Paper 316

Using SAS® Software to Solve the Iron Ore Mixing Problem

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ABSTRACT

This paper presents the data mining techniques applied to the iron ore mixing system of Baosteel, Shanghai, China. We first convert the historical ore mixing data from dBase and Oracle® databases into SAS® format to form a data mart, and then use the data mining techniques, such as the clustering analysis, neural networks, and optimization to solve the problems of iron ore assessing, modeling and quality predicting, and optical low-cost recipe generating respectively. All these techniques are implemented using SAS®. We have applied the system to the sinter production and obtained remarkable benefit (almost 5 million US dollars saved in 1997).

The SAS products included: Base SAS®, SAS/STAT®, SAS/IML®, SAS/AF® for Windows® 95.

The skill level of the intended audience: beginners and above.

1. THE IRON ORE MIXING PROBLEM

The Baoshan Iron and Steel Corporation (Baosteel), China, uses many kinds of imported iron ores, the iron ore mixing problem is then very important to us. The reasons are (1) the recipe of ore mixing determines the quality of the sinter; (2) we need a proper way to assess the property of each kind of ore, especially the ores we have never used before; and (3) we must cut down the cost of the sinter production. Thus the aims of the ore mixing system of Baosteel are (1) building up a database of ore mixing; (2) making a comprehensive assess for various iron ores used by Baosteel; (3) modeling the sintering process to predict the quality of the sinter; and (4) generating optimal low-cost ore mixing recipes.

The process of sintering is as shown in Fig. 1. First various ores are mixed up according the mixing recipe, and then the sinter is produced by the sintering process, finally the sinter is loaded in the blast furnace for iron making. The basic ore mixing problems are then as following:

(a) What ores and what percentage should be used for ore mixing to produce high quality sinter?
(b) How each ore affects the quality of the sinter?
(c) How to generate multiple recipes to cope with various circumstances.
(d) How to cut down the cost while keep the quality of the sinter.

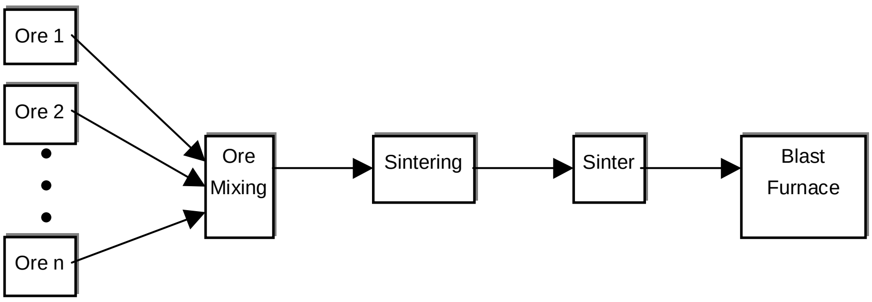

Fig.1. The sintering process

2. PREPROCESSING OF THE DATA FOR ORE MIXING

The data related to ore mixing include all the ore mixing recipes and corresponding quality indexes of the sinter recorded from the first day when Baosteel was put into production, the properties of various kinds of iron ores, the parameters of the sintering process, and so on. All these data are collected from different databases and are loaded into a data mart[1]. All data in the data mart are converted into SAS® format and are filtered and standardized.

3. THE CLUSTER ANALYSIS FOR ORE ASSESSING[2]

Every kind of ore has a lot of chemical, physical, and metallurgical properties. If consider a kind of ore as an object, in terms of the cluster analysis, each of the properties of the ore is then a feature value of the object. By applying the cluster analysis to the ore assessing problem, we find the ores that fall into the same cluster have the similar properties and performance in the sintering. This implies furthermore that these ores may replace one anther in a recipe. Similarly, we also apply the cluster analysis to the ore mixing recipes, finding that some clusters of recipes correspond to high quality sinter.

We mainly use the hierarchical clustering methods. The CLUSTER procedure of SAS/STAT® provides 11 such methods[3], we find, to our problem, the Ward's minimum-variance method has the best performance.

4. MODELING USING NEURAL NETWORKS

We develop a BP network[4] using SAS/IML®[5] for modeling the sintering process and predicting the quality of sinter. The BP network we use to build the models has only one hidden layer, the input layer may have up to 60 input variables, and the output layer has one output variable. The input variables are the percentage of each ore in a mixed ore heap, and the output variable is a quality index of the sinter such as RDI, TI, and RI etc.

We have recorded hundreds of the ore mixing recipes and the corresponding quality indexes of the sinter. We use about a half of the records to train the networks and another half to test the models. A result is as shown in Fig.2. The dark curve in Fig.2 represents the real values of the RDI, and the light one represents the output values of the model (predictive values). The rate of the correct prediction is higher than 85%. Up to now the prediction of the quality indexes of the new recipes is also satisfactory.

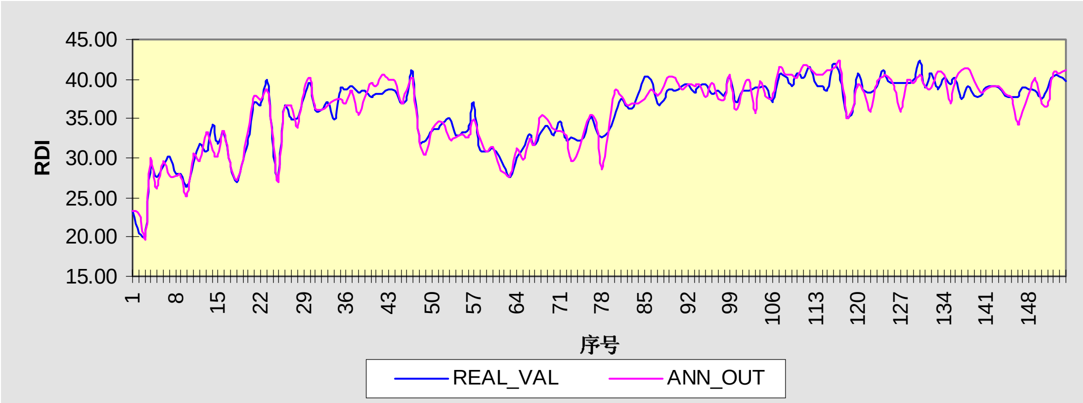

Fig.2. A result of the quality prediction

5. OPTIMIZING THE ORE MIXING RECIPES

Correctly predicting the quality indexes is not the final step of the task yet, because the most important thing to the sinter production is actually not quality predicting, but optimal ore mixing recipe generating, that is generating an optimal and low-cost recipe according to the quality requirements for the sinter. The optimizing algorithm we develop using SAS/IML® is a simple but useful one. We firstly adjust the percentage of ore 1 in a recipe while keeping other ore unchanged, and, based on the model, predict the quality index for every adjustment of ore 1, and then keep the percentage value of ore 1 which corresponds to the optimal quality index. Secondly we use the similar method to process ore 2, and then ore 3, ore 4, …, ore n. Now if the result is not satisfactory yet, we repeat the above process until reach a satisfactory recipe. Since, in practice, only a few kinds of ore are actually adjustable, this method is feasible, and also it is easy to understand, easy to use, and easy to control, therefore it wins plaudits of the engineers of sintering.

6. A FRAMEWORK OF THE ORE MIXING SYSTEM

Fig. 3 shows a framework of the ore mixing system. The original data mainly come from the management information system of Baosteel, which may be Oracle® data or dBase data, and are converted into SAS data to form the ore mixing data mart. The knowledge base consists of neural network models, which is built up by the model training module, and some rules and constraints about the sintering procedure. The predicting and optimizing are implemented based on the models, rules, and constraints in the knowledge base. The users operate the system through the graphical user interface, which is developed using SAS/AF®.

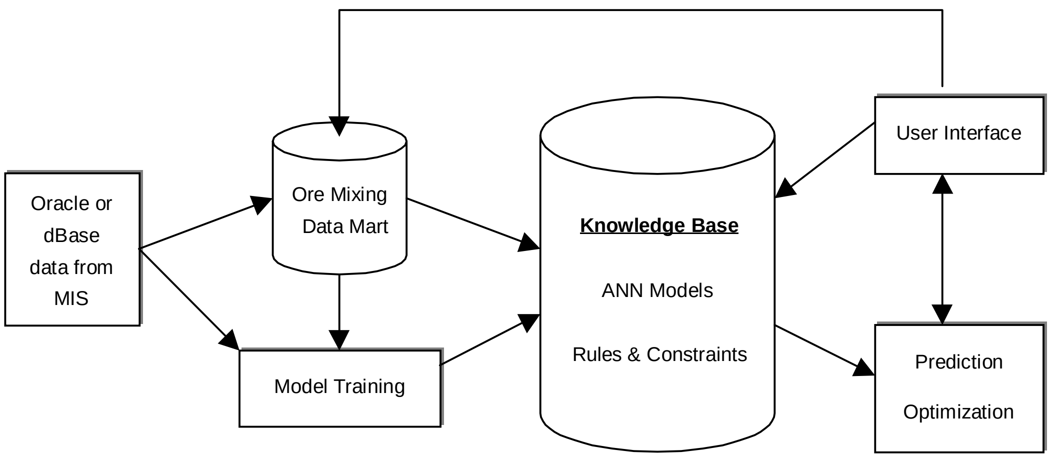

Fig. 3. A framework of the ore mixing system

7. THE ACHIEVEMENTS OF THE ORE MIXING SYSTEM

The ore mixing system has been put in use and has had the following achievements:

(1) The assessment of various kinds of iron ore is identical to that of the sintering experts.
(2) The rate of correct prediction of the sinter quality is higher than 85%.
(3) The optimal ore mixing recipes generated by the system lead to sinter of high quality.

(4) We have obtained remarkable benefit (more than 4 million US dollars saved in 1997).

8. CONCLUSIONS AND REMARKS

We have successfully solved the ore mixing problem by using the data mining techniques and SAS®, and by applying the ore mixing system to the sinter production, we have obtained remarkable benefit (almost 5 million US dollars saved in 1997).

We believe this solution applies to not only the ore mixing problem, but also other problems such as the recipe-related problems, modeling, quality control, process optimization and so on in the chemical, metallurgical, petrochemical, food, and pharmaceutical industries.

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