ECONOMICAL CUPOLA CHARGE MIX OPTIMIZATION USING MAT LAB SUPPORT VECTOR MACHINE

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ABSTRACT:

Cupola Charge Mix calculations (CCMC) are important aspect of foundry industry which are used in ensuring the metal efficiency. Approximating charge of metal is the key area which involves many foundry calculations that are standardized by expertise. However, manual calculations involve many overheads that are not reliable. Recently some computerised techniques are used but require huge input and assumptions. Metal charge calculations using web technology is a prominent solution which targets this problem. Cupola Charge Mix Calculations using Mat lab Support Vector Machine (CCMCMSVM) is a replacement to manual process which is a burden and automated process can be used effectively. Support Vector Machines rely on the concept of decision planes which define decision boundaries. The decision plane separates a set of objects having different class memberships. This is effectively used in calculating CCMC.

Keywords: *Cupola Charge Mix calculations (CCMC), foundry industry, Metal charge calculations, Cupola Charge Mix Calculations using Mat lab Support Vector Machine (CCMCMSVM)*

1. INTRODUCTION

The cupola Furnace produces concerning 2/3 of the cast iron used for castings industry. The easy construction belies the advanced chemical and physical processes are allotted among. Thanks to the inherent

Complexness of the cupola's processes the chamber is tough to work efficiently; energy efficiency is poor, valuable chemical parts are destroyed by oxidization and therefore the composition of the top product varies significantly. The basic problem is there are concerning fifty input variables any of which may have an effect on the six key output variables: %C, %Si, %S, iron temperature, soften rate and the cupola could be a chamber as shown in Figure1 is employed for melting steel scrap, forged iron scrap, and ferroalloys to supply iron. Its main energy source is coal coke. It's one amongst the oldest strategies of manufacturing forged iron, and it remains the dominate technique thanks to its simplicity and low fuel cost. Cupolas home in size from eighteen inches to thirteen feet in diameter, and might manufacture up to one hundred tons per hour of forged iron. Has a long history, automatic management has been elusive as a result of the method has been poorly understood. Most foundries consider the intuition of experienced operators to form management selections. The aim of this work, that has been current for 3 years of an anticipated four year program, is to develop a management for the cupola victimization intelligent and standard control strategies.

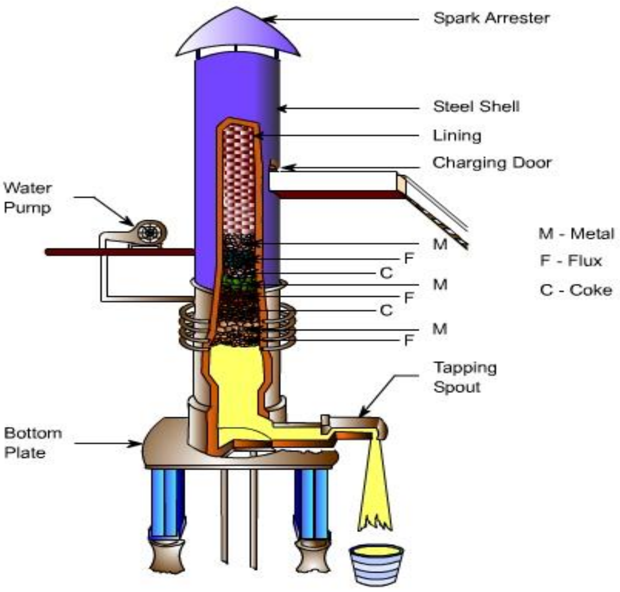


Figure1: Cupola Furnace

Model Description of Cupola Operation:

Foundry software development requires constant interaction with end users on process details and their requirement. In the present work, software package based on C-language was developed for making cast iron charge mix decisions with a focus on attaining related mechanical properties and grade. Systemetic experimental trails were conducted in a cast iron foundry engaged in manufacturing piston pumps to validate the results of software. It has been observed that the results given by the software are in well agreement with experimental trials. The present software is useful not only to calculate charges quickly ,but also it is possible to select the least cost charge mix that will meet the melt chemistry requirements. Also, it is possible to quickly assess the cast iron grade, which eliminates the problem of sample preparation by machine route. In foundry, many decisions are based on thumb rules. To be successful in the present global competition, foundries have to focus on reducing their production costs, lead time with in the quality specifications. Computers can be effectively involved to assist foundry men in their attempts to increase the profitability of the foundry. Manual calculations of cast iron charge mix towards obtaining a particular grade is time- consuming process.

Need for Economic Cupola Charge Mix Optimization:

However this is designed for commercialize a cupolacomputer by adding to intelligence optimization techniques.The model predicts cupola outputs supported given inputs.The model provides the solutions rapidly that creates it useful for period of time corrections to a cupola's operation equally as for long-term deciding.

2.Economic Cupola Charge Mix OptimizationUsing MAT LAB Support Vector Machine:

Support Vector Machine(SVM):

In machine learning, task of deducing a category from supervised training data is known as Supervised Learning. In supervised learning the training data consist of a set of training sets, where each set is a pair consisting of an input and an anticipated output value. A supervised learning algorithm analyzes the training data and then predicts the correct output categorization for given data-set input. For e.g. Teacher teaches student to identify apple and oranges by giving some features of that. Next time when student sees apple or orange he can easily classify the object based on his learning from his teacher, this is called supervised learning. He can identify the object only if it is apple or orange, but if the given object was grapes the student cannot identify it.

Support Vector Machine for linearly separable data:

Consider each image to be a single dot in the Fig. 2.And dot of different colour specifies different category. Here each image is considered to be a single dot in the Fig. 2 and dot of different color specifies different category. Here image of two categories is considered and the boundary separating two images is found. In our case three categories are required. So first test sample is checked if it belongs to first category or others. Next it is checked it belongs to second category or others. Hence the sample that does not belong to these two will be in third category.

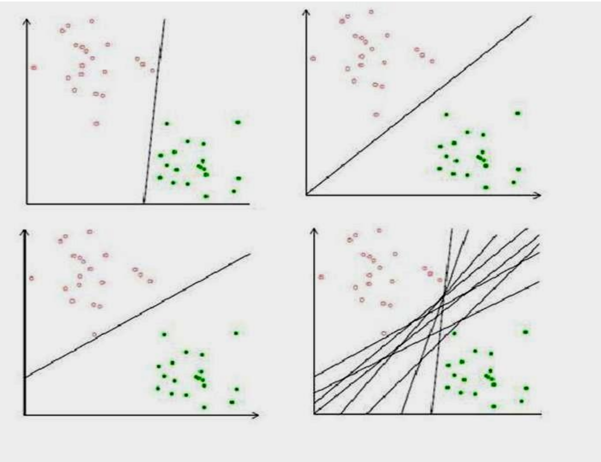


Fig. 2.Support Vector machine for linearly separable data.

The Margin of a linear classifier is the width by which the length of the boundary can be increased before hitting the data points of different category. The line is safe to pick having the highest margin between the two data-sets. The data points which lie on the margin are known as Support Vectors.

The next step is to find the hyper plane which best separates the two categories. Support Vector Machine performs this by taking a set of points and splitting them using different application specific mathematical formulas. From that we can find the positive and negative hyper plane.

The mathematical formula for finding hyper plane is:

(p • q) + r = +1 (positive labels)
(p • q) + r = -1 (negative labels)
(p • q) + r = 0 (hyper plane)

From the equation above and using linear algebra we can find the values of p and r.Thus, we get the model that contains the answers for p and r and with margin value of 2/. The margin is calculated as follow. The Margin in Support Vector Machine, this model is used to categorize new data. With the above solutions and calculated margin value, new coming data can be categorized into different category. The following Figure 3 demonstrates the margin and support vectors for linearly separable data.

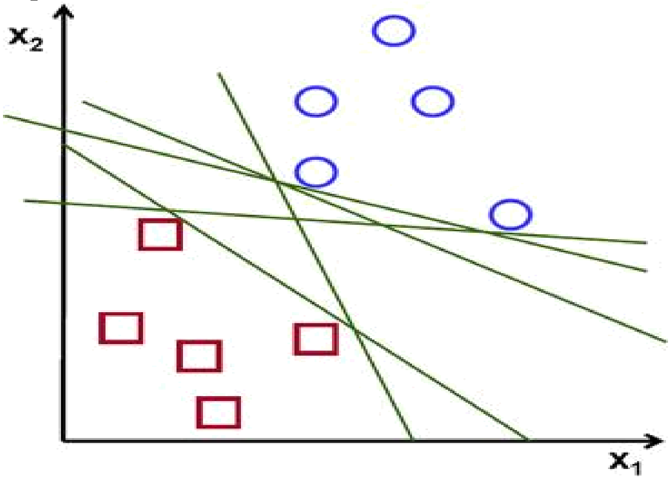


Fig. 3.Support Vector machine Classification with hyper plane

In the above picture you can see that there exist multiple lines that offer a solution to the problem. Is any of them better than the others? We can intuitively define a criterion to estimate the worth of the lines: A line is bad if it passes too close to the points because it will be noise sensitive and it will not generalize correctly. Therefore, our goal should be to find the line passing as far as possible from all points. Then, the operation of the SVM algorithm is based on finding the hyper plane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of **margin** within SVM's theory. Therefore, the optimal separating hyper plane ***maximizes*** the margin of the training data.

Advantages of Support Vector Machine:

There are many folds advantages of using the supervised learning approach of

Support Vector Machine (SVM). They are very effective when we have very high dimensional spaces. Also, when number of dimensions becomes greater than the existing number of samples, in such cases too SVM is found to be very effective.SVM uses a subset of training point also known as support vectors to classify different objects hence it is memory efficient. Support Vector Machines are versatile, for different decision function we can define different kernel as long as they provide correct result. Depending upon our requirement and application we can choose types of kernel which is most productive for our application.

Economical Cupola Charge Mix Optimization using SVM:

Metal charge calculations are automated with the use of support vector machine to suggest the grade of material that will be generated with specified inputs. This is done by using the data that is gathered from various foundry industries. The block diagram in figure 3.4 shows the design view of automation model.

The training set is collected after data preprocessing performed on collected Data and this is given as training input to SVM. Once ECCMO_SVM is trained completely, then test samples are given as input. The ECCMO_SVM suggests the grade that will be obtained by comparing that with the data stored in database. Though Artificial Neural networks are used in wide range of applications this involves two phases of calculations. First, this takes all the inputs and performs charge calculations. Secondly, this involves automation using SVM to take decisions about the grade expected when the inputs are specified

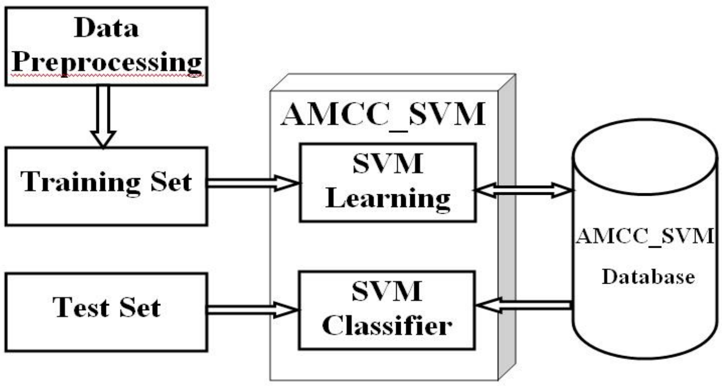


Fig. 4.Design view of Automation model

RESULT AND DISCUSSION:

Economical cupola charge mix optimization is developed with two phases, first performs charge calculations and second calculates grade basing on training data using SVM.

Economical Cupola Charge Mix Optimization:

The resultant screens of the system in Fig. 6 shown below. This application asks the user to enter customer requirements and ask how many materials (charge name).

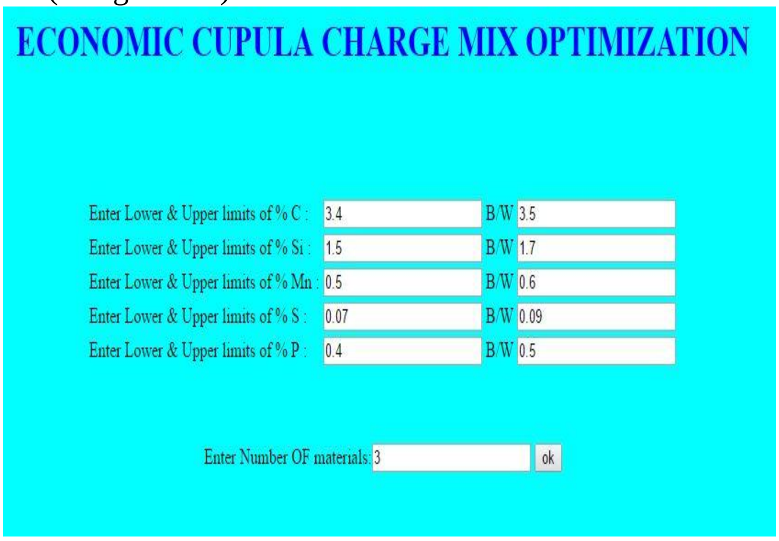


Fig. 6.customer requirements

After entering the customer requirements then we have to enter charge names Fig 7 below.

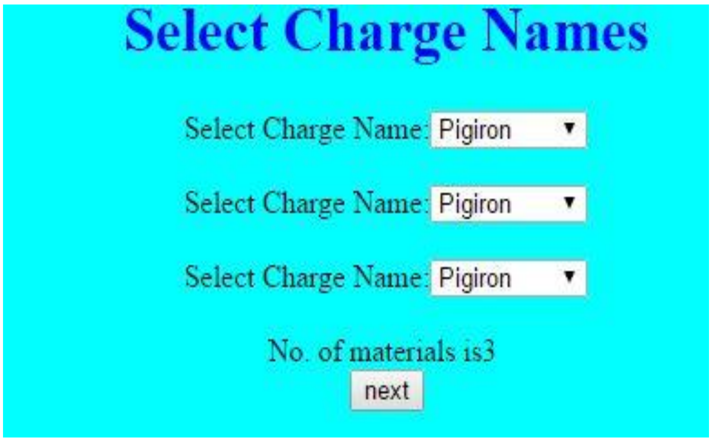


Fig. 7.charge names

After entering the charge names then we have to give the charge percentage and metals (C%, Si%, Mn%, S%, P %) percentages Fig 8 below.

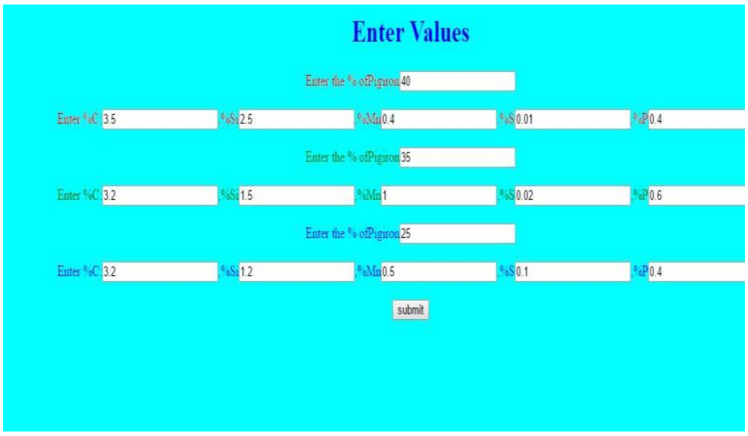


Fig. 8.the charge percentage and metals (C%, Si%, Mn%, S%, P %) percentages.

After entering charge percentage and metals (C%, Si%, Mn%, S%, P %) percentages enter % gain of Carbon Usually between 0.1 to 0.2 , % gain of Sulphur Usually between 0.03 to 0.05 , % loss of Silicon Usually between 10 to 30 , % loss of Manganese Usually between 15 to 20 Fig 9 below.


INPUT DETAILAS

welcome 3

Material Proportion	% C	% Si	% Mn	% S	% P
Pigiron 40	3.5	2.5	0.4	0.01	0.4
Pigiron 35	3.2	1.5	1	0.02	0.6
Pigiron 25	3.2	1.2	0.5	0.1	0.4

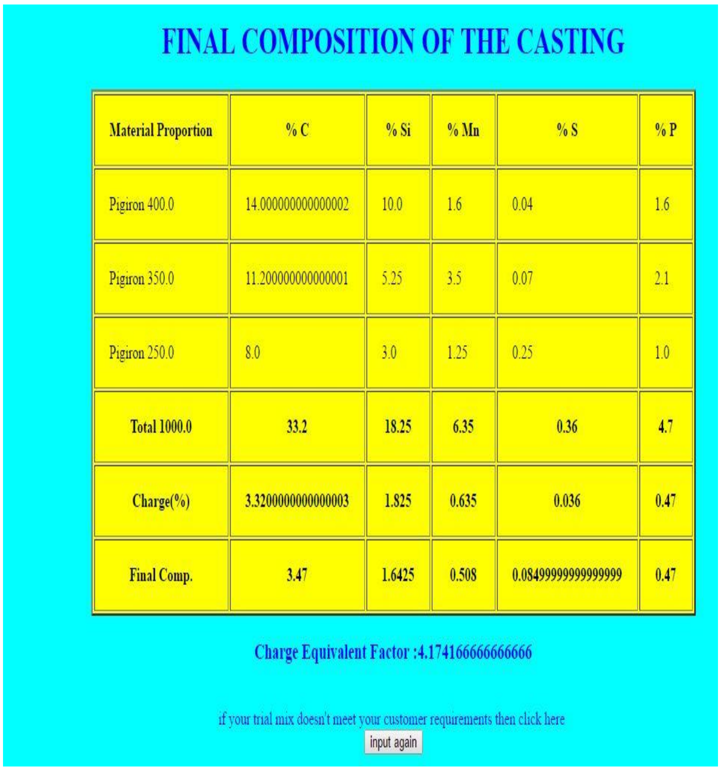
Enter Charge weight : 1000

Enter % gain of Carbon(Usually b/w 0.1 & 0.2): 0.15
Enter % gain of Sulphur(Usually b/w 0.03 & 0.05): 0.049
Enter % loss of Silicon(Usually b/w 10 & 30): 10
Enter % loss of Manganese(Usually b/w 15 & 20): 20

next

Fig. 9. Pickup and loss are added

Final analysis as shown in figure is calculated trying with mixes of charge materials available in the foundry which is in the economical melt and got the which is given customer requirements, Carbon Equivalent Value Fig 10 below.


FINAL COMPOSITION OF THE CASTING

Material Proportion	% C	% Si	% Mn	% S	% P
Pigiron 400.0	14.000000000000002	10.0	1.6	0.04	1.6
Pigiron 350.0	11.200000000000001	5.25	3.5	0.07	2.1
Pigiron 250.0	8.0	3.0	1.25	0.25	1.0
Total 1000.0	33.2	18.25	6.35	0.36	4.7
Charge(%)	3.3200000000000003	1.825	0.635	0.036	0.47
Final Comp.	3.47	1.6425	0.508	0.08499999999999999	0.47

Charge Equivalent Factor :4.174166666666666

if your trial mix doesn't meet your customer requirements then click here

input again

Fig. 10.Carbon Equivalent Value

CONCLUSION:

Metal charge calculations are important in foundry industry. Till now this is totally based on manual decisions. However this paper automates the manual process and performs all the required calculations and finally calculates the grade of the material. This is useful as many industries are based on human expert and they are facing problems regarding manpower turnover. In such cases this AMCC_SVM can be used as a substitute that overcomes arising problems. Future scope includes adding multicore parallel processing features to SVM that reduces run time.

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