a little high from the operational point of view. If one considers an error of 31 mm/min in the estimated feed speed, this may lead to undesirable or inappropriate time estimations and tool life expectations significantly overestimated. Thus the selected configuration was number 3, in Table 2 (with two hidden layers), which MAD is 1,3 mm/min, considered as acceptable from the operational point of view. Moreover, the generalization factor of near 85% seems to be adequate, if one consider that the training set takes into account a wide variety of types of milling tools and workpiece materials. The same type of analysis was conducted to obtain the architecture of the first ANN that performs the estimation of the cutting speed. Table 3 shows the selected configuration parameters for both networks. Figure 3 (left) shows the net output and expected cutting speed values obtained after the network was entirely trained and a comparison between the original testing data and the parameters estimated by the neural network (Fig.3 right). For the selection of feed speed a single layer network with one hidden layer was trained using the same training data set used for training the network that selects the cutting speed. Figure 4 (left) shows the convergence of the output mean error for the network that was trained for selecting the cutting speed, where it can be noticed the low number of epochs needed for attain the minimum required error. Figure 4 (right) shows the convergence of the output mean error for the network during the training process of the network for selecting the cutting speed. Again, the low number of epochs needed for attain the minimum required error can be noticed. Figure 5 (left) shows the net output and expected feed speed values obtained after the network was entirely trained and on the right side of the Figure 5 a comparison between the original testing data and the parameters estimated by the neural network is shown. To evaluate the performance of the two developed networks, an additional test set was prepared for simulation and comparisons ends. The results of the simulation tests were classified according different criteria. Table 4 shows the performance in terms of percent error of the two both networks according to the operation type (refer Figure 1). Table 5 presents the results of the test grouped according to the material workpiece. Finally, table 6 presents the results obtained by the two networks according the hardness of the workpiece. As can be appreciated, from table 5 and 6, network 1 presented the best results with errors within the 3%. As it can be observed in the tables shown above, the approach presents different performance between network 1 and network 2, i.e. network 1 performs better estima-

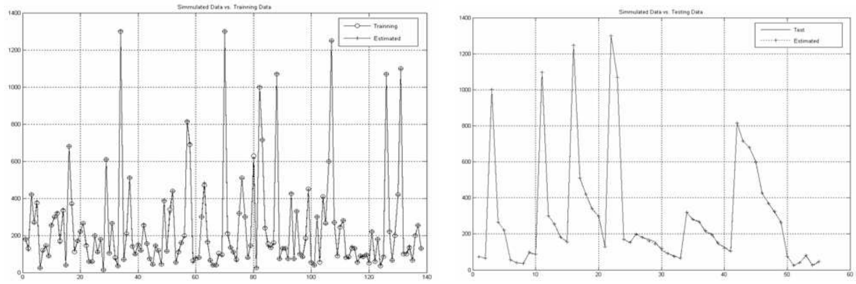

Fig. 3. Comparison between the train data set and the output produced by the trained network(left) and between by the test data set and the output of the trained network (right).

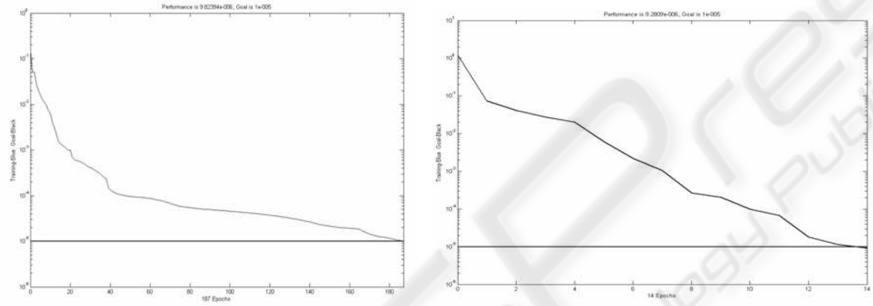

Fig. 4. Convergence during the process of training the first network (left) and during the process of training of the second network (right).

tion of the cutting speed than the estimations performed by the network 2 for the feed speed. This is caused, we believe, by the great variability of the recommended values of feed speed among different materials and operations types. The values used in the test set present a mean value of 6000 mm/min approximately with a standard deviation of 9000 mm/min. However, and it can be observed in tables 5 and 6, there are some applications where the networks presented acceptable results (under 10 % of error), i.e. operation type 3 and milling of High alloy steel and aluminum steel materials.

Table 6. Percent error according to the workpiece material hardness.

Material Hardness	network 1 %	network 2 %
350 HB	0,76	18,02
350 HB	2,37	13,70

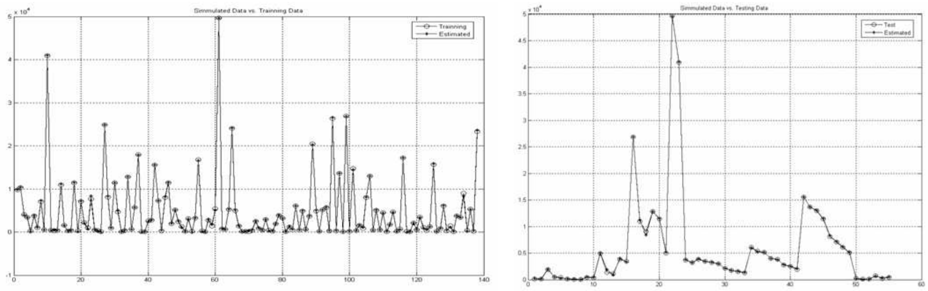

Fig. 5. Comparison between the training data and the data obtained by the trained network for estimating Vf (left) and between test data and the networks output (right side).

4 Conclusions

This paper presented a neural network-based automated approach for cutting conditions selection in milling operations. Two prototype networks were developed. The first network is for selecting cutting speed and the second one for selecting feed speed, both using almost the same set of input parameters. Both neural networks are interrelated, since the output produced by the first network is used as an input in the second one. The developed approach aims at selecting cutting parameters in off-line mode. The main difficulty found in the reported experiments was the fact that the training data set considers a great variety of workpiece materials. That situation leads to a wide interval of cutting conditions affecting convergence mechanism during the training process and the generalization capabilities during the utilization phase. In spite of this fact, the obtained results show that the developed networks have an acceptable performance in simulating cutting conditions selection process, with a generalization performance of about to 85 approximately. Future research points to develop and test new architectures of neural networks to enhance the selection process performance, especially in estimation of feed speed. Also, this work should be extended to other process planning functions such as machine selection, tool and fixture selection and sequence of manufacturing operations.

References

1. Chang T.-C: Expert Process Planning for Manufacturing,Addison Wesley,1990,Massachusetts.
2. Niebel, B.W.: Mechanized Process Selection for Planning new Designs,ASTME Paper 737,1965.
3. Chang P.T., Chang C.: An Integrated Artificial Intelligent Computer-Aided Process Planning System", Int. Journal of Computer Integrated Manufacturing,Vol.13, No.6, pp. 483-497,2000.
4. Leung, H.C.: Annotated Bibliography on Computer Aided Process Planning, International Journal of Advanced Manufacturing Technology, Vol. 12, No. 5, pp. 309-3297, 1996.
5. Marri, H.B., Gunasekaran, A., Grieve, R.J.: Computer Aided Process Planning : a state of art, International Journal of Advanced Manufacturing Technology, Vol. 14, No. 4, pp. 261-268, 1998.

6. Park K.S., Kim, S.H: Artificial Intelligence Approaches to Determination of CNC Machining Parameters in Manufacturing: a Review, Artificial Intelligence in Engineering, Vol. 12, pp. 127-134, 1998.
7. Hashmi, K., L.D.Graham, B. Mills: Fuzzy Logic Based Selection for the drilling Process, Journal of Materials Processing Technology, Vol. 108, pp.55-61, 2000.
8. Nestler A., G.Shulz: Cutting Values Prediction with Neural Networks, Second In- ternational Conference on Industrial Tools ICIT99, 1999.
9. Sukthomya W., J.Tannock: The training of neural networks to model manufacturing processes, Journal of Intelligent Manufacturing, Vol. 6, pp. 39-51, 2005.