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Control strategy of a Multiple Hearth Furnace enhanced by machine learning algorithms

José Valentín Gómez Fuentes, Sirkka-Liisa Jämsä-Jounela, David Moseley, Tom Skuse

Abstract— An enhanced control strategy for a multiple hearth furnace for the purpose of kaolin production is developed and presented in this paper. Mineralogy-driven machine learning algorithms play a key role in the optimization strategy of the furnace. First, the capacity and temperature setpoints for furnace control are determined based on the feed ore mineralogy. Next, the capacity is optimized by combining the prediction of soluble alumina content and mullite content, while maintaining the quality of the product. The stabilizing control level compensates the disturbances with a feedforward control, which uses a spinel phase reaction rate soft sensor, aimed at minimizing the energy use of the furnace. The control concept is successfully tested by simulation using industrial data. Finally, a sampling campaign and software testing of the soft sensors and machine learning algorithms are performed at the industrial site. The results are presented and discussed in the paper..

I. INTRODUCTION

The global competition and growing complexity in industrial processes, such as the increased quality requirements of the products, has led to the improvement of modern process monitoring, data analytics and control methods. Presently, the ambitious idea of Industry 4.0 or Industrial Internet, has been popularized increasingly by different sectors to outline the trend towards digitalization, automation and the rising use of big data analytics, machine learning (ML) and deep learning algorithms in the manufacturing industries. Despite the offered advantages, companies from the mineral processing industry have not fully achieved the integration of these innovative technologies, with operators handling the changes in operating regions and reacting to process faults and disturbances [1]. To optimize the process operations in mineral processing industries, the integration of online measurements, soft sensors and advanced process control is necessary. This paper presents an application of ML and advanced control to a calciner in kaolin production. The development phases of the control strategy are described and the results of the simulation environment and the plant testing are discussed.

Calciner furnaces such as multiple hearth furnaces (MHF) and rotary kilns are broadly utilized in the industry for the calcination of kaolin. The calciner control system has an essential role in ensuring uniform product quality while optimizing the furnace capacity and enhancing the furnace energy efficiency for optimal operation. The quality of the calcined product highly relies on the temperature profile throughout the furnace; thus, a stable and favorable temperature is crucial for creating optimal quality products. However, regulating the temperature of an industrial calciner is very demanding. Concretely, the zones (hearth) present cross-coupling effects between the variables as well as between hearths, which increase the difficulty in regulating the

temperature profile. In many cases, using conventional single-input single-output PI controllers to regulate the temperature independently cannot provide the desired gas temperature profile. Therefore, various control methods, such as multivariable controllers, neural networks, fuzzy logic methods [2], and model predictive controls [3] have been implemented to address this problem.

In process industries, soft sensors are a highly valued tools for estimating and monitoring process variables, specifically for the cases where the measurements of important states are unavailable, difficult to obtain or require time-consuming and costly analyzes [4], [5]. Soft sensors can be designed based on first principles such as mass and energy balances and Computational Fluid Dynamics (CFD). For instance, Copertaro, et al. [6] developed a CFD model to predict critical variables in a cement kiln suggesting a possible use to monitor the process in quasi real-time. Lin et al. [7] proposed a systematic approach to design soft sensors based on principal component analysis and dynamic partial least squares. The authors illustrated their methodology to estimate the free lime and NO_x emissions in a cement kiln system. Furthermore, advanced machine learning algorithms such as Artificial Neural Networks (ANN) have been applied successfully in calciners. Yuan & Liu [8] designed a soft sensor based on a back propagation ANN to estimate the apparent degree of calcination in a new suspension preheater dry process kiln.

This paper demonstrates a new approach for the control strategy of a MHF. The aim is to maximize the capacity of the furnace and to minimize the energy use under the constraints specified by the desired product type. The approach takes into account the trade-off between the soluble alumina and mullite contents in the output product. These targets are achieved by integrating the soft sensors predictions, based on energy balance and/or ANN calculations, as constraints of the control strategy. The soft sensors and control strategy are first tested in the simulation environment and then connected online to the plant automation system.

The paper is structured as follows. Section II presents the process description and Section III describes the enhanced quality control concept for the MHF. Next, Section IV presents the simulation results of the control strategy. Section V delineates the soft sensor testing in the industrial environment as well as the evaluation of the control logic. Finally, Section VI concludes the manuscript.

II. PROCESS DESCRIPTION

This study considers a kaolin calciner, known as a multiple hearth furnace, which features a counter-current solid and gas flows. The furnace has eight hearths, and eight burners located in hearths 4 and 6, combusting natural gas and

providing the necessary heat for the calcination reactions. The airflow supplied to the burners for the gas combustion, is calculated considering the stoichiometric ratio. The burners are disposed in a tangential alignment.

Kaolin is introduced to the first hearth located at the top of the furnace. In the calciner, the material is moved by the metal plates, called blades, which are attached to the rotating rabble arms, designed with the intention of transporting the material outwards on even-numbered hearths and inwards on odd-numbered hearths. The kaolin crossing the even numbered hearths travels outward to descend through the holes at the outside border of the hearth, while in the odd-numbered hearths kaolin falls to the next hearth through a single annulus located around the shaft carrying the rabble arms. Figure 1 illustrates the design of the calciner.

The solid temperature increases as the material moves down through the furnace and reaches the maximum in Hearth 6. Kaolinite reacts to metakaolin in hearths 3, 4 and 5 at a temperature between 400-700 °C. The metakaolin is discharged from hearth 5 at a temperature of 800 °C approximately, which continues to increase in hearth 6, where the reaction of metakaolin to the Al-Si spinel phase occurs [9]. Therefore, the main aim of the hearth 6 is to rise the temperature to expedite the absorption of aluminium into the silica phase. The temperature control in the hearth 6 is critical to avoid overheating, which may result in the undesired formation of a material with a higher crystallinity degree,

Figure 1. Cross-sectional picture of the Herreschoff calciner with direct fire burners.

which may create some abrasion problems. The solid phase temperature begins to decrease in the hearths 7 and 8, and the product exits the hearth 8 through two discharge holes at a temperature of 750 °C.

Kaolin undergoes four physical-chemical transformations inside the calciner. First, the evaporation of the free moisture occurs at 100 °C.

Second, kaolin is transformed to metakaolin through the dehydroxylation reaction, where the chemically bound water is removed at 450 – 700 °C.

The third physical-chemical reaction involves the transmutation of metakaolin to the ‘spinel phase’ by exothermic re-crystallization at 925-1050 °C.

Finally, the nucleation of the spinel phase occurs and the material reacts into mullite at temperatures above 1050 °C.

Mullite is a hard and abrasive material, and it can cause damage to process equipment [10]. The desired final product (within specification) has both a low metakaolin and mullite content.

III. ENHANCED CONTROL CONCEPT

The overall control strategy proposed in this study is aimed at selecting the best operating conditions to improve the production capacity and energy efficiency, while ensuring the required product quality. The process control system comprises optimizing, stabilizing, and basic levels, as shown in Figure 2.

Figure 2 Enhanced quality control scheme of the furnace

The plant personnel determine the final product specifications with regard to the current ore mineralogy. The product quality requirements, e.g., the soluble alumina content and brightness, are defined next to the selected product specifications. A look-up table provides the setpoints for the gas temperatures in hearths 4 and 6 based on the current production capacity and iron content in the ore. The table is based on the classifications of the feed type and process conditions, by the self-organizing map (SOM) technique [11], [12]. Furthermore, the temperature setpoints are adjusted on a regular basis, e.g., once a day, based on laboratory measurements of the product characteristics. This is performed to maintain the product quality within the specifications.

To increase the plant capacity, it is necessary to achieve the maximum production rate. This is indicated by the mullite content and soluble alumina measurements (provided by the soft sensors) and is achieved by solving the following optimization problem.

$$\begin{aligned} & \max F \\ & \min(F_4 + F_6) \end{aligned} \quad (10)$$

With respect to constrains:

$$\begin{aligned} F_{T_4}(F_4, F_6, r, F) &= T_4 \\ F_{T_6}(F_4, F_6, r, F) &= T_6 \\ m(F_4, F_6, T_1, F) &\leq m^* \\ S(F_4, F_6, r, F) &\leq S^* \\ T_6 &\geq T_6^{\min}(F, r) \\ T_4^{\min} &\leq T_4 \leq T_6^{\max} \\ Vio &\geq Vio^* \end{aligned}$$

Where F , F_4 , and F_6 represent the feed rate and gas flows to hearths 4 and 6, respectively; T_1 , T_4 and T_6 are the temperatures in hearths 1, 4 and 6, respectively; r is the current

value of the reaction soft sensor; S and S^* are the soluble aluminium content and its threshold (if applicable). m and m^* are the mullite content and its threshold. The stabilizing level aims to reduce the variations in the calcination reaction. Finally, Vio is the brightness (measured as the percentage of light reflected in the violet spectrum) and its threshold.

The stabilizing level is aimed at attenuating the variations in the calcination reaction that occur in the solid phase of the furnace. In other words, the gas temperature setpoints have to be modified based on the progress of calcination in the solid phase. Thus, if the exothermic reaction starts when the material enters hearth 6 or occurs actively in hearth 4, the temperature setpoints must be lowered to save fuel and avoid over-calcination. To assess the calcination progress, the soft sensor is used to estimate the exothermic reaction rate in hearth 4 and the feedforward control is used to adjust the temperature in hearth 6.

The basic level controls the temperature with a mean temperature control scheme. Due to a possible increased capacity, complications may arise while controlling the temperature in the MHF. These complications are related to the burner-to-burner (BtoB) phenomenon [13], which causes nonlinearities and instabilities in the temperature control [14]. The mean temperature control is aimed at attenuating the effects of the BtoB phenomenon and homogenizing the gas phase temperature in hearth 4 by performing the operation based on the average temperature of the gas phase, instead of individually manipulating each burner [15].

A. Optimal process conditions based on the furnace feed and product

The so-called U-matrix was obtained resulting from the SOM method for the data in June 2017, which associates a point to a product and its corresponding operating conditions. During this period, two different products were produced (P1 and P2). The difference between the products and their respective process conditions were obtained.

The SOM technique facilitated the determination of the optimal process operating conditions for different types of products versus the feed material characteristics. A look-up table based on the feed rate, iron content, and brightness was constructed to identify the best temperature setpoints for hearths 4 and 6 in each operating condition. The capacity and temperature setpoints of the table were corroborated by the mass and energy balance calculations.

B. Mullite content and soluble alumina soft sensor based on an artificial neural network

A soft sensor, based on a feed-forward multi-layer perceptron neural network, was implemented to model the mullite content and soluble alumina in the final product. The five applied input variables included the kiln feed, hearth 4 temperature, hearth 4 gas flow, hearth 6 temperature, and hearth 6 gas flow.

The final design of the network had three hidden layers, each with 20 nodes, and a single node output layer as depicted in Figure 3. During the model training, the performance of different training algorithms was compared to select the best result. The training algorithms included the Levenberg-Marquardt (LM), Bayesian regularization (BR), and Broyden-Fletcher-Goldfarb-Shanno (BGFS) quasi-Newton backpropagation. To develop the model, data from June 2017 were used and randomly divided into three sets: training (70%), validation (15%), and testing (15%). Finally, the model was limited to a maximum of 1000 epochs, and training was performed using the neural network toolbox in MATLAB 2018b.

From Table 1, the performance comparison of the training algorithms show that the LM and BGFS provided similar

Figure 3. Four-layer feed-forward neural network architecture.

results with an MSE of less than 0.4 and a correlation coefficient R^2 of approximately 0.70, taking less than 2 minutes to train. The performance of the BR algorithm was quite superior compared to the other two, with an MSE of 0.2126. The only disadvantage of the BR algorithm was the training time of almost 12 minutes. Although it took longer compared with the other algorithms, the BR algorithm was

considered the best option for the final model training due to its performance.

TABLE 1 PERFORMANCE COMPARISON OF THE TRAINING ALGORITHMS FOR THE MULLITE CONTENT SOFT SENSOR

Training algorithm	MSE	R ²	Training time, min
LM	0.3660	0.6993	0.55
BR	0.2126	0.8936	11.55
BGFS	0.3927	0.6647	1.41

The results of the soft sensor model using the BR algorithm are presented in Figure 5. A regression correlation coefficient of 0.8936 was obtained by the mullite content modeling. In general, the model prediction was fairly acceptable but could be further improved, e.g., by testing different architectures and including more process variables. Furthermore, additional process data would be useful for improving the reliability of the soft sensor model.

Figure 5 Comparison of mullite content: XRD vs. the ANN soft sensor

Table 2 presents a performance comparison of the training algorithms, with every algorithm providing similar MSE results of less than 0.21 and a correlation coefficient R² of approximately 0.90, taking less than 2 min to train for the LM and BGFS algorithms. The results of the BR algorithm are remarkable, with a MSE of 0.1128. As before, the BR algorithm training took a longer time compared with the other two algorithms, requiring almost 14 min. In this case, the BR algorithm may be the optimal choice because of its minimal prediction error.

TABLE 2 PERFORMANCE COMPARISON OF THE TRAINING ALGORITHMS FOR THE SOLUBLE ALUMINA SOFT SENSOR

Training algorithm	MSE	R ²	Training time, min
LM	0.1497	0.8998	1.41
BR	0.1128	0.9540	13.70
BGFS	0.2052	0.8316	1.66

. depicts the results of the soluble alumina soft sensor model trained with the BR algorithm, compared with the

soluble alumina measurement using inductively coupled plasma atomic emission spectroscopy (ICP-AES). The soft sensor presents a regression correlation coefficient of 0.9540, indicating that the ANN soft sensor is a reliable choice for estimating soluble alumina in real time. The inclusion of more process variables and evaluation of various architecture structures provides an opportunity to improve the soft sensor estimations. Furthermore, the addition of extended data sets would enhance the accuracy of the soft sensor model.

Figure 4 Comparison of soluble alumina: ICP-AES vs. ANN soft sensor.

IV. TESTING RESULTS OF THE CONTROL CONCEPT

The testing setup for the modeling and control of the MHF was designed and implemented in the MATLAB® environment. The setup consisted of the dynamic model of the MHF, the two soft sensors (mullite content and spinel phase reaction rate indicators), and the control logic presented in Figure 2., i.e., the basic temperature controller, feedforward control for energy use reduction, and optimizing control for capacity improvement. To speed up the computations, the mechanistic model was converted into C language and precompiled. All other blocks and elements were realized using standard MATLAB® functions. The simulation included an Euler solver with a fixed step of 20s. The data for the control strategy simulation were obtained from samples gathered directly from the calciner in June 2017. This data included the process variables from the history logs, as well as the results from the chemical analyses, such as the X-ray diffraction for the mullite content and inductively coupled plasma atomic emission spectroscopy for the soluble alumina.

A. Spinel-phase soft sensor and simulation of feedforward control

The data analysis demonstrated several instances where the gas flow in hearth 4 fluctuated together with the temperature

measurements in hearth 5. Various ore properties, e.g., particle size, strongly affect the reaction rates and heat. Thus, the reaction (Eq. 3) may have started at the preceding location. Based on these results, a spinel phase soft sensor was developed to estimate the rate of the exothermic reaction occurring in hearth 4. Incorporating this soft sensor into a feedforward control scheme would offer a great opportunity to increase the energy savings in the furnace.

The soft sensor calculates the value of the reaction rate as a conversion percentage from the metakaolin to spinel phases, which is performed for the first part of the furnace (hearth 1 to 4). The data are then sent to the feedforward control.

Under typical process conditions, the spinel phase is formed in hearth 6. Thus, a shift in the reaction location would appear when the soft sensor values are greater than 60%. When this occurs, the feedforward control is activated, and the control is kept active for 240 min. This control interval was obtained from the maximum duration of the exothermic reaction, as suggested by the data obtained in a previous study [14].

Figure 6. presents a comparison between the current control (blue) and feedforward scheme (orange). The variables presented in the figure represent the reaction rate (RR), total gas flow, gas temperature of hearth 6 (T6), and T6 setpoint. A disturbance was introduced 150min after the simulation started, and the RR increased from 60 to 70%. The feedforward control rejected the disturbances by reducing the temperature setpoint by 17 °C, and therefore the energy consumption was reduced. In contrast, the current control did not adjust to the effects of the disturbance.

Figure 6 Comparison of plant current control strategy (blue) vs. feedforward control (orange).

B. Mullite content soft sensor and simulation of feed rate optimization

To test the feed rate optimization, the strategy proposed in Section 3 was built into the simulation environment. Initially, the calciner ran at the specified operating conditions before reaching a steady state. The initial values for the feed rate optimization were as follows: feed rate of 110%, temperature

in hearth 6 of 1080°C, and mullite content of 8.4%. A moving average filter refined the mullite soft-sensor output with a time window of 30 min. The objective was to regulate the mullite content to approximately 4%. The control interval was set to 6 h, which was based on the required period of the calciner to reach the steady state. The feed rate change was limited to 5% due to process constraints. By utilizing the filtered value, the strategy resolved the optimal feed rate setpoint and desired temperature in hearth 6.

Figure 7. illustrates the simulation of the feed rate optimization. The control strategy maximized the feed rate in this simulation study, from the initial value of 110% to 120%, and the setpoint temperature in hearth 6 was reduced by 30°C. The mullite soft sensor presented a small deviation compared with the model output due to the calculation simplifications.

Figure 7 Simulation of the feed rate optimization based on the mullite soft sensor.

V. PLANT TESTING

The control logic of the multiple hearth furnace was then tested by industrial testing and the economic performance evaluated. First, the soft sensors were tested online by implementing the algorithms on a computer connected to the plant automation system. Second, a sampling and data collection campaign was performed to gather measurements from the calciner. Finally, the logic of the control concept was evaluated and validated using the data collected during the sampling campaign.

A. Description of the industrial testing environment

The industrial testing environment was setup to test the soft sensor software. The software was installed on a DELL laptop (Latitude E7450), which was then connected to the local area network of the plant. An Open Platform Communications (OPC) client was developed to read the real-time process data from the OPC server of the site distributed control system (DCS). The computers on the server and client side were configured according to the Distributed Component Object Model (DCOM) configuration document written by the OPC Foundation. On the other hand, the MHF soft sensor software also provided a manual data input interface to record and save

the chemical testing data of the samples from the laboratory information management system (LIMS) data.

The soft sensor algorithms ran in the background to estimate the reaction rate and mullite content. The MHF soft sensor software was developed using Microsoft Visual Studio 2017. The main interface contained the following.

- Real-time key performance indicators: reaction rate, mullite content, burner flow rate, and feed rate.
- Temperature profile of the furnace.
- Real-time trends of the setpoints and actual values of T4 (temperature of hearth 4), and the gas flow of burner 4.
- Real-time trends of the setpoints and actual values of T6 (temperature of hearth 6), and the gas flow of burner 6.
- Real-time trends of the feed rate, mullite content, and reaction rate.
- Three day curve of brightness (VIO) in the feed and product.

The main interface integrates the essential indexes of the MHF production. The testing improved the quality and usability of the MHF soft sensor software. Furthermore, it helped the operators follow the operating conditions of the MHF better.

B. Sampling campaign at the plant

The campaign was executed from August 6th to 10th, 2018. An instrumentation inspection was performed on the first day. The outcomes were satisfactory as the instruments in the calciner were operating correctly. The samples from the feed material and calcined product of the MHF were collected during the following four days, every hour from 10:00 to 16:00 h.

The assays needed for the input of the furnace (feed material) were the brightness, iron content, particle size, and moisture. Furthermore, the analyses for the output of the furnace comprised the brightness, particle size, and moisture. The analyses for the final product comprised the brightness, particle size, mullite, and soluble alumina. The samples were taken with an hourly frequency, by considering the process delays for the feed, furnace, and product. The performed analyses on the samples and equipment are presented in Table 3, including the X-ray fluorescence (XRF) for determining the iron content; X-ray diffraction to quantify the mullite content; and inductively coupled plasma atomic emission spectroscopy to measure the soluble alumina.

C. Testing results

The aim of this section is to study the control strategy logic and soft sensors operation in real time based on the process data and sampling campaign results of the plant. The logic is analyzed following the dynamic behavior of the furnace. Finally, a discussion of the possible improvements of the enhanced control logic to the process is presented.

During the testing period of the soft sensors, the plant dynamic behavior was followed using online process

measurements and the soft sensor software. Data from August 8th, 2018, were used to illustrate the results of the reaction rate, mullite content, and soluble alumina soft sensors.

Figure 8. shows the calculations of the soft sensors and laboratory results of the samples obtained during the sampling campaign on August 8th, 2018. The reaction rate oscillated between 10 and 30% until 14:00 hours where it rose to approximately 40%. The mullite content laboratory results showed a significant variation during the day with a minimum of 4% and maximum of 13%. From the same figure, it can be seen that the soft sensor for mullite content followed the general trend exhibited by the corresponding laboratory results. The soluble alumina content was generally low with assays of ≤ 0.3 wt.% observed during the day.

Figure 8. Soft sensors and lab results during the testing campaign on August 8th, 2018.

On August 8th, the reaction rate presented a low value in general with fluctuations originating from the limitations of the temperature control in hearth 4 due to the BtoB phenomenon. The mullite content showed a high value (above 5 wt.%) during most of the day, implying that the temperature in the furnace was higher than necessary, as also indicated by the low soluble alumina content. In this situation, the enhanced control strategy could drive the process to a more efficient operating condition by increasing the capacity at the beginning of the day, while maintaining the same energy consumption. This new operating condition would reduce the mullite content significantly in the product, while maintaining the required specifications of brightness and soluble alumina.

VI. CONCLUSIONS

This paper presented a control strategy concept for a multiple hearth furnace in kaolin calcination. The main aim is to maximize the capacity of the process and decrease the use of energy while maintaining the desired calcined kaolin quality. The estimations based on ANN play a key role in the optimization strategy of the furnace. The SOM technique was utilized to determine the optimal operating conditions according to different products. The capacity is optimized by

balancing the estimations of mullite content and soluble alumina while maintaining the desired product quality. A simulation environment was used to test the feedforward and capacity optimization control. The simulations results indicate that the control strategy maximizes the capacity and reduces the energy consumption while ensuring the quality requirements. A software testing and sampling campaign was performed at the industrial environment to validate the control concept.

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