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SELF-TUNING MULTI-STEP PREDICTION OF STRENGTH INDEX IN AN IRON-ORE SINTERING PROCESS

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ABSTRACT

Sintering is a complex metallurgical process by which iron ore is converted to sinter before it is fed to the blast furnace. An important property of the sinter is its strength, and present practice requires the plant operator to make adjustments to the input variables as he considers necessary, based on off-line strength tests and on his accumulated experience and empirical understanding of the process. Although the operator may be highly skilled, the complexity of the process and the long time constants involved give rise to relatively crude control of sinter strength.

In recent years significant advances have been made in the area of self-tuning prediction and regulation of stochastic processes and the methods have been applied to a number of industrial problems. In manually controlled processes better results can be achieved by providing the operator with advance information on predicted future performance of the process, which is calculated on the basis of past and present performance together with proposed future input strategy.

The work reported here represents the first known attempt to develop a self-tuning multi-step predictor for sinter strength.

INTRODUCTION

A metallurgical process is often difficult to control with any precision because of a lack of information about the process and the long time delays involved. Usually, the process is non-stationary in nature, multivariable in structure and subject to unknown disturbances. Thus the process defies description using fundamental physical and chemical relationships and a classical approach to control is ruled out. It may, however, be possible to apply adaptive control methods such as self-tuning prediction, for such methods do not necessarily require detailed knowledge of the intricate workings of the plant; they do however require recorded data of plant output for long periods.

Sintering is an important process in the ironmaking industry. Iron-ore fines and concentrates are mixed with coke breeze, flux, re-cycled sinter-fines and water to form pellets. The pellets are loaded onto a moving grate to form a bed of raw material which undergoes a thermal process and is thereby converted into a clinker-like material called sinter. The sinter product is crushed and sieved to form feed-material for the blast furnace. Smooth and efficient operation of the blast furnace demands consistent quality of sinter, but because of variations in the physical and chemical characteristics of the raw materials and fluctuations in operating conditions sinter quality does vary. The control task is to minimise this variation.

The most important aspect of sinter quality is its strength which cannot be measured on-line. Current practice involves physical analysis of samples at intervals of 4-8 hours. The plant operator occasionally adjusts fuel rate (i.e. proportion of coke in raw-mix) taking into consideration the strength analyses but adjustment is based on operator-experience. If the strength-index were too low, the sinter would be weak and a higher percentage would be rejected; if strength-index were high then it would be likely that an excess of coke were being included in the raw-mix. Thus a balance must be achieved and because of the non-stationary nature of the process, decision-making is imprecise and complex.

The paper discusses the application of a self-tuning multi-step predictor to the problem of sinter strength control. This is an adaptive technique, capable of forecasting output of a stochastic process by adapting itself in real time to the changing dynamics of the process. Self-tuning prediction involves re-formulation of the prediction problem into the format of a self-tuning regulator problem. As discussed by Wittenmark (1) the exercise is a two-stage procedure of estimation and prediction. At each sampling interval, the parameters are estimated and used to calculate the minimum variance prediction. After convergence the parameters of the predictor become optimal. Practical results show that even before convergence is achieved, the predictor soon reaches quasi-optimal state, yielding reasonably good prediction.

As shown by Wittenmark (1) and De Keyser and Van Cauwenberghe (2) a multistep self-tuning predictor can be designed to estimate process output several sampling times in advance. This is of special significance for long time-constant processes where the manipulated variable is changed only occasionally. Thus, the multi-step predictor can serve as an open-loop guide for the operator. It also helps the operator to foresee how the output may be expected to respond to any planned pattern of input variation.

The paper presents the case for the application of a self-tuning multi-step predictor to forecast the strength index of sinter-product several hours in advance. Percentage of coke in the raw-mix is used as input. It is demonstrated how the predictor can convey useful advance information to the operator and thereby aid his decision-making.

PROCESS DESCRIPTION

A schematic diagram of the sintering process is given in Fig. 1. The raw-mix is loaded onto a moving strand and the material is levelled to form a flat bed. The upper surface of the bed is subjected to intense heat as the material passes under an ignition hood and the coke particles near the surface become ignited. As the material travels horizontally along the strand the combustion zone is drawn downwards through the bed under the influence of the suction fan, driving off the volatiles and fusing the material to form sinter. At the end of the strand the material is unloaded, crushed and screened. Sinter fines less than 5mm are passed to the return-fines bin and stored for re-use. A reduction in sinter strength manifests itself as an increase in the production of return-fines which represent an unproductive re-circulating load. Although a small percentage of return-fines is inevitable and is recognised as a valuable constituent of the raw-mix, efficient sintering requires that the accumulated volume of return-fines should be held at some optimum level.

The mechanical strength of sinter is important in the operation of the blast furnace. The materials fed into the top of the blast furnace work their way down the furnace against the hot blast. They undergo severe abrasion as they pass through the top zone. Weak charge materials may disintegrate and are wasted as they are carried away by the top exit gas or they remain mixed with the charge material and impair the permeability of the furnace.

In the sintering process greater strength may be produced by;

(a) increasing the percentage content of coke breeze in the raw-mix

(b) increasing the height of the bed, as considered by Fleming and colleagues (3).

An increase in bed-height results in a lower production rate and for this reason (as well as control complexity) the latter procedure is not attractive.

The adjustment of coke-rate is a possibility and it is this measure which is considered herein. At the present time the control of strength through the manipulation of coke-rate is crude for two reasons. Firstly, the plant operator has to depend upon the results of off-line analysis conducted at 4-8 hourly periods to obtain a scientific measure of sinter strength. Secondly, the dependency of sinter strength on coke-rate is by no means direct.

MATHEMATICAL FORMULATION

k-Step Ahead Predictor

The sintering process may be characterised by a discrete time stochastic model

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

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}.

$$A(z^{-1}) = 1 + a_1z^{-1} + \ldots + a_nz^{-n}$$

$$B(z^{-1}) = b_o + b_1z^{-1} + \ldots + b_nz^{-n}$$

$$C(z^{-1}) = 1 + c_1z^{-1} + \ldots + c_nz^{-n}$$

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 $\{u(t),u(t+1),\ldots,u(t+k-d\}$. Introducing the loss function,

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

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

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

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).

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

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 as shown by Astrom and Wittenmark (1,4),

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

where the polynomials

$$F(z^{-1}) = 1 + f_1z^{-1} + \ldots + f_{k-1}z^{-k+1}$$

$$G(z^{-1}) = g_o + g_1z^{-1} + \ldots + g_{n-1}z^{-n+1}$$

are determined from the identity

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

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).

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, Wittenmark, De Keyser and Van Cauwenberghe (1,2).

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,

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

$[q_o = -1]$

using recursive least squares method.

Step 2. Determine the prediction for the next step

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

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.

Continuous Multi-step Prediction

In the case of the sintering process, it is necessary to be able to foresee how the output (i.e. strength index) 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. coke rate). 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 (5)

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

where

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

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

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

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

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).

Because of structural similarity with the self-tuning regulator the above strategy would yield optimal prediction also with $C(z^{-1}) \neq 1$, Astrom and Wittenmark (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.

CONSIDERATIONS CONCERNING IMPLEMENTATION

Plant Data

For the case considered data on sinter strength, expressed as "strength index ISO", was available from off-line measurements taken at intervals of 4 hours. The measurements were noisy as the method of determining strength index involves bulk solid samples of the sinter product which may not be consistently representative. The data were therefore filtered before use. The ratio of coke to blended ore was used as input and this quantity was available from online measurements.

Sampling Time

The input is left unchanged for long periods. Thus it was considered adequate to consider measurements at intervals of one hour. The output was interpolated from the four-hourly records.

Time-delay

It is difficult to estimate the exact time-delay between input and output because of the very complex nature of the process. A conservative estimate of 4 hours was used.

RESULTS AND DISCUSSION

Start-up

The normal practice is to start with low values for the parameters and high values for the diagonal elements of the covariance matrix. It was found, however, that steadiness of the parameters was much improved if the multi-step prediction was allowed to run using past plant data before it was actually put to use. Simulation exercises also show that in the case of any short-term stoppage, the algorithm can be frozen and re-started from that condition when plant operation is resumed.

Multi-step Prediction

The sintering process was modelled by a second order difference equation. As the process is non-stationary an exponential forgetting factor of 0.99 was used to track the slowly time-varying parameters.

In normal circumstances the operator has no information about the likely variation of strength index in between the four-hourly measurements. The foregoing method has been applied to provide a multi-step prediction one to four hours in advance. The results are shown for a total plant time of 150 hours in Fig. 2. It was found that the prediction error is within ±0.75 where the normal ISO reading is approximately 75. The operator may extend the prediction beyond four hours but, naturally, the accuracy of the forecasts will deteriorate.

Parameter Updating

It is adequate for estimation of parameters (7) to be carried out every four hours. It was found, however, that consistency of the parameters and accuracy of prediction were much improved if the estimation algorithm (7) was allowed to "freewheel" through the interpolated data sets between four-hourly intervals when the output is measured. Fig. 3 shows how the set of regulator parameter values varied. For practical reasons the value of r_0 was held fixed at 0.3.

PREDICTION AS AN AID TO CONTROL

Multistep prediction becomes particularly helpful when a change in input is envisaged. Fig. 4a is a sample of data taken from plant records. Control action is apparently taken because of the downward trend in ISO value coupled with the slow system response. It should be emphasised that the present study is based on existing data and does not include online control exercises. However, the behaviour shown in Fig. 4a can be compared with the predicted behaviour shown in Fig. 4b in which no control action is taken and Fig. 4c in which the system is given time to respond to the initial adjustment in coke/ore ratio. There is no way of knowing precisely what ISO value the operator was aiming to achieve by taking the action shown in Fig. 4a, but it is likely that he over-compensated and that if he had had available the predictions shown in Figs. 4b and 4c his control action, if any, would have been milder and some saving would have been made in coke input.

CONCLUSIONS

The method of self-tuning multi-step prediction has been applied to sinter plant-records. The problem investigated is the prediction of sinter strength which probably represents the most important and most complex aspect of sintering. It has been shown that sinter strength index (ISO) can be predicted with reasonable accuracy several hours in advance on the basis of past records of ISO and the percentage of coke in the raw-mix. It has also been demonstrated how ISO prediction can be used as an aid in the regulation of sinter strength and can help to avoid the use of excess coke in the raw-mix when taking control action.

The prediction facility has the capability of providing the operator with a better online appreciation of process behaviour and will thereby lead to more accurate control.

ACKNOWLEDGEMENT

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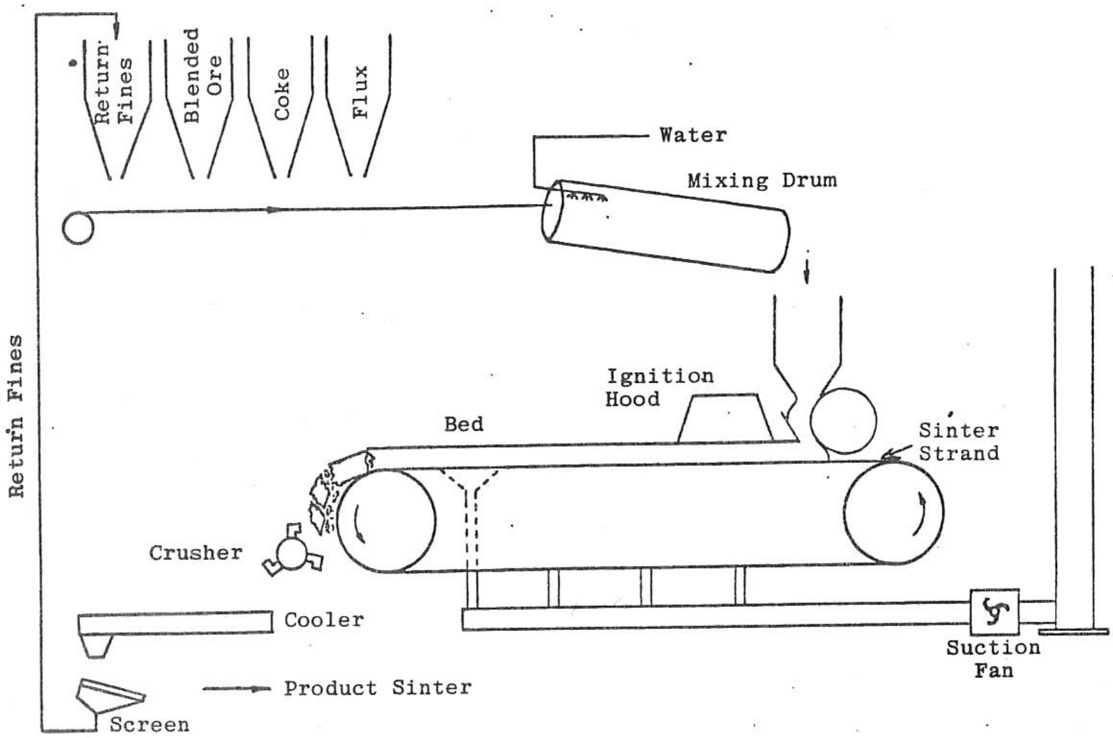

Fig. 1. Schematic Diagram of the Sintering Process

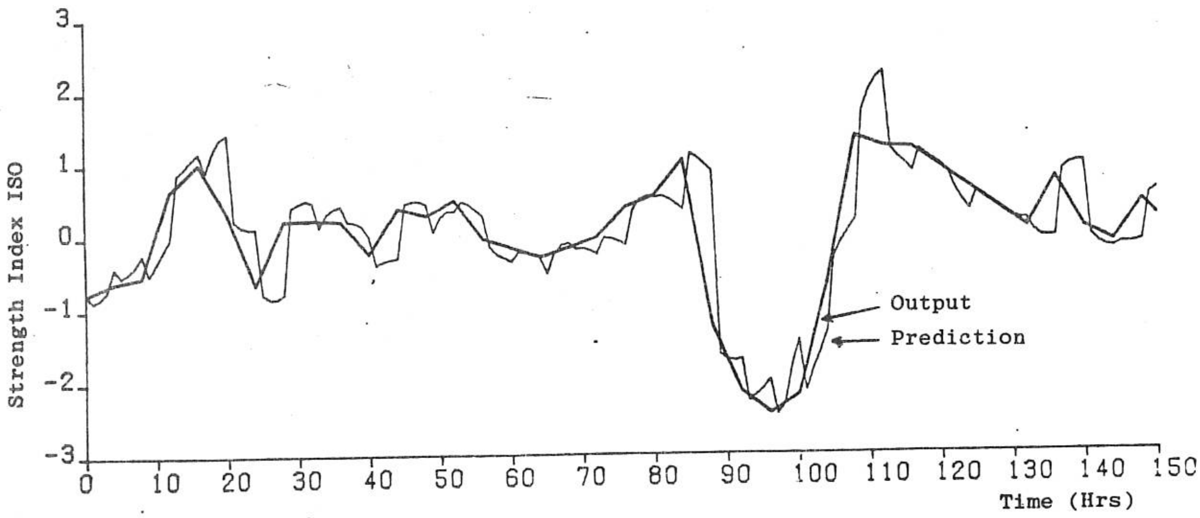

Fig. 2. Multi-step Prediction of Strength Index 1-4 Hours in Advance

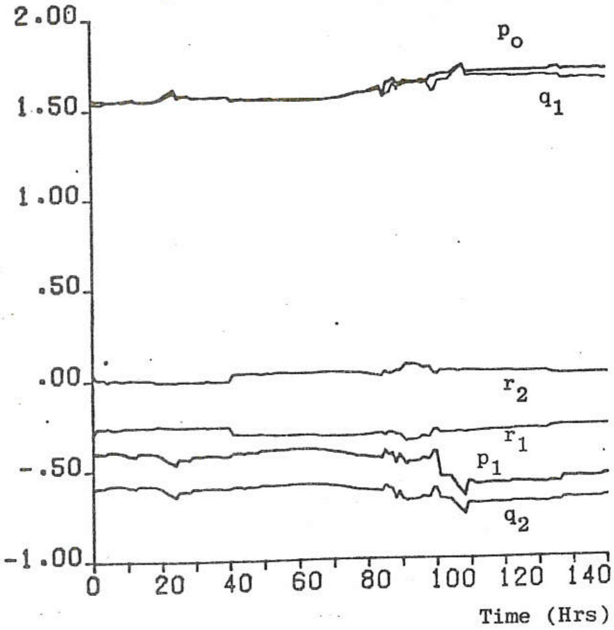

Fig. 3. Parameter Values

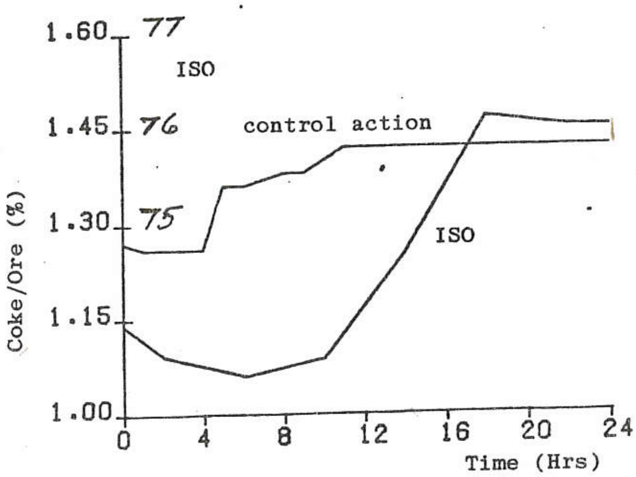

Fig. 4a. Plant Performance

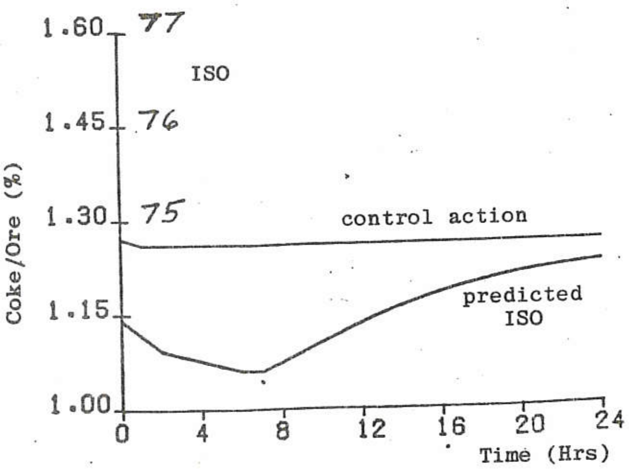

Fig. 4b. Predicted Performance (case 1).

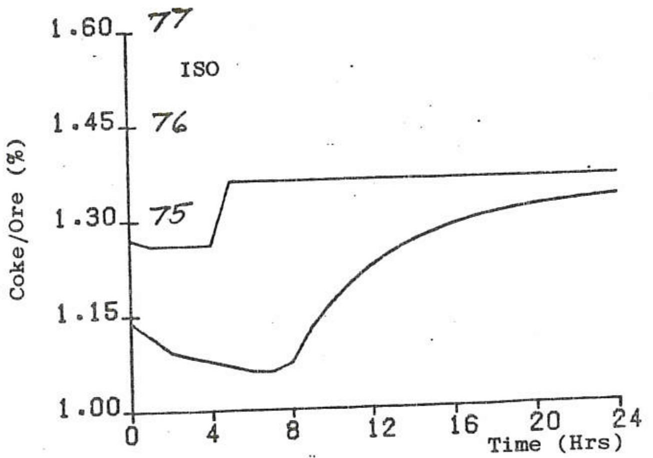

Fig. 4c. Predicted Performance (case 2)