DEVELOPMENT OF AN INNOVATIVE NEURAL NETWORK MODEL FOR MILLING BASED ON A SYSTEMATIC APPROACH FOR STATISTICAL DESIGN OF EXPERIMENTS

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Thesis Presentation

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Purdue School of Engineering & Technology, IUPUI

April 13th, 2007
Outline

- Problem Definition
- Previous Work
- Current Work
  - Overview
  - Experiments
  - More general ANN model for end milling
  - New DOE technique for optimal data collection/sets
  - Systematic approach for optimizing process modeling
- Results
- Conclusions and Future Research
Problem Definition

- The End Milling Operation
  - Process
  - Cutting Conditions & Process Parameters
  - Usability

- Goal
  - Comprehensive
  - Efficient
  - Inexpensive
  - Practical
Previous Work

- Traditional vs. Non-Traditional Techniques

  Mathematical/Analytical models:
  - Kline [1]: Predicted cutting forces and cutter/workpiece deflection
  - Sutherland [2]: Determined chip load for surface error prediction

  ANN:
  - Elanayar [3]: Predicted surface roughness
  - El-Mounayri [4]: Predicted cutting forces using feed, speed and axial depth of cut

- Generality: Cutting Conditions & Process Parameters

  - Oktem [5]: Predicted surface roughness using cut. speed, and ADC and RDC
Previous Work

- **Training and Collection of Data**
  - Optimization
  - Lack of systematic approach

- Oktem [5] used a full factorial DOE to study the effects of cutting parameters on AL end milling
- Ghani [6] performed a three factor full factorial to minimize cutting forces and surface roughness
- Baris [7] investigated the impact of cutting parameters on surface finish using fractional factorial
Overview

Experimental Setup

Data Collection

Optimum Data Set

Training

Validation

Optimization of Cutting Parameters

OE HGL

Systematic Approach

Input Parameters
- Tool Diameter
- Axial Depth of Cut
- Radial Depth of Cut
- Feed per tooth
- Cutting Speed

F & Ra Process Model

Trained ANN
Overview - Summary

- Efficient application of BP ANN to model End Milling
- Unique Cutting Force and Surface Roughness Model
- Simulation of Cutting Force Components
- Implementation of Fractional Factorial DOE
- Development of a Systematic Approach based on reliability to train the ANN Model
Experiments

Experimental Setup for Cutting Force Measurement

3-Component Force Dynamometer

Shielded Connecting cable

LabVIEW Application

Charge Amplifier

PC
Experiments Cont’

Surface Profile Measurement

Chromatic Sensor
Res. 0.1 µm

Non contact Profilometer:
Proscan 2000

Measurement of Surface Profile
at two levels

L1
L2
Overview

Experimental Setup

Data Collection

Optimum Data Set

Training

Validation

Optimization of Cutting Parameters

Trained ANN

DOE HGL

Systematic Approach

Input Parameters
- Tool Diameter
- Axial Depth of Cut
- Radial Depth of Cut
- Feed per tooth
- Cutting Speed

F & Ra Process Model

Process Model

Overview
Experiments Cont’

Cutting Experiments

Control Factors
1. Tool diameter
2. Radial depth of cut
3. Axial depth of cut
4. Feed per tooth
5. Cutting speed

System Responses
1. Cutting Forces
2. Surface Profiles

Material
AL-7075

Cutters:
½” & 1” – 1 flute end mill for AL
→ RUNOUT

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Experiments Cont’

Run Out Effect

Surface Profile using 2 flute cutter
[0.2 mm/tooth & 0.5 mm RDC]

0.2 mm

Distance between peaks:

Feed = 0.14 mm/tooth (approx)
Experiments Cont’

Run Out Effect

Surface Profile using 1 flute cutter
[0.4 mm/tooth]
Experiments Cont’

Cutting Experiments

Control Factors

1. Tool diameter: ½”, 1”
2. Axial depth of cut: 25%, 50%, 75%, 100%
3. Radial depth of cut: 0.5, 2, 4, 6 [mm]
4. Feed per tooth: 0.1, 0.15, 0.2, 0.25 [mm/tooth]
5. Cutting speed: 90, 110, 150 [mm/min]

\[
S = \frac{1000 \times v}{\pi \times D}
\]

v…Cutting Speed
D…Cutter Diameter
S…Spindle Speed

\[
FR = F \times N \times S
\]

F…feed per tooth
N…# of flutes
S…Spindle Speed
F.R…Feed Rate

LevelV₁ \times LevelV₅ \times Level V₂³

2 \times 3 \times 4³

384 experiments
Experiments Cont’
Cutting Force Measurement

Force Measurement: Exp# 60:
t1=1/2”, a2=50%, r1=0.5mm,
f4=0.25mm/tooth, v3=150mm/min

Force FFT: Exp# 60
62.65 rad/sec
3759.6 RPM
Experiments Cont’

Surface Profile Measurement

Surface Profile measured: 1L

Surface Profile measured: 2L

Photo using CCD Camera
Scaling Techniques
[0.25mm/tooth]
Overview

Experimental Setup

Data Collection

Optimum Data Set

Training

Validation

Optimization of Cutting Parameters

Trained ANN

DOE HGL

Systematic Approach

Input Parameters
- Tool Diameter
- Axial Depth of Cut
- Radial Depth of Cut
- Feed per tooth
- Cutting Speed

F & Ra Process Model

Overview

Systematic Approach

DOE HGL

Optimized Data Set

Input Parameters

Experimental Setup

Data Collection

Optimum Data Set

Training

Validation

Optimization of Cutting Parameters

Trained ANN
BP ANN General Topology

Feed-Forward Phase

\[ a_j = \sum_{i=0}^{n} W_{ij} I_i \]

\( W \)…Weight

\( I \)…Input vector

\[ Y_j = SF^l (a_j) \]

\( Y_j \)…Predicted output

\( SF \)…Squashing Function

Back-Propagation Phase

\[ e_j = \frac{1}{2} (t_j - Y_j)^2 \]

\( E = (e_1, \ldots, e_j, \ldots e_k) \)

Adaptation: Levenberg-Marquardt

\[ W_{ij}^{new} = W_{ij}^{old} - \frac{J^T \cdot \delta}{J^T \cdot J + \mu \cdot I} \]
ANN End Milling Model

Experimental Data for Training and Validation

Full Factorial

Experimental Data → 384 experiments

75% Training Set (288 exp.)

25% Validation Set (96 exp.)

Data Preprocessing

Cutting Forces: (each component)

1. Amplitude: “Amp”
2. Mean: “Mean”
3. Standard Deviation: “Std”
4. Period (Avg.): “Period”

Raw Data

Adjusted Data
ANN End Milling Model

Experimental Data for Training and Validation (Cont’)

Surface Profiles
1. Surface Roughness: “Ra”
2. Feed Marks: “FeedM”

\[
Ra = \frac{\sum_{i=1}^{n} y_i}{n}
\]

Surface Profile: Exp. #80: t1a2r3f3v2

- Raw Data
- 2nd order Pol.
- Adjusted Data
- Filtered Data

Position [mm]
Surface Roughness - Height [10^-6 m]

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ANN End Milling Model

Experimental Data for Training and Validation (Cont’)

Normalization

\[ N = \frac{(R - R_{\text{min}}) \times (N_{\text{max}} - N_{\text{min}})}{(R_{\text{max}} - R_{\text{min}})} + N_{\text{min}} \]

Topology: End Milling

ANN model
## ANN End Milling Model

### Validation Results

<table>
<thead>
<tr>
<th>Output Variable</th>
<th>Avg. Error $e_j$ [%]</th>
<th>R value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_x$ Amp</td>
<td>8.54</td>
<td>0.99153</td>
</tr>
<tr>
<td>$F_x$ Mean</td>
<td>12.78</td>
<td>0.99019</td>
</tr>
<tr>
<td>$F_x$ Std</td>
<td>8.53</td>
<td>0.99273</td>
</tr>
<tr>
<td>$F_y$ Amp</td>
<td>8.32</td>
<td>0.99161</td>
</tr>
<tr>
<td>$F_y$ Mean</td>
<td>8.72</td>
<td>0.99140</td>
</tr>
<tr>
<td>$F_y$ Std</td>
<td>7.38</td>
<td>0.99533</td>
</tr>
<tr>
<td>$F_z$ Amp</td>
<td>8.50</td>
<td>0.98811</td>
</tr>
<tr>
<td>$F_z$ Mean</td>
<td>10.43</td>
<td>0.98481</td>
</tr>
<tr>
<td>$F_z$ Std</td>
<td>9.23</td>
<td>0.98696</td>
</tr>
<tr>
<td>Period</td>
<td>6.11</td>
<td>0.99484</td>
</tr>
<tr>
<td>Ra</td>
<td>32.59</td>
<td>0.47328</td>
</tr>
<tr>
<td>Feed Marks</td>
<td>5.58</td>
<td>0.97603</td>
</tr>
</tbody>
</table>

![Graph showing measured vs. simulated amplitude $F_x$ in testing](image)

**Amplitude $F_x$**

Error [%] = 8.5422

Experiment Indices in Testing Set

<table>
<thead>
<tr>
<th>Force [N]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>0</td>
</tr>
</tbody>
</table>
Overview

Experimental Setup

Data Collection

Optimum Data Set

Training

Validation

Optimization of Cutting Parameters

Trained ANN

DOE HGL

Systematic Approach

Input Parameters
- Tool Diameter
- Axial Depth of Cut
- Radial Depth of Cut
- Feed per tooth
- Cutting Speed

F & Ra Process Model

Process Model

Overview
Design of Experiments (DOE)

Process of planning the experiments ➔ appropriate data

Full Factorial ➔ $2 \times 3 \times 4^3 = 384$ experiments

- Screening method
- Investigate effects on the responses
- More efficient
- High amount of experiments

Full Factorial $2^k$-level DOE
DOE for Optimal Data Sets

Fractional Factorials

- Number of design factors is high
- Provides efficient exploration of space – Process behavior
- Experimental constraints

- Three key ideas:
  - Sparsity of effects principle
  - Projection property
  - Sequential experimentation
DOE for Optimal Data Sets

Hyper GRECO Latin DOE (HGL DOE)

- Balanced and orthogonal DOE
- Tabular grid “p x p”, p being the # of levels
- Three Latin Squares superimposed
- Each level occurs once and only once in each row/column

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>B</td>
<td>C</td>
<td>D</td>
<td>A</td>
</tr>
<tr>
<td>C</td>
<td>D</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>D</td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
</tbody>
</table>

Factor: X

Factor: Y

Latin Square Design

- Additive model
- Effect model
DOE for Optimal Data Sets

Hyper Greco Latin DOE (HGL DOE) (Cont’)

→ 4-level 5 design factor DOE: 16 vs. $4^5$ runs (1024 experiments)

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A α 1</td>
<td>B β 2</td>
<td>C γ 3</td>
<td>D δ 4</td>
</tr>
<tr>
<td>2</td>
<td>B δ 3</td>
<td>A γ 4</td>
<td>D β 1</td>
<td>C α 2</td>
</tr>
<tr>
<td>3</td>
<td>C β 4</td>
<td>D α 3</td>
<td>A δ 2</td>
<td>B γ 1</td>
</tr>
<tr>
<td>4</td>
<td>D γ 2</td>
<td>C δ 1</td>
<td>B α 4</td>
<td>A β 3</td>
</tr>
</tbody>
</table>

What if the design is mixed?

$2 \times 3 \times 4^3$
DOE for Optimal Data Sets

Hyper Greco Latin DOE (HGL DOE): Layout Rules

Rules:
1. Column ➔ Axial depth of cut
2. Row ➔ Radial depth of cut
3. Latin letter ➔ Feed per tooth
4. Greek letters ➔ Cutting speed
5. Numbers ➔ Tool Diameter
6. Greek letter equal 0: no fraction
7. Number 1-3, 2-4 are same levels
8. Random definition of levels

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Axial Depth of Cut</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A α 1</td>
<td>B β 2</td>
<td>C γ 1</td>
<td>D δ 2</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>B γ 1</td>
<td>A γ 2</td>
<td>D δ 1</td>
<td>C α 2</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>C β 2</td>
<td>D α 1</td>
<td>A δ 2</td>
<td>B γ 1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>D γ 2</td>
<td>C α 2</td>
<td>B β 2</td>
<td>A β 1</td>
<td></td>
</tr>
</tbody>
</table>

Radial Depth of Cut
DOE for Optimal Data Sets

Hyper Greco Latin DOE (HGL DOE): Sample Fraction

Cutter diameter: \( t = 25.4 \times [0.5, 1.0] = [1, 2] \)
Axial depth of cut: \( a = [0.25, 0.5, 0.75, 1.0] = [1, 2, 3, 4] \)
Radial depth of cut: \( r = [0.5, 2.0, 4.0, 6.0] = [1, 2, 3, 4] \)
Feed per tooth: \( f = [0.1, 0.15, 0.2, 0.25] = [A, B, C, D] \)
Cutting speed: \( v = [0, 90, 110, 150] = [\alpha, \beta, \gamma, \delta] \)

![Experiment Table]

<table>
<thead>
<tr>
<th>Exp. #</th>
<th>Cutter Diameter</th>
<th>Axial depth of cut</th>
<th>Radial depth of cut</th>
<th>Feed per tooth</th>
<th>Cutting Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.4</td>
<td>0.5</td>
<td>0.5</td>
<td>0.15</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>12.7</td>
<td>0.75</td>
<td>0.5</td>
<td>0.2</td>
<td>110</td>
</tr>
</tbody>
</table>
## DOE for Optimal Data Sets

### Hyper Greco Latin DOE (HGL DOE): Sample Fraction

<table>
<thead>
<tr>
<th>Experiment #</th>
<th>Cutter Diameter</th>
<th>Axial depth of cut</th>
<th>Radial depth of cut</th>
<th>Feed per tooth</th>
<th>Cutting Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.4</td>
<td>0.5</td>
<td>0.5</td>
<td>0.15</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>12.7</td>
<td>0.75</td>
<td>0.5</td>
<td>0.2</td>
<td>110</td>
</tr>
<tr>
<td>3</td>
<td>25.4</td>
<td>1</td>
<td>0.5</td>
<td>0.25</td>
<td>150</td>
</tr>
<tr>
<td>4</td>
<td>12.7</td>
<td>0.25</td>
<td>2</td>
<td>0.15</td>
<td>150</td>
</tr>
<tr>
<td>5</td>
<td>25.4</td>
<td>0.5</td>
<td>2</td>
<td>0.1</td>
<td>110</td>
</tr>
<tr>
<td>6</td>
<td>12.7</td>
<td>0.75</td>
<td>2</td>
<td>0.25</td>
<td>90</td>
</tr>
<tr>
<td>7</td>
<td>25.4</td>
<td>0.25</td>
<td>4</td>
<td>0.2</td>
<td>90</td>
</tr>
<tr>
<td>8</td>
<td>25.4</td>
<td>0.75</td>
<td>4</td>
<td>0.1</td>
<td>150</td>
</tr>
<tr>
<td>9</td>
<td>12.7</td>
<td>1</td>
<td>4</td>
<td>0.15</td>
<td>110</td>
</tr>
<tr>
<td>10</td>
<td>25.4</td>
<td>0.25</td>
<td>6</td>
<td>0.25</td>
<td>110</td>
</tr>
<tr>
<td>11</td>
<td>12.7</td>
<td>0.5</td>
<td>6</td>
<td>0.2</td>
<td>150</td>
</tr>
<tr>
<td>12</td>
<td>12.7</td>
<td>1</td>
<td>6</td>
<td>0.1</td>
<td>90</td>
</tr>
</tbody>
</table>
DOE for Optimal Data Sets

Fractional Factorial Back Propagation ANN
- Identify optimal fraction sets to successfully train the model
- Full Factorial as a benchmark

Topology: End Milling ANN model

Input

2 Hidden Layers

Output

- Amplitude of Forces Fx
- Amplitude of Forces Fy
- Amplitude of Forces Fz
- Mean of Forces Fx
- Mean of Forces Fy
- Mean of Forces Fz
- Standard Deviation of Forces Fx
- Standard Deviation of Forces Fy
- Standard Deviation of Forces Fz
- Period
- Ra (Surface Roughness)
- Feed Marks
DOE for Optimal Data Sets

Fractional Factorial Back Propagation ANN

Results: Validation (Overall E)

Fraction Performance Comparison

\[
e_j = \frac{\sum_{i=1}^{n} \left| \frac{t_{ji} - Y_{ji}}{t_{ji}} \right|}{n} \times 100\%
\]

\[
E = \frac{\sum_{j=1}^{12} e_j}{12} \times 100\%
\]

<table>
<thead>
<tr>
<th># of runs</th>
<th># PE per Hidden Layers</th>
<th>E [%]</th>
<th>Epochs</th>
</tr>
</thead>
<tbody>
<tr>
<td>96</td>
<td>16 - 16</td>
<td>23.5</td>
<td>25</td>
</tr>
<tr>
<td>120</td>
<td>18 - 18</td>
<td>17.12</td>
<td>21</td>
</tr>
<tr>
<td>132</td>
<td>18 - 18</td>
<td>16.36</td>
<td>24</td>
</tr>
<tr>
<td>144</td>
<td>19 - 19</td>
<td>15.86</td>
<td>54</td>
</tr>
<tr>
<td>156</td>
<td>18 - 18</td>
<td>13.12</td>
<td>62</td>
</tr>
<tr>
<td>168</td>
<td>20 - 20</td>
<td>14.12</td>
<td>24</td>
</tr>
<tr>
<td>180</td>
<td>20 - 20</td>
<td>12.99</td>
<td>31</td>
</tr>
<tr>
<td>192</td>
<td>22 - 22</td>
<td>13.19</td>
<td>31</td>
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<td>204</td>
<td>23 - 23</td>
<td>12.92</td>
<td>15</td>
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<td>216</td>
<td>23 - 23</td>
<td>12.95</td>
<td>24</td>
</tr>
<tr>
<td>228</td>
<td>26 - 26</td>
<td>12.73</td>
<td>13</td>
</tr>
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<td>240</td>
<td>26 - 26</td>
<td>12.54</td>
<td>36</td>
</tr>
<tr>
<td>252</td>
<td>27 - 27</td>
<td>12.43</td>
<td>13</td>
</tr>
<tr>
<td>288</td>
<td>22-22-22</td>
<td>10.55</td>
<td>15</td>
</tr>
</tbody>
</table>

F. F.
DOE for Optimal Data Sets

Validation Results: Fraction of 156 exp.

<table>
<thead>
<tr>
<th>Output Variable</th>
<th>Avg. Error [%]</th>
<th>R value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amp</td>
<td>9.03</td>
<td>0.993</td>
</tr>
<tr>
<td>Mean</td>
<td>12.61</td>
<td>0.992</td>
</tr>
<tr>
<td>Std</td>
<td>9.26</td>
<td>0.994</td>
</tr>
<tr>
<td>Fx Amp</td>
<td>9.24</td>
<td>0.990</td>
</tr>
<tr>
<td>Mean</td>
<td>14.21</td>
<td>0.987</td>
</tr>
<tr>
<td>Std</td>
<td>8.03</td>
<td>0.993</td>
</tr>
<tr>
<td>Fy Amp</td>
<td>11.36</td>
<td>0.989</td>
</tr>
<tr>
<td>Mean</td>
<td>16.21</td>
<td>0.986</td>
</tr>
<tr>
<td>Std</td>
<td>14.95</td>
<td>0.990</td>
</tr>
<tr>
<td>Fz Amp</td>
<td>10.95</td>
<td>0.997</td>
</tr>
<tr>
<td>Mean</td>
<td>44.98</td>
<td>0.542</td>
</tr>
<tr>
<td>Std</td>
<td>6.23</td>
<td>0.972</td>
</tr>
</tbody>
</table>

Measured vs. Simulated Amplitude Fx in Testing

Error [%] = 9.031
Statistical DOE Validation Approach

- How do we know the selected fraction is the optimum set to train and validate the ANN?
- Is the fraction set capable to fully represent the end milling process behavior?
  - Determine best DOE fraction to be statistically comparable to the full factorial fraction

“Process Response Distributions”
Statistical DOE Validation Approach

Probability Density Function “PDF”: (Fraction of 96 experiments)

\[ pdf = f(t) = \frac{CumN(t) - CumN(t - \Delta t)}{N \times \Delta t} \]

Frequency distribution of Amplitude of Force in X direction 'Fx'

Frequency Distribution at t = 7

Data Distribution “pdf” of Amplitude of Force in X Direction

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Statistical DOE Validation Approach

PDF of the End Milling Process

Amplitude Fx

Experimental fraction size increases

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Statistical DOE Validation Approach

PDF of the End Milling Process

Surface Roughness

Experimental fraction size increases
Chi-Square Goodness of Fit Test: Distribution Comparison

Comparison between two distributions:
1: Observed (o)  2: Expected (e)
95% confidence level

\[ \chi^2 = \sum_{j=1}^{k} \frac{(o_j - e_j)^2}{e_j} = \sum_{j=1}^{k} \frac{(o_j - e_j)^2}{e_j} \]

\[ f = k - m - 1 \quad \quad \quad \quad (\chi^2) \leq (\chi^2)_{1-\alpha,f} \]
**Statistical DOE Validation Approach**

**Distribution Comparison: Fraction vs. Full Factorial Fraction**

<table>
<thead>
<tr>
<th>f = 6</th>
<th>Observed Fraction</th>
<th>$\chi^2$</th>
<th>f = 5</th>
<th>Observed Fraction</th>
<th>$\chi^2$</th>
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$\chi^2_{0.95,6} = 12.6$

Amp Fx

Ra

$\chi^2_{0.95,5} = 11.1$
Statistical DOE Validation Approach

Distribution Comparison: 18th vs. Full Factorial Fractions

Amplitude Fx

Surface Roughness
Overview

1. Experimental Setup
2. Data Collection
3. Optimum Data Set
4. Training
5. Validation
6. Input Parameters
   - Tool Diameter
   - Axial Depth of Cut
   - Radial Depth of Cut
   - Feed per tooth
   - Cutting Speed
7. DOH HGL
8. Systematic Approach
9. F & Ra
10. Process Model

Optimization of Cutting Parameters

Trained ANN
Basic Idea

1. Assume the End Milling Process is reliable (based on the definition of Reliability shown below)

2. Determine the Law Probability Distribution of the process (i.e. distribution of the process parameters)

3. Track the distributions of the data set

4. Identify the minimum set as the data set with distribution that fits closely the process distribution as determined in step 2.

Definition of Reliability:

Probability that a system will adequately perform under stated environmental conditions for a specific time.
Systematic Approach for Optimizing the Modeling

Law Probability Distributions considered

\[ \text{pdf}(y_t) = \frac{\beta}{\theta} \left( \frac{y_t}{\theta} \right)^{\beta-1} e^{-\left( \frac{y_t}{\theta} \right)^\theta} \]

\[ \text{pdf}(y_t) = \frac{1}{\theta} e^{-\left( \frac{y_t}{\theta} \right)} \]

\[ \text{pdf}(y_t) = \frac{\mu}{\Gamma(r)} \left( \mu y_t \right)^{r-1} e^{-\mu y_t} \]

Weibull

Gamma

Exponential
Systematic Approach for Optimizing the Modeling

Fitting Process Parameters to a Law Probability Distribution

![Amplitude Fx Graph](image1)

- Response pdf
- Full Factorial
- Exponential pdf
- Weibull pdf
- Gamma pdf

![Standard Deviation Fx Graph](image2)

- Response pdf
- Full Factorial
- Exponential pdf
- Weibull pdf
- Gamma pdf

Amplitude Fx

Standard Deviation Fx

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Gustavo A. Rengifo
Systematic Approach for Optimizing the Modeling

Fitting Process Parameters to a Law Probability Distribution

Data Distribution Fitting of Amplitude $F_Y$

- Full Factorial
- Exponential pdf
- Weibull pdf
- Gamma pdf

Data Distribution Fitting of Mean $F_Y$

- Full Factorial
- Exponential pdf
- Weibull pdf
- Gamma pdf

Amplitude $F_Y$  
Standard Deviation $F_Y$
Systematic Approach for Optimizing the Modeling

Fitting Process Parameters to a Law Probability Distribution

Amplitude Fz

Standard Deviation Fz
### Systematic Approach for Optimizing the Modeling

#### End Milling Reliability Analysis: Distribution Comparisons

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</table>
Systematic Approach for Optimizing the Modeling

Identifying Optimum Fraction

Systematic Approach to find the optimum fraction

![Graph showing probability density function vs. force for different fractions](image)

- Frac #1: Actual
- Frac #1: Exp
- Frac #2: Actual
- Frac #2: Exp
- Frac #6: Actual
- Frac #6: Exp
- Frac #10: Actual
- Frac #10: Exp

Probability Density Function (pdf)

Force [N]
Systematic Approach for Optimizing the Modeling

Identifying Optimum Fraction

![Diagram showing systematic approach to find the optimum fraction. The x-axis represents Force [N] ranging from 600 to 2400, and the y-axis represents Probability Density Function (pdf) ranging from 0 to 1 x 10^-3. The graph includes lines and markers for different fractions, labeled as Frac #12: Actual, Frac #12: Exp, Frac #15: Actual, Frac #15: Exp, Frac #17: Actual, Frac #17: Exp, and Frac #18: Actual, Frac #18: Exp.]
Results

Full Factorial ANN:

- Extended end milling ANN model (Force + Ra)
- Training and validation successfully completed. R > 0.9.
- Improvement with respect to literature. 32% vs. (20% and 53%) (only Ra)

DOE for Optimal Data Sets & Validation

- HGL DOE: efficient method of selecting fractions (balanced/orthogonal)
- Validation ➔ 13th fraction: E = 13.12% (Compromise: accuracy, cost and time)
- End milling behavior captured progressively

Systematic approach for optimizing process modeling

- End milling: statistical similarity behavior to exponential distribution (95%)
- Selection of the optimum fraction can be systematized
- Similar correlation found using AL6061
Conclusions

- Development of an efficient and accurate predictive end milling model
  - Prediction of cutting force and surface roughness
  - Reconstruction of force signal components

- Implementation of DOE techniques: HGL
  - Optimization of the data collection process
  - More design factor levels / orthogonal & balanced experiments

- Systematization of the optimum fraction data set selection
  - Exponential behavior: Chi-Square test + 95% confidence level

- Proposed technique is applicable for machining other material types.

- Extensive collection of accurate data
Future Work

- Extension of the ANN: (Attractive for implementation in industry)
  - Cutting Parameters: # of cutting flutes, tool geometry
  - Similar cutting tools: ball end mill, taper end mill

- Incorporation of additional process responses
  (development of self monitoring and control systems)
  - Flatness, chatter, tool wear

- Integration of dynamic effects:
  - Cutter/workpiece deflection and runout

- Extension of the reliability analysis:
  - Tool/workpiece material and end milling cutter types
Acknowledgement

- Hazim El-Mounayri, Advisor, ME department, IUPUI
- Committee Members, ME department, IUPUI
- Behnam Imani and Affan Badar
- School of Dentistry, Oral Health Research Institute
- Colleagues from the AEML, ME department, IUPUI
- Family members
References


Question Session

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Thesis Presentation

Advisor: Dr Hazim El-Mounayri

Advanced Engineering Manufacturing Laboratory (AEML)
Mechanical Engineering Department
Purdue School of Engineering & Technology, IUPUI

April 13th, 2007
Thanks!!!

Gustavo Augusto Rengifo
Thesis Presentation

Advisor: Dr Hazim El-Mounayri

Advanced Engineering Manufacturing Laboratory (AEML)
Mechanical Engineering Department
Purdue School of Engineering & Technology, IUPUI

April 13th, 2007
EXTRA!!!!
## ANN End Milling Model

### Training Results

\[
e_j = \frac{\sum_{i=1}^{288} (t_{ji} - Y_{ji})}{288} \times 100\%
\]

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<th>R value</th>
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ANN End Milling Model

Training Results (Cont’)

Amplitude Fx

Surface Roughness

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Gustavo A. Rengifo
ANN End Milling Model

Validation Results (Cont’)

Surface Roughness

Feed Marks
DOE for Optimal Data Sets

Training Results: Fraction of 156 exp.

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Error [%] = 3.4323

Measured vs. Simulated Amplitude Fx in Training

Amplitude Fx
DOE for Optimal Data Sets

Training Results: Fraction of 156 exp. (Cont’)

Surface Roughness

- Measured vs. Simulated Surface Roughness Ra in Training
  - Error [%] = 0.63207

Feed Marks

- Measured vs. Simulated Feed Marks in Training
  - Error [%] = 3.9864

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Validation Results: Fraction of 156 exp. (Cont’)

**Surface Roughness**

- Measured vs. Simulated Surface Roughness Ra in Testing
- Error [%] = 44.9807

**Feed Marks**

- Measured vs. Simulated Feed Marks in Testing
- Error [%] = 6.2295
Reliability:

Probability that a system will adequately perform under stated environmental conditions for a specific time.

Reliability, operational reliability, inherent reliability, probability of survival

Probability of failure

\[ P(T \leq t) = F(t) \quad t \geq 0 \]

\[ R(t) = 1 - F(t) = P(T > t) \]
Statistical DOE Validation Approach

Probability Density Function “PDF”

\[ R(t) = 1 - F(t) = 1 - \int_0^t f(\tau) d\tau = \int_t^{\infty} f(\tau) d\tau \]

\[ pdf = f(t) = \frac{N(t) - N(t + \Delta t)}{N \cdot \Delta t} \]

\[ pdf = f(t) = \frac{CumN(t) - CumN(t - \Delta t)}{N \cdot \Delta t} \]
### Statistical DOE Validation Approach

**Distribution comparison between consecutive fractions**

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Amp Ex $\chi^2_{0.95,6}=12.6$

Ra $\chi^2_{0.95,8}=11.1$