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제품품질 개선을 위한 가공조건의 생성과 지속적 향상 방법론

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Generation and Continual Improvement of Cutting Conditions for an Enhancement of Product Quality

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절삭가공에서 가공조건은 가공비용의 감소와 제품 품질의 향상에 영향을 주는 주요 요인 중의 하나이다. 본 논문에서는 밀링작업을 대상으로 가공조건을 보다 효율적으로 수정하고 이를 지속적으로 향상시킬 수 있는 방법론과 이를 기반으로 개발된 작업설계시스템을 소개한다. 개발된 시스템은 (1) 표준 가공조건을 세부 공정별 요구 사항이 만족되도록 수정하고, (2) 퍼지아트맵 신경회로망 모델을 이용하여, 생성된 가공조건을 온라인(incremental) 학습한 후, (3) 보다 효율적인 새로운 가공조건이 생성되었을때 이를 교체알고리즘이라 불리는 제안된 알고리즘을 이용하여 기존의 가공조건을 대체하는 3가지 핵심 기능으로 구성된다. 우선 새로운 방법론이 적용된 작업설계시스템의 전반적인 내용을 소개한 후, 다음으로 다양한 시뮬레이션을 통하여 제안된 방법론의 성능을 예시한다. 마지막으로 실제 부품에 적용한 실행 결과를 기술하고 토의한다.

Keywords : Product Quality, Neural Network, CAPP, Operation Planning, Cutting Conditions

1. Introduction

In metal cutting processes, cutting conditions have an influence on reducing the production cost and deciding the quality of a final product. In information driven manufacturing systems, computer-aided process planning (CAPP) links design to manufacturing (Marri, 1998). It identifies machining features, selects machine tools and operations for those features, generates various parameters required in each operation, routes the selected operations, and so on. While there has been some success in the systematization of the feature recognition and the operation sequencing (Bhaskara, 1999), the process of selecting cutting conditions has not been as successful because it largely depends on human experience. For turning operation, quite practical CAPP systems have been developed. For optimization of cutting parameters Taguchi's method (Nalbant, 2007; Singh, 2005) and genetic algorithm (Sardinas, 2006) and any other methods (Minqiang, 2005) have been adopted in turning operation.

Compared to the relatively simple cutting mechanism and small number of cutting tools required for turning operations, many different mechanisms depending on the type of cutting tool are involved in machining of prismatic components. Therefore, most of the research for determination of cutting parameters in milling operation has been performed for specific cutting tools (Aslan, 2007) and material (Yong, 2006), and practical CAPP systems for milling operations do not calculate or decide cutting conditions by analytical methods,

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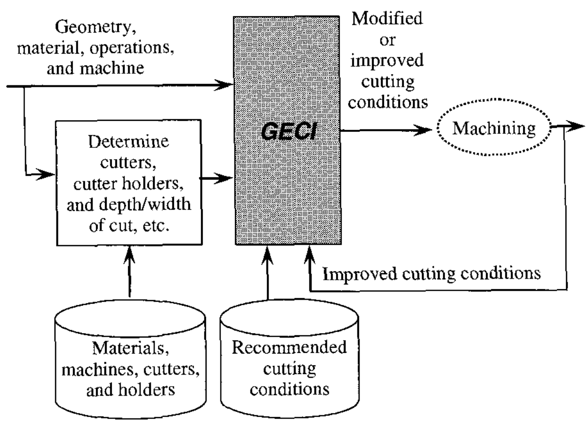
but offer the means to retrieve the recommended cutting condition from a handbook type database (Lee, 2002; Van Houten, 1989; Zhiyong, 2003). The approach is viable since the content of machining data handbooks can be regarded as an accumulation of many years' experience and has been tested through the metal cutting experiments. However, the cutting conditions recommended in the handbook need to be modified because only a few factors affecting the operation are considered in selecting cutting conditions. Furthermore, because the set of recommended or modified cutting conditions may not be optimal, it is necessary for the imperfect data to be improved continually.

In this paper, an operation planning system for milling operations is presented as a part of a CAPP system. GECI (GEneration and Continual Improvement of cutting conditions for an enhancement of product quality), which is capable of generation and incremental learning of cutting conditions, is a key component of the operation planning system. In previous study (Park, 2001; Park, 2005), the performance of two essential algorithms was suggested, and verified in various experimental conditions. These algorithms are utilized to the GECI. GECI has three major functions. The first one is the generation of modified cutting conditions. Generally, machinists make a modification of the cutting conditions recommended from a machining data handbook in order to satisfy requirements for individual operations. Using a back-propagation neural network (BPNN), it models the modification procedure. The second function is the incremental learning of obtained cutting conditions. The methodology of a fuzzy ARTMAP neural network (FAMNN) is applied to model the process. The FAMNN implements an incremental and on-line supervised learning mechanism in response to input patterns (Carpenter, 1992). The last function is the substitution of more effective cutting conditions for those learned previously using a newly suggested replacement algorithm. When more effective cutting conditions are newly obtained through actual machining processes, the replacement algorithm deletes the old information learned by the FAMNN and then makes the network learn the better ones. These functions enable the system to improve cutting conditions while it is in continual use.

First, a variety of simulations such as the modification, on-line and off-line learning of cutting conditions illustrate the performance of GECI, and then, for a given part, the simulation results are provided and discussed.

<Figure 1> shows the architecture of the proposed operation planning system. The system is composed of GECI, other auxiliary components, and machining databases. With respect to a set of input data, the functions described above are performed in GECI.



<Figure 1> Architecture of the operation planning system

2. Generation and Continual Improvement of Cutting Conditions

For generation and continual improvement of cutting conditions, GECI performs following three functions :

- Generation of modified cutting conditions by the BPNN.
- Incremental learning of obtained cutting conditions by the FAMNN.
- Substitution of more effective cutting conditions for those learned previously by the proposed replacement algorithm.

2.1 Generation of Modified Cutting Conditions

When a previously learned cutting condition does not exist for input data, GECI performs modification of the cutting condition obtained from handbook type database. For modelling of this modification procedure, BPNN has been adopted where the influences of the factors, which are not taken into account in recommended cutting conditions, are considered. By using the BPNN for expressing the non-linear relations among many factors simultaneously through the parallel processing of input data, influence factors such as surface condition, insert geometry, chip disposability of a feature, etc. are considered.

Information provided by references (Sirotani, 1984; Machinability Data Center, 1986) was mainly utilized for preparation of learning data. These data were refined, and then approved by expert machinists.

The 4-layer neural network was used to generate the modified cutting conditions. In order to decide the structure of the BPNN, the convergence rate of error was checked by changing the number of hidden layers, the number of nodes in each layer, and also by adjusting learning rate η and momentum term α. Here, η and α are constants whose values are between zero and one. The structure of the BPNN consists of an input layer with 15 nodes, two hidden layers with 15 nodes each, and an output layer with one node. The training of the BPNN took 115 seconds for 124 learning patterns on a personal computer. When η and α were 0.9 and 0.1 respectively and the number of iterations was 50,000, the mean error percentage was 0.0099 (Park, 2005).

The generation of the modification ratio by the trained neural network is carried out as follows :

Step 1 : When input data are given, the neural network is constructed by retrieving coefficients from the neural network database, and then the class numbers are given to each input data.

Step 2 : If the value of an input parameter is a real number, and does not belong to any class, the class number of the parameter is interpolated by the nearest two class numbers.

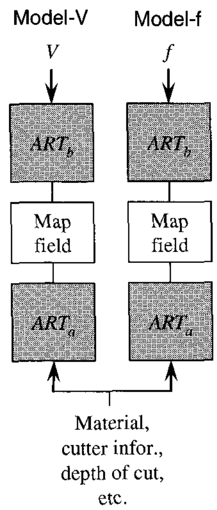
Step 3 : Using the selected class numbers for input parameters, the neural network is propagated in order to obtain the modification ratio of feed f.

Step 4 : Input feed f is modified by the modification ratio generated by the neural network.

2.2 Incremental Learning of Cutting Conditions in the FAMNN

For incremental learning of obtained cutting conditions, FAMNN is selected. Compared with other popular neural networks, it showed the most efficient and robust learning performance. In addition, it has the unique property of incremental supervised learning, and overcomes the problems of long training and catastrophic forgetting associated with many popular networks. The FAMNN has been applied to some machine learning problems, and compared favorably with other neural networks and traditional AI machine learning algorithms. However, regardless of these advantages, applications of this network to deciding cutting conditions have not been found in the previous works. Further details on this network can be found in the reference (Carpenter, 1992).

The models shown in <Figure 2> were considered for GECI to learn cutting conditions incrementally. They have two FAMNNs, called Model-V and Model-f, for learning cutting speed V and feed f separately.



<Figure 2> FAMNNs for incremental learning of cutting conditions

<Table 1> Input parameters for *ARTa*

Input Parameters	Real values		Input values of ART_a
Workpiece Material	Medium carbon leaded (ANSI : 10L45, 10L50)		0.9000
	:		:
Hardness (*BHN*)	50~400	225	0.5000
		:	:
Cutter type	Face mill		0.8750
	:		:
Cutter material	Carbide-Uncoated (ISO : P20, P30, P40)		0.8000
	:		:
Depth of cut (*mm*)	0.01~13.0 (15.0)	10	0.6664
		:	:
:	:		:
Tool life (*min*)	0.01~60	60	0.9999
		:	:
Nose radius (*mm*)	0.1~3.2	2.4	0.7419
		:	:

<Table 1> and <Table 2> show input parameters, their real values, and encoded values for the FAMNNs. The encoded input values range from zero to one in FAMNNs. 16

input parameters are used for the ART_a of the FAMNNs. The input parameters described in <Table 1> are commonly used for all the models. For the Model-V and Model-f, the input parameters in <Table 2> are applied.

<Table 2> Input parameter(s) for ART_b

(a) Model-V.

Input Parameters	Real values		Input values of ART_b
Cutting speed, V (*m/min*)	18~160	80	0.4366
		:	:

(b) Model-f.

Input Parameters	Real values		Input values of AART_b
Feed, f (*mm/tooth*)	0.01~0.5	0.415	0.8265
		:	:

2.3 Replacement Algorithm for Improvement of Cutting Conditions

Because modified cutting conditions are not optimal solutions, they may also need to be improved. When more effective cutting conditions are obtained through actual machining, the replacement algorithm deletes the old information learned by the FAMNN, and then makes the network learn the better ones.

This algorithm is composed of deletion and creation procedures. By the deletion procedure, the previously learned category J and K link of the FAMNN is removed, and then new category J and $K^{(new)}$ link for more effective learning patterns is generated by the creation procedure (Park, 2001). This algorithm can be described as follows :

2.3.1 Deletion Procedure

Step 1 : Perform complement coding of ith input pattern $\mathbf{a}^{(i)}$ on layer F_0^a for ART_a, and then present the complement coded input pattern $\mathbf{I}_a=(\mathbf{a}^{(i)}, \mathbf{a}^{c(i)})$ to layer F_1^a.

Step 2 : Determine a winner neuron J at layer F_2^a by a choice function $T_j(\mathbf{I}_a)$, and then perform the vigilance test.

Step 3 : Search weight $\mathbf{w}_{jk}^{ab}$ that has a value of one, and category $k=K$ using category $j=J$.

Step 4 : Set the previously found weight $\mathbf{w}_{jk}^{ab}$ to zero.

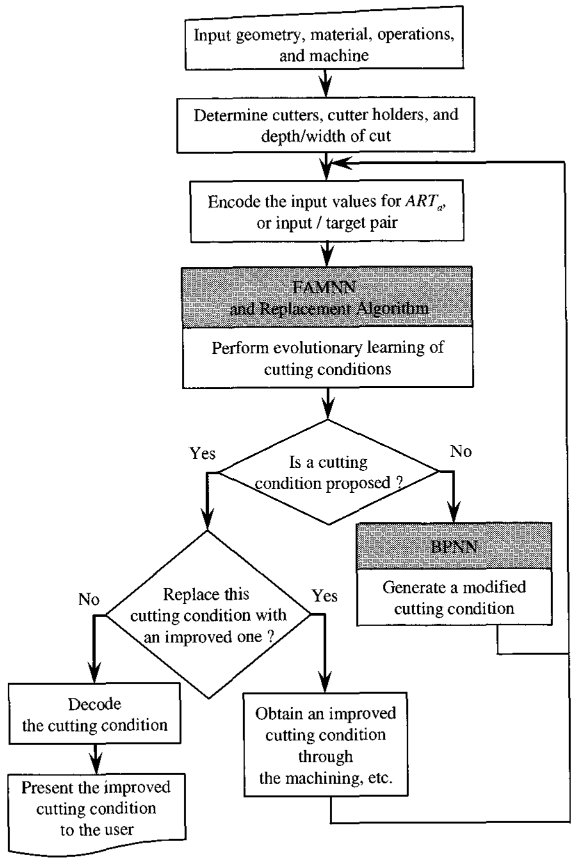
2.3.2 Creation Procedure

Step 1 : Perform complement coding of input pattern $\mathbf{b}^{(i)(new)}$.

Step 2 : Using $\mathbf{I}_a$ and $\mathbf{I}_b=(\mathbf{b}^{(i)(new)}, \mathbf{b}^{c(i)(new)})$, call the learning procedure of FAMNN.

2.4 Procedure for Generation and Continual Improvement of Cutting Conditions

The flowchart in <Figure 3> shows overall procedure in GECI. When machining features, individual machining operations, a machine tool, and a material are presented in systems such as CAD and CAPP, the operation planning system automatically determines cutters, cutter holders, and depth and width of cut. These data are sent to GECI, and encoded into the input format for ART_a. Next, the FAMNNs check the encoded data if its corresponding cutting condition is already available. If a cutting condition is not available, or the pattern is not previously learned, GECI generates a modified cutting condition. This is encoded, and then learned



<Figure 3> Overall procedure for generation and continual improvement of cutting conditions

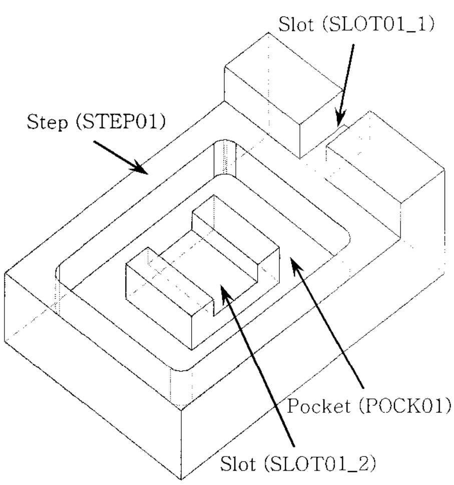
incrementally in the FAMNNs. Otherwise, GECI performs a step to confirm whether or not the proposed cutting condition is improved by the replacement algorithm. If the cutting condition has to be improved, a more effective one is encoded again and substituted for the old one by the replacement algorithm. Otherwise, the cutting condition is decoded, and then presented to the user.

3. Case Study

The operation planning system was implemented on a personal computer. A commercial database management system and a CAD system were employed in the system.

<Figure 4> shows an example part used in this case study. The example part has a pocket, a step, and two slot features. The specifications of a workpiece material, a machine, and cutting fluid are as follows :

- Machine tool data
  - Type : Vertical CNC milling machine
  - Motor power, P_m = 8.5 kw
  - Machine tool efficiency factor, e = 95%
- Material data
  - Quality : 10L50 leaded steel
  - Hardness = 225 BHN
- Cutting Fluids
  - Emulsifiable oils (General purpose)



<Figure 4> An example part

Machining operations and cutter data for each operation on the given part are shown in <Table 3> and <Table 4>.

<Table 3> Required machining operations

Operation no.	Operation name	Feature	Cutter no.	Depth of cut (*mm*)
1	Face milling	STEP01	1	10
2	End milling	POCK01	2	5
3	End milling	POCK01	2	10
4	End milling	SLOT01_1	3	10
5	End milling	SLOT01_2	3	5

<Table 4> Cutter data for each operation

Type	Material	Dia. (mm)	No. of cutting tooth	Lead Angle (degree)	Side rake angle (degree)	Tool life (min)
Face mill	Carbide-uncoated	50	6	45	7	60
End mill	HSS	10	4	0	5	40
End mill	HSS	12	4	0	5	40

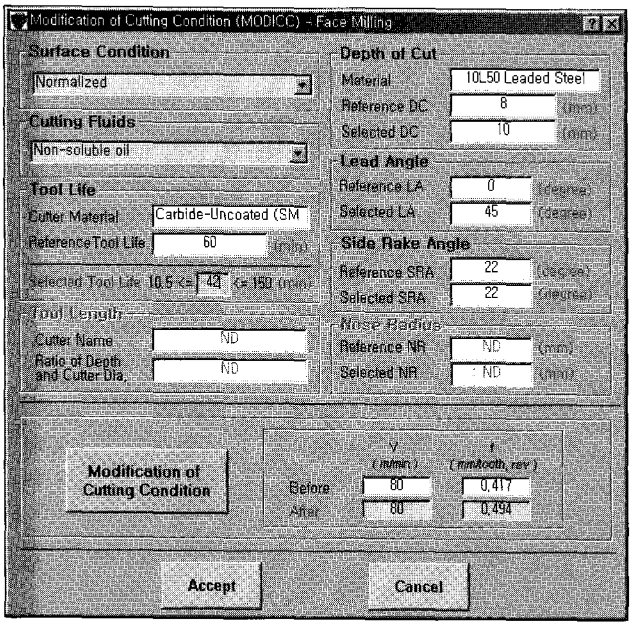
The following two cases show the execution results with these given data. In the first case, the generation and the incremental learning of the modified cutting condition is performed when the relevant information does not exist for the given data in GECI. In the other case, the old cutting conditions are replaced with the more effective ones by the replacement algorithm in GECI.

3.1 Generation of Modified Cutting Conditions

In the case of the face milling operation on the step feature in <Table 3>, the cutter data were selected as shown in <Table 4>. The depth and width of cut were 10.0 and 33.3 mm, respectively. These data are encoded into the input format of ART_a, and then checked if the FAMNNs have already learned of this pattern. Because the cutting condition learned previously did not exist, a modified cutting condition was generated. With the data above, the recommended cutting condition, V = 80 m/min and f = 0.415 mm/tooth, has been retrieved from the database. On the face milling operation, some modifications have been made to tool life, depth of cut, lead angle, and side rake angle. <Table 5> shows the procedure for determining the modification ratio of feed and the results. The cutting speed and feed were modified from 80 m/min and 0.415 mm/tooth to 80 m/min and 0.494 mm/tooth as shown in <Figure 5>. For other operations, the same modification procedure can be applied. <Table 6> shows the recommended and modified cutting conditions for the operations. The FAMNNs have learned the modified cutting condition incrementally.

<Table 5> Procedure for determining the modification ratio

Factors	Input parameters	Value of input parameter	Class no.	Modification ratio of the feed f
Tool Life	Cutter material	Carbide-uncoated	3	1.19
	R_{TL}	2	6	
Depth of cut	Material	10L50 leaded steel	3	
	R_{DC}	1.25	4,5	
Insert geometry	R_{LA}	4	8	
	Reference SR angle	8	1	
	Selected SR angle	7	1	



<Figure 5> Modification results on the given operation

<Table 6> Recommended and modified cutting conditions

Operation no.	V_{hb}^{*} (m/min)	f_{hb} (mm/tooth)	V_{mod}^{**} (m/min)	F_{mod} (mm/tooth)
1	80	0.415	80	0.494
2	24	0.025	24	0.038
3	20	0.013	20	0.018
4	20	0.025	20	0.038
5	24	0.038	24	0.057

Note) $^{*}V_{hb}$, f_{hb} : Cutting speed and feed recommended from the handbook,

$^{**}V_{mod}$, f_{mod} : Cutting speed and feed modified in the GECI.

3.2 Replacement of the Cutting Condition with a New One

When the material, the cutter, and the depth of cut, etc. are given, the FAMNNs check whether this pattern is learned or not. If the cutting condition is not previously learned, the modified cutting condition is generated. Otherwise, the old cutting condition is replaced by the effective one obtained through actual machining using the replacement algorithm in GECI. For an application of the replacement algorithm, learning patterns 4', 15', 18', 26' and 29' in <Table 7> were used. These data have been collected from the reference (Machinability Data Center, 1986) instead of actual machining. It is assumed that the data are more effective than those presented in GECI. These data are identical with learning patterns 4, 15, 18, 26 and 29 except ART_b input values as shown in the learning patterns of <Figure 6>. In <Table 7>, the cutting conditions learned previously are the modified cutting conditions for the operations described in <Table 3>.

:	:	:	:	:	:	:	:	:
4	0.8750	0.8000	0.8333	0.6664	...	0.0001	0.4366	0.9878
:	:	:	:	:	:	:	:	:
15	0.7500	0.9000	0.3333	0.8000	...	0.1765	0.0423	0.0959
:	:	:	:	:	:	:	:	:
18	0.7500	0.9000	0.3333	0.9999	...	0.1765	0.0141	0.0571
:	:	:	:	:	:	:	:	:
26	0.7500	0.9000	0.6667	0.8000	...	0.0588	0.0423	0.0571
:	:	:	:	:	:	:	:	:
29	0.7500	0.9000	0.6667	0.9999	...	0.0588	0.0141	0.0163
:	:	:	:	:	:	:	:	:

<Figure 6> Learning patterns for the FAMNNs

In <Table 8>, the application results of the replacement algorithm on the given data are presented. <Table 8> shows that mean test errors (%) were 0.00 and 0.06, and maximum test errors (%) were 0.00 and 0.38 for V and f respectively. These mean or maximum test errors (%) were within the acceptable error boundaries for V and f. In the case of Model-V, all learning patterns were assigned to new categories, because the new data were not close enough to be allocated to previously formed categories. On the other hand, in the case of the Model-f, learning patterns 4', 18' and 29' were assigned to existing categories.

<Table 7> Cutting conditions for the application of the replacement algorithm

Previously learned cutting conditions					Effective cutting conditions				
Pattern no.	Real values		Coded values		Pattern no.	Real values		Coded values	
	V (m/min)	f (mm/tooth)	V	f		V (m/min)	f (mm/tooth)	V	f
4	80	0.494	0.4366	0.9878	4'	101.15	0.415	0.5856	0.8265
15	24	0.057	0.0423	0.0959	15'	42.72	0.388	0.1741	0.7714
18	20	0.038	0.0141	0.0571	18'	47.46	0.248	0.2075	0.4857
26	24	0.038	0.0423	0.0571	26'	63.26	0.214	0.3187	0.4163
29	20	0.018	0.0141	0.0163	29'	55.02	0.179	0.2607	0.3449

<Table 8> Application results of the replacement algorithm

Model no.	Value of vigilance parameters, ρ_a and ρ_b	No. of category		Mean test errors (%)		Max. test errors (%)	
		ART_a	ART_b	V	f	V	f
Model-V	$\rho_a = 0.99,\ \rho_a = 0.99$	31	15	0.00	-	0.00	-
Model-f		31	16	-	0.06	-	0.38

4. Concluding Remarks

In this paper, a new methodology called GECI, which is capable of generation and incremental learning of cutting conditions, was presented for milling operations. GECI is a major component of the operation planning system, and performs following three functions to improve the cutting conditions continually :

- Generation of modified cutting conditions.
- Incremental learning of obtained cutting conditions.
- Substitution of better cutting conditions for ones learned previously by the proposed replacement algorithm.

These functions facilitate the improvements of cutting conditions through the continual use of the system. A variety of simulations are performed. Especially, in-depth simulations have been performed to validate the performance of the FAMNN and the replacement algorithm. In addition, the operation planning system is tested on the given part for showing the usefulness of the proposed methodology. Based on the preliminary test of the system, it was verified that cutting conditions are improved continually and efficiently.

In this work, the proposed methodology has been applied only to milling operations. However, it also can be applied to turning operations with a little modification on the input parameters of the FAMNN.

The extensions of this study will include the following :

- The development of a sub-module for obtaining effective cutting conditions through actual machining processes is required. Because the operation planning system has been implemented on Client/Server environment, it is possible for the system to acquire the data manually or automatically.
- Although only 31 learning patterns were used in the FAMNN, more learning patterns of cutting conditions will be collected.
- The metal cutting experiment will follow this work to validate and enhance the practicality of the system.

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