An Integrated Approach To Determine Near Optimal Conditions for a Two-Stage CNC Grinding Processes

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Abstract :

Two-stage grinding processes are usually too complex to optimize, due to large number of interacting process variables. The objective of this study is to apply empirical modelling technique for prediction of a two-stage computer numeric-controlled (CNC) grinding process behaviour, and determine overall near-optimal strategy to meet the desired process requirements. In order to achieve the above objective, the study proposes an integrated approach using multivariate regression, desirability function, and real-coded genetic algorithm. The integrated approach offers applicability to broad range of other metal-cutting process problems.

Keyword Desirability Function; Real-Coded Genetic Algorithm; Two-Stage Grinding; Honing; Multivariate Regression

Notations

$P_{(i)}$: number of response characteristics considered at any i-th stage, for i=(1, 2)

$X_{I\,(i-1)}$: input variables at any i-th stage, which is output(s)/response(s) of (i-1)-th stage, for i=(1, 2)

$X_{P\,(i)}$: in-process parameters at any i-th stage, for i=(1,2)

$X_{(i)}$: complete set of input state space at any i-th stage, consisting of $X_{I(i-1)}$ and $X_{p(i)}$, for i=(1,2)

$d_{j\,(i)}$: individual desirability measure of j-th response characteristic for i-th stage of operation, based on g_c function, for j=(1,....., $p_{(i)}$) and i=(1,2)

$\lambda_{(i)}$: composite desirability measure for i-th stage, based $d_{j(i)}$ on values m_c and function, for j =1,...., $P_{(i)}$ and i=(1,2)

$\hat{y}_{i(j)}$: predicted j-th response after any i-th process stage based on empirical model function, for j =(1....,$P_{(i)}$) and i=(1,2)

1. Introduction

Grinding being a primary manufacturing operation has been considered to be an accurate and economical means of shaping the parts into the final products with required surface finish and high dimensional accuracy. However, because of the inherent complexities of the grinding processes, its modelling and optimization still remains one of the most critical and difficult task for researchers and practitioners (Luong and Spedding, 1995; Shin and Vishnupad,1996).

Several techniques of modelling and optimization technique in grinding process parameter optimization problems has been reported in the literature. Shin and Vishnupad (1996) provide an intelligent grinding process control scheme based on neuro-fuzzy optimization approach. Lee and Shin (2000) combine

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fuzzy set theory and evolutionary stategy algorithm for optimization of grinding processes. Saravanan and Sachithanandam (2001) claims the superiority of genetic algorithm over quadratic programming approach in a surface grinding process. Mitra and Gopinath (2004) apply a nondominated sorted genetic algorithm for a multiobjective optimization problem. Kwak (2005) propose a second order response surface model for determining the setting of process parameters for minimization of part reponse characteristics.

The modelling and optimization of grinding processes remain as a challenging problems in manufacturing industry mainly because of the following reasons:

a) Unlike in many other conventional machining processes where cutting is performed by a defined cutting edge, grinding is performed by a number of abrasive particles which are randomly oriented in a grinding stone. Therefore, it is not possible to maintain close surface finish or control dimensional accuracy of hard particles which affect the cutting process (Chen and Kumara, 1998),

b) Despite the extensive development in process control theory, conventional control techniques still fall short of providing effective control means for complex grinding processes (Shin and Vishnupad,1996).

Moreover, search for exact optimal path condition by sequential experimentations, using conventional design of experiment approach in a mass-scale multiple stage production process are difficult, if not impossible, as the whole production process can be disrupted for off-line experimentations. In view of the above mentioned conditional requirements in grinding processes, optimization problem often becomes a discrete, multi-dimensional, and multi-modal distribution of response characteristics. It is in this sprit, that it is proposed to integrate appropiate multivariate regression (Rencher, 1995), desirability functions (Derringer and Suich, 1980), "minimum" operator composite desirability function (Kim and Lin, 2000), and a real-coded genetic algorithm (RGA)[Haupt and Haupt, 1998], to determine overall near-optimal conditions for a two-stage grinding (honing) processes. The application of these techniques is determined based on data analysis of a two-stage 6-cylinder engine liner honing processes in an leading automotive manufacturing unit in India.

2. Case Study

This section demonstrates the integrated approach using a case, which is undertaken to determine near-optimal solutions for a two-stage grinding (honing) process.

2.1 Introductions and Background

A typical two-stage honing processes with its inputs, in-process parameters, and reponses is shown in **Figure1**, wherein each stage represents one type of honing machine.

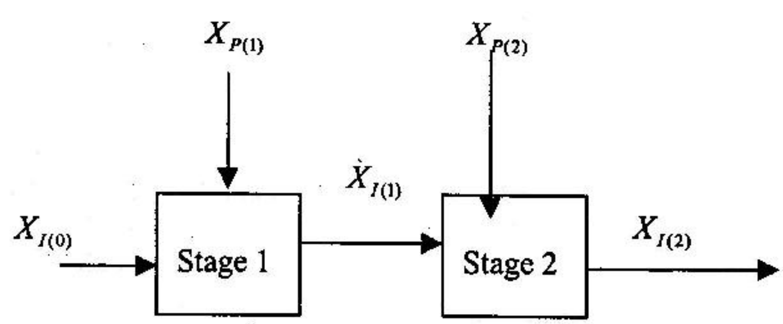


Figure1. Schematic diagram of a two-stage honing process and relationship(s) between inputs, in-process parameters and responses

A typical problem in two-stage part or component development by honing processes involve the selection of a set of inputs and in-process parameter conditions (X) at each stage, such that the desirable combination of response quality properties (Y), is achieved at the final stage. The desired combination of response properties can be said as a measure of the degree of customer satisfaction (Kim and Lin, 2000). The empirical response surface model at each stage may be of different dimension, form or degree, and there may be numerous practical process and/or variable constraints for the underlying problem. The attempt to deal with such problem recourses to the integrated approach, and is the focus here.

In this study, the honing operations on engine liner bores of a typical 6-cylinder diesel engine are considered. The grinding operations are carried out in two consecutive stages: rough and finish honing processes. The rough honing operation is a computer numeric-controlled (CNC), bore diameter sensor-based (air sensor) and hydraulic oil pressure-based single pass machining process. The finish honing is a numeric-controlled, two-pass (rough and finish) hydraulic oil pressure-based machining operation.

In particular the objective is to determine the optimal levels of nine in-process parameters at the rough honing stage [viz. hydraulic oil temperature $x_{1(1)}$, cutting oil temperature $x_{1(2)}$, sensor air pressure $x_{1(3)}$, sensor-based air filter pressure $x_{1(4)}$, rough honing time $x_{1(5)}$, air sensor-based honing stone zero-setting correction $x_{1(6)}$, air sensor-based honing stone cutting correction $x_{1(7)}$, and dog-length $x_{1(8)}$], the levels of three input variables[viz. average input liner bore diameter $x_{1(9)}$, maximum input liner bore ovality $x_{1(10)}$ and maximum input liner bore taper $x_{1(11)}$], and the levels of seven in-process parameters at the two-pass finish honing stage[viz. rough pass hydraulic pressure $x_{2(1)}$, finish pass hydraulic pressure $x_{2(2)}$, rough pass honing time $x_{2(3)}$, rough pass honing time $x_{2(4)}$, cutting oil temperature $x_{2(5)}$, vertical stroke speed $x_{2(6)}$, and dog-length $x_{2(7)}$], such that the degree of customer satisfaction in relation to five specific response characteristics[viz. average surface finish ($y_{2(1)}$), average cross hatch angle or honing angle ($y_{2(2)}$), average finish liner bore diameter ($y_{2(3)}$), maximum finish liner bore ovality ($y_{2(4)}$) and maximum finish liner bore diameter taper ($y_{2(5)}$)], at the final stage of process is optimized.

2.2 Problem Formulation

For the formulation of the problem, the following assumptions are used:

1. Each honing process is considered to be stable.
2. X (input conditions) and Y (responses) follow multivariate normal distribution at each stage.
3. Error vectors of the empirical model as developed are random and uncorrelated with one another.

2.2.1 Determination of Objective Function

The problem may be mathematically stated as

$$\underset{X}{Maximize}\ \lambda_{(2)} \tag{1}$$

subject to:

$$\lambda_{(i)} \geq \lambda_{iD}, \tag{2}$$

$$\mathrm{X}_{I(0)\min} \leq \mathrm{X}_{I(0)} \leq \mathrm{X}_{I(0)\max} \tag{3}$$

$$\mathrm{X}_{P(1)\min} \leq \mathrm{X}_{P(1)} \leq \mathrm{X}_{P(1)\max} \tag{4}$$

$$\mathrm{X}_{P(2)\min} \leq \mathrm{X}_{P(2)} \leq \mathrm{X}_{P(2)\max} \tag{5}$$

where, equation (2) represents process constraint/requirement, equations (3) and (4) can be said as primary state space zone or initial stage state space bound. Equation (5) may be said as the auxiliary state space zone or in-process parameter state space bounds of final process stage. $\mathrm{X}_{I(0)\min}$ and $\mathrm{X}_{I(0)\max}$ are the minimum and maximum bounds of initial stage input variables, respectively. $\mathrm{X}_{P(1)\min}$ and $\mathrm{X}_{P(1)\max}$ are the minimum and maximum bounds of initial stage in-process variables, respectively, $\mathrm{X}_{P(2)\min}$, $\mathrm{X}_{P(2)\max}$ are the minimum and maximum bounds of the final stage state space, respectively. λ_{1D} is the user-specified first stage acceptable degree of customer satisfaction.

2.3 Empirical Models Development

Once the input variables, in-process parameters and responses of the honing process are identified at each stage, pertinent and reliable online production data are collected through direct observation, discussion with the concerned personnel, reference to the relevant documents and standard operating practices of the manufacturing unit. The data were collected during the period of 2004-2005 in two-stage honing processes (Nagel-make and Gehring-make) required for diesel engine cylinder blocks, which are used for commercial heavy utility vehicles. Periodic calibration and maintenance of the gauges and measuring instrument during data collection ensure accuracy, precision and minimum measurement error.

The multivariate models developed at each distinct stage of the honing process are based on random x-case modelling technique (Rencher, 1995). The final empirical models as developed and cross-validated are found to be adequate based on various test statistic. The overall test of regression is given below:

2.3.1 *Test of Overall Regression*

Considering the null hypothesis that none of the input conditions predict any of the responses at any particular stage, may be mathematically expressed as

$H_0: \hat{B}_{1s} = O$ and the alternate hypothesis is

$H_1: \hat{B}_{1s} \neq O$

where, $\hat{B}_s$ is expressed as

$$\hat{B}_s = \begin{pmatrix} \hat{B}_{0s} \\ \hat{B}_{1s} \end{pmatrix} \tag{43}$$

The four different test statistic selected for this study to test the null hypothesis are, Wilky's Λ_w, Roy's θ_R, Pillai's V_P, and Lawley-Hotelling's U_{LW} test statistic, respectively (Rencher, 1995). When H_0 is true, all four-test statistics have a probability, α (assumed 0.05) of rejecting H_0. The results as obtained for both the stages are provided in **Table 1.** The results confirms the model adequacy at each stage.

Table 1 Test Statistic Values for Overall Regression

Stage wise Mode	Test Statistic									
	Wilky's Λ_w		Roy's θ_R		F-approximation of Pillai's V_P				Lawley-Hotelling's U_{LH}	
					F_2		F_3			
	Calc[b]	Tab[c]	Calc[b]	Tab[c]	Calc[b]	Tab[c]	Calc[b]	Tab[c]	Calc[b]	Tab[c]
Rough Honing	.5296[a]	0.7776	0.282[a]	0.1392	3.7212[a]	1.5977	3.8885[a]	1.6288	12.2801[a]	4.4835
Finish Honing	.0935[a]	0.6581	0.6727[a]	0.1576	8.8901[a]	1.4518	9.1343[a]	1.4852	70.2125[a]	6.9221

[a] Significant at 95% Confidence level [b] Calculated Value [c] Tabulated Value

2.4 Determination of Near-Optimal Solutions

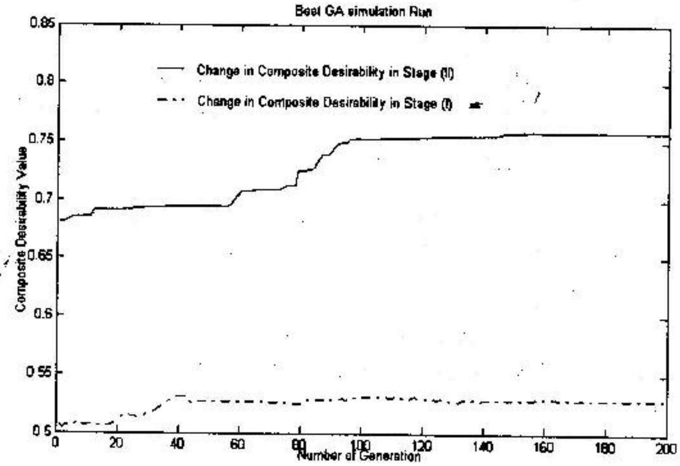
Based on the multivariate model functions developed at each stage of honing processes, near-optimal solutions are determined, based on RGA (Haupt and Haupt, 1998). In case of RGA, search conditions such as population size of 200, blending method crossover, and mutation at a rate of 4% (or $\mu = 0.04$) is selected. The termination condition selected for the RGA is 200 maximum number of generation.

During all the computational runs, search space of $X_{1(0)}$ $X_{p(1)}$; and $X_{p(2)}$ are restricted to bounds/ constraints conditions. Also in this study, the initial stage acceptable degree of customer satisfaction is selected as 0.5 (or λ_{1D} =0.5). The value of 0.5 is a reasonable and accepted value of degree of customer satisfaction (Kim and Lin, 2000), and has a basic physical interpretation. A summary statistics of maximum $\lambda_{(2)}$ value, corresponding , average computational times based on 30 consecutive computational run, is provided in Table 2. All the computational runs are executed in a single specific personal computer, having basic configuration as Intel Pentium (IV) processor, 1.8 GHz CPU, compatible to 256 MB RAM, and Matlab 6.5 programming environment.

Table 2 Summary statistics of near-optimal solutions based on 30 consecutive runs of RGA selected

Metaheuristic Techniques	Near-optimal $\lambda_{(2)}$ value attained at stage-II	Corresponding $\lambda_{(1)}$ value at the initial stage-I	**Average CPU time (in seconds)**
RGA	0.7584	0.5282	104.4218

Figure 2 illustrates the progress of search for the highest $\lambda_{(2)}$ value obtained and its corresponding $\lambda_{(1)}$ value as obtained by the RGA.



The results show an acceptable degree of customer satisfaction measure at stage-II, along with ensuring a satisfactory $\lambda_{(1)}$ value (as $\lambda_{(1)}$ must be $\geq$ 0.5) at stage-I. The corresponding input setting conditions and predicted responses ($\hat{y}_{i(j)}$) at each stage can be easily obtained, according to $\lambda_{(2)}$ and corresponding $\lambda_{(1)}$ value selected.

3. Concluding Remarks

In this paper, acceptable near-optimal process conditions for a two-stage honing have been determined numerically, using an integrated approach of multivariate regression models, desirability functions, "minimum" operator composite desirability function, and real-coded genetic algorithm. The approach can be easily adopted for different types of multivariate empirical modelling techniques, such as non-linear regression, artificial neural network, and fuzzy set approach. Further investigation on performance of real-coded genetic algorithm and influence of model complexity on solution quality, using nonlinear multivariate models and artificial neural network, at each stage of grinding is presently under investigation of the authors. The integrated approach can also be easily extended to other metal-cutting problems, such as boring, turning and milling.

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