Optimization Design of Electrochemical Machining Process of SKD11 Tool Steel Using Weighted Principal Component Analysis (WPCA)

N Lusi, D R Pamuji, A Afandi and G S Prayogo

Mechanical Engineering Department, State Polytechnic of Banyuwangi, Jalan Raya Jember Km. 13 Kabat Labanasem Banyuwangi, Indonesia.

E-mail: nurainilusi@poliwangi.ac.id

Abstract. This research was carried out on electrochemical machining (ECM) process using a workpiece material of SKD 11 tool steel and electrode of brass. Three process variables, i.e., voltage, electrolyte concentration and gap width with three levels for each process variables investigated. Based on the number of process variables and its level, an orthogonal array of L9 and two times replications employed in the design of the experiment. Setting a combination of significant machining parameters to maximize the material removal rate and minimize the surface roughness of the workpiece based on the results of optimization using the Taguchi method and weighted principal component analysis is a combination of voltage factors at level 3 of 48 V, electrolyte concentration at level 2 of 150 g/l, and gap width at level 1 of 1 mm. Machining parameter that has the greatest contribution is an electrolyte concentration which is 41.98%, then the contribution of voltage of 32.33%, and the gap width is 5.63%. Based on the results of confirmation experiments reveal that principal component analysis can effectively acquire the optimal combination of cutting parameters.

1. Introduction

ECM is a type of non-conventional machining process where the tool does not come into contact with the workpiece. The working principle of ECM is based on Faraday's law. The process of ECM applies chemical reactions and is accelerated with electrical energy; it is due to the oxidation reaction and reduction during electrolysis. At ECM the reduction and oxidation reactions are indicated by the decay (electron loss) of the work piece, and the addition of mass positive metal ions mass (attachment of positive metal ions to the tool). In the machining process, the ECM tool (electrode) does not come into direct contact with the work piece. In the machining process, the ECM tool (electrode) does not come into direct contact with the work piece. An electrical current passes through an electrolyte solution between a cathode tool and an anode workpiece [1].

The ECM machining process has been widely used in machining hard-to-cut materials that cannot be processed by conventional machinery, such as stainless steel materials, ceramics, fiber-reinforced composites, super alloys, etc. Material due to its high hardness, strength, brittleness, toughness, and compatibility with low machining properties. Also, with the implementation of the ECM process, all products with complex shapes can be produced with high accuracy and precision [2]. Another advantage of this process is that there is no mechanical energy or thermal energy involved and free-stress [3]. ECM applications are very popular and have been widely used in industries such as automotive, the aircraft...
industry to engine turbine blades, gears, aerospace, biomedical equipment, construction, and tribology [4]–[8].

ECM processes involve several parameters that will affect ECM machining performance. The use of optimal parameters in the ECM process can significantly improve product quality. Therefore, optimization of process parameters to determine the optimal combination of parameter values in ECM machining is very important to do. Electrolytes are a critical part of ECM which influences the machining process. One of the functions of electrolytes is to absorb the oxidation of metals produced in cutting. Determination of the type of electrolyte solution has a significant effect on the product quality of the ECM process. The use of NaCl can provide higher machining current efficiency compared to NaNO3. This is because the removal of metal starts from a low current density.

Liu et al. [9] experimented micro electrochemical machining (Micro ECM) of Stainless Steel 304 by using composite electrolyte containing neutral salt solution and complexing agents. The complexing agents in electrolyte compete for metal ions to dissolve the insoluble electrolytic products. Experimental results show that the material removal rate (MRR) increased 35% and verified to be effective to increase the machining depth of micro-holes.

Sankar et al. [10] investigated the effect of electrolyte concentration on the Abrasive Assisted-Electrochemical Machining on material removal rate, surface roughness and radial overcut. Aluminium 6061 -boron carbide (5-15 wt.%) composites used as work piece. Surface roughness increase with an increase in electrolyte concentration. The material removal rate of composite material decreased with increasing in boron carbide reinforcement as a result of reinforcement particles disturbed the composite’s continuous electrical conductivity. Another machining characteristic such as radial overcut of machined work material increased with increases in electrolyte concentration due to excessive dissolution in and around the reinforced particles.

In the ECM process, the material removal rate is not only influenced by the electrolyte liquid concentration. There are several other process parameters such as gap width, voltage, and current. Determination of the combination of the right process parameters achieving optimum response has been the focus research on ECM processes. In this case, selection of method will be directly related to the quality of the product.

Taguchi method is one method used in process optimization. The application of the Taguchi method was initially only to optimize a single response, while for multiresponse cases there are several researchers who develop multiresponse optimization methods. Chakradhar et al. [11] presented the optimization of the electrochemical machining of EN-31 steel by using Taguchi method combined with grey relational analysis (GRA). The optimal process parameters, i.e., material removal rate can be maximized, and the overcut, cylindricity error and surface roughness can be minimized through this method. Soni et al. [12] applied a genetic algorithm (GA) and Taguchi method to maximize the metal removal rate and minimize the surface roughness and overcutting. The result obtained by using GA, electrolyte concentration and Voltage is the most significant machining parameters for affecting the MRR and Overcut & Surface Roughness. Hoda et al. [13] used an artificial neural network (ANN) to predict values of process parameters such as metal removal rate (MRR), and surface roughness (Ra). Based on experiments that have been carried out it can be stated that ANN is an efficient approach because it reduces the time & effort needed to predict MRR & surface roughness if they are found experimentally using trial and error methods. Deepanshu et al. [14] optimize the response of MRR, overcut and surface roughness (Ra) of material mild steel with a diameter of 50 mm by using a copper electrode and solution of salt water as electrolyte. The method used is the orthogonal array Taguchi L9.

Based on evaluations from existing studies, research on determination setting ECM process parameters to optimize multiple responses that can be observed simultaneously still need to be done. In this study a multi-response optimization was carried out on SKD 11 material processed by ECM, the response to be observed was MRR and surface roughness. Experiment design using the L9 orthogonal array. The multiresponse optimization method that will be used is Taguchi combined with weighted principal component analysis (WPCA).
2. Experimental Procedure
Experiments are conducted by using the prototype of electrochemical machining equipment which is shown in Figure 1. The ECM device consists of a machining chamber, control panel, and electrolyte circulation system [15]. The workpiece position is fixed inside the machining chamber, and the cathode (tool) is attached to the main screw which is driven by a stepper motor. A rectangular block of 20 mm X 12 mm and 6mm height made of SKD 11 tool steel and brass as an electrode which is shown in Figure 2 are chosen as the work piece for carrying out the experiment to optimize the material removal rate. Sodium chloride (NaCl) electrolyte tends to produce a matte finish with alloy steels[16].

Material removal rate (MRR) = Loss of weight /Machining time (g/min)  \hspace{1cm} (1)

![Figure 1. The dimension of The tool](image1)

![Figure 2. The Electrochemical Machining](image2)

Determination of design of experiments is crucial before the experiment began. In these experiments involves three parameters of machining processes, namely voltage, electrolyte concentrations, and the gap width are varied. Each process parameters have three different levels as described in Table 1.

| Machining Parameters | Units | Level of Machining Parameters |
|----------------------|-------|------------------------------|
| Voltage              | Volt  | 1   | 2   | 3   |
| Electrolyte concentrations | g/l  | 100 | 150 | 200 |
| Gap width            | mm    | 1   | 2   | 3   |

Table 1. Machining Parameters And Their Level
This research aims to find out and determine the value of the best response from the response of the material removal rate (MRR) and surface roughness (SR), considering the number of parameters included. Taguchi experimental design method was chosen to decide the grouping of investigations. Taguchi method offers some run fewer compared to the full factorial design, with the sequence run as is shown in Table 2.

An L9 orthogonal array has been chosen based on Taguchi quality design concept for experimented. The process parameters interaction effect has been assumed to be imperceptible[17]. The experiment was run randomly and rerun two times to attain the accuracy and validity of the test. Taguchi design method is to identify the machining parameter settings which render the quality of the product or process robust to unavoidable variations in external noise.

### Table 2. An L9 Orthogonal Array for Experimentation

| Run No. | Voltage (v) | Electrolyte Concentrations (g/l) | Gap width (mm) |
|---------|-------------|----------------------------------|----------------|
| 1       | 24          | 100                              | 1              |
| 2       | 24          | 150                              | 2              |
| 3       | 24          | 200                              | 3              |
| 4       | 36          | 100                              | 2              |
| 5       | 36          | 150                              | 3              |
| 6       | 36          | 200                              | 1              |
| 7       | 48          | 100                              | 3              |
| 8       | 48          | 150                              | 1              |
| 9       | 48          | 200                              | 2              |

3. Weighted Principal Component Analysis (WPCA)

The Weighted Principal Component Analysis (WPCA) method is used to eliminate correlations between responses and to convert correlated responses into uncorrelated response indices called with the principal components (principal components). Then, a value of Combined Quality Loss (CQL) which is defined as the deviation of the MPI (Multi Performance Index) value from the desired ideal value. This CQL functions as a single response function with the aim of reducing the correlation between responses in the process. In this WPCA method, all components are taken into consideration in order to completely explain variation in all responses [18].

### 3.1. Multiresponse Optimization

The Couple of the Taguchi method and WPCA method following steps to be performed:

1. Converting the experimental data into S/N values.

   The relative quality of a particular parameter design is evaluated using a generic signal to noise (S/N) ratio. Depending on the particular design problem, different S/N ratios are applicable, including larger is better and smaller is better. The S/N ratios for each type of characteristics can be calculated as follows:

   **Larger is better (maximize):**

   \[
   S/N = -10 \log \left[ \frac{1}{n} \sum_{i=1}^{n} \left( \frac{1}{y_i^2} \right) \right] \tag{2}
   \]

   **and**

   **Smaller is better (minimize):**

   \[
   S/N = 10 \log \left[ \frac{1}{n} \sum_{i=1}^{n} \left( \frac{1}{y_i} \right) \right] 
   \]
2. Normalizing the S/N ratio by using the following equation:

$$S/N = -10 \log \left[ \frac{\sum_{i=1}^{n} \frac{y_i^2}{n} }{ \left( \max X_i - \min X_i \right)^2} \right]$$

3. Calculating pearson of correlation.

4. Calculating the principal component (PCA)

5. Calculating Multi Performance Index (MPI) using the following equation:

$$MPI = \sum_{j=1}^{n} W_j Y_i$$

6. Selecting the optimal levels of process parameters.

7. Conducting confirmation experiments and verify the optimal process parameters setting.

4. Experimental Result and Discussion

The experimental result and S/N ratio data for the MRR and surface roughness are depicted in Table 3.

| Run No | MRR (g/min) | S/N    | Ra (µm) | S/N    |
|-------|-------------|--------|---------|--------|
| 1     | 0.067       | -23.479| 1.992   | -11.097|
| 2     | 0.08        | -21.938| 2.367   | -7.484 |
| 3     | 0.06        | -24.437| 3.449   | -10.754|
| 4     | 0.052       | -25.680| 2.728   | -8.717 |
| 5     | 0.07        | -23.098| 3.562   | -11.034|
| 6     | 0.053       | -25.514| 4.24    | -10.555|
| 7     | 0.069       | -23.223| 4.193   | -7.952 |
| 8     | 0.153       | -16.306| 4.271   | -12.002|
| 9     | 0.07        | -23.098| 4.828   | -6.188 |

Hence the range of data series is too large, and the optimal value of the quality characteristics is too large, and the influence of some parameters might be ignored. The experimental data must be normalized first to eliminate the effect above. A linear normalization of the S/N ratio of experimental result for the experiment for the responses are performed in the range between 0 and 1. There are three different types of data normalization according to whether we require the LB (lower-the-better), the HB (higher-the-better) and NB (nominal-the-best). The S/N ratio obtained from Table 3 was normalized in Table 4.

The next step is converting correlated responses into uncorrelated quality indices called principal components (PC1 and PC2). Principal components are independent (uncorrelated) of each other. Simultaneously, the explained variance of each principal component for the total variance of the responses is also obtained in Table 7. To calculate the value of principal component scores using the following equation[19]:

$$Y_i (k) = \sum_{j=1}^{n} X_i^* (j) \beta_{kj}$$
for \( j = 1, 2, \ldots, k \), the coefficient \( \beta_j \) is called eigenvector.

| Table 4. Normalization of Experimental Data |
| Run No. | Normalized Data | MRR | Ra |
|-------|----------------|-----|----|
| Ideal Condition | 1.0000 | 1.0000 |
| 1 | 0.2349 | 0.1557 |
| 2 | 0.3992 | 0.7771 |
| 3 | 0.1326 | 0.2147 |
| 4 | 0.0000 | 0.5651 |
| 5 | 0.2754 | 0.1665 |
| 6 | 0.0177 | 0.2489 |
| 7 | 0.2621 | 0.6967 |
| 8 | 1.0000 | 0.0000 |
| 9 | 0.2754 | 1.0000 |

| Table 5. Pearson’s correlation coefficient |
| NO | Correlation between | Pearson’s Correlation coefficient | Remarks |
|-----|---------------------|-------------------------------|---------|
| 1 | Xi*1 & Xi*2 | -0.270 | Correlation |

| Table 6. Results of principal component analysis |
| Eigen value | Y1 | Y2 |
|------------|----|----|
| Eigen vector | -0.707 | 0.707 |
| AP | 0.622 | 0.365 |
| CAP | 0.635 | 1 |

In weighted principal component method, all principal components will be used, thus the explained variance can be completely explained in all responses. The principal components are independent to each other. Accountability proportion \( W \) of individual principal components has been treated as individual priority weights[19]. Finally, multi-response performance index (MPI) has been computed using the following equation:

\[
MPI = \sum_{j=1}^{k} W_j Y_i
\]

(7)

| Table 7. Principal Components and MPI |
| No | PC1 | PC2 | MPI |
|----|-----|-----|-----|

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4.1. Analysis of Variance (ANOVA)
Analysis of variance or commonly referred to as ANOVA used to find out which machining parameters significantly affect the responses, in this case, are MRR and surface roughness. ANOVA is a statistical method that can infer some important conclusions by analysis of the experimental data. The method is very useful for revealing the level of significance of the influence of parameters or interaction of parameters on a particular response [15]. Table 8 shown ANOVA of the response quality characteristic.

|        | \( Y_1 \)  | \( Y_2 \)  | \( Y_2 \)  |
|--------|-------------|-------------|-------------|
| 1      | -0.2761     | 0.3053      | -0.0603     |
| 2      | -0.8316     | 1.1373      | -0.1021     |
| 3      | -0.2455     | 0.3253      | -0.0339     |
| 4      | -0.3995     | 0.6819      | 0.0004      |
| 5      | -0.3124     | 0.3385      | -0.0707     |
| 6      | -0.1884     | 0.3092      | -0.0043     |
| 7      | -0.6778     | 0.9718      | -0.0669     |
| 8      | -0.7070     | 0.4998      | -0.2573     |
| 9      | -0.9017     | 1.3445      | -0.0701     |

The percentage of error can be used to evaluate if an experiment possesses feasibility and sufficiency or not, since it is related to the uncertain or uncontrollable factors. The percentage contribution of each parameter also can be seen in the Table 8. The contribution of machining parameters in order are electrolyte concentration, voltage, and, gap width. The Taguchi method response table is used to calculate the average MPI value for each level in the machining parameter. This is done by sorting the MPI value according to the machining parameter level in each orthogonal array column and taking the same level average. The greater the MPI value, the better the corresponding multiple performance characteristic, so that a level that can give the largest average response can be chosen. Based on the response table for the MPI shown in Table 9, the best combination of cutting parameters is the set with a voltage of 48 Volt, electrolyte concentration of 150 g/l, and the gap with of 2 mm.

| Machining Parameters | DF | SS   | MS   | Contribution | \( F_{Value} \) |
|----------------------|----|------|------|--------------|-----------------|
| Voltage              | 2  | 0.0172 | 0.00863 | 32.33        | 6.77            |
| Electrolyte          | 2  | 0.0217 | 0.01087 | 41.98        | 8.52            |
| Concentration        |    |       |       |              |                 |
| Gap Width            | 2  | 0.0049 | 0.00250 | 5.63         | 1.96            |
| Error                | 2  | 0.00255 | 0.0012  | 20.06        |                 |
| Total                | 8  | 0.01727 | 0.00863 | 100.00       |                 |

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| Machining Parameters | Level 1 | Level 2 | Level 3 | Max-Min |
|----------------------|---------|---------|---------|---------|
| Voltage              | 0.6547  | 0.2518  | 0.1314  | 0.1062  |
| Electrolyte          | 0.4526  | 0.1434  | 0.0361  | 0.1072  |
| Concentration        |         |         |         |         |
| Gap Width            | 0.1073  | 0.5756  | 0.5721  | 0.051   |
Figure 1 performed ratio plot of MPI. The optimal setting has been evaluated from this plot. In the MPI graph (Figure 3), it is mentioned that the optimal combination of machining parameters for multiple performance characteristics are the third level of voltage, the second level of electrolyte concentration, and Second level of gap width (A₃B₂C₂). After the optimal level of machining parameters has been identified, a verification test needs to be carried out in order to check the accuracy of the analysis.

After the optimal level of machining parameters has been identified, the final step is a verification test which needs to be carried out to verify the accuracy of the analysis. The purpose of these tests also to predict and verify the improvement of the performance characteristic using the optimal level of the machining parameters.

Table 10 compares the result of the confirmation test using the optimal machining parameters A₃B₂C₂ obtained by the proposed method and with those of the initial cutting parameters A₂B₂C₂. As observed in Table, the material removal rate increases from 0.0768 g/min to 0.1928 g/min and surface roughness was reduced from 4.109 µm to 3.641 µm. Based on the results, it is observed quality characteristics can be greatly improved through this study.

| Setting Level of machining parameters | Initial  | Optimal Process Condition |
|--------------------------------------|---------|--------------------------|
|                                      | A₂B₂C₂  | A₁B₂C₂                   |
| Material Removal Rate (g/min)        | 0.0768  | 0.1158                   |
| Surface Roughness (µm)               | 4.109   | 3.188                    |
| MPI                                  | 0.5317  | 0.7616                   |

5. Conclusion
This research presents an application of the Taguchi Method coupled with WPCA as an optimization design of Electrochemical Machining for SKD11 tool steel. The results are summarized as follows:

1. Based on analysis of variance, the major controllable parameters significantly affecting the multiple performance characteristics are voltage, gap width and electrolyte contribution with a desired total contribution of 99.96%.

2. The optimal combination of the machining parameters obtained from the proposed method is the set with voltage at level 3, electrolyte concentration at level 2, and gap width at level 2. The corresponding confirmation tests show that metal removal rate increase by 60.17% and surface roughness decrease by 11.49%. The MPI also increases by 17.87%.

3. The proposed algorithm greatly simplifies the optimization design of machining parameters with multiple performance characteristics. Thus, the solutions from this method can be a useful reference for tool manufacturers and operators who are willing to search for an optimal solution of machining conditions.

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