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SELF-TUNING MULTI-STEP PREDICTION APPLIED TO SPEED CONTROL OF A SINTER STRAND

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The processing of iron-ore to form sinter is a complex metallurgical process carried out on a moving grate. The production rate of good quality sinter is affected by significant variations in the properties of the raw input materials and in operating conditions. In large production units the emphasis is on overall steadiness of the process and the sinter strand is driven at constant speed for long periods. In principle, the efficiency of the process can be improved by manipulating strand speed, but the control problem is complicated by the high order of time delay involved in the system.

The paper presents a case for the application of multi-step prediction methods which can provide the operator with advance information on waste-gas temperature variation and guide his action in adjusting strand speed.

INTRODUCTION

Sintering is an important process in the iron making industry. The iron ore is mixed mainly with coke, flux, water and returned sinter fines to form the raw material which is loaded onto a continuously moving strand to form a flat bed. The surface of the bed is ignited and, under the influence of a suction fan, a combustion zone is drawn downwards through the material, driving off the volatiles to produce clinker-like material called sinter. The sinter product is crushed and sieved to form feed material for the blast-furnace. Modern blast-furnaces run on 50%-100% sinter.

The sintering process is subjected to multifarious disturbances in the form of fluctuations in operating conditions, as well as variations in the physical and chemical characteristics of the raw materials. These greatly influence the on-strand process. To ensure that the material is properly sintered by the time it reaches the end of the strand, proper adjustment of the strand speed is required. If the speed were high, weak sinter would be produced. This means that an excessive amount of the final product, after crushing and sieving, would be returned for re-processing. On the other hand, if strand speed were low, the sinter produced would be excessively strong and this would require increased fuel consumption in the blast furnace. The complexity of the problem is increased by the fact that if speed is varied, the rate of supply of the raw materials need to be similarly adjusted, causing fluctuations in the long-time-constant loops involved in the raw-mix preparation.

Present practice involves the use of a feedback control strategy |1|, based on a P.I.D. algorithm. Because of the time delays in the system and the various disturbances working on the process, this strategy very often fails to provide satisfactory control. In practice, to avoid undesirable consequences of speed variations, the plant operator often prefers to hold strand speed constant in open-loop for long periods, making only occasional adjustments based on the waste gas temperature. Feedforward control |2| which is not affected by the long system time-constant has not found practical acceptance because of the difficulty of making online measurement of permeability, which is the usual control variable. Also, because of the nonstationary nature of the process, it is difficult to obtain a precise formulation for the feedforward model. Under these circumstances, the principle of self-tuning prediction offers a promising alternative.

Self-tuning prediction is an adaptive technique capable of forecasting the output of a stochastic process by adapting itself in real-time to the changing dynamics of the process. Basically, self-tuning prediction is a re-formulation of the self-tuning regulator problem |3|. It involves a two-stage procedure of estimation of the process parameters and minimum variance prediction of the output at each sampling interval. Self-tuning prediction has good stability and convergence properties similar to the self-tuning regulator |3,4|. After convergence, the parameters of the predictor become optimal. Practical results show that even before convergence is achieved, the predictor soon reaches a quasi-optimal state, yielding reasonably good prediction. The self-tuning multi-step predictor can predict the process output several sampling intervals in advance if the future input strategy is known. This feature is particularly attractive for long-time-constant processes.

The aim of the present investigation is to study the application of self-tuning multi-step prediction techniques to forecast waste-gas temperature several time-steps ahead and to show how the prediction can provide a guide for strand speed control.

THE SINTER STRAND PROCESS

A diagram of the sinter strand is shown in Fig.1. The raw-mix is loaded onto a moving grate, also called the sinter strand. Windboxes underneath the strand are connected to a wind-main and a large suction fan at the end of the wind-main draws air through the bed. The top surface of the bed becomes ignited as it passes under the ignition hood and the air drawn into the bed causes the combustion zone to work its way downwards through the bed, driving off the volatiles and fusing the material to form sinter. The exhaust gases pass into the windboxes and along the windmain to the fan and precipitator. In an ideally steady process, the heat-wave leading the combustion zone reaches the bottom of the bed at the output end of the strand. Because of variations in the physical and chemical characteristics of the raw-mix and in operating conditions, the vertical progression of the heat-wave through the bed varies and this needs to be countered by manipulating strand speed.

The values of temperature of the waste gas at the individual windboxes below the strand are related to the sintering condition. The windbox temperature is maximum where the heat-wave just reaches the bottom of the bed. Classical strand speed control strategy is based on an estimate of the position where the windbox temperature reaches its peak value. However, this policy is less than satisfactory because (a) the states of the sections of the bed nearer the loading end are not considered and (b) control becomes imprecise when the windbox temperature profile is too flat. Waste gas temperature measured just before the suction fan is considered as an alternative output variable which may be controlled by manipulation of the strand speed. By this method the status of the whole bed is implicitly taken into consideration.

MULTI-STEP PREDICTION ALGORITHM

Process Model

The sinter strand process may be characterised by a discrete time stochastic model

$$A(z^{-1})y(t) = B(z^{-1})u(t-d) + C(z^{-1})e(t) \quad \ldots(1)$$

where y is the output; u is the input (or control variable); $\{e(t),t\}$ is a sequence of uncorrelated random variables; t is the discrete time index and d is a non-negative time-delay index.

$A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are time invariant polynomials in the backward shift operator z^{-1}.

$$A(z^{-1}) = 1 + a_1 z^{-1} + \ldots + a_n z^{-n}$$

$$B(z^{-1}) = b_o + b_1 z^{-1} + \ldots + b_n z^{-n}$$

$$C(z^{-1}) = 1 + c_1 z^{-1} + \ldots + c_n z^{-n}$$

k-Step Ahead Prediction (Explicit Method)

We can define $\hat{y}(t+k/t)$ as the optimal k-step ahead prediction of the output based on the available measurements $y(t), y(t-1), \ldots, u(t), u(t-1) \ldots$ and the future planned input sequence $\{u(t+1), \ldots, u(t+k-d\}$. Introducing the loss function,

$$V = E\{\varepsilon^2(t+k)\} \quad \ldots(2)$$

where $\varepsilon(t+k)$ is the prediction error

$$\varepsilon(t+k) = y(t+k) - \hat{y}(t+k/t) \quad \ldots(3)$$

For the purpose of self-tuning prediction, the process model (1) may be reconstructed as a fictitious process having output $\varepsilon(t)$, input $\hat{y}(t+k/t)$, measurable disturbance u(t) and unknown stochastic disturbance e(t), |3|.

$$A(z^{-1})\varepsilon(t) = -z^{-k}A(z^{-1})\hat{y}(t+k/t) + z^{-d}B(z^{-1})u(t) + C(z^{-1})e(t) \quad \ldots(4)$$

Thus the k-step ahead prediction is reconstructed as the well-known self-tuning regulator problem. It is intended to determine the control input $\hat{y}(t+k/t)$ which would minimise the variance of the output of the process $\varepsilon(t)$. The optimal predictor that minimises the loss function can be expressed |3,4| as

$$\hat{y}(t+k/t) = \frac{G(z^{-1})}{A(z^{-1})F(z^{-1})}\varepsilon(t) + \frac{B(z^{-1})}{A(z^{-1})}u(t+k-d) \quad \ldots(5)$$

where the polynomials

$$F(z^{-1}) = 1 + f_1 z^{-1} + \ldots + f_{k-1} z^{-k+1}$$

$$G(z^{-1}) = g_o + g_1 z^{-1} + \ldots + g_{n-1} z^{-n+1}$$

are determined from the identity

$$C(z^{-1}) = A(z^{-1})F(z^{-1}) + z^{-k}G(z^{-1}) \quad \ldots(6)$$

When the parameters of the process (1) are unknown, they can be estimated. The least squares k-step ahead predictor $\hat{y}(t+k/t)$ can be calculated from (5) and (6).

k-Step Ahead Prediction (Implicit Method)

An alternative approach for the determination of the optimal k-step ahead predictor $\hat{y}(t+k/t)$ is to use the indirect or implicit identification technique. This method designs the predictor directly without the knowledge of the process parameters. Similar to the last case, the prediction problem works out to be the determination of the minimum variance control variable $\hat{y}(t+k/t)$ for the process (4). The solution is a two-tier procedure of estimation and prediction |3,5|.

Step 1. Estimate the parameters $p_o, \ldots, p_{n-1}, q_1, \ldots,$

$q_{n+k-1}, r_o, \ldots, r_{n+k-1}$, such that the equation error $\delta(t)$ is minimised in the model,

$$\varepsilon(t) = P(z^{-1})\varepsilon(t-k)+Q(z^{-1})\hat{y}(t/t-k)+R(z^{-1})u(t-d)+\delta(t) \quad \ldots(7)$$

$[q_o = -1]$

using recursive least squares method.

Step 2. Determine the prediction for the next step

$$\hat{y}(t+k/t) = P(z^{-1})\varepsilon(t)+[1+Q(z^{-1})]\hat{y}(t+k/t) +R(z^{-1})u(t+k-d) \quad \ldots(8)$$

using the estimated values of the parameters.

This method of computing the prediction involves estimation of 2k-2 more parameters compared with the earlier procedure of solving the process model (1) and the identity (6). This is however compensated for, since it is possible to use least squares (even if $C(z^{-1}) \neq 1$) and the identity (6) need not be solved at each step, |3,5|.

Stochastic Extension

In the case of the sinter strand process, it is necessary to be able to foresee how the output (i.e. waste-gas temperature) is going to vary over a future time scale. At the same time the operator would like to know the expected response to a step change in the input (i.e. strand speed). This involves running ℓ numbers of k-step ahead predictors ($k = 1,\ldots,\ell$) in parallel which would consume a large amount of computing time, as the size of the algorithms (7) and (8) increase with k. A much simpler approach is to use the relationship by Akaike |6|,

$$A(\tilde{z}^{-1})\hat{y}(t+k/t) = B(z^{-1})u(t+k-d) \quad \text{for } k>n \quad \ldots(9)$$

where

$$A(\tilde{z}^{-1})\hat{y}(t+k/t) = \hat{y}(t+k/t)+a_1\hat{y}(t+k-1)\ldots +a_n\hat{y}(t+k-n/t) \quad \ldots(10)$$

Following (9), the multistep prediction becomes a simple recursive relationship

$$\hat{y}(t+k/t) = -a_1\hat{y}(t+k-1/t)-\ldots-a_n\hat{y}(t+k-n/t) +b_o u(t+k-d)+\ldots+b_n u(t+k-d-n)$$

$$\text{for } k = n+1,\ldots,\ell \quad \ldots(11)$$

This latter method involves running only n self-tuning predictors in parallel which can be extended further ahead into the future using (11).

The parameters of (11) can be easily identified in terms of the estimated parameters of (7). Assuming $C(z^{-1}) = 1$, it follows from (4), (6) and (7) that $P(z^{-1}) = G(z^{-1})$, $Q(z^{-1}) = -A(z^{-1})F(z^{-1})$ and $R(z^{-1}) = B(z^{-1})F(z^{-1})$. For k = 1, (6) yields $F(z^{-1}) \equiv 1$. So parameters a_i and b_i in (11) can be replaced by the estimated parameters $-q_i$ and r_i respectively from self-tuning 1-step-ahead predictor (7), |3|.

Because of structural similarity with the self-tuning regulator, the above strategy would yield optimal prediction also with $C(z^{-1}) \neq 1$, |4|. The multi-step predictor is optimal after the convergence of the parameters but practical results demonstrate that the prediction is soon quasi-optimal, even before convergence is achieved. This signifies less sensitivity of the prediction exercise to the bias in the estimated parameters.

Control Aspects

In the present study, it is also intended to ascertain the best possible change in the input variable which could yield a desirable change in the output variable. This calls for reformulation of (11) as

$$u(t+k-d) = \frac{1}{b_o}\{-\hat{y}(t+k/t)-a_1\hat{y}(t+k-1/t)-\ldots-a_n\hat{y}(t+k-n/t) +b_1u(t+k-d-1)+\ldots+b_nu(t+k-d-n)\} \quad \ldots(12)$$

where $y(t+k/t)$ is assumed to be the known targetted output. This implies that the roots of $B(z^{-1})$ have to be accommodated within the unit disc. From practical considerations b_o may be fixed at a particular value.

PRACTICAL CONSIDERATIONS

Data Preparation

The data used in this work were recorded direct from conventional analogue transducers, except for strand speed which was filtered to suppress the noise generated by the jerky motion of the pallet sections forming the strand. Measurements of strand speed and waste-gas temperature were recorded at 2-minute intervals. The operating conditions were; strand speed open-loop, suction floating, hood-temperature control in operation.

Time-delay

The choice of proper time-delay is of great importance in the present context. In the sintering process, due to the unknown influences on the process, it is very difficult to estimate the time-delay between the strand speed and the waste gas temperature. As a conservative approach is advisable in ascertaining the time-delay, for the present investigation a delay of 8 minutes was assumed.

RESULTS AND DISCUSSION

Output Predictions

The on-strand process was modelled by a second order difference equation. An exponential forgetting factor of 0.99 was used to track the slowly varying parameters of the process. It was found that it is possible to predict the waste gas temperature within an accuracy of $\pm0.5^{\circ}C$ 6 minutes in advance, Fig.2, and within $\pm1.5^{\circ}C$ 14 minutes in advance, Fig.3. The normal value of waste gas temperature is of the order $140^{\circ}C$ and the full-length run-time approximately 30 minutes. Fig.4 shows how the prediction information presented to the operator tallies with the actual output.

Robustness of Algorithm

It is common practice to use the Kalman algorithm for updating of the covariance matrix in recursive least squares estimation (7) but the following problems may arise;

(a) if the data is insufficiently varying the covariance matrix tends to increase exponentially,

(b) numerical instability could occur if the algorithm were implemented on a short word-length machine.

It has been shown that the UDU^T covariance matrix updating method |7| is more robust than the Kalman algorithm method |8|. The UDU^T method was used in this study.

Fig.5 shows the typical variation in the parameter values during normal running of the strand. From start-up, the parameters reach fairly steady values within approximately 10 sampling intervals. If there is a brief stoppage of the strand, the algorithm retains the parameter values and, on restart, the prediction again becomes reliable after approximately 6 sampling intervals.

Use of Prediction for Control

At any sampling instant, the desired control action to achieve a targetted output may be obtained from the inverse algorithm (12). Having determined this desired control action, the predicted change in waste-gas temperature several time-steps ahead becomes available. Fig.6 shows, for a typical case, the predicted temperature with and without control action.

Visual presentation of this information to the plant operator allows him to weigh the advised action with his practical experience of the plant. As a result, the operator may wish to observe additional predictions for different control actions and to base his control decisions on the overall picture.

CONCLUSIONS

A self-tuning multi-step predictor for on-strand processing of sinter has been developed. It has been shown that, in spite of the complex non-stationary nature of the process and the long system time-delays involved, waste-gas temperature can be accurately predicted several minutes ahead. The way in which the predictor can be used to provide advice on strand speed control has been described.

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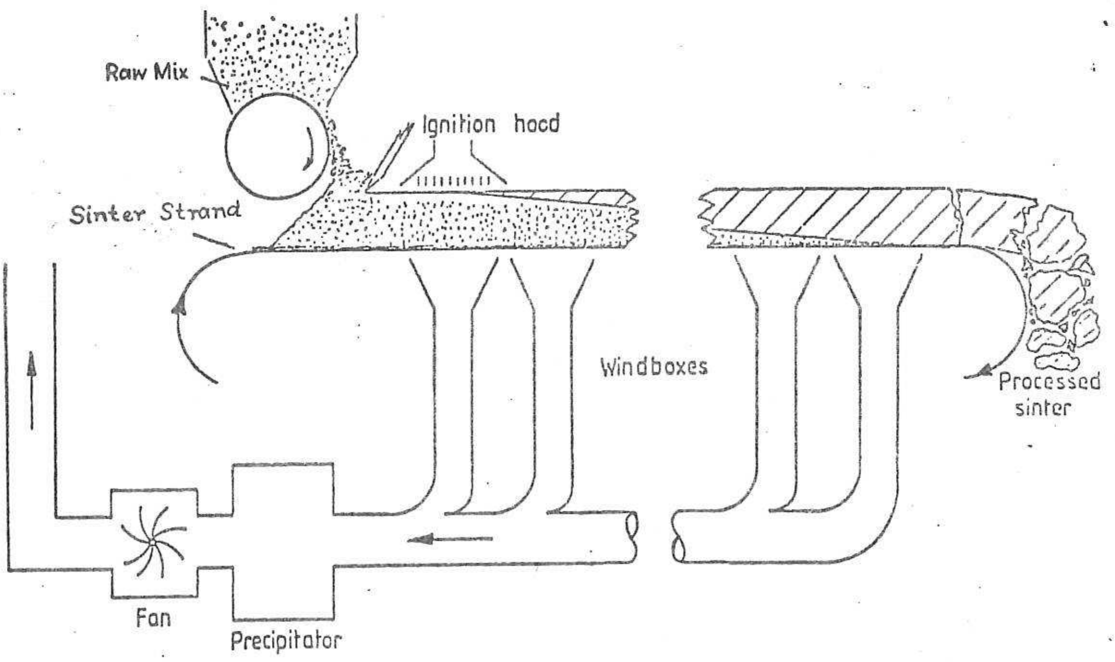

Fig.1. Schematic diagram of the sinter strand

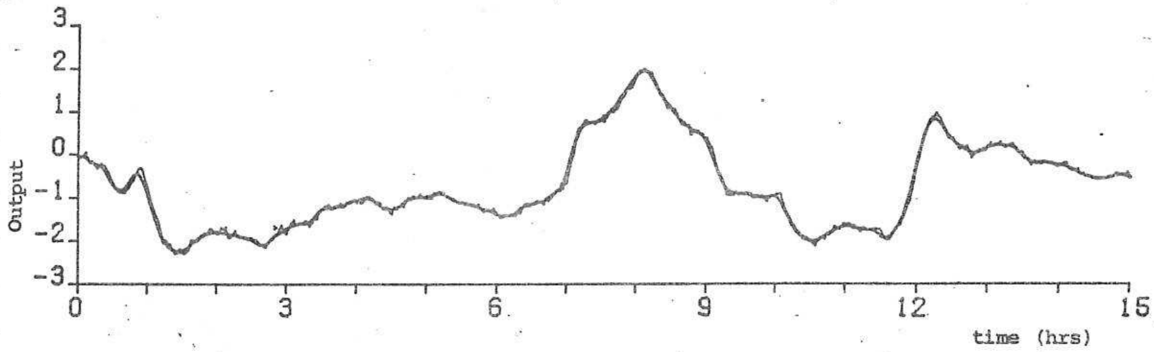

Fig.2. Measured output and 6 min prediction

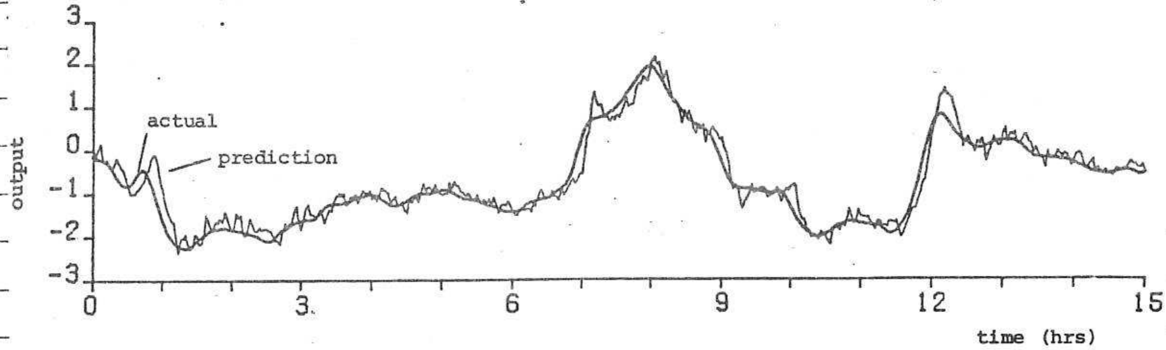

Fig.3. Measured output and 14 min prediction

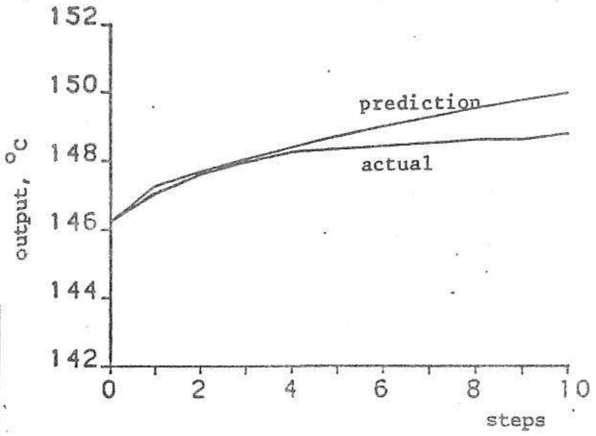

Fig.4. Actual output and multistep prediction (step = 2 min)

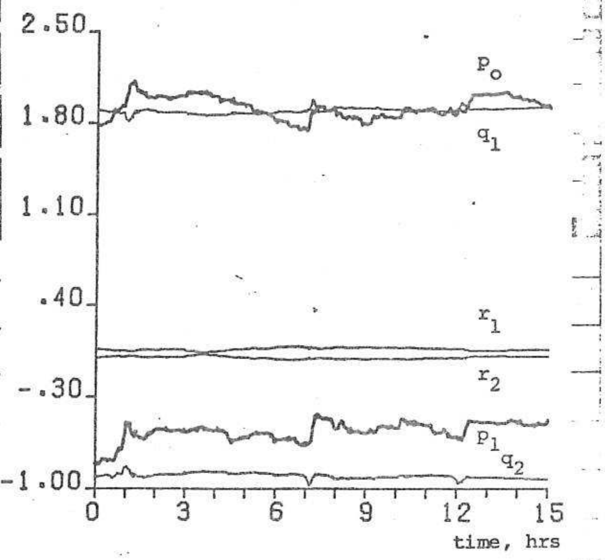

Fig.5. Parameter values

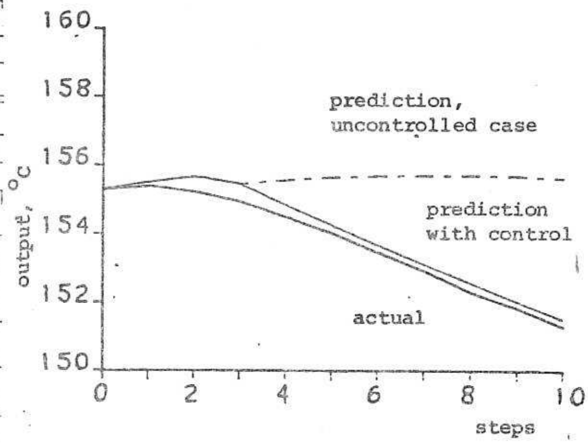

Fig.6. Actual output and prediction