Applied Statistical Analysis on the Calcination Process in the Ferronickel Production

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Abstract Ferronickel is mainly produced by the RKEF (Rotary Kiln Electric Furnace) process. The ore is extracted, crushed and dried before calcination. Rotary kilns are usually about 100 m long and rotate to facilitate material flow. Due to this length, in addition to rotation speed, the material takes a variable time to cross the whole kiln, and thereby changing the chemical and temperature profile, making the control of calcine temperature a great challenge. However, statistical analysis are a great tool for finding interesting patterns that are of valuable help to control the kiln variables, that are very sensitive to inertia caused by rotation and changes in temperature profile. We present a study based on real data taken from a processing plant, whereby we applied data mining techniques to extract information on which variables have influence on kiln's key performance index variables, such as calcine temperature.

Keywords Rotary kiln control · Applied statistics · Chemical process

Introduction

Statistics has been applied on process control for decades by means of techniques like Analysis of Variance (ANOVA), Statistical Process Control (SPC), Principal Components Analysis (PCA) and Projection to Latent Structures (PLS) [1]. These techniques offer great help to control very sensitive process variables.

Nowadays every industry maintains huge process databases that implicit reflect the process dynamics, whereby these data provide the underlying base for all kinds of process analysis. In this sense, it seems reasonable to look back at those data to examine some unexpected deviation, or investigate some process phenomena [2]. In addition, the history database hides invisible patterns, even for experts in operation,

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but detectable by statistics [3]. Understanding these patterns is fundamental for carrying out a great control.

In this work, we present a statistical procedure to find patterns in the calcination phase of the Ferronickel RKEF (Rotary Kiln Electric Furnace) process.

The Rotary Kiln in the Ferronickel Production

One of the ferronickel production forms is by the RKEF process. In this process, run-of-mine ore is extracted, crushed, dried before being fed into rotary kilns [4]. The main role of rotary kilns is to transform chemically the ore into calcine by heating it up to around 900 °C over the time needed to calcination process. The rotary kilns for this process are usually long, extending over 100 m, leading the material to take hours to cross the entire kiln, therefore resulting in a temperature gradient over the kiln and three defined zones: drying, heating and reduction zones (Fig. 1).

Other processes, such as cement and lime calcining, also apply rotary kilns [5]. The length should be compatible to a proper heating and reduction time, wherein rotation acts as a significant component to the material passage. A burner is located at a lower level to provide heat throughout the kiln, and gas exhausters account for the flame extension and a smother temperature gradient. An exhauster pulls out the hot gas through a bag filter, cleaning it before throwing into atmosphere. This exhauster helps also in the flame length due to the pressure drop. A blower injects additional (secondary) air into the kiln, to help combustion. Figure 2 shows a schema of the whole process.

The Calcine Temperature Challenge

In every rotary kiln application (not only for ferronickel production), calcine temperature is the most important KPI (key performance index). Insufficient calcine temperatures lead to bad calcine quality [6, 7]. On the other hand, a very high temperature can cause problems to the refractory lining at the hot end [4]. For those reasons, there is an optimum range for the calcine temperature. However, it is influenced by many factors in the kiln, including:
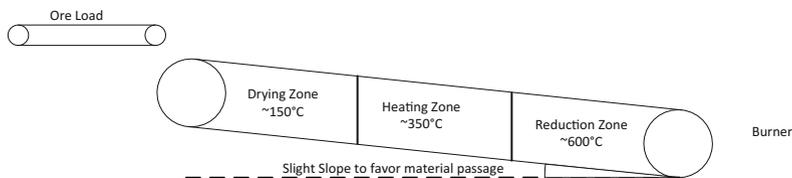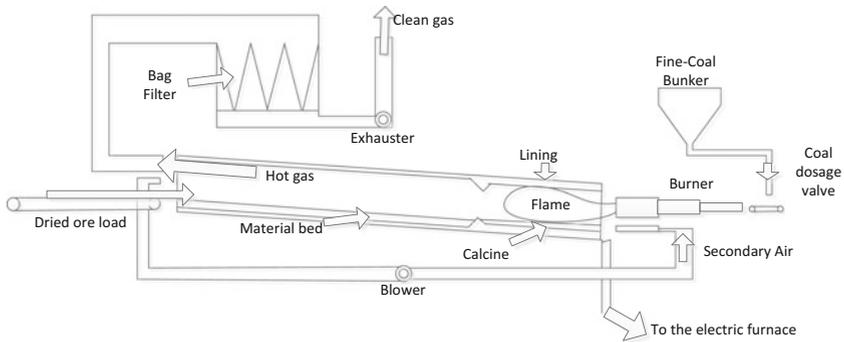

Fig. 1 Kiln scheme with three zones

Fig. 2 The rotary kiln full system

- Pressure drop
- Temperature profile
- Chemical profile
- Kiln rotation
- Primary, secondary and tertiary air flows
- Material inflow and outflow rate.

The kiln rotation is tightly linked with the material flow. Kiln should rotate faster as ore load increases. However changes in rotation cause changes in temperature profile. Thereby calcine temperature responds to control actions only after a variable time. This fact makes both the modelling and control of the rotary kiln very complex tasks [8, 9]. Current approaches are just approximations of the time-varying plant. However, artificial intelligence and data mining based models are able to give good results [5].

Data Mining and Statistical Analysis in Industrial Processes

Data mining and statistical analysis techniques are helpful in finding interesting patterns in the plant operation [3]. As the technology evolved to collected millions of data over a very short time, the analyses of such data are still in development though [2]. Computer control does not rely only on the classical digital control techniques anymore, but also on the tons of data produced by huge sensor networks. This calls for the data mining techniques to find useful information in this huge dataset.

Pattern Recognition

In industrial processes, there are a number of data mining applications to formally define the process patterns. Wang et al. [10] exploited data mining to predict,

optimize and diagnose parameters in oil field. Namikka and Gibbon [2] applied data mining for exploratory analysis and process modelling making use of multivariate statistical methods for dimensionality reduction. Meré et al. [11] reviewed the typical environments where data mining is applied, and presented a series of tools to deal with outliers in the galvanized steel production. Sadoyan et al. [12] sought patterns in manufacturing process control using Rough Sets (RS) for identifying if-then type rules.

Regarding process control, artificial intelligence techniques like Fuzzy Systems and Neural Networks are used in the works of Yang et al. [9] and Meré et al. [11], however these techniques have a complex implementation and require large computational time [12]. In addition, neural networks are black box, i.e. one does not know how the results are produced [8]. Techniques like Association Rules [13] and Decision Trees [14] are able to find relevant patterns in the process in a clearly understandable text form.

Control Variables Histogram

Considering the process as an N-dimensional space, rules define a subspace wherein each variable will have a new statistical distribution, in a histogram form. By classifying the variables into control (U) and observation (Y), and assuming that the control will reflect after some time on the observation, we can apply joint probability distribution (JPD) to statistically determine the relation between control and observation:

$$P(Y, U) = P(Y)P(Y|U) \qquad (1)$$

Where *P(Y)* is a probability for the vector of observations *Y* to have a certain set of values, *P(Y|U)* is the conditional probability of the observations *Y* to have a set of values given that *U* has a set of control values. The conditional probability can be interpreted as the value of *Y* depends or is influenced by the value of *U*. In a complex system, this may be modelled as a Bayesian Network, which is a diagram of causation theoretically design by an expert in the field of application. Deventer et al. [15] show an example of a Bayesian Network applied in control of dynamic process (Fig. 3).

The probability distributions (PD) are determined based on the process history in the form of histograms. By applying one rule (filter or slice in the n-dimensional

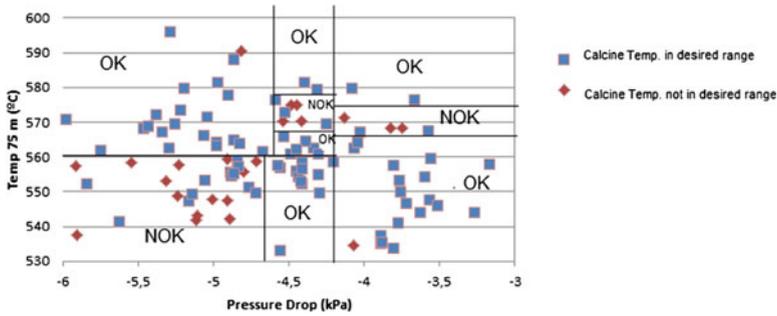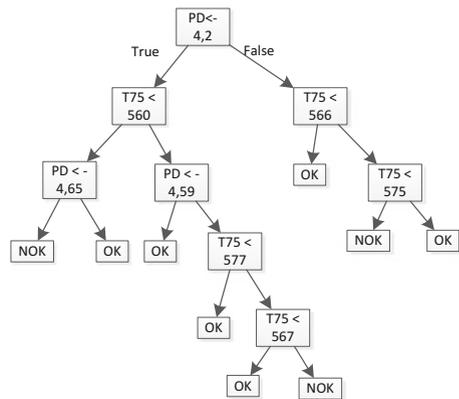**Fig. 3** Schema of a multivariate Bayesian Network with 2 controls and 4 observations
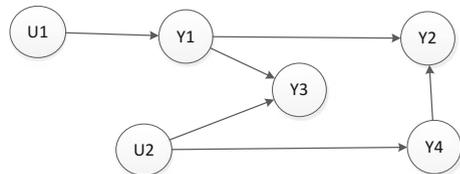
Fig. 4 Scatter plot of two variables where the desired range points are separated by slicing the dataset

Fig. 5 A decision tree that separates the desired from the undesired range in the previous dataset, considering variables Pressure Drop (PD) and Temperature at 75 m (T75)

data hyperspace), the PD's change until we drill down to a single record containing only one single value for each variable.

Determining Optimal Control Ranges

For the main performance index, we define the range on which it should be. That would be our target parameter Y_p, and $P(Y_p = [y_{pmin} \; y_{pmax}])$. So, we need to find the slices in the data for the control and observable variables that would maximize $P(Y_p = [y_{pmin} \; y_{pmax}] | slices)$. These slices will compose a certain rule of the type *"if $Y = [y_{min} \; y_{man}]$ and $U = [u_{min} \; u_{max}]$ then $Y_p = [y_{pmin} \; y_{pmax}]$ with probability P"*.

Since we are interested only on the desired performance index Y_p, we can leave only the desirable values, reducing the rule to the form *"if $Y = [y_{min} \; y_{max}]$ then $U = [u_{min} \; u_{max}]$ with a probability P"*. The rules can be determined using information criteria applied via association rules and decision trees techniques (Figs. 4 and 5).
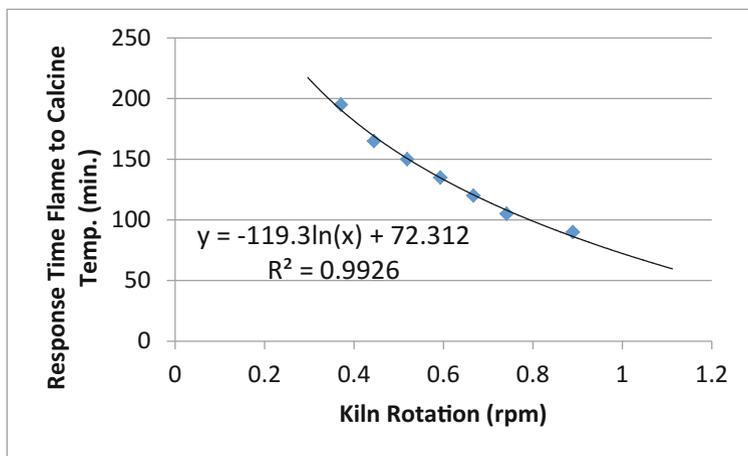
Fig. 6 Response time of Flame to Calcine Temperature according to Saeman [16]

Dynamic Part of the System

To handle the delays of the system, we applied two approaches. Firstly, we used the Saeman [16] residence time equation to determine proportionally the response time to control according to kiln's rotation.

That resulted in the following relation with the response time (Fig. 6).

Another additional strategy to determine time differences is by tracking the influences via the theoretical causal relations. It is known by the work of Naud & Emond [7], that the fuel combustion causes the flame to heat up the lining, which is a refractory material, i.e. it retains the heat. The material then receives the heat from the lining, besides the flame itself. So the more accurate way to investigate the temporal response is by determining the influence of the fuel valve on a temperature point nearest to the flame's highest temperature, and then the influence of this point to the calcine's temperature. In our case, this point is 75 m from the cold end (Figs. 7 and 8).
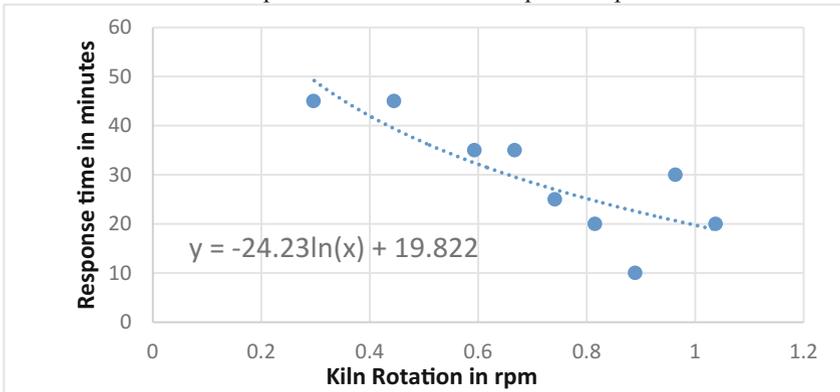
By performing correlation analyses and filtering out noisy data, we found the following relation.

Fig. 7 Dependency relation between Fuel, Material and Calcine Temperature
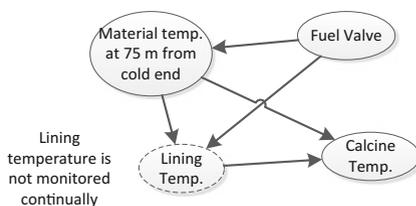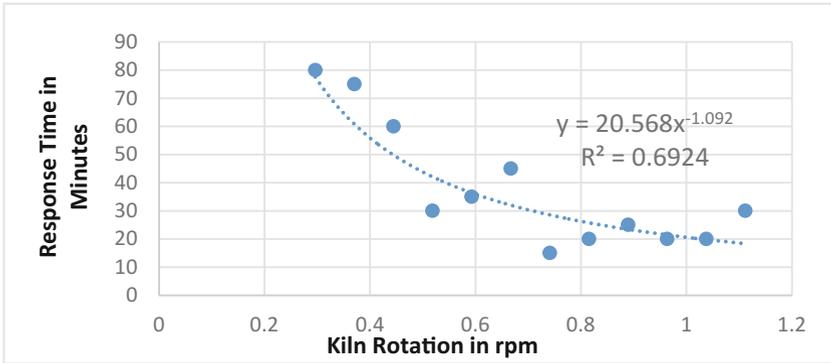
8a – Response time of calcine temp. to temp. 75m

8b – Response time of flame to temp. 75 m.

Fig. 8 a Response time of calcine temp. to temp. 75 m **b**– Response time of flame to temp. 75 m

Finally, to find the rules, we collected 4 months (April thru August 2016) of data from our process plant and sliced up this dataset into 10 zones corresponding to 10 rotation speeds (from 50 T/h to 140 T/h). The total size of the database was about 152000 records sampled by minute. The variables included in the control were:

- Ore Load
- Temperature at 48 and 75 m from cold end
- Oxygen concentration
- Pressure drop before exhausters
- Secondary air pressure
- Calcine Temperature
- Fuel load.

Comparison with Current Control

The realization of a control algorithm involves a number of practices including programming and integration with production environment [5]. This step can be unexpectedly long on account of technical resources. In every case, it is possible to make comparisons with the current control used and somehow determine if the new strategy is able to detect or prevent undesirable deviations in the process. At the time of writing this article, the control algorithm was not yet implanted in production environment, but we performed a simulation of what control actions would be taken for every minute of operation.

In Fig. 9 we plotted the results of a comparison over one work day in the plant. The light yellow line with circles at the top refers to the calcine temperature; the dark line with triangles is the actual control actions taken, and the dark blue line with circles at the bottom refers to the ore load. The gray lines represent optimal the interval for the control that was determined via the rules found by the decision tree or general association rules algorithm.

Some interesting and worth noting cases are discussed as follows. During the preheating phase, the lining may heat up very quickly while the material that remained in the kiln takes longer time to heat, causing sudden variations in temperature profile. Moreover, during preheat the ore load and rotation is low, leading to a long response time of the calcine temperature, and because of that, we take into account only ore loads greater than 50 T/h. In this figure, although the lining heated up quickly, the material that came afterwards was not sufficiently heated, as the kiln rotated faster. The algorithm suggested for that state (ore load around 50 T/h) one extra ton for coal dosing (3.5 T/h instead of 2.5 T/h).

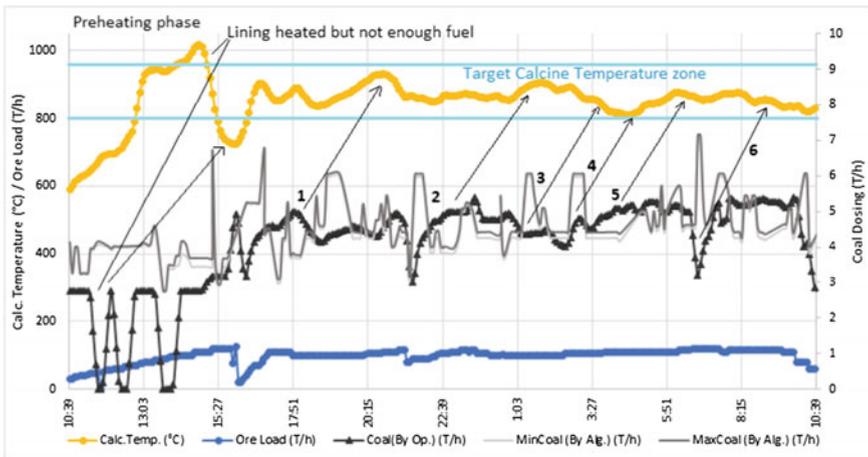The numbers in the figure indicates some other cases:

Fig. 9 Comparison of this data analysis approach with current control

1. The calcine temperature was in a rise trend and the algorithm suggested a lower level of fuel
2. Same case of 1
3. Forecasting a fall in the calcine temperature, suggested an additional fuel load
4. Although the calc. temperature was falling, the algorithm caught signs that the temperature was about to rise again, and suggested a lower level of fuel after having suggested a higher level
5. To prevent temperature rise, suggested a lower level
6. Some event may have cause calcine temperature to fall in the next hours and the control suggested a high load of fuel.

It is worth noting that this simulation should be dynamic, i.e. if the control actions taken by operators were the same of the suggested ones, the next suggestions would surely be different, provided that the observable variables would have changed. This may explain sudden and abrupt variations in the coal dosing suggestions. Since this algorithm is purely based on statistics, it is very likely that the kiln eventually matches a rule, which would suggest a very different coal dosing level than the previous or current level. Fuzzy decision trees [17] would certainly prevent such sudden changes in suggestions, as the bounds between rules would be soft and gradual instead of crisp hard limiting. It should also be considered that this algorithm is based on real data, events that actually happened in the plant, so new events that can affect calcine temperature are not detected. In any case, actions that an experienced operator or an expert in kilns would take are likely to be represented by these rules; therefore, new staff will have access to this knowledge by means of this system.

Conclusions

In this paper we have showed a statistically based approach to find patterns in the calcination process in ferronickel production. Since this is a very complex and hard to control environment, statistics arise as a powerful tool to discover relations between events and variables towards a satisfactory end. In our case the task was to find the fuel levels that would provide the desirable range in calcine temperature with the maximum likelihood. By applying data-based algorithms, like association rules and decision trees, we found the searched patterns in the form of rules, whereby the optimum control ranges are determined by probability.

Although this control is not applied to production yet, we could get a glimpse of some results by static simulation with real time process data. The results found in this article will support the adoption of this methodology to search for new patterns in this process.

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