A DECISION MAKING PROCESS APPLICATION FOR THE SLURRY PRODUCTION IN CERAMICS VIA FUZZY CLUSTER AND DATA MINING

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(Communicated by Xiaojun Chen)

Abstract. To increase productivity, companies are in search of techniques that enable them to make faster and more effective decisions. Data mining and fuzzy clustering algorithms can serve for this purpose. This paper models the decision making process of a ceramics production company using a fuzzy clustering algorithm and data mining. Factors that affect the quality of slurry are measured over time. Using this data, a fuzzy clustering algorithm assigns the degrees of memberships of the slurry for the different quality clusters. An expert can decide on acceptance or rejection of slurry based on calculated degrees of memberships. In addition, by using data mining techniques we generated some rules that provide the optimum conditions for acceptance of the slurry.

1. Introduction. Due to globalization and especially recent developments in information technology, business is experiencing rapid and necessary changes. Therefore, manufacturing companies, in order to better respond to customer expectations, have to take quick and accurate decisions. Fuzzy logic has been shown to be a useful tool in addressing many of the new challenges in manufacturing. From past to present, many researchers are using fuzzy grouping algorithms for modeling very different systems.

Furthermore, with the rapid growth of databases in many modern enterprises data mining has become an increasingly important approach for data analysis. Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner. The relationships and summaries derived through a data mining exercise are often referred to as models or patterns. Examples include linear equations, rules, clusters, graphs, tree structures, and recurrent patterns in time series (see [12]).

Corporations are interested in innovative ways of conducting their business. Some innovation can be attributed to the growing use of data in design and manufacturing.

2000 Mathematics Subject Classification. Primary: 58F15, 58F17; Secondary: 53C35.
Key words and phrases. Data mining, fuzzy cluster analysis, decision trees, ceramics.
Next we summarise some studies about data mining and fuzzy cluster analysis used in manufacturing and in decision making.

In [21] the author explores the use of data mining for lead time estimation in make-to-order manufacturing. The regression tree approach is chosen as the specific data mining method. In [18] the author propose a non-parametric learning algorithm instead of using parametric statistics for small-data-set learning. In [17] the author propose a novel use of data mining algorithms for the extraction of knowledge from a large set of flow shop schedules. In [4] the author propose the Root-cause Machine Identifier (RMI) method using the technique of association rule mining to solve the problem efficiently and effectively. In [5] the author present an integrated relational database approach for modeling and collecting semiconductor manufacturing data from multiple database systems and transforming the data into useful reports in the study. In [1] the author use a new approach to flexible goal programming: by means the fuzzy logic they have tried to lessen both drawbacks. In [10] the author introduce a Borda-type decision procedure taking into account agents’ intensities of preferences by means of linguistic labels.

[3] proposes a hybrid fuzzy c-means (FCM) and back propagation network (BPN) approach is in his study, to further enhance the effectiveness/accuracy of job completion time prediction in a semiconductor fabrication factory. [2] discuss a modified fuzzy c-means clustering method where an ordinal to numeric mapping for the ordinal features is obtained as part of the clustering process. [27] present a product concept generation and selection (PCGS) approach, which was proposed to assist product designers in generating and selecting design alternatives during the product conceptualization stage. [8] propose a systematic methodology of fuzzy logic modeling as a generic tool for modeling of complex systems. [14] presents a new approach for GT part family and machine cell formation. It involves the integrated use of two fuzzy clustering algorithms: fuzzy c-means and fuzzy k-nearest neighbors. [24] concerns with rule extraction from data by means of fuzzy clustering in the product space of in-and outputs where each cluster corresponds to a fuzzy if-then rule. [11] developed an intelligent process planning in feature-based computer-aided process planning method using fuzzy clustering for the cylindrical part of an engine.

In this paper we consider the decision making process of the ceramics production company using fuzzy clustering algorithm and data mining techniques. In Section 2 we describe the system identification by using fuzzy cluster analysis. In Section 3 we shortly define what data mining is. And in Section 4 we explain the application of fuzzy cluster and data mining techniques and the results. Finally, in Section 5 we make some brief conclusions.

2. Fuzzy cluster analysis. System identification using fuzzy modeling is divided into two category: structural and parameter identification. Structural identification is performed in two steps: (i) to determine the input variables between possible input candidates, (ii) description of input-output relationships (if-then rules) (see [22]). Fuzzy clustering is considered to be an intuitive approach for modeling to generate fuzzy rules. Parameter identification is the determination of the optimum extraction parameters and adjustment of the membership functions of input and output structures.

2.1. Fuzzy structural identification. Structural identification of fuzzy systems consists of, creating rules with input and output membership functions. This process is described below were carried out in steps.
2.1.1. Generating rules; fuzzy clustering. The idea of fuzzy clustering is to divide the output data into fuzzy sections that conflict with each other. Therefore, each data is defined in each group the range from 0 to 1 with a membership degree. Formally, $N$, the number of data vectors and $h$, will show the size of each vector $X = \{x_1, x_2, \ldots, x_N\} \subset \mathbb{R}^k$; the grouping of unlabeled data, the partition vectors in $X$ will be able to assign the labels of number $c$. The sections of $X (c)$ can be listed as $(c \times N)$-dimensional $U = [u_{ik}]$ matrix.

The fuzzy grouping problem is to find the optimum membership matrix $U$. The objective function that most widely used to fuzzy grouping in $X$, is $J_m$, used for defining the following constrained optimization problem to minimize the total square error of the weights in the groups:

$$\min_{U,V} \left\{ J_m(U, V; X) = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m \| x_k - v_i \|^2_D \right\}. \quad (1)$$

$$\sum_{k=1}^{N} U_{ik} \leq 1, U_{ik} \geq 0, \sum_{k=1}^{N} U_{ik} \leq 1; \quad (2)$$

Here, $V = \{v_1, v_2, \ldots, v_c\}$ is the group centers’ of unknown vectors, $v_i \in \mathbb{R}^k$ and $\| x \|_D = \sqrt{x^T D x}$. $D$ determines the shape of groups, and is a positive definite matrix of size $h \times h$ (see [22]).

Fuzzy partitions are obtained by the FCM algorithm given in Figure 1 (see [22]). The FCM grouping algorithm has two difficult steps (see [7]):

1. To identify the number of groups ($c$),
2. To determine the exponential weight ($m$)’s optimal value.

2.1.2. Group validation; determining number of groups. Theoretically, the structure of scattering criteria that describes the distance of the groups is used to determine the number of groups and to obtain a general criterion (see [7, 8]):

- Fuzzy scatter matrix in the groups:

$$S_w = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m (x_k - v_i)(x_k - v_i)^T \quad (6)$$

- Fuzzy scatter matrix out of the groups:

$$S_B = \sum_{i=1}^{c} \left( \sum_{k=1}^{N} (u_{ik})^m \right) (v_i - \overline{v})(v_i - \overline{v})^T \quad (7)$$

Here $\overline{v}$ is the total fuzzy average vector, $v_i$ is the fuzzy group centers and are shown in equations 8 and 9.

$$\overline{v} = \frac{1}{\sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m} \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m X_k \quad (8)$$
1. SELECT
   Number of groups (c), exponential weight (m), number of steps (iter), stopping
criterion (ε > 0), for norm, error=∥ Vₜ − Vₜ₋₁ ∥ for norm.
2. ESTIMATE The initial position of the group center:
   \[ V₀ = \{ v_{1,0}, v_{2,0}, \ldots, v_{c,0} \} \subset \mathbb{R}^h \]
3. DEFER \( t = 1 \) to iter; CALCULATE
   \[ U_{ik,t} = \left( \sum_{j=1}^{c} \frac{\| x_k - v_{i,t-1} \|^2 D}{\| x_k - v_{j,t-1} \|^2 D} \right)^{m-1} \]
   \[ v_{i,t} = \frac{\sum_{k=1}^{N} (u_{ik,t})^m x_k}{\sum_{k=1}^{N} (u_{ik,t})^m} \]
   IF error = ∥ Vₜ − Vₜ₋₁ ∥ < ε, or t = 10000 THEN stop and equate
   \( (U_f, V_f) = (U_t, V_t) \)
   ELSE NEXT t

**Figure 1. FCM Algorithm**

\[ v_i = \frac{1}{\sum_{k=1}^{N} (u_{ik})^m} \sum_{k=1}^{N} (u_{ik})^m x_k \] (9)

\( S_B \) is the farness between the fuzzy groups and \( S_w \) is the closeness in the fuzzy
groups. Thus, \( iz(S_w) \) must be minimized to obtain the best groups, \( iz(S_B) \) must
be maximized to increase the distance between the groups or in other words, \( S_{cs} \) given in equation 10 must be minimized.

\[ S_{cs} = (U, V; X) = iz(S_w) - iz(S_B) = iz(S_w - S_B) \]
\[ = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m (\| x_k - v_i \|^2 - \| v_i - \overline{v} \|^2) \] (10)

2.1.3. *Determination of the exponential weight.* Another parameter that will be
decided in fuzzy clustering is the exponential weight (m), used in equations 4 and
5. The exponential weight checks the dimension of fuzzy memberships'. Therefore,
in the range 1 to \( \infty \) bigger values of \( m \) means higher fuzziness. Here we used the
method described below to find the value of \( m \).

- The exponential weight \( m \) should be far enough from one and the infinite
boundary to get “safe” performance of the group’s validity of \( S_{cs} \).
  \( m \)’s end point should be clearly defined to fulfill the above conditions. Limit
“one” is absolutely clear. But what should be the infinite value of \( m \). This
usually depends on the available data (see [22, 7]).
  An index of how far you can increase \( m \), a sparse matrix \( S_t \) is defined as
total fuzzy scattering matrix is known as shown in equation 11:

\[ S_T = S_w + S_B = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m (x_k - \overline{v})(x_k - \overline{v})^T \] (11)

- While a change \( m \) from one to infinity \( iz(S_T) \) decreases of monotonous toward
zero as a constant \( K \) value shown in equation 12. \( K \) depends only on the data
set.

\[ K = \sum_{k=1}^{N} \left( \frac{1}{N} \sum_{k=1}^{N} x_k \right) \left( \frac{1}{N} \sum_{k=1}^{N} x_k^T \right) \] (12)

Therefore, \( m \)'s appropriate value is the value that corresponds to the \( S_i \)'s \( K/2 \) value for the data set will be grouped.

2.1.4. Establishment of membership functions; classification problem. In fuzzy modeling algorithm, output data are divided into several fuzzy groups. A step needed as known a classification problem to expand assigned fuzzy groups to the all output space. Grouping in the process, we make a division according to the \( X \subset \mathbb{R}^2 \) data set. However, in the classification procedures, each data point in \( \mathbb{R}^2 \) space is labeled. Therefore, to determine membership functions’ shape is a classification problem for all output space.

Graphics of the classified data are drawn to obtain a simple membership functions after data of all the space assigned to the fuzzy partition. Convex points are adjusted for each fuzzy group and they are keeping a triangular or trapezoidal (see [25]).

3. Data mining. Nowadays, there is a huge amount of data stored in real-world database and this amount continues to grow fast (see [9]) so data mining is an important real-life application for businesses (see [13]) and have been successfully applied to different fields (see [12]).

The goal of data mining is to extract valuable, non obvious information from large quantities of data (see [19]). So the science of extracting useful information from large data sets or databases is known as data mining. It is a new discipline, lying at the intersection of statistics, machine learning, data management and databases, pattern recognition/artificial intelligence, and other areas. Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner. The relationships and summaries derived through a data mining exercise are often referred to as models or patterns. Examples include linear equations, rules, clusters, graphs, tree structures, and recurrent patterns in time series (see [12]).

Data mining, also popularly referred to as knowledge discovery in databases (KDD), is the automated or convenient extraction of patterns representing knowledge implicitly stored in large databases, data warehouses, and other massive information repositories (see [15]). The KDD process is outlined in Figure 2 (see [6]).

\[ \text{Figure 2. The knowledge discovery in databases process.} \]

Some of the most widely used data-mining algorithms are (see [28]): decision-tree algorithms, decision-rule algorithms, Bayesian algorithms, neural networks, clustering, regression. The goal of data mining may range from obtaining a general
understanding of the nature of data to very accurate modeling and prediction, e.g. (see [16]):

- Data description and summarization: Description of data characteristics, typically in elementary and aggregated form.
- Segmentation: Separation of data into interesting and meaningful subgroups or classes.
- Concept description: Description of concepts or classes in an understandable form.
- Dependency analysis: Finding a model that describes significant dependencies between objects or events.
- Classification: Building classification models that assign a correct class (label) to previously unseen and unlabeled objects.

4. Assignment of slurry quality in ceramics on by utilizing fuzzy system approach. The quality of the slurry is assigned by use of fuzzy clustering algorithm for a ceramics production company that is located in Kayseri.

The company would like determine the conditions that will maximize the strength of the ceramic. The strength of the ceramics is measured by the thickness of the slurry which is measured as the thickness in the standard pot, in millimeters. The factors that affect thickness \( k \) are determined as follows:

1. Temperature \( s \): The temperature of the slurry at the measurement, in centigrade.
2. First viscosity \( V_1 \): The flow velocity of the slurry from the standard pot, in centimeters.
3. Second viscosity \( V_2 \): The measurement of viscosity that is taken after the measurement of \( V_1 \).
4. Thixotropy \( t \): The value of \( (V_2 - V_1)/V_2 \).

4.1. The use of fuzzy system: rule generation, fuzzy clustering. Rule generation is the clustering of the data. To generate the rules 168 observations of thickness are taken from the production.

4.1.1. Determination of the number of clusters. To determine the number of clusters first exponential weight, \( m \), is calculated. Then for different numbers of clusters fuzzy within-cluster scatter matrix, \( S_w \), and fuzzy between-cluster scatter matrix, \( S_b \), are calculated. Optimum number of clusters are find by minimizing \( \text{iz}(S_w) \) and maximizing \( \text{iz}(S_b) \). In another words the cluster validity index, given in equation 10, is minimized. Figure 3 illustrates the cluster validity index as a function of number of clusters. The minimum occurs when the number of clusters equals to five. Also it is seen that the cluster validity index becomes approximately constant.

4.1.2. Determination of the degree of fuzziness for the clusters; determination of exponential weight. The exponential weight, \( m \), controls the degree of the membership partition of the data among the clusters. The exponential weight is determined intuitionally from the calculation of the fuzzy total scatter matrix. Figure 4 illustrates the projection of fuzzy total scatter matrix as a function of the exponential weight. Note that the exponential weight is increased from 1.1 and seven by the step size of 0.01 and the number of clusters is varied between two and 21. For each set of different values of exponential weight and the number of clusters, the projection...
of fuzzy total scatter matrix is calculated. The optimum value of the exponential weight is determined as two which is the half of the value of $K$ in equation 12.

![Graph showing cluster validity index as a function of number of clusters.](image)

**Figure 3.** The cluster validity index as a function of number of clusters.

Using the determined values of the exponential weight and the number of clusters in the fuzzy c-mean algorithm (FCM) the optimum fuzzy membership matrix, $U$, is calculated. In Table 1 the membership degree of some data points for different clusters are given.

### 4.1.3. Determination of the membership functions; classification problem

In fuzzy modeling algorithm, data points are partitioned into fuzzy clusters. The classification process brings in a general meaning to the determined fuzzy clusters. The determination of the shape of the membership functions is a classification problem. The behavior of the data points in each cluster is graphed and these graphs are evaluated intuitionally. As a result of the evaluation classified data points are result in triangle or trapezoid membership functions which are the decision making model of the system.

To test the model, a program is written by [11]) is used. This program calculates the output values of the system for the observed input values. Figure 5 illustrates the observed output values and calculated output values. As it can be seen model can approximate the reality well.

### 4.1.4. Results

In this paper FCM algorithm are used to assign the slurry quality. By the use of algorithm, an effective decision can be made in a short period. This application shows that the fuzzy clustering and decision making can be used in industry effectively.

When modeling the system by fuzzy approach, factors that do not affect the system are determined and eliminated from the model. This reduced the rule number. By the use of the developed fuzzy system model an expert can get the value of the
Table 1. The membership degree of some data points for different clusters.

| Inputs | Membership Values |
|--------|-------------------|
| s      | $V_1$ | $V_2$ | $T$  | $k$ | $c_1$ | $c_2$ | $c_3$ | $c_4$ | $c_5$ |
| 27     | 29    | 57    | 49   | 7.20| 0.97  | 0.00  | 0.01  | 0.01  | 0.01  |
| 37     | 37    | 76    | 51   | 8.60| 0.02  | 0.78  | 0.05  | 0.01  | 0.14  |
| 31     | 30    | 66    | 55   | 8.10| 0.02  | 0.02  | 0.88  | 0.00  | 0.07  |
| 25     | 29    | 49    | 41   | 6.60| 0.01  | 0.00  | 0.00  | 0.98  | 0.00  |
| 31     | 33    | 68    | 51   | 8.20| 0.02  | 0.04  | 0.13  | 0.01  | 0.80  |
| 26     | 30    | 55    | 45   | 7.00| 0.64  | 0.03  | 0.07  | 0.21  | 0.05  |
| 28     | 28    | 60    | 53   | 7.20| 0.49  | 0.04  | 0.33  | 0.04  | 0.09  |
| 35     | 36    | 75    | 52   | 8.50| 0.01  | 0.94  | 0.01  | 0.00  | 0.04  |
| 36     | 36    | 76    | 53   | 8.60| 0.01  | 0.92  | 0.02  | 0.00  | 0.05  |
| 30     | 31    | 66    | 53   | 8.00| 0.01  | 0.01  | 0.91  | 0.00  | 0.06  |
| 31     | 29    | 66    | 56   | 8.00| 0.05  | 0.05  | 0.78  | 0.01  | 0.12  |
| 32     | 29    | 63    | 54   | 8.20| 0.11  | 0.05  | 0.70  | 0.02  | 0.12  |
| 24     | 29    | 46    | 37   | 6.70| 0.05  | 0.01  | 0.02  | 0.91  | 0.02  |
| 25     | 29    | 50    | 42   | 6.80| 0.06  | 0.01  | 0.02  | 0.90  | 0.01  |
| 35     | 32    | 70    | 54   | 8.10| 0.04  | 0.28  | 0.18  | 0.01  | 0.49  |
| 34     | 33    | 68    | 51   | 8.00| 0.03  | 0.09  | 0.12  | 0.01  | 0.75  |

Figure 4. Decision Making Model of the system.

output variable (thickness) for a given set of input values. If the value of the output variable is between the optimum interval [7.8, 8.2] the slurry will be accepted otherwise it is rejected. Testing of the model showed that it gives accurate results.

4.2. Assignment of slurry quality in ceramics production by utilizing data mining approach. The aim of this data mining application is to find the optimum thickness of slurry that maximize the strength of the ceramics. The data set used for this application is divided into two groups as training and testing data. 30% of the data set is the testing data and the remaining 70% of the data set is training data. They were selected randomly. At the first stage of data mining application we
found the dependencies between the parameters by Find Dependencies algorithm of Polyanalyst. And then the classification algorithms of Polyanalyst are applied for data mining analysis.

4.2.1. Find dependencies. Before we begin our analysis, we wanted to determine whether the present parameters really affect the value of thickness or not. For this purpose, we used find dependencies tool of Polyanalyst. Find dependencies algorithm is used to find relations and dependencies in the data quickly. It tells you how strong the connections between attributes are, so that you can further explore those attributes with other engines. In this way, it is a statistical data preprocessing module that is aimed primarily at creating the best operating conditions for Find Laws or another predictive algorithm. As a result find dependencies is often the first engine used in a data mining exploration and most useful for preprocessing data before running other exploration engines. Yet, in some cases interesting final results may be obtained by the Find dependencies method is on its own. The main purpose of this method is recognizing the presence of a dependence of a target numerical attribute on other attributes, with no a priori assumption made about the nature of this dependence. This method may discover multidimensional, non-linear, and very diffuse dependencies (see [26]).

When Find Dependencies is used for preprocessing its main purposes are the following:

1. Finding a subset of independent variables which influence the target attribute most significantly.
2. Finding (and possibly discarding) far located outliersthose records that do not obey the dependency revealed by the majority of the records.

Find Dependencies exploration engine utilizes an algorithm called Arnava described below:

Arnava algorithm is based on a procedure that can evaluate a measure of the dependence of a target attribute on a fixed subset of attributes in the explored datasets. Depending on a time limitation specified for this exploration method by the user, Arnava uses different search strategies for determining a subset of attributes for which the measure of the dependency has its maximum (see [26]).
According to $P$ value which is among the outcome values that are obtained by processing find dependencies module is used for determining the degree of dependencies. The closer the P values to zero, the more dependencies exist among these parameters. If the $P$ value is less than $10^{-7}$, it is accepted as zero (see [26]). The result of the analysis with find dependencies is shown in Table 2.

| Parameter | $P$ Value |
|-----------|-----------|
| $V_1$     | $5.52e^{-018}$ |
| $s$       | $4.930e^{-010}$ |
| $T$       | $1.025e^{-007}$ |
| $V_2$     | $7.810e^{-006}$ |

4.2.2. Classification. Classification is one of the most widely used techniques in data mining function (see [12]). The goal of classification is to build a concise model of the distribution of the dependent attribute in terms of the predictor attributes. The resulting model is used to assign values to a database in which the values of the predictor attributes are known but the value of the dependent attribute is unknown. Classification has a wide range of applications, including scientific experiments, medical diagnosis, fraud detection, credit approval, and target marketing. Many classification models have been proposed in the literature: neural networks, genetic algorithms, Bayesian methods, log-linear models and other statistical methods, decision tables, and tree-structured models (see [20]).

The Classify algorithm of Polyanalyst is used to solve a very common problem in data mining. Classify produces both a scoring rule and a threshold, finding not only a way to score records but also the point at which most accurate classification is achieved (see [26]).

The Classify algorithm is one of Polyanalyst’s derived exploration engines. When it is run, you can select which data mining algorithm will be used to develop the classification rule. Find Laws, Polynet Predictor, and Linear Regression are all choices for the development of the classification rule, and which one you choose should depend on the data available. Find Laws develops excellent high-order rules, but may be slow for large datasets. Polynet Predictor is often faster for large datasets, but in many cases does not produce symbolic rules like Find Laws and Linear Regression. Linear Regression will perform the fastest, but will not correctly model nonlinear dependencies in the data (see [26]).

We used find laws and linear regression choices for this study. And also, we used decision tree tool of Polyanalyst for classification described in Section 4.2.3.

The results of classification by Polyanalyst tools are shown in Table 3. And in Table 4 the classification probabilities and efficiencies are also given. The formulations of classification probability and classification efficiency are shown in Table 5 (see [26]). The resulting rules were used to estimate the thickness.

4.2.3. Classification by decision trees. The name of decision tree (DT) is often used to represent a large family of machine learning algorithms for the automated construction of tree-like classification rules for categorizing structured data. Decision trees work best and are a rapid and effective method for solving classification tasks.

A decision tree is a tree in which each non-leaf node denotes a test on an attribute of cases, each branch corresponds to an outcome of the test, and each leaf node
denotes a class prediction. The quality of a decision tree depends on both its
classification accuracy and its size. Classification using decision trees categorizes a
set of cases in a database into different classes according to a classification model.

Two kinds of data sample are used for the classification task. A training sample
(i.e., a set of cases whose class labels are known) is first analyzed and a classification
model is constructed based on the features available in the data of the training
sample. Such a classification model is then used to categorize a test sample (i.e., a
set of cases whose class labels are unknown) (see [23]).

Decision trees algorithm is Polyanalyst’s fastest algorithm when dealing with a
large amount of records and/or fields. Decision tree works on data of any type. The
DT algorithm is well poised for analyzing very large databases because it does not
require loading all the data in machine main memory simultaneously. The Decision
tree exploration engine is used for task such as classifying records or predicting
outcomes. Decision Trees provide easily understood rules that can help you identify
the best fields for further exploration (see [26]).

In this study we used the decision trees to find the rules that obtain the optimum
values of the slurry thickness- 8 ± 0.2 millimeters.

The rules obtained by the analysis by decision trees are shown in Table 3. And
also the classification probabilities and efficiencies are given in Table 4.

**Table 3.** The rules obtained from classification and decision tree analysis.

| Find Laws          | Linear Regression k = (−63.3177) + (4.11526 × V₁) |
|--------------------|--------------------------------------------------|
| Decision Trees     | If S ≤ 31.5 and 65 ≤ V₂ ≤ 67 and V₁ ≤ 29.5 Then k will be rejected
|                    | If S ≤ 31.5 and 65 ≤ V₂ ≤ 67 and V₁ ≥ 29.5 Then k will be accepted
|                    | If S ≤ 31.5 and V₂ ≥ 67 Then k will be rejected
|                    | If S ≥ 31.5 Then k will be rejected                  |

**Table 4.** Classification probabilities and classification efficiencies
of analysis results.

|                      | Find Laws | Linear Regression | Decision Tree |
|----------------------|-----------|-------------------|---------------|
|                      | Train     | Test              | Train         | Test         |
| Classification Probability % | 0.3453   | 0.3209            | 0.2916        | 0.2803       |
| Classification Efficiency %   | 0.2265   | 0.2416            | 0.2290        | 0.2500       |
| 100 × \(N_{\text{corr}0} + N_{\text{corr}1} - \max(N_{\text{corr}0}, N_{\text{corr}1} + N_{\text{err}0}, N_{\text{err}1})\) | 0.9821   | 0.9700            | 0.7500        | 0.7300       |

**Table 5.** The formulations of classification probability and classification efficiency.

| Total Classification Error | \(100 \times \frac{N_{\text{corr}0} + N_{\text{corr}1}}{N_{\text{corr}0} + N_{\text{corr}1} + N_{\text{err}0} + N_{\text{err}1}}\) |
|----------------------------|------------------------------------------------------------------------------------------------------------------|
| Classification Probability | \(100 \% \times \frac{N_{\text{corr}0} + N_{\text{corr}1} - \max(N_{\text{corr}0}, N_{\text{corr}1} + N_{\text{err}0}, N_{\text{err}1})}{\min(N_{\text{corr}0}, N_{\text{corr}1} + N_{\text{err}0}, N_{\text{err}1})}\) |
| Classification Efficiency  | \(100 \times \frac{N_{\text{corr}0} + N_{\text{corr}1} - \max(N_{\text{corr}0}, N_{\text{corr}1} + N_{\text{err}0}, N_{\text{err}1})}{\min(N_{\text{corr}0}, N_{\text{corr}1} + N_{\text{err}0}, N_{\text{err}1})}\) |
4.2.4. Results. When the classification probabilities and efficiencies of the training and the testing analyses are compared for three different data mining algorithms, it is discussed that decision-tree algorithm is useful in ceramics production. Moreover, find-dependencies algorithm is discussed to be effective in the pre-processing stage. It is shown that application of these two algorithms efficiently detects correct and useful data, and the outcomes are easy to be interpreted by users. In particular, using find-dependencies algorithm, it is observed that temperature, first viscosity, and the second viscosity are the most important variables affecting slurry thickness. Furthermore, analyses of the results of the decision-tree algorithm imply that targeted thickness of slurry is achieved under the following three conditions: (i) the temperature is lower than 31.5 °C, (ii) second viscosity is between 65 and 67 seconds, and (iii) first viscosity is greater than 29.5 seconds. This application of data mining to slurry production shows that data mining tools can be used effectively in ceramics industry.

5. Conclusion. The purpose of this study was to develop an easy-to-use and flexible multi-period decision making process for the slurry production in ceramics. The flexibility of the approach arises from the possibility of choosing different objectives and constraints for each project, and from the variety of variable types that the decision makers can use to express their preferences. For future research, the problem studied here could be expanded to on the other process of ceramics production.

Acknowledgments. This study originated from the project supported by the Scientific Research Unit of Erciyes University (SRU Project Number is FBA-09-823)

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Received December 2010; 1st revision June 2011; final revision July 2011.

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