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A hot metal temperature predictor based on hybrid decision tree techniques

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Abstract

HEAT level control (HLC) is one of the important elements for operating an iron-making blast furnace (BF). The goal of HLC is to maintain the hot metal temperature (HMT) as close to a preset aim as possible. HMT is an important indicator of both the product quality and fuel efficiency, and is measured from tapped out liquid iron. For instance, high values of HMT mean unnecessary fuel consumption together with sub-optimal hot metal chemistry, whilst low values of HMT may indicate insufficient fuel consumption, which may consequently lead to dangerous situation of freezing the slag inside the BF. Once an aim HMT is decided, based on production and plant constraints, several inputs of the BF can be adjusted by operators to control this HMT. However, any change of the inputs requires time to take effect, due to inherent time lags, and the best practice control relies heavily on an operator's experience and judgment. This is due to the complexity of the numerous BF processes, which essentially can be described as highly non-linear, stochastic and nonstationary in nature. The goal of this work is to employ a data mining approach to analyse the BF system and build a dynamical modelling system, which will generate a set of understandable symbolic rules for prediction of HMT changes. The model is regularly generated by decision tree applications, See5 and Cubist, in order to adapt any significant contextual variations of the BF. This rule based system can help the operators increase the BF's efficiency by making timely control adjustments with the goal of minimising variation of HMT with time. These models also provide a corpus of driving factors that can also be analysed by domain experts as an objective knowledge source.

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A Hot Metal Temperature Predictor Based on Hybrid Decision Tree Techniques

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Abstract: HEAT level control (HLC) is one of the important elements for operating an iron-making blast furnace (BF). The goal of HLC is to maintain the hot metal temperature (HMT) as close to a preset aim as possible. HMT is an important indicator of both the product quality and fuel efficiency, and is measured from tapped out liquid iron. For instance, high values of HMT mean unnecessary fuel consumption together with sub-optimal hot metal chemistry, whilst low values of HMT may indicate insufficient fuel consumption, which may consequently lead to dangerous situation of freezing the slag inside the BF. Once an aim HMT is decided, based on production and plant constraints, several inputs of the BF can be adjusted by operators to control this HMT. However, any change of the inputs requires time to take effect, due to inherent time lags, and the best practice control relies heavily on an operator's experience and judgment. This is due to the complexity of the numerous BF processes, which essentially can be described as highly non-linear, stochastic and nonstationary in nature. The goal of this work is to employ a data mining approach to analyse the BF system and build a dynamical modelling system, which will generate a set of understandable symbolic rules for prediction of HMT changes. The model is regularly generated by decision tree applications, See5 and Cubist, in order to adapt any significant contextual variations of the BF. This rule based system can help the operators increase the BF's efficiency by making timely control adjustments with the goal of minimising variation of HMT with time. These models also provide a corpus of driving factors that can also be analysed by domain experts as an objective knowledge source.

Keywords: Decision Tree, Hot Metal Temperature, Iron-making, Non-stationary System

Introduction

HEAT LEVEL CONTROL (HLC) is one of the important elements for efficiently operating an iron-making blast furnace (BF). The goal of HLC is to maintain the hot metal temperature (HMT) as close to the aim HMT as possible. HMT is an important indicator of both the product quality and fuel efficiency, and is measured when the liquid iron (so called pig-iron) is tapped out. For instance, high values of HMT might mean unnecessary fuel consumption together with sub-optimal hot metal chemistry, whilst low values of HMT may indicate insufficient fuel consumption, which may consequently lead to a dangerous situation of freezing the slag inside the BF.

Once an aim HMT is decided, based on production and plant constraints, several inputs of the BF can be adjusted by operators to control this HMT. However, any change of the inputs requires time to take effect, due to inherent time lags, and the best practice control relies heavily on an operator's experience and judgment. Whilst there are set procedures which must be followed at times when HMT is significantly away from aim (±20°C), under normal conditions there are no set rules for optimising heat level. A major reason is due to the complexity of the numerous BF processes, which essentially can be described as highly non-linear, stochastic and non-stationary in nature.

In order to improve the HLC of the BF, the goal of this work is to employ a data mining approach to analyse the BF system and build a dynamical HMT modelling system, which will generate a set of understandable textual explanations (or symbolic rules) for prediction of HMT changes. These models also provide a corpus of driving factors that can also be analysed by domain experts as an objective knowledge source. The following section is a brief literature review of previous related research. Section 3 analyses the problems and difficulties associated with HMT prediction. Section 4 describes how the system has been designed and techniques used. The HMT prediction with results is presented in Section 5 and Section 6 is the summary.

Previous Work

The importance of HLC is well known, and has been studied for many years. Heat and Mass Balance models, based on known thermo-chemical fundamental behaviour, are used to analyse and understand the BF process. These models simulate the BF processes at a "steady state" condition using a number of non-linear equations [2]. Heat and mass balance models take a wide range of inputs, including material compositions and process flows, and subsequently predict important variables such as HMT. The outputs of a heat and mass balance model are generally treated as part of the control variables that reflect the current status of the BF. However as typical heat and mass balance models are based on steady state conditions, the performance of these models can suffer when the dynamic changes are made to the BF process, i.e. rapid change to input process flow or significant material composition change.

Other researchers have previously employed data mining technique in modelling HMT. De Ayala et al [3] utilised a neural networks technique to develop parametric models for HMT prediction with selected variables. Their models however only achieved an average error of ±20°C on predicting HMT, and have a poor extrapolation performance (outside the training data). Although ±20°C seems to be a small variance on a typical HMT of 1500°C, such a model would not be useful for the operational staff when attempting to optimise HMT and maintain within ±10°C of the aim HMT.

In the year 2007, Mochón et al [6] combined an adaptive neuro-fuzzy inference system and subtractive clustering algorithms to build an HMT model that predicts and simulates future HMT. Similar to our work, Mochón's system was aimed to assist the BF operator to achieve better control. Their models advise the operator whether the BF is in a cooling or heating stage, and from the figures they present, their HMT prediction error was generally within ±10°C.

Qubbaj [7] investigated the possibility of using decision tree techniques to analyse the HMT within of a "G" blast furnace in the year 2000. In this work, decision trees were used and analysed with minimal number of rules to get the maximum coverage, and relations between the input variables and HMT were analysed. However, the training data in this work was small and fixed, and in practice a fixed decision tree model (rule set) was observed to be invalid for continuous usage as the condition of a blast furnace changes with time.

Kaneko et al [4] recently published an article on predicting future HMTs values using JIT (Just-in-Time) modelling [9]. This is based on local multiple Regression and Bayesian Learning models which are generated from the latest neighbouring HLC data when a prediction is required. The combined prediction results have a correlation coefficient of over 0.8 with the real HMT values when predicting in a 1-hour ahead mode, and 0.6~0.7 correlation coefficient when predicting in a 2-hours ahead mode.

In these studies the focus is on predicting the value of HMT, however the average error was generally over 10°C, and the neuro-networks models are not easily persued by operational staff. In the present work, the aim is to generate a system that provides direct-viewable predictions 2 with similar or better accuracy than previous studies and ultimately assist the operational staff to minimise variation of HMT with time.

Project Analysis

From the data mining view point, a BF represents one of the richest and challenging spatio-temporal domains, embodying hundreds of dynamic and noisy data measurements that only partly reflect the underlying complex process phenomena. The Iron-making BF is a traditional process which continuously improves its operations by employing a wide range of techniques from various fields. The following list describes a number of major issues encountered in this project:

Complex Data Structure

Over 40 different process variables were considered in this work. All are electronically recorded in the BF data system and are used by operational staff to perform HLC. However each process variable has its own spatial interpretation, granularity and sampling errors. The variables are a mixture of BF input data (e.g. the charge rate – introduction of feed materials, the blast volume – hot air and fuel), output data (e.g. the top gas composition and the %–silicon in the iron) and derived data (e.g. theoretical aims or calculated indices based on accepted iron-making BF practice).

Unclear Relationships

Since the thermo-chemical behaviours in a BF are very complex, the relationships between the HLC variables and the HMT require significant interpretation by experienced operators. The measured HMT is a result of numerous metallurgy reactions inside the BF, and most of the observable HLC variables only indirectly reflect these internal processes. Because of the extremely high temperature inside the BF, precise measurements of the temperature and material compositions are not possible. Even though some of the HLC variables are considered to have a stronger influence on the HMT, according to experiences of various process experts and associated metallurgical theory, these variables alone are not enough to predict HMT. The preliminary modelling trials showed that models based on only "key" variables give very poor performance.

Methodology

The intention of this work is to create a dynamic HMT modelling system based on textual rules that can easily pursueable by operational experts and personnel. Dynamic rule-based modelling tools, Cubist and See5 [1], were used to generate decision trees that predict the change of direction of HMT (i.e. the trend), as well as forecasting the next HMT zone.

Data Pre-processing

The data used in this work represents a one year time period, and is primarily related to HLC, as nominated by a domain expert. The data has a range of granularity from top gas composition which is recorded every 6 minutes, charge rate which is recorded every hour up to the nominated aim pulverised coal rate (set by operational staff) which is updated weekly to fortnightly. The target variable, HMT, and a laboratory assessed variable, %-silicon in pig-iron, are manually sampled approximately once per hour. During initial pre-processing it was found that the HMT data contained erroneous values, usually as a result of an incorrect manual sampling procedure. The %-silicon in pig iron measurement is not prone to these sampling errors so it was utilised to identify and to remove those erroneous HMT records.

Domain experts associated with this work indicated that an approximate linear relation exists between the silicon content and the prevailing HMT, and an example scatter plot was provided as a guide. Based on these observations, a minimum message length (MML) [8] model was trained to cluster %-silicon and HMT data, this in turn provide a means to automatically remove invalid HMT records, as seen in Figure 1.

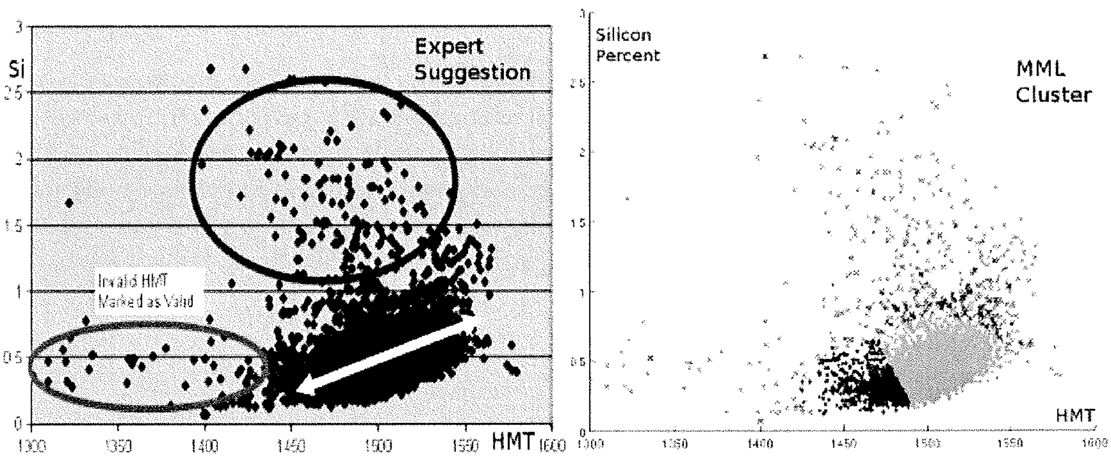


Figure 1: HMT-Silicon Relationship and MML Clustering Result

Since the time interval between consecutive HMT samples is relatively long, there is currently no appropriate way to estimate the HMT value between the samples, thus only the valid HMT measurements were taken into account. This means when an HMT sample is correctly probed, the associated HLC data are the coincident or closest associated records at that time of the HMT collection.

Some historical values are included as well, such as the two previous HMT and silicon values. Because all the past data are known, these historical values are linearly accommodated according to their current and past records, i.e. these inputs are values estimated at exactly 1 and 2 hours before, rather than the actual previous readings.

Temporal misalignment in the HMT and HLC data is an known difficult problem. Previous research attempts on this problem did not provide consistent improvement on the prediction performance. The initial time alignment was similar to that used by both De Ayala and Mochón [3, 6] where suggestions from operational experts are used, in this case, sourced from an internal tech-note. However, the performance of the resultant models with these suggested alignment parameters dramatically decreased in a fashion similar to Leonida's work [5]. Thus, this approach was not adopted in the current work. One idea is by combining symbolic time series representation and a group-based classifier, which is not heavily relying on the correctness of temporal alignments. Developing such a technique will form the basis of future work.

Decision Tree Generation

Cubist and See5 are similar decision tree tools developed by RuleQuest [1]. The function of See5 is to classify a fixed value-attribute dataset into a number of hyper-cubes that are subsequently identified as various classes in the parameter space. Whilst Cubist also segments the multi-dimensional data space into hyper-cubes in a similar fashion, the difference is it also forms a linear regression model within each hypercube, in order to form a numeric prediction of a target attribute. Example See5 and Cubist Rules can be viewed in Figure 2.

See5 sample rule:

```
Rule-11:
    HMB2 > 1508.4
    PCR <= 54.5
    HMT > 1506.5
    HMTp > 1506
then class 5 0.859
```

Cubist sample rule:

```
Rule-8:
if      HMB2 > 1507.5
        deltaCOCO2 > -0.45
        HMT > 1494.5

then    HMT_Next = 219.4 + 0.83*HMT - 2*COCO2 +
        0.12*HMB2 + 0.03*HMTpp - 0.12*PCR
```

Figure 2: Example Rules from See-5 & Cubist Models

The See-5 rule in Figure 2 indicates that when the foregoing four conditions are satisfied, the next HMT should occur in Zone5. And the Cubist rule shows that if the preceding three conditions are satisfied, the value of next HMT can be calculated using the given linear formula with selected variables.

After numerous trials and experiments, 21 variables identified and utilised for the decision tree data, covering a range of different HLC variables, and there were some 7,000 valid HLC-HMT records within the final dataset.

In the training data for cubist, the next valid HMT is used as training target variable, whilst for the See5, a number of class values needed to be identified, or labelled within the data. Five zones are considered as a possible segmentation across the typical distribution of HMT values. Here each zone is defined as a precise temperature range of HMT. The label associated with each zone is also used as the class-value. All 5 zones are required to contain approximately an equal number of HMT records, thus the boundaries of zones are established as: [1488 1498 1506 1514]°C. With these boundaries, any HMT record lower than 1488°C will be classified as in Zone1, and between 1488°C and 1498°C will be in Zone2 and so on.

HMT Varying Threshold

Whilst the See5 models are used to identify the next HMT zone, the next HMT temporal trend is alternatively predicted through a Cubist model. Three simple directions are defined as Up, Down and NoChange, and a comparison threshold T is required to decide whether the HMT is changing enough between two records. For instance, if the next HMT is higher than the current HMT for more than T degrees, then the temporal trend direction is classified as an Up, otherwise if the extent is less than T, it will be a NoChange. The threshold T is a subjective variable, as in practice what really matters is the occupancy of an HMT zone, more over a well predicted trend will significantly benefit the operator. Different process personnel have different opinions as to the value of this temperature change, and the domain expert would accept any threshold between 4 and 12°C as long as it is consistent. Without any further guidance, it would seem be reasonable to derive a natural estimate for T such that, for any given period of HMT variation, this threshold T should "reasonably" divide the HMT variations into 3 comparable sized classes. Although a seemingly subjective concept, in the experiments we utilised a standard deviation of the normalised numbers in all classes as a quantitative index.

Model Training and Prediction

A significant issue for this study is determining the size of the training and testing data sets with a non-stationary process such as the BF. A question of whether the system is in a stable or unstable state significantly influences how much data would be appropriate for training such a model. Also, given a non-stationary system to model, what longevity would an initially successful model be expected to possess, or how long would one expect an initially effective model to last before the prediction accuracy significantly declines? In order to find the optimised settings, exhaustive modelling was carried out across different combinations of training and testing sizes, also the threshold (T) for determining temporal trends of the HMT variation. Combinatorially, this required the formation of some 200,000 individual models, together with the associated analysis and assessment of each according to the prediction accuracy on (unseen) test data, the distribution of various false positives and negatives across testing data, as well as, how well a model performed on predicting different classes.

After considering the average accuracy, stability and feasibility, an overall acceptable combination for this specific application appears to be 800 for the size of training, and 90 for the testing data, with an HMT variation threshold of 8°C. As on the average there are some 20 valid HMT records a day, this is equivalent to building a model based on the operation of previous 40 days to predict the following 4.5 days.

Arbiter Model and Result Validation

Various arbiter models are employed to provide an ensemble of predictions on both the HMT zone and its temporal behaviour. Typically, the See5-based model provides a series of predictions indicating which temperature zone the next HMT is most likely to occur in. However, in many cases, multiple rules may be triggered simultaneously, and as such models select the zone with the highest confidence as a prediction. As one of the motivations in this work is to identify new understanding and plausible mechanisms of influence (driving factors) of the HMT, it is believed that the triggered rules with less confidence may also be useful to the operational personnel, and thus this information is also disclosed.

Multiple cubist-based models generate a series of predicted next HMT values each based on the available HLC testing data and individual trained models. The current HMT is then subtracted from these predictions and the differences are compared with the given threshold T, thus converting the numeric predictions into class-based temporal behaviours. In this work, currently two models are utilised to predict a onestep-ahead HMT value for each new current sample. The first is a model based on the most recent training data, whilst the second is the best historical model. The accuracy of either model is updated in real-time during the testing period, and these accuracies are then used as the influence weights for a final prediction of HMT temporal trends.

Results

For the exhaustive modelling stage, one selection criteria for assessing a good model was the overall HMT trend prediction accuracy being greater than 65%, thus the selected cubist-based models shall have a minimum of such accuracy on average. In comparison the See5-based models generally achieve over 70% accuracy on predicting the next HMT zone. The example plots in Figure 3 illustrate what information this combined decision tree model is able to provide to the operational personnel.

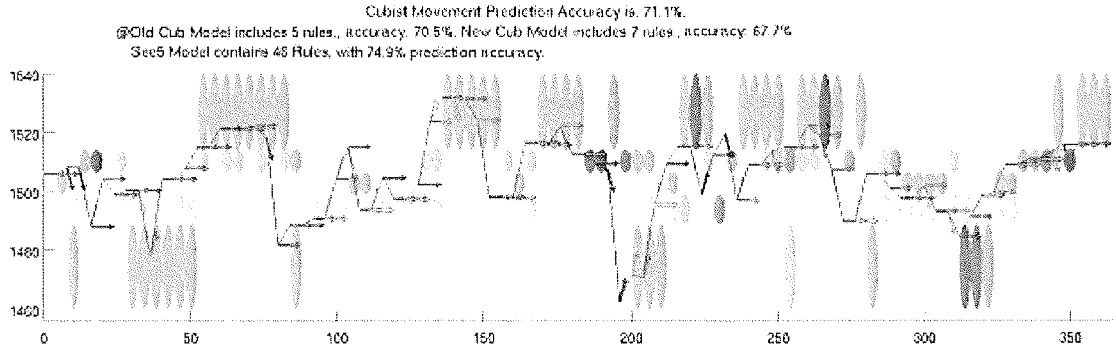
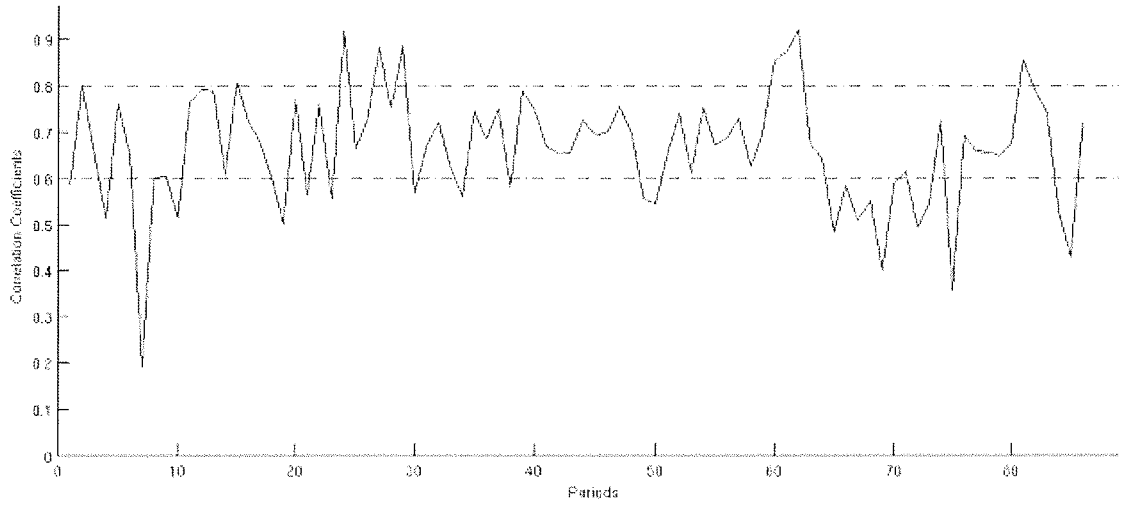


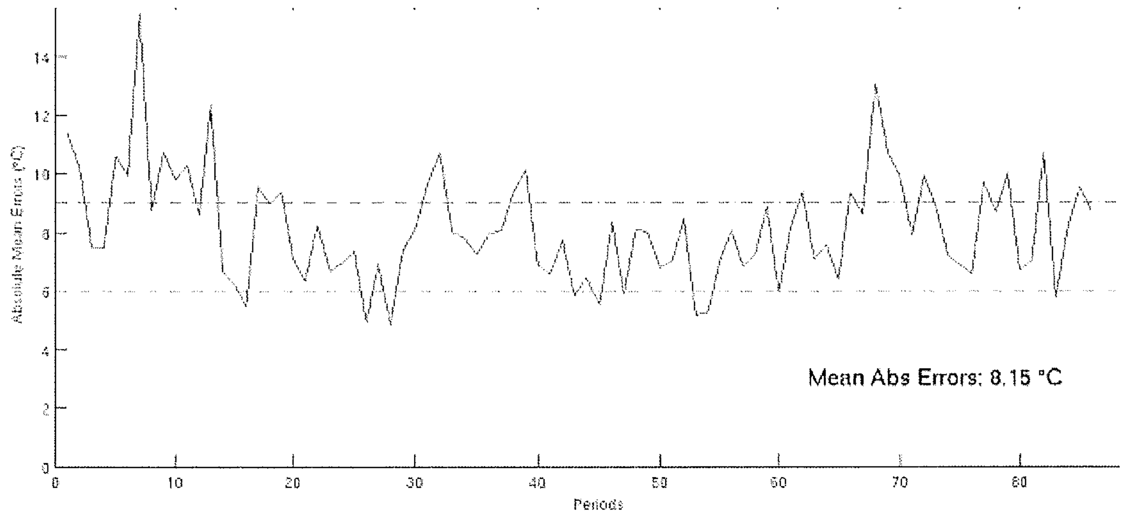
Figure 3: An Example of Prediction from Combined See5 & Cubist Models

Predicted HMT Trends and Zones

In Figure 3, the final accuracy of predicting next HMT changes is approximately 71%, and it is better than both the historic and new cubist models. The blue arrows mean that the predicted HMT trends match the actual trend, while red arrows show falsely predicted directions, accompanied with green arrows that indicate the actual direction of HMT change. The coloured ovals stand for the next HMT zones predicted by See5, and the yellow ovals represents a low-confidence and pink ovals signify a high-confidence of the corresponding rules. It can be observed that multiple zones appear sometimes when the HMT values are close to the boundaries, indicating that different rules are triggered. In this case, suggesting all possible zones is better than releasing the one with the highest confidence.



(a) CorrCoef Change in each Modelling Period

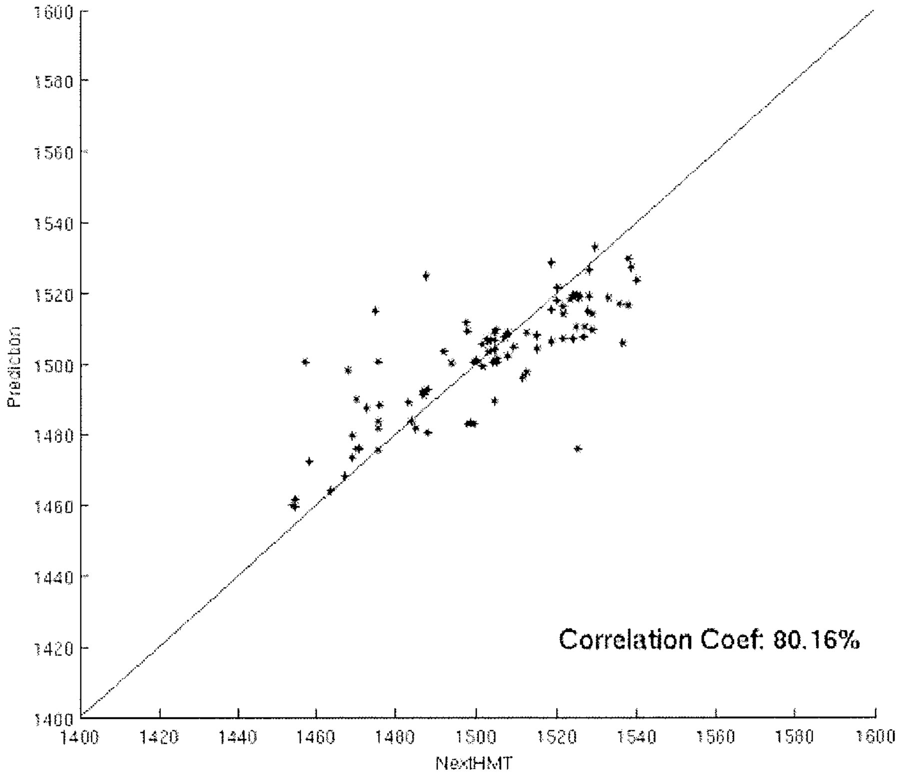


(b) Average Error on Predicting HMT 1hr Ahead

Figure 4: HMT Real Value Prediction Performance over Time

Predicted HMT Real Values

Apart from predicting the HMT trends and approximate temperature zones, our model also predicts the next HMT value. By dynamically weighting predictions from both cubist models, the average error in predicting HMT values in 1-hour is 8.15°C over one year period. In addition, the major correlation coefficients during each modelling period (4.5 days) fall in the range of 0.6~0.8. The performance of the HMT real value predictions is presented in Figure 4, and Figure 5 shows two scatter plots of prediction vs. real HMT, each from one modelling period (90 predictions).



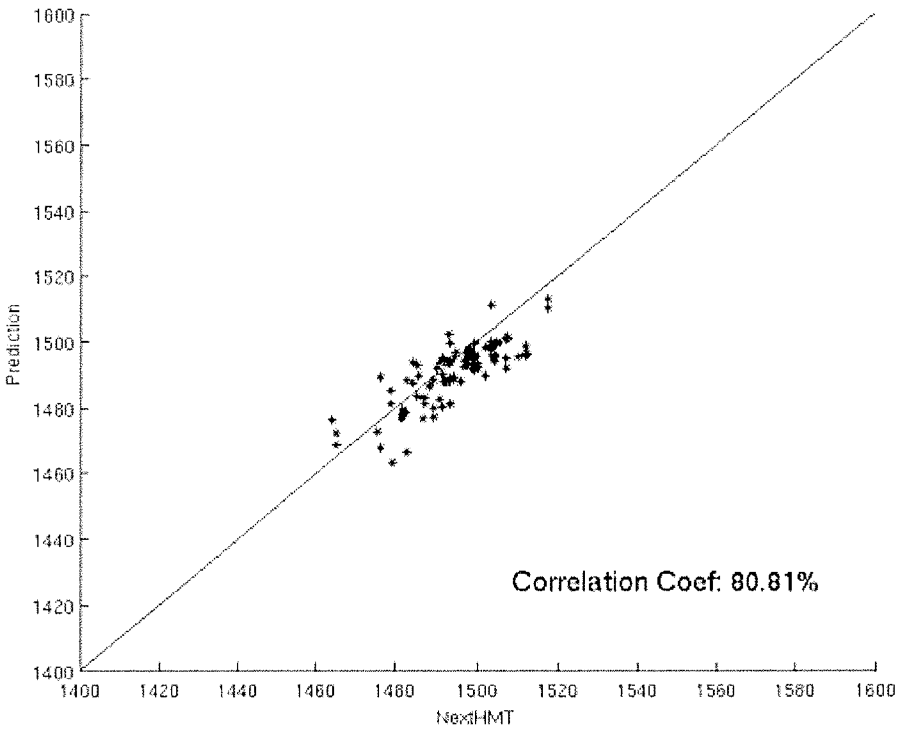


Figure 5: Prediction vs. Real HMT within one Modelling Period

The results shown above indicate that the decision tree models produce an acceptable level of accuracy on forecasting significant changes in HMT. These models provide clear predictions of next HMT movements and possible zones to the operational personnel and assist foreseeing HLC. Dynamic weighted Cubist models also predict HMT with an average error less than 10°C. Comparing to similar works mentioned in Section 2, the advantage of decision tree based models is the higher accuracy and easily understandable rules for analysis. Either the zone-based or the value-based HMT predictions can be disclosed to the BF operator depending on various needs, and in most cases the predicted temperature trends and zones reflect the BF heat level change correctly.

Conclusion

This paper presents a decision tree based HMT modelling system designed to improve the efficiency of the iron-making blast furnace. This rule based system will help the operators to make timely control adjustments with the goal of minimising variation of HMT with time. The model produces human understandable rules and can predict the magnitude and direction of HMT changes with acceptable accuracy (>70%). The HMT model is regularly generated by decision tree applications, See5 and Cubist, in order to adapt to any significant contextual variations of the blast furnace process.

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