An Integrated CAD-CAPP-CAM System for Machining Mold Die With Optimal Cutting Parameters

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Abstract **– The main purpose of this paper was to integrate CAD-CAPP-CAD system with optimizing cutting parameters for machining mold die. Due to the complexity of the machining process injection mold, its optimization as well as its optimal control is difficult to perform. Optimization of the cutting process needs efficient means for determining the optimal cutting parameters in order to minimize machining time and simultaneously preserve the quality of machining surface. With the recent development in CAD/CAM software, manufacturing engineers can proceed with the process planning problems, without knowing functional relationship between process input and process output in advance. In this study, the machining simulation in CATIA is used to obtain the results as initial inputs of optimal analysis. The Response Surface Methodology (RSM) is used to analyze the cutting parameters such as cutting speed, feedrate, radial and axial depth of cut, and machining tolerance. Then this process will be integrated into process chain system that we have developed in the previous research.**

I. INTRODUCTION

In the worldwide market for the injection die/mold, many large companies have attempted to introduce flexible manufacturing systems as their strategy to adapt to the ever-changing competitive market requirements. Normally, the design of die/mold requests many complex surfaces and the quality of manufactured surface. To ensure the quality of machining surface, to reduce the machining costs and increase the machining effectiveness, it is very important to select the machining parameters in CNC machining. The quality of products manufactured by injection molding process is highly influenced by that of mold surfaces obtained from selecting optimal machining parameters such as cutting speed, feedrate, radial and axial depth of cut, machining tolerance, and surface roughness. The optimization of these parameters is the key component in the planning of machining processes.

For optimization of machining parameters, the quantitative methods have been developed with consideration of a single object only, such as minimization of cost, maximization of production rate, or maximization of profit, etc. Several different techniques have been proposed for the process of the single objective optimization, such as the differential calculus, regression analysis, linear programming, geometric and stochastic programming, neural network, etc. In addition, it is also known that cutting time and tool life affects the cost and the quality of machining product. Most of recent studies in optimization of cutting parameters have concentrated on developing exact methods to solve above problems. Normally, we usually assume that the equations (such as equation of cutting time, tool life, surface roughness, etc.) describing relative machining parameters are known before a problem is analyzed. However, these equations are established in his experiment and usually are unknown during the early stage of process planning.

In some of previous researches [5, 7, 8], the relative problems are considered in isolate aspects and some of traditional optimization methods are successful in locating the optimal solution, but they are usually slow in convergence and require much computing time. These usually cannot ensure that machining parameter values are actually optimal values.

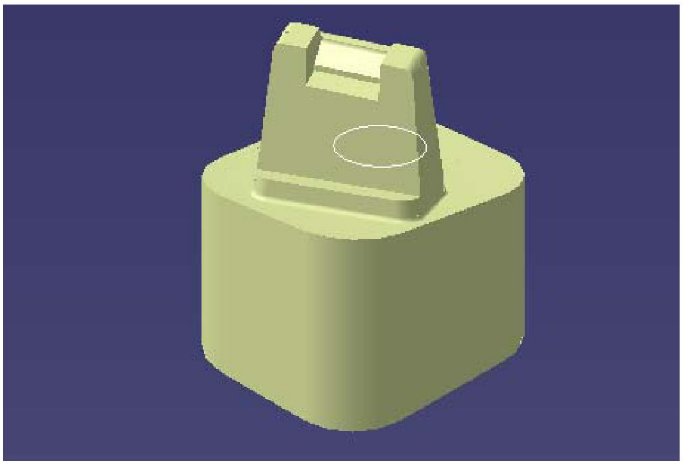

Fig.1. The experiment model of mold part

In this study, we used machining simulation functions of CATIA R16 for predicting cutting parameters in milling the part of injection mold (Fig. 1). Cutting condition is represented with cutting parameters of cutting speed, feedrate, axial and radial depth of cut, and machining tolerance. The cutting parameters used as input values of machining simulation are

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taken from recommendation of Han-Gook Mold Company, manufacturing handbooks, and previous experiences. The outputs of machining simulation then are analyzed by Response Surface Methodology (RSM) to obtain the relative equations of cutting time and surface roughness. Finally, these equations are substituted into objective function for finding the optimal cutting parameters. It is easy to find out optimal values through some of normal optimization technologies.

The whole works integrated into the process chain: "Design-Planning-Manufacturing" that we have developed in the previous researches [6].

II. Background and Experiment Procedures

A. RSM and Experiment Preparation

RSM is a collection of statistical and mathematical methods that are useful for the modeling and analyzing engineering problems. In this technique, the main objective is to optimize the response surface that is influenced by various process parameters. It uses approximations of the objective and constraint functions. The approximations are based on functional evaluations at selected points in the design space. The approximations are constructed using polynomial functions and generally, a polynomial of any order can be used. RSM also quantifies the relationship between the controllable input parameters and the obtained response surfaces. However, in order to keep the number of evaluations reasonably low linear functions are usually used. To fit a linear function, at least (n+1) function evaluations are required, where n is the number of design parameters. To achieve a more accurate approximation, an over sampling of 50% or more is recommended [1].

An important stage of RS Model generation by RSM is the planning of experiments and the selection of order of polynomial that is used to analyze the response surfaces of model. In this study, we will predict the cutting conditions based on considering five cutting parameters: cutting speed (v, rpm), feedrate (f, mm/min), axial depth of cut (a_a, mm), radial depth of cut (a_r, mm) and machining tolerance (m_t, mm). Our target is the reduction of surface roughness for machining mold dies and minimum of machining time.

The quality of products manufactured by injection molding process is highly influenced by that of mold surfaces obtained from the milling process. In milling operations, the theoretical surface roughness is generally dependent on the cutting tool geometry, the tool material, the work-piece geometry, the work-piece material, the cutting conditions, the cutter run-out, the model of milling, the machine-tool rigidity, etc. For a particular work-tool geometry, the surface roughness in milling is assumed to be a function of cutting speed v, feed-rate f, and axial depth of cut a_a [3]. However, in this study, we consider the surface roughness as a function influenced on cutting conditions (v, f, a_a, a_r, m_t). Surface quality of these products is generally associated with surface roughness and can be determined by measuring surface roughness.

For cutting time, the surface roughness R_a vs. cutting time T_c curve was found to have the same general shape as the conventional wear land (w vs. T_c) curve which starting with a rapid increase in R_a for the first three to ten minutes and followed by a more gradual increase in R_a with T_c [3]. In this study, we use machining simulation function of CATIA R16 to take cutting time values and consider cutting time as a function of cutting parameters.

B. Plan and Condition of Experiments

A well-designed experiment can reduce substantially the number of experiments required. Several types of experimental designs have been performed in several of previous researches. In this study, the Central Composite Design (CCD) has been used. This design consists of fifty-three runs and provides five factors with respect to five cutting parameters as five independent variables (v, f, a_a, a_r, m_t). Initially, an experiment is performed through machining simulation function of CATIA R16. Then, the part model is machined by five-axis CNC machine (DMU 60 TS) in semi-finishing process. Low-middle-high levels of cutting parameters for the CCD are shown in TABLE I.

TABLE I
VALUE LEVELS OF CUTTING PARAMETERS

Cutting parameters	Value levels		
	Low	Middle	High
v: cutting speed (rpm)	1000	3000	5000
f: feedrate ($mm.min^{-1}$)	300	600	900
$\mathbf{a_a}$: axial depth of cut (mm)	0.3	0.6	0.9
$\mathbf{a_r}$: axial depth of cut (mm)	1	1.5	2
$\mathbf{m_t}$: machining tolerance (mm)	0.001	0.0055	0.01

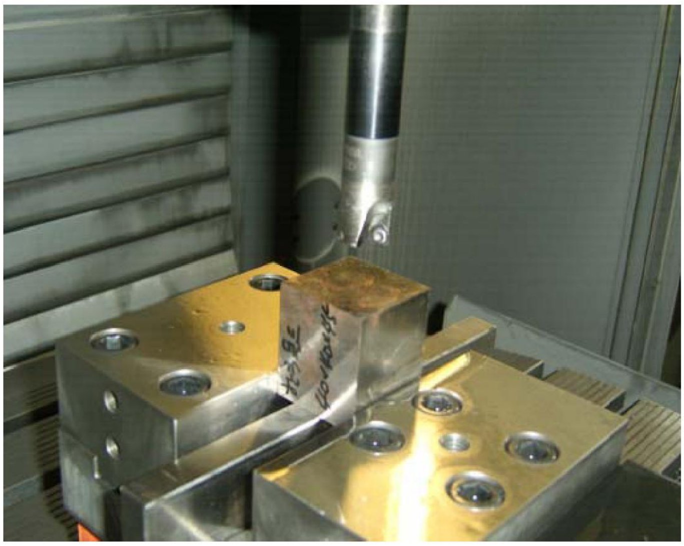

Fig. 2. Setting work-piece on machine table

Ranges of cutting parameters are selected based on machine documentation (Project #403831, Machine #1150000213). Machining material made of steel (C45E4) with the chemical composition: 0.42-0.48 C, 0.15-0.35 Si, 0.60-0.90 Mn, -0.030 P, -0.035 S and typical mechanical properties in TABLE II. The dimensions of work-piece are a cubic block of 40mm x 40mm x 45mm. It is machined on five-axis CNC machine of DECKEL MAHO DMU 60 TS and controller of HEIDENHAI iTNC 530 with the determined cutting conditions. The cutting tool using for machining experiment is MITSUBISHI Φ21 FLAT QOMT 1035R-M2 VP15TF. The finished product is tested surface roughness.

TABLE II
TYPICAL MECHANICAL PROPERTIES OF C45E4

Condition	Tensile Strength Mpa	Yield Strength Mpa	Elongation In 50mm %	Hardness Brinell HB
Hot Roll	570 - 700	300 - 450	14-30	170-210
Normalization	640	610	22	187

C. *Experimental Design*

The experiment was designed based on a five level factorial central composite design (CCD) with full replication. Each numeric factor is varied over five levels: plus and minus alpha (axial points), plus and minus 1 (factorial points) and center points. They include 8 center points and 42 outer points through 53 times of runs. The value levels for CCD are shown in TABLE I. In this design, we have used second-order approximating function that it can be expressed as Eq. (1). The model of Eq. (1) is the second-order response surface model [1, 2]. It is an interesting and widely usable model to describe experimental data in which system curvature is readily abundant. We do not mean to imply here that all systems containing curvature are well accommodated by this model.

$$\begin{aligned}\hat{y} = {} & \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \beta_{11} x_1^2 + \ldots + \beta_{kk} x_k^2 \\ & + \beta_{12} x_1 x_2 + \beta_{12} x_1 x_3 + \ldots + \beta_{k-1,k} x_{k-1} x_k\end{aligned} \quad (1)$$

The data set for CCD and accompanied response values are given as TABLE III.

TABLE III
DATA SET FOR CENTRAL COMPOSITE DESIGN

Std	Run	Block	v	f	a_a	a_r	m_t	T_c	R_a
14	1	1	3840.896	473.8655	0.726134	1.710224	0.003608	537	1.00825
33	2	1	3000	600	0.6	1.5	0.0055	465	1.09533
20	3	1	3840.896	726.1345	0.473866	1.289776	0.007392	450	0.903545
1	4	1	2159.104	473.8655	0.473866	1.289776	0.003608	665	0.827362
25	5	1	2159.104	473.8655	0.473866	1.710224	0.007392	523	0.827362
...	...	...	...	...	...	...	...	...	...
53	48	5	3000	600	0.6	1.5	0.0055	512	1.09533
46	49	5	3000	600	0.9	1.5	0.0055	512	1.643
44	50	5	3000	900	0.6	1.5	0.0055	378	1.48047
43	51	5	3000	300	0.6	1.5	0.0055	922	0.654411
50	52	5	3000	600	0.6	1.5	0.01	499	1.09533
41	53	5	1000	600	0.6	1.5	0.0055	391	1.6955

III. ANALYSIS OF RESULTS AND DISCUSSION

The second-order model of machining time and surface roughness were developed by utilizing the least-squares method [1, 2]. Using fifty-three runs and five blocks, the parameters in Eq. (1) were estimated, yielding the machining time and surface roughness predicting equation as

$$\begin{aligned}\hat{y}_{T_c} = {} & 451.21 + 14.67 x_1 - 96.02 x_2 - 48.17 x_4 \\ & - 11.70 x_5 + 20.41 x_2 x_4 - 12.72 x_2 x_5 \\ & + 30.15 x_2^2 + 24.23 x_4^2 + 10.88 x_5^2\end{aligned} \quad (2)$$

$$\begin{aligned}\hat{y}_{R_a} = {} & 1.11 - 0.14 x_1 + 0.18 x_2 + 0.23 x_3 - 0.02 x_1 x_2 \\ & - 0.027 x_1 x_3 + 0.037 x_2 x_3 + 0.031 x_1^2 - 0.0088 x_2^2\end{aligned} \quad (3)$$

The mathematical models furnished above can be used to predict machining conditions. Fig. 3 is contours for each of the response surfaces plotted from equations (2) and (3). From left graph in Fig. 3, it is possible to select a combination of feedrate and cutting speed that reduce the machining time without increasing the surface roughness. We can see that the machining time decreases as both the cutting speed and feedrate increase. However, the rate of decrease of machining time with increase of cutting speed is more than of feedrate. Hence, in order to reduce machining time, the cutting speed and feedrate should be as high as possible. From the contours shown in right graph of Fig. 3, an increase in either the feedrate or the axial depth of cut increases the surface roughness, whilst an increase in the cutting spread decreases the surface roughness. The analysis of variance (ANOVA) was used to check the adequacy of the second-order model.

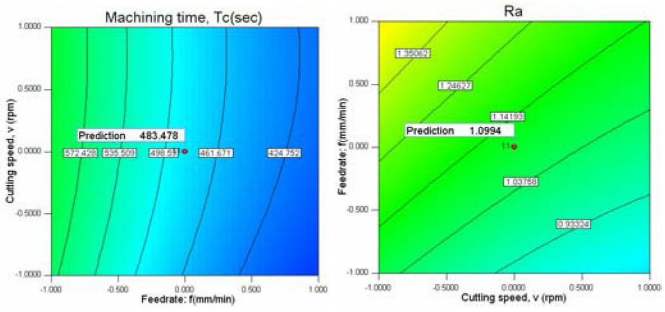

Fig.3. Cutting time contours and surface roughness contours.

The results of variant analysis (ANOVA) for the second-order model were shown in TABLE IV and TABLE V. For ANOVA for response surface of surface roughness (machining time), it is seen that the predicted R-Squared value of 0.978091 (0.8469) is in reasonable agreement with the adjusted R-Squared value of 0.99095 (0.9179). The adequate precision measures the signal to noise ratio. It compares the range of the predicted values at the design points to the average prediction error. Ratios which are greater than 4 indicate adequate model discrimination. Our ratio of 82.32902 (30.932) indicates an adequate signal. The second-order effect of speed, feedrate, radial depth of cut, axial depth of cut, and machining tolerance is significant.

The precision of these quantities has been estimated by calculating confidence intervals on machining time or surface roughness and comparing them to experimental values. The confidence intervals for the predicted response are given by ($\hat{y} \pm \Delta\hat{y}$). The $\Delta\hat{y}$ values for the predicted models are given in TABLE VI. The 99% confidence intervals for the $\hat{y}$ values were found to be quite satisfactory when compared with the corresponding experimental values. Hence, models were found to be fully adequate to present the relationships between the responses and investigated independent variables.

TABLE IV
ANOVA FOR RESPONSE SURFACE OF MACHINING TIME

Std. Dev.	33.76654	R-Squared	0.933301
Mean	506.0377	Adj R-Squared	0.917909
C.V. %	6.672733	Pred R-Squared	0.846929
PRESS	102049.8	Adeq Precision	30.93183

TABLE V
ANOVA FOR RESPONSE SURFACE OF SURFACE ROUGHNESS

Std. Dev.	0.029746	R-Squared	0.992459
Mean	1.117956	Adj R-Squared	0.99095
C.V. %	2.660707	Pred R-Squared	0.978091
PRESS	0.102819	Adeq Precision	82.32902

Finally, optimization of one response or the simultaneous optimization of multiple responses can be performed graphically or numerically. In this study, we use numerical optimization algorithm. Our goal is to desire surface roughness and machining time to be as low as possible. Low surface roughness and machining time values can be achieved efficiently by adjusting cutting conditions with the help of numerical optimization method.

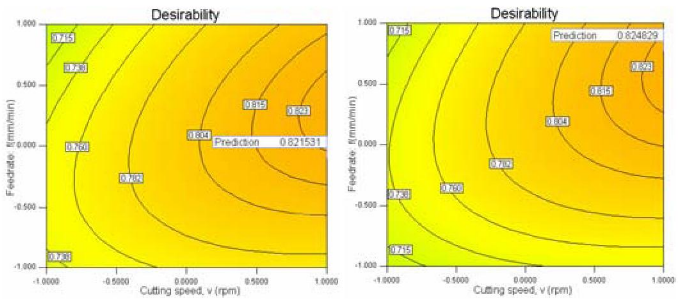

Fig.4. Optimization contours of one response.

For these, our problem is to find cutting parameters (v, f, a_r, a_a, m_t) with surface roughness and machining time as low as possible (i.e. objective function is minimum, constrain conditions in Table I). Finding an initial feasible region can be difficult. We start with a small value of a penalty function in a downhill simplex (Nelder-Mead) multi-dimensional pattern search [2] which converges at either a stationary point or a design space boundary. Limits of the design space are maintained by evaluating the f(X) to +1010 at the design boundaries. The search around the initial convergence point is restarted using a larger penalty function. Convergence is achieved when the distance moved or objective function change is less than a 10^{-6} ratio. The surface roughness value is searched within ranges (0.547666, 1.741) and machining time value within ranges (353, 922). Results are graphed in Fig. 4 and some of optimal cutting parameters are shown in Table VI.

TABLE VI
SOME OF OPTIMAL CUTTING PARAMETERS

No	v	f	a_a	a_r	m_t	T_c	R_a
5	3840.5	641.1	0.473	1.63	0.0065	415.9	0.824
6	3840.8	645.1	0.473	1.64	0.0061	414.8	0.827
10	3652.5	611.8	0.474	1.71	0.0066	428.0	0.810
12	3566.5	643.3	0.474	1.65	0.0073	409.0	0.847
13	3763.6	676.2	0.474	1.60	0.0059	402.4	0.860
14	3840.8	603.4	0.479	1.70	0.0074	438.7	0.798
15	3699.5	693.9	0.476	1.71	0.0065	391.5	0.885
16	3840.8	643.5	0.480	1.62	0.0055	420.1	0.837
18	3359.4	652.2	0.474	1.63	0.0074	401.0	0.876
19	3840.8	626.4	0.474	1.71	0.0045	438.4	0.810

V. CONCLUSIONS

In this study, CCD with five levels of factors can be employed easily for developing mathematical models for predicting cutting parameters. Response surface of roughness and cutting time can be used effectively in analyzing the relationship and the effect of machining conditions on response. The optimal cutting parameters are established in table for usefulness of selecting parameters in machining process.

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