▩ 응용논문

Continual Enhancement of Cutting Conditions Using Neural Network for Milling Process
밀링 가공조건의 지속적인 향상 방법론

Byoung Tae Park*
박 병태*
Ji Han Seo**
서 지한**

Abstract

가공조건은 가공비용과 시간을 줄이고 제품의 품질을 결정하는데 영향을 주는 주요 요인중의 하나이다. 본 논문에서는 밀링 공정을 위한 작업설계 (Operation Planning) 시스템에서, 가공조건을 지속적으로 향상시키기 위한 새로운 방법론을 제안한다. 제안된 방법론은 밀링 작업에 대하여 (1) 퍼지 아트맵 신경회로망 모델에 의해 가공조건을 실시간 학습하고, (2) 교체 알고리즘이라 불리는 새로운 알고리즘을 포함한다. 제안된 교체 알고리즘은 기존의 학습 정보보다 효율적인 새로운 가공조건이 얻어졌을 때, 이를 이용하여 기존의 학습 정보를 대체하는 기능을 수행한다. 본 논문에서는 우선 작업설계 시스템의 전반적인 기능을 간략히 소개한 후, 제안된 방법론에 의한 의사결정 과정을 자세히 기술한다. 또한, 다양한 시뮬레이션을 통하여 제안된 방법론의 성능을 예시하도록 한다.

1. Introduction

In information driven manufacturing systems, CAPP (Computer-aided Process Planning) (ElMaragy, 1993) links design to manufacturing. It determines a set of instructions and machining parameters required to manufacture a part. There are generally two approaches to CAPP systems, namely variant one and generative one. The variant approach is basically a computerized database retrieval approach. The variant or retrieval approach is based on group technology methods of classifying and coding parts for the purpose of segregating these parts into family groups. It is strongly restrictive in that new parts to be planned have to be similar to those already in the data file. The second approach to CAPP is the generative type. Systems of this type synthesize the process plan for a new part. These systems usually employ either a set of algorithms or knowledge-based techniques to progress through the various technical and logical decisions toward an appropriate process plan for a part. The generative approach provides fast advice to designers early in the stage of design process and is closely coupled with the product-modeling activities. Once the manufacturing technology and the type of equipment or process have been chosen, further detailed planning is carried out as usual. In this point

*CAD/CAM Research Center, Korea Institute of Science & Technology (KIST)
**Dept. of Industrial Engineering, Myung-Ji College

of view, process planning is divided into high-level process planning and low-level process planning stage. After high-level process planning, low-level process planning is performed. In the high-level process planning, the machining processes, machines and tooling capable of performing these processes, and the machining groups are established. In the low-level process planning called operation planning, partial operations are selected, cutting parameters are determined, and time and cost are calculated to convert a piece part from its initial form to a predetermined shape as per the engineering drawing.

While there has been some success in the systematization of the feature recognition (Kim, 1992; Waco, 1994) and the operation sequencing (Bhaskara, et. al, 1999; Barkocy and Zdeblick, 1984), the process of selecting cutting conditions largely depends on human experience. Mathematical models of cutting mechanisms and empirical equations representing the cutting process have been suggested for several decades by numerous researchers (Gupta, et. al, 1995, Kee, 1996), but the results of those studies were not general enough to be applied for the systematization of the selection of cutting parameters. Especially in the case of the milling process, the models are operative only for limited situations. Therefore, most of the CAPP systems do not calculate or decide cutting conditions by analytical methods, but offer the means to retrieve the recommended cutting condition from a handbook type database (Van Houten and Vant Erve, 1989). The approach is sensible 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.

The problem is that the retrieved data should be modified according to the actual operation conditions because only a few - i.e. material type, tool type - among many factors affecting the operation are considered for selecting cutting parameters.

In the previous study (Park, et. al., 1996), the retrieved data was modified through a neural network and filtered by the rules including analytical equations. The point of interest of the study was to model the process of modifying the retrieved cutting condition by an experienced machinist using a back-propagation neural network. The result of the study was satisfactory by the initial point of interest. The next issue was that the quality of the output of the neural network depends on that of the training data set. As the set of reference cutting conditions may not be perfect from the beginning, the model trained through the imperfect data needs to be enhanced while the system is in continual use.

In this study, for efficient enhancements of the function for generating cutting conditions, EVOLS (EVOlutionary Learning System of cutting conditions) for milling processes has been developed. In the system, the methodology of the fuzzy ARTMAP neural network, including the newly suggested replacement algorithm, is applied to model the process of learning and enhancing cutting conditions. The fuzzy ARTMAP neural network (Carpenter, et. al., 1992) implements a supervised learning mechanism capable of self-organizing stable recognition categories in response to arbitrary sequences of input patterns. Three classes of experiments will illustrate the performance of the fuzzy ARTMAP with the replacement algorithm. Figure 1 shows the architecture of the operation planning system containing EVOLS.

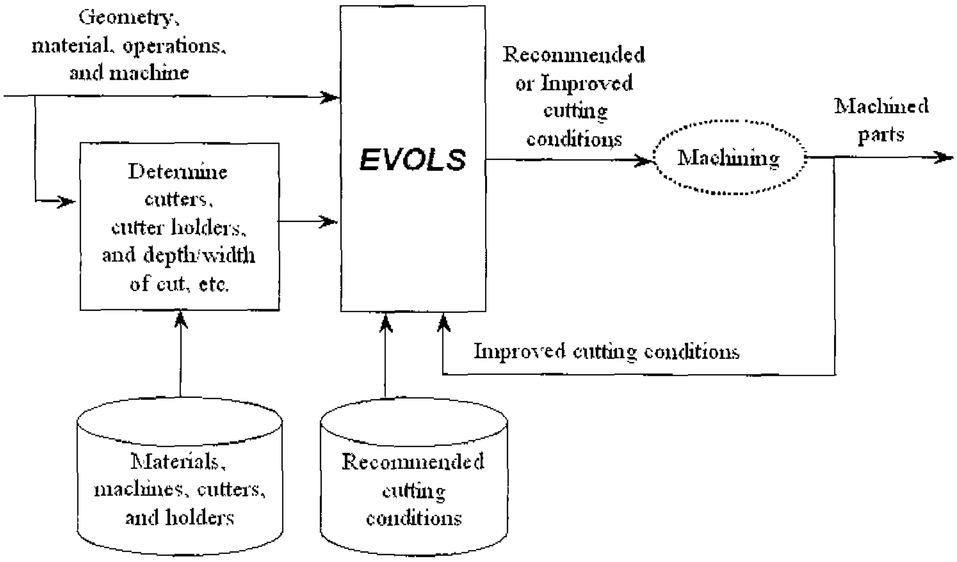


Figure 1. Architecture of the proposed operation planning system.

2. Review of fuzzy ARTMAP Neural Networks

The fuzzy ARTMAP neural network is capable of on-line and off-line supervised learning in response to arbitrary sequences of analogue and binary input/target vector pairs. As shown in Figure 2, the fuzzy ARTMAP network is composed of two fuzzy ART networks (ART_a, ART_b), and these networks are linked together by a map field (F^{ab}). The fuzzy ART network classifies the given learning patterns into the categories according to similarities among them. Its parameters such as choice parameter α, learning rate β, and vigilance parameter ρ, have an influence on deciding the numbers of category. The higher the vigilance level, smaller or more specific categories will be created. When an input pattern is presented to the network, the F^{ab} layer will receive inputs from both the ART_a and the ART_b. If the two F^{ab} inputs match, the network will learn by modifying the weight vectors of the chosen categories J and K respectively on the F_2^a and F_2^b of the ART_a and ART_b. If there is a mismatch at the F^{ab} layer, the baseline vigilance level of the ART_a will be raised. The network will subsequently search another ART_a category. This process continues until the network either finds an ART_a category that predicts the category of the current target correctly, or creates a new category in ART_a and a corresponding link in the map field, which will learn the current input/target pair. Further details on this network can be found in the reference (Carpenter, et. al., 1992).

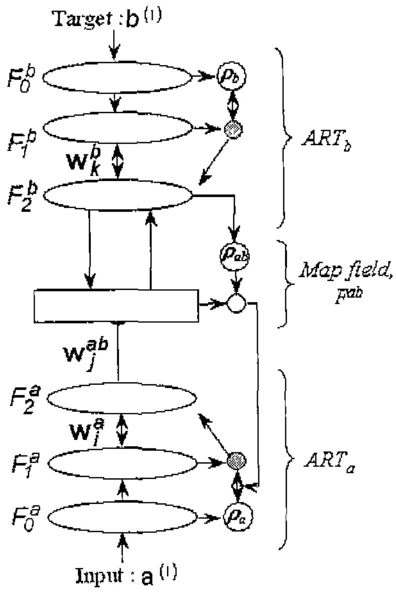


Figure 2. Architecture of the fuzzy ARTMAP neural network.

3. Replacement Algorithm for the Enhancement of Cutting Conditions

When new cutting conditions that are more effective are obtained through real machining experiments, etc., the replacement algorithm proposed here deletes the old information learned through the fuzzy ARTMAP, 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 Fuzzy ARTMAP is removed, and then new category J and $K^{(new)}$ link for more effective learning patterns is generated by the creation procedure. This algorithm can be briefly described as follows:

Deletion Procedure

Step 1 [Input pattern coding and presentation] Perform complement coding of input pattern $\mathbf{a}^{(i)}$ on layer $\mathbf{F}_0^a$ for ART_a, and then present the complement coded input pattern $\mathbf{I}_a = (\mathbf{a}^{(i)}, \mathbf{a}^{c(i)})$ to layer $\mathbf{F}_1^a$.

Step 2 [Category choice] Determine a winner neuron J at layer $\mathbf{F}_2^a$ by a choice function $\mathbf{T}_j(\mathbf{I}_a)$, and then perform the vigilance test.

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

Step 4 [Unlearning previously learned information] Set the previously found weight $\mathbf{w}_{JK}^{ab}$ to zero.

Creation Procedure

Step 1 [Input pattern coding for ART_b] Perform complement coding of input pattern $\mathbf{b}^{(i)(new)}$.

Step 2 [Learning new pattern] Using $\mathbf{I}_a$ and $\mathbf{I}_b$= ($\mathbf{b}^{(i)(new)}$, $\mathbf{b}^{c(i)(new)}$), call the Fuzzy ARTMAP learning procedure described in section 2.

4. Evolutionary Learning Procedures

EVOLS consists of two fuzzy ARTMAP networks with the replacement algorithm and other auxiliary sub-modules. The first fuzzy ARTMAP (Model-V) is for learning and enhancing cutting speed *V*, and the second fuzzy ARTMAP (Model-f) is for learning and enhancement of feed *f*. Table 1 and 2 show input parameters defined for the fuzzy ARTMAP networks, real values, and encoded input values which range from 0 to 1 for ART_a, ART_{bV}, and ART_{bf}. For the Model-V, input parameters described in Table 1 and Table 2 (a) are used, and for the Model-f, input parameters described in Table 1 and Table 2 (b) are used.

Table 1. Input parameters for ART_a.
(a) Model-V

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 2. Input parameters for ART_b.

(a) ART_{bV}

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

(a) ART_{bf}

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

The flowchart in Figure 3 summarizes the overall procedure in EVOLS. Real values of input parameters for ART_a sent to EVOLS are encoded to the input form for ART_a in module ENC-IP, and then checked in module FA-PRA. If a cutting condition is not proposed, or in other words, the pattern is previously unlearned in the networks, the cutting condition generated in module GEN-CCis sent to the module ENC-IP, and then learned in the module FA-PRA. Otherwise, EVOLS performs the step to confirm whether the proposed cutting condition is enhanced through the replacement algorithm or not. If the cutting condition has to be enhanced, the better one generated through machining experiments, etc. is sent to the module ENC-IP, and enhanced by the replacement algorithm in the module FA-PRA. Otherwise, the cutting condition is presented to the user through module DEC-CC.

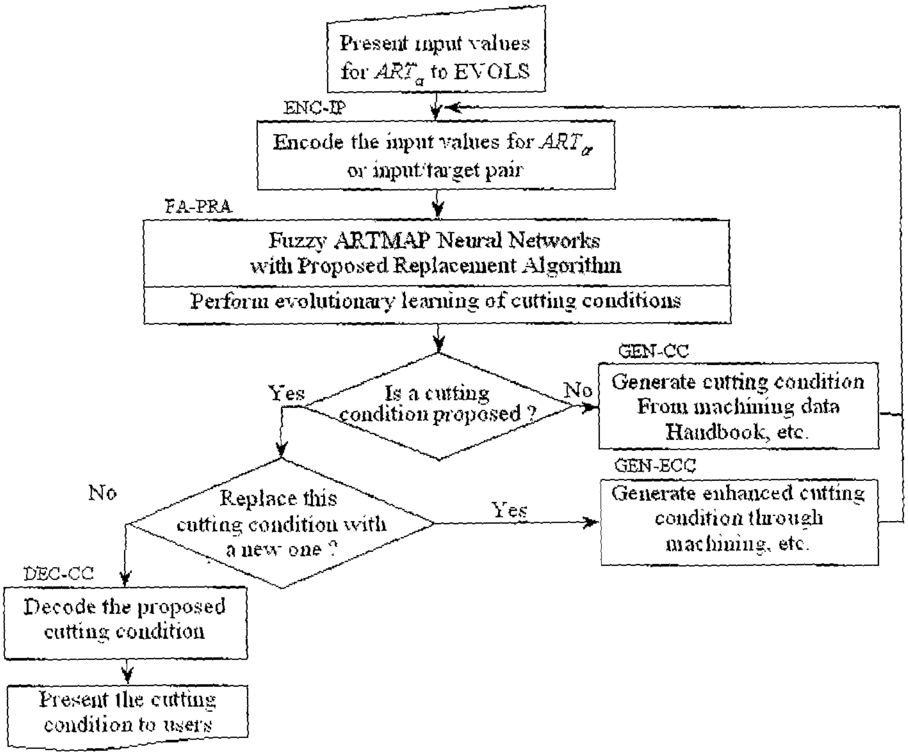


Figure 3. Flowchart of learning and replacement procedures in EVOLS.

5. Results

As mentioned earlier, the fuzzy ARTMAP neural network is capable of on-line and off-line learning in response to arbitrary sequences of analogue and binary input/target patterns. The performance of the fuzzy ARTMAP and the replacement algorithm is simulated through three classes of experiments on a personal computer (CPU: Pentium II, 266MHz). These experiments are (1) off-line learning performance of the fuzzy ARTMAP neural network in relation to back-propagation system, (2) on-line learning performance of the fuzzy ARTMAP neural network, and (3) an application of the replacement algorithm. Figure 4 shows encoded learning patterns collected to perform these experiments. The 36 learning patterns are composed of 31 machining data presented in the handbook (Machinability Data Center, 1986) and five effective cutting conditions obtained from the reference (Tolouei-Rad, M. and Bidhendi, 1997). The first column in Figure 4 presents pattern number, and the rest of the columns are mapped with input parameters in Table 1 and 2. The following show procedures and results of experiments performed when the value of choice parameter α, learning rate β, and vigilance parameter in map field ρ_{ab} are 0.001, 0.999, and 1.0 respectively.

:	:	:	:	:	:	:	:	:	:
4	0.9000	0.5000	0.8750	0.8000	...	0.8000	0.7500	0.4366	0.8265
15	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.0423	0.0571
18	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.0141	0.0306
26	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.0423	0.0306
29	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.0141	0.0061
:	:	:	:	:	:	:	:	:	:
4'	0.9000	0.5000	0.8750	0.8000	...	0.8000	0.7500	0.5856	0.8265
15'	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.1741	0.7714
18'	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.2075	0.4857
26'	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.3187	0.4163
29'	0.9000	0.5000	0.7500	0.9000	...	0.8000	0.7500	0.2607	0.3449

Figure 4. Examples of learning patterns.

Case 1　Off-line Learning Performance of the Fuzzy ARTMAP Neural Network

First, the experiments for deciding the values of the network parameters providing the best learning performance were carried out with the given 31 learning patterns in off-line learning mode. The network showed the best performance when the values of vigilance parameters ρ_a and ρ_b were both 0.99. In this case, mean test errors (%) were 0.02 and 0.01, and maximum test errors (%) were 0.64 and 0.41 for V and f respectively. Target values were compared with decoded values that were proposed by the fuzzy ARTMAP in Table 3. In the case of the seventh pattern, the decoded values of V_T and V_C in the Model-V were 80.0 and 79.6, and the decoded values of f_T and f_C were 0.250 and 0.249 respectively in the Model-f.

Table 3. Comparison with target values and calculated values proposed from fuzzy ARTMAP neural network, in case ρ_a and ρ_b are 0.99 and 0.99 respectively.

Type of Model	Pattern no.	Encoded values				Decoded values			
		V_T (*m/min*)	V_C (*m/min*)	f_T (*mm/tooth*)	f_C (*mm/tooth*)	V_T (*m/min*)	V_C (*m/min*)	f_T (*mm/tooth*)	f_C (*mm/tooth*)
	:	:	:	:	:	:	:	:	:
Model-V	7	0.4366	0.4338	-	-	80.00	79.60	-	-
	:	:	:	:	:	:	:	:	:
	:	:	:	:	:	:	:	:	:
Model-f	7	-	-	0.4898	0.4878	-	-	0.2500	0.2490
	:	:	:	:	:	:	:	:	:

V_T : Target V,　V_C : Calculated V,　f_t : Target f,　f_C : Calculated f

The results tested with same learning patterns in the back-propagation system showed that mean test errors (%) were 7.6 and 9.1, and maximum test errors (%) were 46.7 and 146.1.

Case 2　On-line Learning Performance of the Fuzzy ARTMAP Neural Network

For the test of on-line learning ability of fuzzy ARTMAP neural network, 31 learning patterns were presented one by one to the network in an arbitrary order. Table 4 shows on-line learning results of the network. As shown in this table, compared with off-line learning results, the performance of on-line learning does not fall behind that of off-line learning.

Table 4. On-line learning results of the fuzzy ARTMAP neural network.

Type of Model	Value of vigilance parameters, ρ_a, ρ_b	# of category		Mean test errors (%)		Max. test errors (%)	
		ART_a	ART_b	V (m/min)	f (mm/tooth)	V (m/min)	f (mm/tooth)
Model-V	ρ_a= 0.99, ρ_b= 0.99	31	10	0.02	-	0.64	-
Model-f		31	14	-	0.01	-	0.41

Case 3 An Application of the Replacement Algorithm

For an application of the replacement algorithm, learning patterns 4′, 15′, 18′, 26′ and 29′ were used. These new data are identical with learning patterns 4, 15, 18, 26 and 29 except ART_b input values, as shown in Figure 4. In Table 5 and Figure 5, the applied results of the replacement algorithm are presented. 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 5. Categories allocated in an application of the replacement algorithm.

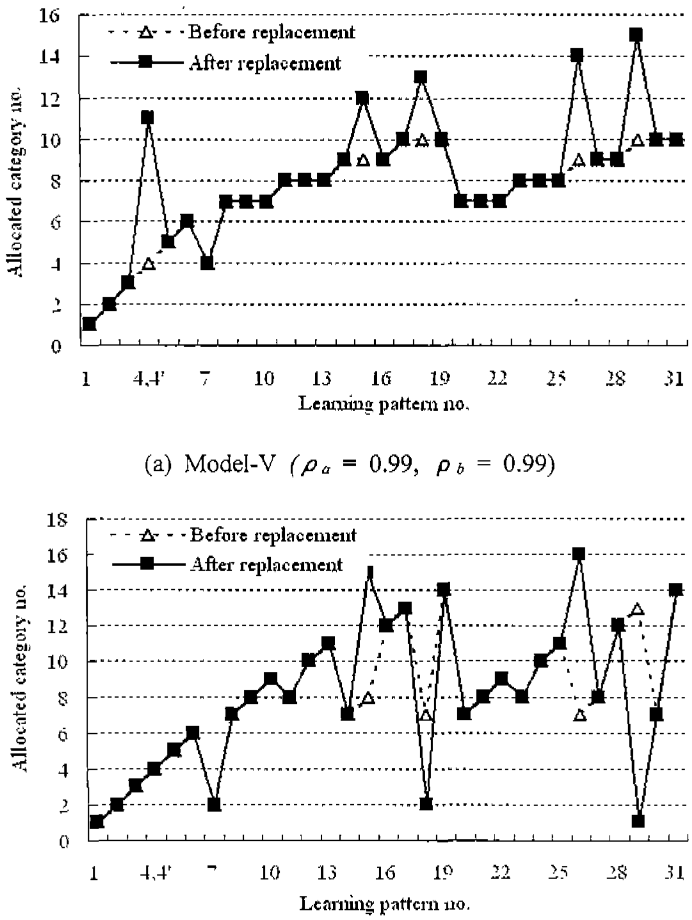
(a) Model-V (ρ_a = 0.99, ρ_b = 0.99)

Pattern no.	Allocated categories (Before the replacement)	Pattern no.	Allocated categories (After the replacement)	Notes
4	4	4'	11	N
15	9	15'	12	N
18	10	18'	13	N
26	9	26'	14	N
29	10	29'	15	N

(b) Model-f (ρ_a = 0.99, ρ_b =0.99)

Pattern no.	Allocated categories (Before the replacement)	Pattern no.	Allocated categories (After the replacement)	Notes
4	4	4'	4	E
15	8	15'	15	N
18	7	18'	2	E
26	7	26'	16	N
29	13	29'	1	E

N, E : Assignment to new and existing categories respectively



(a) Model-V (ρ_a = 0.99, ρ_b = 0.99)

(b) Model-f (ρ_a = 0.99, ρ_b = 0.99)

Figure 5. Categories allocated in an application of the replacement algorithm.

The results of the on-line and off-line learning of the fuzzy ARTMAP neural network show that mean or max. test errors (%) are in acceptable error boundaries for V and f respectively, and by the proposed algorithm, the previously learned information - weights, categories, etc. - of the network on the cutting conditions is replaced to the new ones.

6. Conclusion

In this paper, a new methodology that enables the model of generating cutting conditions to be enhanced while the system is in continual use has been proposed; EVOLS

(EVOlutionary Learning System of cutting conditions) for milling processes was developed and integrated in an operation planning system. Through the experimental run, it was verified that the necessary part of the model was replaced and improved during its use without time consuming re-training of the back-propagation neural network.

Although this methodology has been applied only to milling operations in this work, it also can be applied to turning operations with a little modification on the fuzzy ARTMAP input parameters. Furthermore, the proposed methodology can be adopted in other software systems, which make decisions based on knowledge represented by numerical or literal values.

References

[1] ElMaragy, H.;""Evolution and Future Perspectives of CAPP", *Annals of the CIRP*, 42(2), pp.739-751, 1993.

[2] Kim Y. S., and Wilde D. J.; "A convergent convex decomposition of polyhedral objects", *ASME J. Mech. Des.*, 114, pp. 468-476, 1992..

[3] Waco D. L., and Kim Y. S.; "Geometric reasoning for machining features using convex decomposition", *Computer-Aided Design*, 26(6), pp. 477-489, 1994.

[4] Bhaskara Reddy S. V., Shunmugam M. S., and Narendran T. T. ; "Operation sequencing in CAPP using genetic algorithms", *International Journal of Production Research*, 37(5), pp. 1063-1074, 1999.

[5] Barkocy, B. E., and Zdeblick, W.J. ; "A Knowledge-Based System for Machining Operation Processing", *Autofact 6 Conf. Proceedings*, Anaheim, CA, pp. 2-11, 1984.

[6] Gupta R., Batra J. L., and Lal G. K., "Determination of optimal subdivision of depth of cut in multipass turning with constraints", *International Journal of Production Research*, 33(9), pp. 2555-2565, 1995.

[7] Kee P. K., "Development of constraint optimisation analysis and strategies for multi-pass rough turning operations", *Int. J. Mach. Tools Manufact.*, 36(1), pp. 115-127, 1996.

[8] Van Houten, M. and Vant Erve, H. ; "PART:A CAPP System with a Flexible Architecture", *Proc. of CIRP Int. Work Shop on CAPP*, pp.57-69, 1989.

[9] Park, M. W., Rho, H. M. and Park, B. T. ; "Generation of Modified Cutting Condition Using Neural Network for an Operation Planning System", *Annals of the CIRP*, 45(1), pp.475-478, 1996.

[10] Carpenter, A., et. al.. ; "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps", *IEEE Transactions on Neural Networks*, 3(5), pp.698-713, 1992.

[11] Machinability Data Center ; Machining Data Handbook, Metcut Research Associates Inc., 1986.

[12] Tolouei-Rad, M. and Bidhendi, I.; "On the Optimization of Machining Parameters for Milling Operations", *Int. J. Mach. Tools. & Manufact.*, 37(1), pp.1-16, 1997.