Multi-Objective Optimization based on Robust Design for Etching Process Parameters of Hard Disk Drive Slider Fabrication

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Abstract: - This paper investigated the ability of the etched wall angle and depth controllable. The silicon plates with a patterned wet film photo resistance as a base substrate are used to demonstrate this research. The reactive ion etching (RIE) is main process for hard disk drive slider fabrication. This process is much more complicated to set its parameters to the slider with the right customer specification. Therefore, this paper presents a hybrid response surface methodology (RSM) based on robust parameter design (RPD) concept and data mining (DM) for the multi-response optimization of a RIE process. The approach firstly, a designed experiment (DOE) was employed to collect the process data and to indicate the critical parameters of the process. Then, support vector regression (SVR) was used to establish the nonlinear multivariate relationships between process parameters and responses. Data obtained from DOE were used in the training process. Last but not least, the regression decision tree and desirability function were adapted to the DOE Model. While grid search and desirability function were adapted to the SVR model to find the optimum parameter setting. The technique with the highest prominent accuracy performance was selected to build a RIE process model which is SVR. As a result, the optimum condition from the final model is effectively enabled to apply in the real production based on its confirmation experiment.

Key-Words: - Reactive Ion Etching (RIE), Response Surface Methodology (RSM), Support Vector Regression (SVR) Multi-response Optimization, Robust Parameter Design (RPD)

1 Introduction

In most of quality improvement in industrial process, based on design of experiments (DOE), used extensively in to optimize and model manufacturing processes, has been often optimize only target of yield factors devoid of concerning the impact from their variance. Therefore, the results of this method might be reached the appropriated long term improvement in term of process stability. To conquer this problem, the robust design concept will be applied to handle it through multi-objective optimization. In addition, Taguchi method also constructed signal-to-noise ratios: these bring the standard deviation and mean together to give a single response variable to minimize or maximize. It can be more helpful in term of application because Taguchi method [4,5] use the experiment resource less than the classical DOE; however, some of statistical analysis through this method encounters the lack information according to fractional structure in orthogonal array. At this discussion point, the roust parameter design (RPD) in the classical DOE perspective is provided the optimization alternative to industry that not only give a sounder and more competent logic to design and analysis but also let us to make use of Taguchi’s robust
design concept[2]. On the view of statistical experiment design, Central composite design (CCD) is a potent technique not only for the prediction of the interested system’s responses but also to find the primary optimum process parameter setting to achieve the desired quality of the optimized process [6]. Recently, there has been rapid growth in the manufacturing industry driven by the advances of both technologies and computer. This dramatically changing environment has made the production process turn into more complicated, usual analytical methods are not always suitable with this environment, due to the quantity of process variables and the non-linear nature of the problems. To acquire real data for the analysis, authentic experimentations have to be conducted as historical data cannot be used to build a DOE model. This might result in interruption or disruption in the production process.

Presently, Problem solving using computational Intelligence (CI) in terms of robustness, fault tolerance, self-learning, and self-organizing. It has been found to be a good alternative in process modelling, as a number of accomplishments. Many publications have recently been reported. Most of CI has offered advantages over traditional techniques for manufacturing field. It solely comprises of machine learning science-based fuzzy logic, ANN, probabilistic belief network, and genetic algorithms (GA).

Recently SVM has been reported in the literature to be superior to ANN. Traditional ANN approach using empirical risk minimization is inferior to SVM using structural risk minimization. While the popular feedforward ANN learning with back-propagation algorithm (BP) by means of gradient descent algorithm has suffered from local minimum problem. SVM determines center, weights, threshold, and minimized an upper bound of the expected test error automatically. It is a novel type of learning machine based on hyperplane and the statistical theory. On the other hand, some ANN parameters must be determined on a trial-and-error. As a result, optimum solution cannot be guaranteed. In this study, parameters of SVM were selected by DOE. SVM can be used for either classification or regression task. The latter is called support vector regression (SVR) [1,7] is the type of SVM adopted in this study.

In this paper a novel alternative by integrated SVR, and DOE together was developed to find the optimum setting of production process parameters. A case study of the RIE process parameters for hard disk drive slider for product A was used to demonstrate the proposed approach. The accuracy of the model developed by SVR trained with data collected from DOE and RSM were compared based on the mean absolute percentage error (MAPE) of the overall, training, and testing dataset. This paper is organized as follows. In section 2, the SVR algorithm was briefly described. In section 3, the problem statement case study of the RIE process parameters was analyzed. In section 4, the methodology of the proposed approach was shown. Results and discussion of the proposed framework were shown in section 5. This section has three main sub-sections. These are the experiment phase, model performance comparison and process optimization. Finally, conclusions were provided in section 6.

2 Background

Support Vector Regression

The main objective of SVR is to provide a function \( f(x) \) that consists of \( \epsilon \) deviation from the actual obtained target \( y_i \) for all training set, \( \{x_i, y_i\} \), \( x \in \mathbb{R}^n, y \in \mathbb{R}^m \) with \( l \) observations. The beginning of SVR was described by the linear function using the form \(\langle w \cdot x \rangle + b \), then the nonlinear problem was transferred into a linear problem by a nonlinear map \( \Phi(x) \) from the low dimensional input space to a higher-dimensional feature space. At the same time, \( f(x) \) is as flat as possible. SVR approximates function using the following form:

\[
 f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) \langle x_i \cdot x \rangle + b
\]

Let the nonlinear transformation function be \( \Phi(x) \). \( b \) is the “bias” term and the kernel functions are defined as

\[
 K(x, x) = \langle \Phi(x) \cdot \Phi(x) \rangle
\]

The result of dot product in high dimensional space is equivalent to kernel function of the input space as shown in equation (2)

3 Problem Statement and Case Study

Slider fabrication based on reactive ion etching is a deserved method due to better process control, high etching rate and cleanliness. To achieve high etching quality, it is vital to pick etching parameters. Normally, the domain engineers choose the level of the desired etching parameters by determining based on experience or handbook values. Conversely, this does not ensure that the selected etching parameters result in optimal or near optimal etching quality for that particular RIE machine and environment. Thus, several mathematical models have been developed to correlate etching quality with etching parameters.

In the RIE process, there are three necessary parameters: Pressure, Coil Power and Platen Power. The wall angle and depth is a vital response in the concerning of customer specification in the slider fabrication. In this study, we consider both responses due to the proposed reason.
All of the etched profiles obtained from this trial experiment are a taper profile feature which is affected by the redeposition phenomenon. The SEM image of the etched profile with redeposition along the etched side wall is shown in Figure 2. The minimum wall angle in this trial experiment is 47.98 deg and the maximum wall angle is 75.75 deg.

4 Methodology

A schematic diagram of the proposed procedure is shown in Figure 3. This comprises of the combination of SVR and CCD applied to find the optimum setting of the process parameters in the RIE process parameters for hard disk drive slider for product A. According to the RPD concept to optimize the mean and variance of both responses; therefore, both of response variance were transformed by the natural log. On the ground of the sample variance does not have a normal distribution (it shown in chi-square scale). Hence, it is typically best analyze the natural log of variance [3]. At this state, we have a four responses; two from mean of responses and the others from variance of responses. The study started from obtaining data from real designed experiments. These data, consisting of input parameters and the corresponding outputs, are then used to train both SVR concurrently (indicated in computational intelligence learning process). At the same time, statistical model was developed by CCD using the same data. After the SVR learning process was finished, prediction accuracy of testing data in terms of mean absolute percentage error (MAPE) was used to compare models performance developed from SVR and CCD.

5 Result and Discussion

5.1 The Experiment Phase

After CCD experiment design with three replications, 60 experiment settings were designed. To perform the experimental design, high, low and axis level of the machining parameters (Pressure, Coil Power and Platen Power) were selected and shown in Table 1. We conducted the experiment with three replicates and three center points. The machining time for each work piece is constantly 20 minutes.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Etching parameter</th>
<th>Unit</th>
<th>Level 1</th>
<th>Level 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>X₁</td>
<td>Pressure</td>
<td>mTorr</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>X₂</td>
<td>Coil Power</td>
<td>Watt</td>
<td>200</td>
<td>700</td>
</tr>
<tr>
<td>X₃</td>
<td>Platen Power</td>
<td>Watt</td>
<td>150</td>
<td>300</td>
</tr>
</tbody>
</table>

Figure 1. RIE Process in company case study.

Figure 2. Example of Si etch profile with redeposition along etch side wall.

Figure 3. Schematic diagram of the proposed framework.

Regression decision tree, namely CRT, was performed to indicate the initial point for optimization phase corresponding with domain engineering knowledge. Finally, the grid search method was employed to the best model (in this case was SVR) to find optimum process parameter setting. The optimum condition from CCD, based on the reduced gradient search algorithm and a hill-climbing procedure in the desirability improvement was used to confirm the optimum condition found from grid search.
After building the final RSM model for each response, the reduced gradient search algorithm and a hill-climbing procedure were employed to maximize the negative natural of log of each response variance and achieve the target optimization of both mean of each response. In this study, all computational experiments are performed on Intel Centrino Core(TM) 2 Duo, 2.4 GHz CPU and 3 GB of memory. A total of 60 experimental results obtained from CCD experiment were divided into two sets. The first 80% of data (approximately 48 samples) were used for training, while the rest 20% (approximately 12 samples) were used in the testing process. Accuracy of each model was measured by MAPE. This data set comprises of the inputs vector and the corresponding output vector. Firstly, input data were mapped from the input space into a high dimensional feature space using radial basis function kernel (RBF). This function was deservedly used for regression problems [2]. The amplitude of RBF was controlled by the vital parameter $\gamma$. For example, we found that $\gamma$ of 3.762175 provide the best predictive results. Also, $\varepsilon = 0.003126$ and $C = 579438.273497$ from component grid search. These were used in final SVR model construction for mean of wall angle.

The example of the estimated regression coefficients from mathematical response model structure and analysis of variance for mean of wall angle response following

<table>
<thead>
<tr>
<th>Term</th>
<th>Coef</th>
<th>SE Coef</th>
<th>T</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>125.797</td>
<td>17.0160</td>
<td>7.393</td>
<td>0.000</td>
</tr>
<tr>
<td>Pressure</td>
<td>1.331</td>
<td>1.1461</td>
<td>1.161</td>
<td>0.251</td>
</tr>
<tr>
<td>Coil Power</td>
<td>0.048</td>
<td>0.0242</td>
<td>1.967</td>
<td>0.055</td>
</tr>
<tr>
<td>Platen Power</td>
<td>-0.636</td>
<td>0.1203</td>
<td>-5.289</td>
<td>0.000</td>
</tr>
<tr>
<td>Pressure*Pressure</td>
<td>-0.167</td>
<td>0.0387</td>
<td>-4.320</td>
<td>0.000</td>
</tr>
<tr>
<td>Coil Power*Coil Power</td>
<td>-0.000</td>
<td>0.0000</td>
<td>-10.464</td>
<td>0.000</td>
</tr>
<tr>
<td>Platen Power*Platen Power</td>
<td>0.001</td>
<td>0.0002</td>
<td>2.312</td>
<td>0.025</td>
</tr>
<tr>
<td>Pressure*Coil Power</td>
<td>-0.006</td>
<td>0.0010</td>
<td>-5.361</td>
<td>0.000</td>
</tr>
<tr>
<td>Pressure*Platen Power</td>
<td>0.013</td>
<td>0.0042</td>
<td>3.011</td>
<td>0.004</td>
</tr>
<tr>
<td>Coil Power*Platen Power</td>
<td>0.001</td>
<td>0.0001</td>
<td>7.855</td>
<td>0.000</td>
</tr>
</tbody>
</table>

$S = 1.01742$ $PRESS = 80.1853$ $R^2 = 87.47\%$ $R^2(pred) = 80.59\%$ $R^2(adj) = 85.22\%$

Analysis of Variance for Mean of Wall Angle

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj SS</th>
<th>Adj MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>9</td>
<td>361.342</td>
<td>361.342</td>
<td>40.1491</td>
<td>38.79</td>
<td>0.000</td>
</tr>
<tr>
<td>Linear</td>
<td>3</td>
<td>119.720</td>
<td>119.720</td>
<td>15.7619</td>
<td>15.23</td>
<td>0.000</td>
</tr>
<tr>
<td>Square</td>
<td>3</td>
<td>138.623</td>
<td>138.623</td>
<td>46.2077</td>
<td>44.64</td>
<td>0.000</td>
</tr>
<tr>
<td>Interaction</td>
<td>3</td>
<td>102.999</td>
<td>102.999</td>
<td>34.3331</td>
<td>33.17</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Error</td>
<td>50</td>
<td>51.757</td>
<td>51.757</td>
<td>1.0351</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lack-of-Fit</td>
<td>5</td>
<td>42.482</td>
<td>42.482</td>
<td>8.4965</td>
<td>41.23</td>
<td>0.000</td>
</tr>
<tr>
<td>Pure Error</td>
<td>45</td>
<td>9.274</td>
<td>9.274</td>
<td>0.2061</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>59</td>
<td>413.099</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.2 Model Performance Comparison

The results from SVR and CCD based on the test set data are shown in Figure 4. The performance of each model was compared by using MAPE of the overall data set, training data set and testing data set. According to the overall data set error, it was found that SVR is lower error than DOE (higher error). It is clearly seen that SVR provides a good results and suitable to deal with the real problem. As a result, it was used for further optimization.

Figure 4. MAPE comparison between DOE and SVR approach of test set data.

5.3 Process Optimization

Before optimization method performing, CRT tree was drawn tree diagram to identify the potential range of parameter based on customer specification (60° of Wall Angle and 2.5 µm of depth). While the domain engineers take these four CRT tree to brainstorm to indicate the initial point for optimization. Therefore, we also developed the four models from all of response. The example of CRT tree for mean of depth response is shown in Figure 5.

Figure 5. CRT tree for mean of depth response

From the result of the mean of depth response CRT tree, we can simply conclude that the potential range of platen power is more than 237.5 Watt and coil power is less than 500 Watt. These results lead to the initial solution of optimization. It is 2.5 mTorr of pressure, 250 Watt of platen power and 300 Watt of coil power.
In this process, SVR, the most accurate model identified in section 5.2, was used to find the optimized parameter setting. The following procedures were adopted. Firstly, desirability function was assigned weight based on the domain engineer brainstorm for mean of wall angle, mean of depth, variance of wall angle and variance of depth following 0.25, 0.25, 0.5 and 0.5 respectively. Secondly, grid search was opted for optimization. Grid search step size for each factor is based on the setting precision. The final optimum condition for the RIE process parameters obtained were from SVR model, It is 2.6364 mTorr of pressure, 267.045 Watt of platen power and 346.3746 Watt of coil power. To simplify optimization result analysis, this condition was put to each SVR response model. These settings result in the prediction for mean of wall angle, mean of depth, variance of wall angle and variance of depth following 60.1766, 2.4270, 1.3246 and 4.2020, respectively.

![Figure 6. The Optimization Result from CCD](image)

In addition, the variance of this process slightly important response on the ground that these value always in customer requirements. Therefore, we will use only two of mean response in case of CCD. On the same way, we found that the optimization of CCD model provides closely results following in the prediction for mean of depth of depth following 60.08 and 2.36 respectively. Then the desirability function result was drawn in the single graph for domain engineer explanation as the example of CCD model result in Figure 6. The confirmation of SVR condition resulted in closely with the confirmation of CCD condition resulted in 60.83 and 2.36 for mean of wall angle mean of depth, respectively. Finally, The SVR was chosen to model the process in term of accuracy; however, this condition has to deploy in long-run for stability and process capacity analysis in the future before real usage.

### 6 Conclusions

This paper has described the application of SVR trained with CCD data to obtain the high accuracy modelling of manufacturing process using the RIE process parameters for hard disk drive slider fabrication dataset. Moreover, the modelling of this application uses the output based on RPD concept. The integration of SVR, DOE, decision tree and grid search to achieve optimization of complex process was proposed. This research has shown the contribution in simply performing and easy understanding way of optimization in real practical such as the initial point for optimization identification using decision tree. It is also make domain engineers to understand much more in their process nature. Further potential research may be embraced by combining output vector from each SVR model using fuzzy desirability function to achieve optimum condition or apply other local search methods such as GA, ant, tabu search algorithm. Moreover, we can use the optimum condition from this proposed study to suggest feasible level determinations of factors in final process modelling and optimization.

### Acknowledgement:

The financial is supported by department of materials engineering and operations management of University of Naples “Federico II” in Italy and The National Electronics and Computer Technology Center, National Science and Technology Development Agency and Industry/University Cooperative Research Center (I/UCRC) in HDD Component, the Faculty of Engineering, Khon Kean University.

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