Fuzzy Based Approach for Assessing Amount of Alloy Additives in Steel Production Process

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Abstract—Steel production involves three basic steps. At first, the heat source is to be produced to melt the iron ore. Next in a furnace iron is melted. Lastly, to produce steel the molten iron is processed. The advantage of steel over iron is greatly enhanced strength. The properties of steel are highly reliant on the amount of alloying elements, so that their levels are carefully controlled during its manufacture. The addition of alloying elements is usually made based on the professional experience of experts and thus an operator determines the amount of alloying elements to be added to produce the steel of a particular kind. This paper presents the K-Means clustering method to assess the proportion of alloying elements that has a fuzzy nature. The simulation results show that the proposed method can be applied effectively in steel making.

Keywords—alloying elements, clustering, fuzzy, steel.

I. INTRODUCTION

Steel industry is an essential and sizable sector for industrialized economies. Since it is capital and energy extensive, companies have been putting consistent emphasis on technology advances in the production process to increase the productivity [6]. Steel is one of the basic building blocks of the modern world such that automobiles, appliances, bridges, buildings, etc. all are made with steel [8]. Steel-making has vied a significant role within the growth of contemporary industrial societies. Cast iron is a rigid brittle material that is hard to work, whereas steel is ductile, quite effortlessly formed and an adaptable material. For ample of human history, steel has solely been able to be produced in lesser amounts however the invention of the Bessemer process in the nineteenth century and successive technological progresses in injection technology and process control, bulk manufacture of steel has become a primary part of the world’s economy and technological innovation [12]. Steel is the most important metal in the recent world, with the yearly worldwide production of over 700 million tonnes dwarfing the almost 17 million tonnes of the next most prolific, aluminium. Due to the nature of the steel making process, large amounts of solid, liquid and gaseous wastes are generated in the steel plant. Careful planning is necessary to ensure that these do not have a negative impact on the environment [3]. Modern steel manufacturing methods are of two types: primary and secondary steel-making. Primary steel-making is concerned with converting molten iron from a blast furnace and steel scrap into steel through the basic oxygen furnace (BOF) and electric arc furnace (EAF) [11].

The primary steelmaking furnaces, such as the basic oxygen furnace and electric arc furnace, are not capable of meeting quality demands. This has led to the growth of what is known as Secondary steelmaking. Secondary steel-making is concerned with refining of the crude steel before casting and several operations are usually carried out in ladle heating furnace (LHF). Secondary steelmaking is a major thrust area in modern steelmaking technology. In secondary metallurgy, alloy addition, desulfurization, degassing, de-oxidation, homogenization, temperature control, inclusion removal and modifications are performed to make sure that high-quality steel is made after casting [2].

The main control problem of a human operator in the steel making process is to determine the amount of alloying elements that is to be added to produce the steel of a particular kind. In order to overcome the human errors and to reduce the computation time in determining alloying elements to be added, k-means clustering method is proposed in this paper. Clustering partitions a dataset into several groups such that the similarity within a group is larger than that among groups. The clustering technique is used in conjunction with fuzzy modeling to determine initial locations for fuzzy if-then rules [4, 10].

II. METHODOLOGY

The previous researches by Mohammad Hossein Fazel Zarandi et al [1, 7] and Pravin Kumar et al [9], considered only few number of input and output attributes for steel process optimization. The number of data considered is also very less. In this paper, steel process dataset comprising of 69 inputs and 11 outputs with 3000 data are considered for optimization. The sample data for some of the inputs and outputs collected is given in Table 1. The input variables represent the steel composition, temperature and time before the start of the secondary steel making process. The output variables are the
amount of alloying elements needed to be evaluated based on the process inputs to obtain the steel of the desired parameters.

As more number of input and output attributes is considered, defining the fuzzy rule base quickly becomes difficult. So the k-means clustering method is proposed to generate optimum rules without compromising the quality of control. In the clustering method the cluster center is calculated and each cluster center is taken as a single rule.

<table>
<thead>
<tr>
<th>Input Data</th>
<th>Output Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>e-Mn (%)</td>
<td>S (kg/Mg)</td>
</tr>
<tr>
<td>0.0750</td>
<td>3.0503</td>
</tr>
<tr>
<td>0.0700</td>
<td>3.0224</td>
</tr>
<tr>
<td>0.1210</td>
<td>2.3977</td>
</tr>
<tr>
<td>0.0570</td>
<td>3.1972</td>
</tr>
<tr>
<td>0.0570</td>
<td>3.1345</td>
</tr>
<tr>
<td>0.0640</td>
<td>3.3713</td>
</tr>
<tr>
<td>0.0680</td>
<td>5.7076</td>
</tr>
<tr>
<td>0.0720</td>
<td>2.3391</td>
</tr>
<tr>
<td>0.0600</td>
<td>4.0001</td>
</tr>
<tr>
<td>0.0740</td>
<td>2.5271</td>
</tr>
<tr>
<td>0.0410</td>
<td>3.0455</td>
</tr>
<tr>
<td>0.0830</td>
<td>2.8855</td>
</tr>
<tr>
<td>0.0620</td>
<td>3.2485</td>
</tr>
<tr>
<td>0.1040</td>
<td>1.9574</td>
</tr>
<tr>
<td>0.0870</td>
<td>2.4081</td>
</tr>
<tr>
<td>0.0470</td>
<td>3.0635</td>
</tr>
<tr>
<td>0.0570</td>
<td>3.2230</td>
</tr>
</tbody>
</table>

III. K-MEANS CLUSTERING

The K-means clustering, or Hard C-means clustering [4, 5], is an algorithm based on finding data clusters in a data set such that a cost function (or an objection function) of dissimilarity (or distance) measure is minimized. In most cases this dissimilarity measure is chosen as the Euclidean distance. A set of \( n \) vectors \( X_j, j = 1, \ldots, n \), are to be partitioned into \( c \) groups \( G_j, i = 1, \ldots, c \). The cost function, based on the Euclidean distance between a vector \( X_k \) in group \( j \) and the corresponding cluster center \( c_i \), can be defined by:

\[
J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{k \in G_i} \| X_k - c_i \|^2
\]

Where \( J_i = \sum_{k \in G_i} \| X_k - c_i \|^2 \) is the cost function within group \( i \).

The partitioned groups are defined by a \( cmn \) binary membership matrix \( U \), where the element \( u_{ij} \) is 1 if the \( j^{th} \) data point \( X_j \) belongs to group \( i \), and 0 otherwise. Once the cluster centers \( c_i \) are fixed, the minimizing \( u_{ij} \) for Equation (1) can be derived as follows:

\[
J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{k \in G_i} \| X_k - c_i \|^2
\]

Which means that \( X_j \) belongs to group \( i \), if \( c_i \) is the closest center among all centers. On the other hand, if the membership matrix is fixed, i.e. if \( u_{ij} \) is fixed, then the optimal centers \( c_i \) that minimize Equation (1) is the mean of all vectors in group \( i \).

\[
c_i = \frac{1}{|G_i|} \sum_{S_{ij} \in G_i} X_k\]

The algorithm is presented with a data set \( X_j, i = 1, \ldots, n \); it then determines the cluster centers \( c_i \) and the membership matrix \( U \) iteratively using the following steps:

1. Initialize the cluster center; \( c_i, i = 1, \ldots, c \). This is typically done by randomly selecting \( c \) points from among all of the data points.
2. Determine the membership matrix \( U \) by Equation (2).
3. Compute the cost function according to Equation (1). Stop if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.
4. Update the cluster centers according to Equation (3). Go to step 2.

The performance of the K-means algorithm depends on the initial positions of the cluster centers, thus it is advisable to run the algorithm several times, each with a different set of initial cluster centers.

IV. RESULTS AND DISCUSSIONS

The K-means clustering method is applied to the dataset of the steel making process and its performance is evaluated using MATLAB. The 20 cluster center’s obtained using K-means clustering is shown in Fig. 1 and the root mean square error is found to be 0.9982. The fuzzy inference system generated using K-means clustering is shown in Fig. 2 and the number of rules obtained is shown in Fig. 3.
The cluster centers for one input and one output is shown in Fig. 1 as sample, likewise the cluster centers for all other inputs and outputs can be obtained. As each cluster center is taken as a single rule in clustering method, there are only 20 rules to represent 3000 data to assess the amount of alloying elements to be added in ladle furnace.

V. CONCLUSION

This paper presented the K-means clustering technique to optimize large steel dataset containing more number of inputs and outputs. The simulation results indicate that the proposed method optimizes the fuzzy rule base effectively by removing the redundant rules. This method can be employed in the steel production process to support the human operator in assessing the amount of alloying elements with reduced error and computation time.

REFERENCES

