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Coordinating fuzzy control of the sintering process ⋆

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Abstract: The sintering process is an important step in the iron and steel making process and features strong complexity, nonlinearity and large time-delay. This paper presents a coordinating control method that two fuzzy controllers are designed to control the burning through point (BTP) and the bunker-level. First, the BTP control is the main control task with the sinter strand speed as the control variable, and a predictive fuzzy control scheme is developed where an intermediate process model is used to perform on-line controller design to meet a closed-loop performance specification that is associated with desired process output. Then, a fuzzy controller is designed to control the charging bunker-level via adjusting the strand speed. The two fuzzy controllers are proposed for these two closed-loops and it is shown that the satisfactory response of the closed-loop system can be achieved by handling the strand speed. Results of simulation and actual running illustrate the performance of the proposed method.

1. INTRODUCTION

Sintering may be represented as a multivariable, nonlinear, complex process with time-varying parameters. Due to the increasing cost of production, the iron and steel making industry is continuing the efforts to optimize the production and processes (Shigaki [1999]).

A sintering process is the initial one in an iron and steel making plant (Augustin [1995]). In this process, ores, which are mixed with fine particles of limestone and coke breeze, are agglomerated by combustion heat of coke breeze to become the main material of the blast furnace burden. The raw sinter materials are granulated with moisture in a mixer, and are charged on the pallet of a sintering machine. Under the ignition hood hot gases and air are drawn down through the bed by draught fans. Provided the temperature reached the top layer of the bed is high enough and conditions are suitable for combustion, the coke will start to burn and the sintering of the ore begins. After the sinter material leaves the ignition hood, the combustion continues by drawing only cold air through the bed. A relatively thin combustion zone then progresses down through the bed. The strand speed has to be controlled at a value which enables the bed to be completely sintered by the time the ore reaches the end of the strand. After being discharged and cooled, the sintered ores are crushed into a proper size and fed to the blast furnace. Fig. 1 shows the schematic of the plant.

The main objective of this paper is to fully consider two control problems associated with the burning through point (BTP) and the bunker-level.

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Problem 1: The BTP control problem. The BTP is largely governed by the ignition conditions, the height of the bed, the water addition, the suction at the draught fans and the strand speed (Upadhyaya [2001]). In practice, the ignition conditions are maintained by a local control loop, the fan suction is usually kept at maximum, and the height of the bed and the water addition are determined by other requirements. Thus the BTP can be controlled by manipulating strand speed. The aim of BTP control is to counteract external disturbances by adjusting strand speed in the uncertain situation.

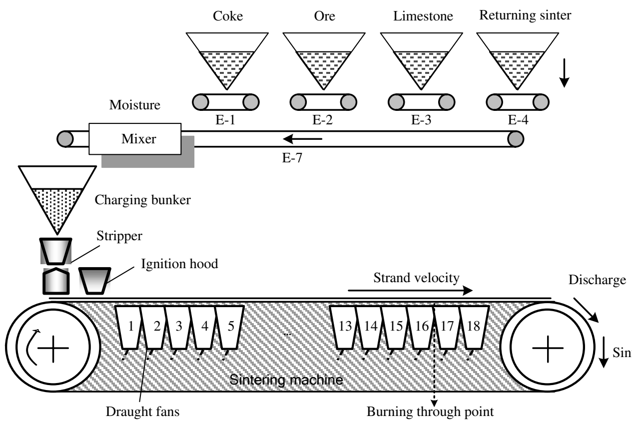

Fig. 1. Schematic of an iron ore sintering process

Problem 2: The bunker-level control problem. After the different components have been mixed together at the sinter material preparation site, the material is deposited on the strand via a charging bunker. To guarantee a continuous operation of the process, it is necessary to avoid the bunker becoming empty or overflows. Due to the rather long distances the mixture is transported from the sinter material preparation site to the bunker using conveyors, a significant time delay is introduced, which makes the bunker-level control problem more difficult to deal with.

In a practical production process, due to the complexity of the process, exogenous disturbances, changes of environment, etc., conventional control methods cannot obtain satisfactory control performance. At present, most of the sinter process control methods ignore the influence of the bunker-level control, which often causes fluctuations in the BTP control. So, it is urgent to devise a coordinating control method to solve the BTP control and the bunker-level control problems in sinter process.

Over the past few years, the steady progress has been made in the research on the iron and steel sinter process (ISSP), and the level of practical automatic control of the ISSP has been improved remarkably (Venkataramana [1999], Radhakrishnan [2001]). For example, some intelligent techniques including neural networks (Ning [2004]) are successively used to solve the problem of sintering process control. Especially, fuzzy sets and their applications to control engineering - fuzzy logic control (FLC) - provide a useful tool to cope with uncertainty and ill defined systems (Hu [1996], Gorez [2000]). The self-organizing fuzzy logic controller (SOFLC) provides an adaptation to the dynamics of the controlled process (Shigaki [1999], Frey [2000], Mahfouf [2002]).

However, both the FLC and the SOFLC assume that the required controller output response is independent on the current process output state, while is only dependent on the error. It is not true of a general nonlinear process. The model-based fuzzy logic controller (Kiendl [1997], Torra [2005], Li [2006]) generates the controller according to the fuzzy model of the process, and works based on the current process output state and desired process output. It is suitable for nonlinear systems.

This paper presents a coordinating control method that two fuzzy controllers are designed to control the BTP and the bunker-level. Firstly, a predictive fuzzy controller for BTP control is established with the sinter strand speed as the control variable. The designed controller consists of a predictor and a model-based fuzzy controller, both of which work on the basis of a fuzzy model of the controlled process. Secondly, a fuzzy controller is designed to control the total sinter material mass in the bunker. That is equivalent to the bunker-level control. Here, the changes in the mass density of the sinter material and the strand speed are the main disturbances. Both control loops are coupled via the strand speed, which is the manipulated control variable for the first loop and acts as a disturbance variable in the second control loop.

2. BTP CONTROL

The BTP is characterized by the maximum of the exhaust gas temperature, which is measured at six locations towards the end of the strand. It is primarily controlled by variable strand speed. As shown in the Fig. 2, the temperature is measured at a certain point. The method employed here is not to explicitly control the temperature maximum, but to yield the expected BTP by keeping the exhaust temperature distribution on a pre-defined curve.

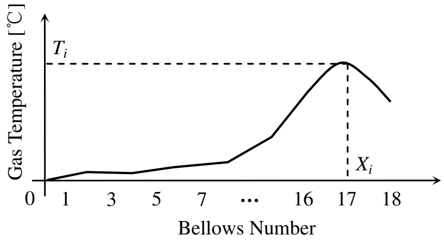

Fig. 2. Measurement points for the exhaust gas temperature

2.1 Mathematical model of the temperature distribution curve

The BTP can not be tested on-line, and the judgment based on the observation data by operators is usually inaccurate (Fan [1999]). Although many successful attempts have been made to model the sintering process (Wang [2002]), it is very difficult to obtain some important parameters in these models, which indicate the physical properties of the sinter material. Therefore, Soft-sensing method is adopted to solve this problem. In the simulation, the distribution curve is approximated by polynomials of order two:

$$T_i = AX_i^2 + BX_i + C \tag{1}$$

where T_i is the temperature of the exhaust gas, X_i is the number of the draught fans, and A, B and C denote the binomial coefficients, which are calculated by using the fitting method of the practical data.

2.2 Predictive fuzzy control of the BTP

To illustrate the attributes of the predictive fuzzy control, the technique is used to solve the control problem of the sinter process characterized by BTP control. It is required to regulate strand speed in order to maintain the controlled process output around a pre-specified value so that a steady BTP can be obtained. The output of the controller is referred to the set point of the strand speed. The Gaussian-type function is employed as the membership function of the fuzzy set. The actual production operation is used to obtain the intersection of the fuzzy sets, and the max operation for the union of the fuzzy sets.

(1) Model identification

The predictive fuzzy control (PFC) requires a little priori process knowledge and has simple design parameters. Fig.3 illustrates the structure of PFC. The predictive fuzzy controller consists of a predictor and a model-based fuzzy controller, both of which work on the basis of a fuzzy model of the controlled process. The fuzzy controller is obtained by causality inversion of the fuzzy model representing the sinter process dynamics, and is dependent upon the current process output and a closed-loop performance specification, which is generated from the desired process output and the predicted process output.

A given process can be described by a first-order fuzzy relation equation:

$$Y_{t+T} = (Y_t \times U_{t+T-\tau}) \circ G \tag{2}$$

where T is a sample interval, $U_{t+T-\tau}$ is a fuzzy set of control delayed for a dead time τ, Y_t is a fuzzy set of current process output and Y_{t+T} is a fuzzy set of process output at the next instant, G is the fuzzy relation governing the model dynamics. The task of model identification is mainly concentrated on the estimation of G and the distribution of fuzzy sets. In the PFC application the identification must be based on the observation data in real time, and should have the ability to learn the process dynamics.

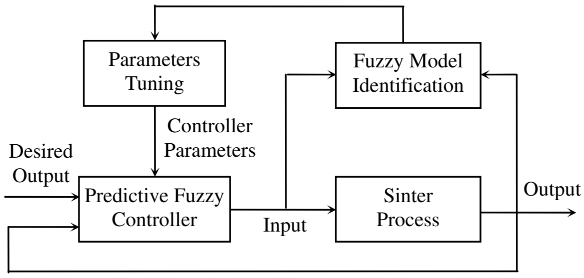

Fig. 3. Architecture of the PFC

(2) Prediction by fuzzy model

Given the fuzzy relation G, the process output in further time is iteratively predicted based on the model given by equation (2):

$$\hat{Y}_{t+kT} = (Y_{t+(k-1)T} \times U_{t+kT-\tau}) \circ G \tag{3}$$

where $k = 1,\ 2,\ \ldots,\ n$, n is the prediction horizon. In the on-line application the prediction is based on the information available at the current time instant. When $k > 1$, the predicted output should be used in equation (2):

$$\hat{Y}_{t+kT} = (\hat{Y}_{t+(k-1)T} \times U_{t+kT-\tau}) \circ G \tag{4}$$

When kT is equal or greater than τ the control signals are unknown. Therefore the fuzzy set of control signals in equation (3) and (4) will be replaced by U_{t-T}. This is referred to as free prediction:

$$\hat{Y}_{t+\tau|t} = (Y_{t+\tau-T} \times U_{t-T}) \circ G \tag{5}$$

$$\hat{Y}_{t+nT|t} = (\hat{Y}_{t+(n-1)T|t} \times U_{t-\tau}) \circ G \tag{6}$$

The accuracy of the prediction is controlled mainly by set shape and set distribution. For multi-step prediction, the accuracy decreases as the prediction horizon is increased. The longer the prediction horizon, the more approximate the predicted process output.

(3) Controller algorithm

The goal of designing a predictive fuzzy controller is to minimize the cost function:

$$E = D(Y^{\tau}_{t+nT},\ \hat{Y}_{t+nT}) \tag{7}$$

where Y^{τ}_{t+nT} is the desired process output at the time instant $t + nT$, usually it is the set point. $D(\cdot)$ is the distance measurement of fuzzy sets Y^{τ}_{t+nT} and $\hat{Y}_{t+nT}$.

Suppose that a control signal $u(t)$ is applied to the process at current time instant t, and subsequent control signals are the same as $u(t)$. The process output at time instant $t + \tau$ is estimated by:

$$\hat{Y}_{t+\tau} = (\hat{Y}_{t+\tau-T} \times U_t) \circ G \tag{8}$$

and accordingly:

$$\hat{Y}_{t+nT} = (\hat{Y}_{t+(n-1)T} \times U_t) \circ G \tag{9}$$

The problem is how to determine $u(t)$ so that equation (7) can be minimized. A general expression for the input/output differential equation is:

$$dy/dt = f(y, u) \tag{10}$$

The process outputs at time instants $t + \tau$ and $t + nT$ can be approximately expressed as:

$$\hat{y}(t+\tau) = \hat{y}(t+\tau|t) + T\frac{\partial f}{\partial u}\delta u \tag{11}$$

$$\hat{y}(t+nT) = \hat{y}(t+nT|t) + ((n+1)T - \tau)\frac{\partial f}{\partial u}\delta u \tag{12}$$

Therefore, the cost function (7) can be rewritten in terms of the ordinary process output as:

$$E = \frac{1}{2}[y^{\tau}(t+nT) - \hat{y}(t+nT)]^2 \tag{13}$$

Minimizing equation (13):

$$\hat{y}(t+nT) = y^{\tau}(t+nT) \tag{14}$$

and according to equations (11) and (12) the closed-loop performance specification is given by:

$$\hat{y}(t+\tau) = \hat{y}(t+\tau|t) + \frac{y^{\tau}(t+nT) - \hat{y}(t+nT|t)}{n+1-\tau/T} \tag{15}$$

which is the required process output under control after a time delay. Recalling equation (8) and using the causality inversion of fuzzy relation G, the control signal at the current time instant is determined by:

$$U_t = (\hat{Y}_{t+\tau-T} \times \hat{Y}_{t+T}) \circ G^{-1} \tag{16}$$

which G^{-1} is the causality inversion of fuzzy relation G, $\hat{Y}_{t+\tau-T}$ is given by the prediction, $\hat{Y}_{t+T}$ is given by equation (15) followed by the fuzzification. Fig. 4 represents the internal structure of the predictive fuzzy controller.

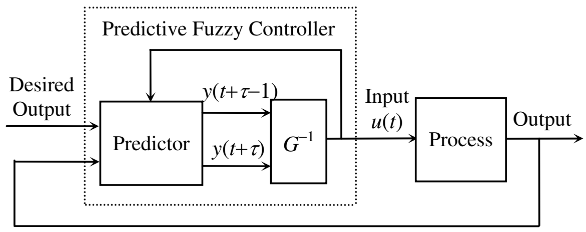

Fig. 4. Internal structure of the predictive fuzzy controller

Applying a series of pseudo-random strand speed signals with sample interval $T = 0.1L/V$, where L is the length of the strand and V denotes strand speed, a set of input/output observations are obtained. From the correlation analysis of the observation data, the time delay τ is determined as T. Therefore, the fuzzy model is formulated as:

$$Y_{t+T} = (Y_t \times U_t) \circ G \tag{17}$$

where U_t is the fuzzy set of strand speed at the current time instant, Y_t and Y_{t+T} are the fuzzy sets of measured process output at the current and the next time instant respectively.

In the identification of the fuzzy model given by equation (17) an adaptive fuzzy modeling technique is used, which simultaneously estimates the distribution of fuzzy sets and the fuzzy relation G by data clustering using Self-Organizing Feature Map (Su [2000]) with a modified learning algorithm. Adaptation is provided by the learning algorithm, a decay factor and a non-zero learning rate.

3. BUNKER-LEVEL CONTROL

Charging bunker deposits the sinter material on the strand, and it is necessary to avoid the bunker becoming empty or overflows (Arbeithuber [1995]). We denote the manipulated input (control variable) of the plant as v_{in}, the mass flow rate of sinter material put on the conveyor at the sinter material preparation site and the main disturbance as the strand speed v_s. There is a transport delay time τ between the preparation site and the bunker. The plant output variable is not the bunker level itself, but is defined as $h = v_b/v_{bl100} \cdot 100[\%]$, which is the volume percentage of material in the bunker. Here v_b denotes the volume of the sinter material in the bunker, and v_{bl100} denotes the total volume of the bunker.

3.1 Mathematical model of the bunker

A simple linear model of the bunker is used as follows. The mass balance for the bunker yields:

$$dm_{bl}/dt = v_{in}(t-\tau) - v_{out}(t) \tag{18}$$

and for the mass flow rate out of the bunker the relation is expressed as:

$$v_{out}(t) = A\rho v_s(t) = K_s v_s(t) \tag{19}$$

In equations (18) and (19), the variables are defined as follows: m_{bl} is mass in the bunker; v_{in} is input mass flow rate; τ is delay time; v_{out} is output mass flow rate; v_s is strand speed; A is cross-sectional area of bed; ρ is mass density of the sinter material.

Considering the total volume of the bunker, the plant output variable (controlled variable) can be written as:

$$h = m_{bl}/\rho v_{bl100} \cdot 100[\%] \tag{20}$$

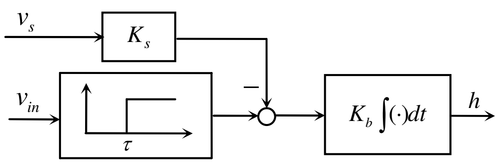

Fig. 5. Block diagram of the bunker model

Fig.5 shows the block diagram of the bunker model. If the mass m_{bl} from equation (20) is substituted in equation (18), the following plant model is achieved as equation:

$$dh(t)/dt = K_b[v_{in}(t-\tau) - v_{out}(t)] \tag{21}$$

where:

$$K_b = 100/\rho v_{bl100} \tag{22}$$

3.2 The bunker-level control

In order to control the bunker level, the sum of the masses m_{tot} in the entire sinter material transportation system including the bunker should be controlled. To be able to handle ramp changes of the strand speed, the influence of the disturbance v_s is extrapolated over one half of the delay time τ. One obtains:

$$m_{tot,d} = A\rho(v_s + \frac{dv_s}{dt}\frac{\tau}{2})\tau + \frac{v_{bl100}\rho}{100}h_d \tag{23}$$

where h_d and $m_{tot,d}$ are the respective desired values. The actual value of the total mass is:

$$m_{tot} = \int_{t-\tau}^{t} v_{in}(\lambda)d\lambda + \frac{v_{bl100}\rho}{100}h \tag{24}$$

The control error is defined as:

$$e = m_{tot,d} - m_{tot} \tag{25}$$

The input variables of the fuzzy controller are the error e and the error rate of change de/dt. For each input variable and the controller output u, five linguistic labels are defined. The membership functions are defined based on a normalized universe of discourse, which are shown in Fig. 6.

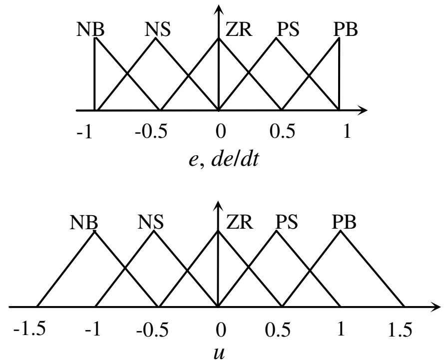

Fig. 6. Input and output membership functions of the bunker-level controller

The MAX-PROD compositional rule of inference is adopted to evaluate the rules. The Center of Gravity method is used to fuzz the inferred output fuzzy subset. To adjust the fuzzy controller, the inputs and the output are weighted with the weighting factors c_e, c_{de}, and c_u, which are appropriately tuned by expert experience. Fig. 7 shows the bunker-level controller block diagram, where Corr.ρ denotes the correlation between ρ and the related variables.

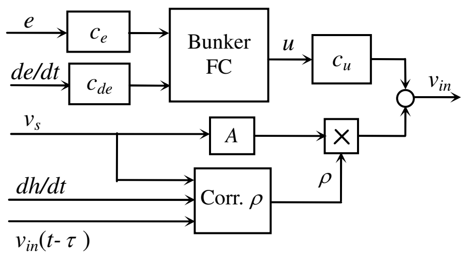

Fig. 7. Block diagram of the bunker-level controller

To the output of the fuzzy controller, the mass flow needed in the stationary case is added. The input mass flow rate is then given by:

$$v_{in} = c_u u + A\rho v_s \tag{26}$$

Furthermore, changes of the sinter material density can be taken into account by the following relationship:

$$\rho = v_{in}(t-\tau)/(v_s A + \frac{v_{bl100}}{100}\frac{dh}{dt}) \tag{27}$$

4. SIMULATION RESULTS

All simulations are carried out using data taken from an existing sintering plant with $A = 3.73\text{m}^2$, $l = 55\text{m}$, $v_{bl100} = 20\text{m}^3$, $\rho = 1.75\text{t/m}^3$, $t = 15\text{min}$.

4.1 BTP control

In all simulation runs, the strand drive is modeled as a first-order system with a time constant of 6 minutes and a gain of 1.

Example 1: In this example the performance of the BTP control and the bunker-level control systems is demonstrated for the realistic case of random temperature and density disturbances occurring simultaneously.

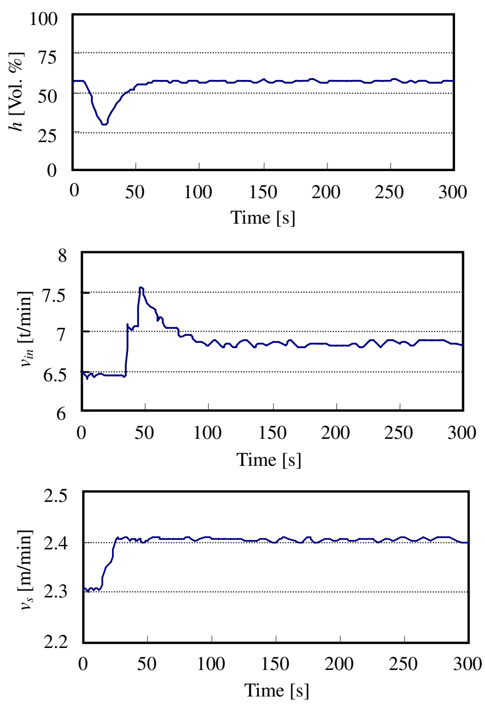

Fig. 8. Bunker lever h [Vol. %], input sinter material mass flow rate v_{in} [t/min] and strand speed v_s [m/min]

Fig. 8 shows the control variable strand speed v_s of the BTP control system which, at the same time, acts as a disturbance for the bunker level control system. As additional disturbance for the bunker level, a randomly varying sinter material density is considered. Also depicted in Fig. 8 are the bunker-level control variable v_{in} and the bunker-level h with its set value of 60%.

4.2 Bunker-level control

The sinter material transport system is modeled with the transport delay time only, where no actuator element is considered. The controller weighting factors used in the simulations are $c_e = 0.1$, $c_{de} = 1$, $c_u = 3$.

Example 2: In this simulation run the performance of the bunker-lever control system after a step change of the strand speed is demonstrated. Fig. 9 shows the bunker-level h and the input mass flow rate v_{in} after a step change of v_s from 2.3m/min to 2.4m/min.

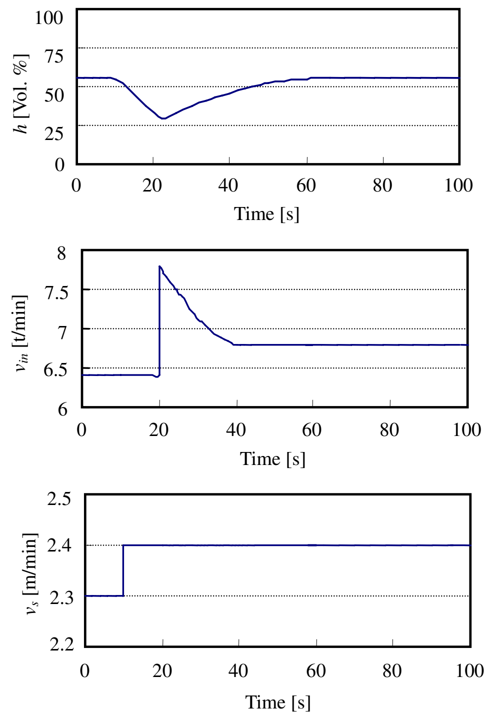

Fig. 9. Bunker-level h [Vol. %] and mass flow rate v_{in} [t/min] after a step change of the strand speed v_s [m/min]

4.3 Results of actual runs

Some practical data are chosen to analyze obtained coordinating models. The results of real-word application of coordinating fuzzy control system are shown in Fig. 10. Time interval of BTP samples is 3 minutes. In Fig. 10, the former figure indicates practical operation and the latter one indicates the coordinating control effects of the proposed method.

Clearly, from the control results of BTP, we can see the fluctuation of BTP has been decreased about 5% $\sim$ 8% and the effects of BTP control are greatly improved after using the coordinating fuzzy control techniques.

A comparison with the manual control method is also shown, and the statistical data of one month are listed in Table 1. Compared with the manual control method, statistical data show that not only the agglomeration output is increased by 10.4%, but also the fluctuation of BTP is decreased by 5.16%. The control results of the BTP are improved obviously, and the stabilization of the

Table 1. Statistical results of the coordinating control

Control methods	Indices	
	Fluctuation of BTP (%)	Output (t/h)
Manual control	20.132	503.0
Coordinating control	13.282	555.1

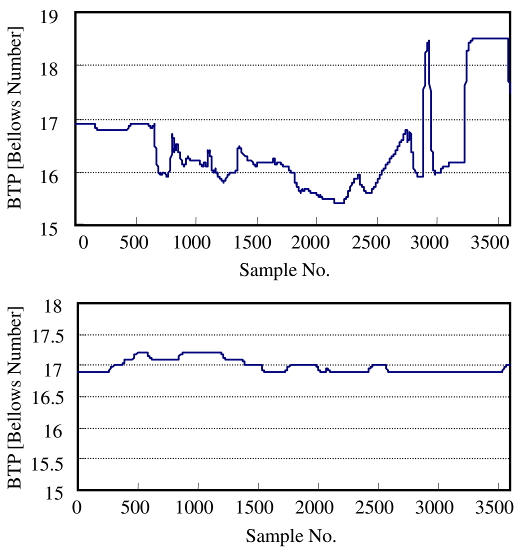

Fig. 10. Control results of the BTP

sintering process is increased by coordinating control of the BTP and the bunker-level through the strand speed.

5. CONCLUSIONS

This study focuses on using the sintering strand speed as the coordinating variable to control the BTP and the bunker level. In addition, fuzzy logic concepts are successfully applied to control a sintering plant. Firstly, the predictive fuzzy control scheme based upon a fuzzy model of the process is perfectly suitable for the control task of the BTP. The fuzzy model is used to perform the on-line multi-step prediction and the controller design. This is deferent from other model-based fuzzy controllers where the performance specification requires a given fuzzy relation. Secondly, although the bunker-level control problem, due to the linear plant behavior, could be solved by employing a traditional linear controller, the bunker-level control task is a suited application example for fuzzy control. The research reveals that the combination of the BTP control and the bunker-level control could achieve a very good control performance.

The presented concepts are in the process of being implemented in an industrial sintering plant. Since nowadays all commercially available distributed control systems offer fuzzy control modules, the application causes no essential problems.

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