Neural Network Model of Burden Layer Formation Dynamics in the Blast Furnace

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A model of the thickness of burden layers in the ironmaking blast furnace is presented. Local layer thickness estimates are calculated on the basis of signals from stockrods that measure the burden (stock) level in the furnace. These estimates are used in developing a model for the relation between the layer thickness and variables such as stock level and movable armor settings. Because of the nonlinear dependence of the variables, the models are based on feedforward or recurrent neural networks. The network size is carefully selected based on a cross-validation procedure. The resulting neural model is first studied by analyzing its predictions for different inputs. By further introducing a simplified scheme for considering the practical constraints of the charging process, an autonomous model, where the neural network plays an important role, is formed. This hybrid model is applied to yield insight into the dynamics of the layer formation process; the effect of movable armor settings, stock level and burden descent rate are analyzed and compared with practical experience.

KEY WORDS: blast furnace; burden distribution; neural network; hybrid model.

1. Introduction

In the operation of the blast furnace, the iron-bearing material (usually sinter or pellets) and coke are charged in separate layers to yield sufficient gas permeability in the dry part of the shaft. The radial distribution of the burden is of great importance, since it influences the distribution of reducing agents and gas in the furnace. The distribution affects both thermal and chemical phenomena in the lumpy zone, and it also plays an important role for the formation of the cohesive zone, i.e., the “ mushy” region where the iron-bearing materials start to soften and finally melt. In the cohesive zone, the coke layers act as windows through which the gas can flow. The burden distribution can be controlled by applying different movable armor positions for the dumps in furnaces with bell-type charging equipment (as depicted in Fig. 1), or by using different tilting angles for the rotating chute in furnaces with bell-less tops. Furthermore, the charging sequence (i.e., the order of the dumps), the dump size and the stock level, and even the gas flow, affect the distribution.

A variety of methods for measuring the burden distribution in operating blast furnaces have been proposed. The burden surface (stockline) can be detected by mechanical profile meters, or by non-contact methods based on radar, microwaves or laser, infra-red and gamma radiation techniques. The thicknesses of burden layers (at the wall) can also be measured by magnetometer. However, since most of the above-mentioned techniques are expensive and require major installation and maintenance efforts, mainly due to the extremely hostile atmosphere and wear in the furnace, a number of models for indirect estimation of the burden distribution have been proposed, many of these being based on measurements of temperature and/or gas composition by above-burden or in-burden probes. The present paper presents an alternative approach, where the local thickness of a burden layer is estimated on the basis of
signals from the stockrods (see Fig. 1), which measure the stock level close to the wall. Stockrod signals have been logged at high frequency and processed to provide burden layer thickness estimates. The relation between the layer thickness and variables affecting the burden distribution has been modeled by feedforward and recurrent neural networks. The study shows that the variation in the burden layer thickness can be described by the networks, given information about the stock level at the instant of charging and the movable armor position.

However, the neural model requires information about the stock level, which is a variable that is affected by the layer thickness of the dumps, i.e., the output of the model. In order to resolve this dilemma, the network has been implemented in a hybrid model, which considers the effects of the descent of burden and practical constraints of the charging process. By this procedure, the dependence between the stock level prior to charging and the resulting layer thickness can be considered. The hybrid model can be used to simulate the effect of stock level set-point, movable armor positions and burden descent rate on the layer thicknesses. The results obtained conform well with observations from the Finnish blast furnace studied in this work and are also in general agreement with practical experience.

2. Measurements

The stockrods in the blast furnace are sounding devices (as illustrated schematically in Fig. 1) that sense the burden level after each dump and are elevated before a new dump of burden is charged into the furnace. The main function of the rods is to measure the vertical position of the bed surface (stock level) in order to trigger the charging of the burden at an appropriate moment to maintain a stable stock level. In practice, charging is triggered when the rods have descended below a given set-point. From the stockrod signals it is also possible to detect larger irregularities in the descent of the burden, such as hangings (when the burden surface stands still; a phenomenon often caused by partial fluidization of flooding of the bed) or slips (i.e., sudden major downward movements of the stock column). Figure 2 shows a typical appearance of the signals from a stockrod of the blast furnace studied in this work; the rods report the vertical distance, z, between a reference level, e.g., the lower level of the large bell in its upper position, and the stock level (see Fig. 1). In what follows, the symbol \( z \) will be used to denote the vertical position of the rod.

The stockrods provide one of the most important signals for the operation of the process, but it is interesting to note that the rationale of using these measurements for other purposes has been largely overlooked. Even though efforts to automatically detect irregularities in the operation using stockrod information have been proposed in the literature, short-term measurements from the rods have been used by very few investigators only. This may partly be due to the fact that the signals exhibit a rich variety of patterns (cf. Fig. 2) that are complicated to classify. Another reason is that the signals should be available at short sampling time, and such high-frequency data are seldom interesting in the analysis of the blast furnace process because of its inertia. In the present work, it was found that the stockrod signals should be sampled at least every two seconds in order to be able to provide accurate and useful information, especially in abnormal situations (such as slips).

In this work, data from the BF1 of Rautaruukki Steel in Raahe, Finland, were used. The furnace has a working volume of approximately 1000 m\(^3\) and a production rate of about 3 500 metric tons/day. The iron-bearing material consists of sinter (70–80%) and pellets (30–20%), while about 330–350 kg of coke and 80–100 kg of oil are used as reducing agent. The furnace is equipped with bell-top and movable armors with ten different positions (MA = 1,…,10, cf. Fig. 1), and the stockrods are located 0.6 m from the furnace wall. A sampling time of 2 s was applied in logging the stockrods by a PC with a data acquisition board.

Routines for detection of whether the rods were on the burden surface, on their way down (immediately after a dump) or on their way up (before a dump) were developed on the basis of information about the level, \( z \), and the velocity, given as the time derivative of \( z \) approximated by differences. It is important to filter out cases where the leads have collapsed because of lack of strain in the wires and other irregularities caused by the features of the mechanic device. Extrapolating the stock level during periods when the rods are elevated, the burden layer thickness under the rods, \( \Delta z \), can be estimated after each dump, as depicted schematically in Fig. 3.

3. The Dataset

Data from a measuring campaign at BF1 of Rautaruukki carried out in September 1999 were used, during which the furnace was operated with a ten-dump charging sequence reported in the first two columns of Table 1. From the table, where C denotes coke, S sinter and P pellets, it is seen that the charging program, in effect, is a 5-dump sequence,
which repeats with minor modifications of the armor settings of the last coke dump. Armors with a setting of 2 do not interfere with the falling parabola of the sinter dumps, while the higher settings of coke for dumps number 2 and 7, followed by coke + pellet dumps with “normal” settings, are applied to implement center-coke charging.

A carefully selected period of 68 h of operation was considered. From the furnace supervising system, the charging data (time label, material, weight, charging program, movable armor position) were retrieved and synchronized with the pre-processed logged data (time label, layer thickness, burden level) to create a data set including 1284 consecutive dumps. Due to occasional disturbances in the measurements some filtering of the data had to be undertaken. The sinter dumps preceding the coke dumps with MA/H = 10 were found to be problematic. The reason is that a high stock level set-point is applied for the latter dump in order to maintain stock level (at the wall) despite the center-charged dump. Consequently the stockrods were lifted as, or even before, they touched the burden surface. This can be seen in Fig. 2, where the stockrod after every fifth dump (dumps number 3 and 8) usually show a spike with max(\(z_r\)) = 2.5 m, e.g., at \(t = 0.6\) h. The filtering was done by replacing all thickness estimates and stock levels smaller than \(-0.20\) cm and 2.3 m, respectively, by these limits. It should be noted that negative estimates of the layer thickness may occur occasionally, and that these observations, most likely, correspond to cases where the stock has slipped in conjunction with a dump of where the charged dump has exerted a pushing effect on the previous layer on the stockline. In cases where no reasonable layer thicknesses could be calculated from the stockrod signals, the average value for the corresponding dump was used. Figure 4 illustrates the stock level after this pre-processing.

Columns 4 and 5 of Table 1 report average values of the stock level and layer thickness of the dumps in the data set. The sinter layers are seen to be considerably thicker (at the position where the rods carry out their measuring) than the coke layers, and the center-charged coke layers (dumps number 3 and 8) are clearly thinnest. These dumps trap the following dumps (number 4 and 9) at the wall, which results in the thickest dumps in the sequence. The information was aggregated into a set of 1284 data vectors, where each vector corresponds to the data pertaining to a specific dump, \(k\). The data set is in the following used to develop models of the burden layer thickness.

### 4. Neural Network Modeling

In an earlier study\(^9\) of the burden distribution in a blast furnace on the basis of the dynamics of above-burden probe temperatures, it was concluded that neural networks were well suited for describing the relation between the distribution and process variables related to the charging. Since the problem studied in the present work is similar, and the relationship between the (local) layer thickness of the charged burden materials and other process variables is expected to be complex and nonlinear, neural networks were used as modeling tools.\(^16\) The networks utilized in the study were small multi-layer feedforward networks with a single hidden layer (of nonlinear nodes) and recurrent networks with nodes in the output layer linked to corresponding added nodes in the input layer through lagged connections.\(^17\) It should be noted that the feedforward networks are static non-linear modeling tools, while the recurrent networks can capture dynamic relationships that may be required for solving the modeling task at hand.

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**Table 1. Dumps, movable armor positions and average values of the stock level and layer thickness under the stockrods, as well as predicted layer thicknesses by feedforward (FNN) and recurrent neural networks (RNN).**

| Dump number | Material | Movable armor notch | Observed \(z/m\) | Observed \(\Delta z/m\) | Predicted by FNN \(\Delta z/m\) | Predicted by RNN \(\Delta z/m\) |
|-------------|----------|---------------------|-----------------|---------------------|---------------------|---------------------|
| 1           | S        | 2                   | 2.93            | 0.411               | 0.434               | 0.366               |
| 2           | C        | 10                  | 2.78            | 0.187               | 0.238               | 0.168               |
| 3           | C+P      | 6                   | 2.89            | 0.050               | 0.089               | 0.088               |
| 4           | S        | 2                   | 3.09            | 0.544               | 0.499               | 0.554               |
| 5           | C        | 5/6                  | 2.88            | 0.108               | 0.086               | 0.102               |
| 6           | S        | 2                   | 2.92            | 0.406               | 0.430               | 0.373               |
| 7           | C        | 10                  | 2.84            | 0.192               | 0.271               | 0.193               |
| 8           | C+P      | 6                   | 2.88            | 0.075               | 0.086               | 0.081               |
| 9           | S        | 2                   | 3.00            | 0.462               | 0.463               | 0.516               |
| 10          | C        | 6                   | 2.88            | 0.091               | 0.086               | 0.128               |

**Fig. 3.** Estimation of burden layer thickness, \(\Delta z\), from the stockrod signal, \(z_r\).

**Fig. 4.** The 1284 values of the stock level after pre-processing of the data set.
where prediction errors on the sets were computed as

\[ \varepsilon_i = \frac{1}{M_i} \sum_{k \in I_i} \left( \Delta z(k) - \hat{\Delta z}(k) \right)^2 / \epsilon_i ; \ i = \text{tr, te} \ldots \ldots (1) \]

where \( \Delta z \) denotes the prediction by the network. In the equation, \( I_{\text{te}} \) and \( I_{\text{tr}} \) are indices for the data vectors in the training and test sets, respectively, and \( M \) is the number of observations in the corresponding sets (here \( M_{\text{tr}} = M_{\text{te}} = 642 \)).

In the analysis it was found that the inaccuracy of the thickness estimates, which, as noted above, occasionally showed negative values, made it disadvantageous to use the previous layer thickness(es) as input variable(s). The results showed that networks with the present stock level and the movable armor setting as the only inputs were able to predict the layer thickness reasonably well. The mass of the dump, the material type, and the burden descent rate did not improve the quality of the models but only resulted in an increased number of parameters (weights) to be estimated. The fact that the mass of each dump was practically constant, 25 t of “ore” and 6 t of coke (except for the centered charged dumps), throughout the period studied explains the occasional exhibited very large or very low values. In accordance with results from earlier studies, the analysis shows that there is a need for non-linearity in the models. However, by contrast to the results of a preliminary analysis, the training and test errors are here very similar, which indicates that the data set is of sufficient size and that the networks are not over-parameterized.

4.1. Network Training and Validation

A set of measurable variables potentially influencing the burden distribution was selected, and a systematic analysis of these as inputs to the neural networks was carried out. Input variables considered were the stock level and the burden descent rate prior to the dump, the movable armor position, the burden material type (ore or coke, expressed in Boolean terms) and weight. Also lagged values of the variables were included.

Different architectures (feedforward vs. recurrent) and sizes (i.e., number of hidden or recurrent nodes) of the networks were trained and evaluated using a neural network development tool \( ^{18} \) applying a cross-validation procedure to select a proper network. The process data were divided into four sets, each consisting of 321 dumps. Using these sets, partly considering the change in characteristics exhibited by the stock level around the middle of the period studied (cf. Fig. 4), four different combinations of training (tr) and test (te) data were formed as shown in Table 2. The prediction errors on the sets were computed as

\[ \varepsilon_i = \frac{1}{M_i} \sum_{k \in I_i} \left( \Delta z(k) - \hat{\Delta z}(k) \right)^2 / \epsilon_i ; \ i = \text{tr, te} \ldots \ldots (1) \]

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With the average values reported in Table 1 for the stock levels (prior to each dump) and the movable armor sequence 2, 10, 6, 2, 6, 2, 10, 6, 2, 6 as inputs to the feedforward network with three hidden nodes (FNN) and the recurrent network with two “output nodes” (RNN), the layer thicknesses reported in columns 6 and 7 of Table 1 are predicted. These results illustrate that both networks, and the recurrent one (see Fig. 5) in particular, have been able to capture the dynamics of the layer formation. Figure 6 gives an example of the fits these two networks provide on a set of 40 dumps, using the actual values of \( \Delta z \) and MA as inputs. A reason why the networks exhibit very similar performance is that their inherent complexity is comparable in terms of number of trained parameters: The FNN has 13 weights while the RNN has 10 weights and 2 initial states. From the theory of linear systems it is also a well-known fact that a time-series representation (FNN) can be cast into

| Alternative | Vectors in training set | Vectors in test set |
|-------------|------------------------|---------------------|
| 1           | 1...321, 322...642    | 643...963, 964...1284 |
| 2           | 1...321, 964...1284   | 322...642, 643...963 |
| 3           | 643...963, 964...1284 | 1...321, 322...642  |
| 4           | 322...642, 643...963  | 1...321, 964...1284 |

Table 2. Division of the four data periods into training and test sets for the neural network analysis.

| Network | Nodes | \( \Delta z(k) \) | MA(k) |
|---------|-------|----------------|-------|
| 1       | Hidden| 0.1857         | 0.190 |
| 2       | Recurrent| 0.1453       | 0.1485 |
| 3       |        | 0.1428         | 0.1469 |
| 4       | 2      | 0.1448         | 0.1472 |

Table 3. Training and test errors of some neural networks averaged over the different combinations of data sets (cf. Table 2) using the stock level and the movable armor position as inputs.

Fig. 5. Recurrent network with burden level and movable armor notch as external inputs. The two nodes in the output layer have sigmoidal transfer functions.
state-space form (RNN).

4.2. Network Tests

In this section a brief analysis of the neural model is given, where it will be applied to predict the layer thickness of specific dumps under different input conditions. Here, and in the remaining parts of the paper, the analysis will be confined to the performance of the recurrent network for the sake of brevity, since the predictions by the feedforward network were similar.

4.2.1. Effect of Stock Level

The effect of the stock level is illustrated by predicting the layer thickness of a sinter dump and a coke dump, i.e., dumps 1 and 5 in the sequence (cf. Table 1). The results for the two cases given in Fig. 7 illustrate that there is a slightly nonlinear dependence between the stock level and the layer thickness, and that the thickness grows considerably along with an increase in the falling distance of the material. At this point, three facts should be stressed. First, the results only represent “local predictions”, where all other variables are fixed. For instance, the fact that the layer thickness implicitly affects the stock level of the subsequent dumps is not considered; this problem is, however, treated in Sec. 5. Second, in analyzing the effect on a single dump it should be remembered that the charging sequence consists of ten dumps. Therefore, the summed thickness of two consecutive dumps is not necessarily constant, in spite of the constraints imposed by the volume balance. Third, it is likely that the accuracy of the results suffers when the model is used to predict conditions close to the extreme values of the variables of the data sets used in developing the models. Here one may note that a very high stock level (z=2.5 m, say) in the data set may correspond to cases where the stockrod barely touched the burden surface before it was withdrawn because of a high set point z_set applied (as discussed in Sec. 3). Very low stock levels (z>3 m, say), in turn, may correspond to conditions after irregularities in the burden descent (e.g., slips) where the stockrod measurements also become less reliable. Such inaccuracies in the training set may naturally yield a bias in the models developed.

4.2.2. Effect of Movable Armor Position

Since the movable armor positions in the data set used to develop the model do not vary for the sinter dumps, the attention is here focused solely on the effects on the distribution of coke. For comparison with the findings presented above, dump number 5 is studied, using a fixed stock level but a variable movable armor setting. Figure 8 shows the predicted layer thickness for MA=5,...,10, where the increased notch forces the coke into the center, yielding a thinner layer under the rod. However, the effect is much less clear than changes caused by z, which stresses the important role played by the stock level in controlling the burden distribution.
5. Hybrid Model

As illustrated above, it is possible to analyze the “local” effects of perturbed inputs with the neural model. However, since the model makes use of the burden level and the movable armor setting as inputs, both variables should be known in order to make true predictions off-line. Even though the stock-level set-point, $z_{\text{set}}$, can be assumed to be given, a complication is that the burden level is not known, but it varies along with changes in the layer thickness. After a dump that forms a thin layer, there is very little time until the stock level—and the stockrods—pass the set-point, and the likely outcome is that the burden surface will descend well beyond this point before the next dump is ready to be charged. Conversely, after a dump forming a thick layer, several minutes will elapse until the stock level passes the set-point that will trigger the charging, and at this moment the next dump will (most likely) be ready on the bell and can be charged immediately. This can be verified by studying the connection between $z$ and $\Delta z$ in Table 1: After a thick layer the next dump will enter at a small $z$ (i.e., at a high stock level), while thin dumps result in large values of the next $z$.

These findings can be captured in a simplified way in a hybrid model that, in addition to the neural network predicting the layer thickness, also considers the practical constraints of charging by modeling the interaction between the (simulated) stockrod signals and the triggering of the charging events. In the simulations, the stock level is lowered in accordance with a (user-defined or stochastic) burden descent rate, $w$, until $z_{\text{set}}$ is reached and charging is triggered. The time the stockrods are elevated, $t_{\text{up}}$, as well as the minimum time between the dumps, $\Delta t_{\text{d}}$, which in practice depends on the burden weighing and skip transportation to the furnace top, were also considered. Figure 9 gives a flowsheet of the hybrid model.

5.1. Hybrid Model Constraints

In order to find appropriate values for the constraints in the hybrid model, a statistical analysis of the process data was undertaken. The average time periods the stockrods were elevated and the time between the dumps were found to be $\Delta t_{\text{up}}=50\ s$ and $\Delta t_{\text{d}}=110\ s$, respectively. For the stock level, the set-point value of $z_{\text{set}}=2.70\ m$ reported by the ironworks was used. Observe that this value is smaller than the average values of $z$ given in Table 1, partly because the latter values represent the (extrapolated) stock levels at charging and not at the moment of elevating the rods, and partly because the time constraints are active at the high production rate achieved with the furnace. As for estimating the burden descent rate, it was decided to use information about charged quantities of burden. Dividing the charged volumes by the time elapsed a moving average of the volume flow rate, $\dot{V}$, of charged material calculated over the ten latest dumps, i.e., a full charging sequence, is obtained as

$$
\dot{V}(t_{d}(k)) = \frac{1}{t_{d}(k)-t_{d}(k-10)} \sum_{j=k-9}^{k} \frac{m(j)}{\rho(j)},
$$

where $k=11,\ 12,\ldots,\ 1284$. 

![Fig. 9. Flowsheet of the hybrid model, applied with a time-step of $\Delta t$.](image)
where \( t_d(k) \) and \( \rho(k) \) are the time and the bulk density of the \( k \)th dump. An estimate of the average descent rate is now given by

\[
\bar{w}(k) = \frac{\dot{V}(t_d(k))}{\pi R^2} \tag{3}
\]

where \( R \) is the radius of the furnace throat. Figure 10 shows that the descent rate from Eq. (3) varies between 0.10 m/min and 0.13 m/min, with an average value of \( \bar{w} \approx 0.117 \) m/min.

5.2. Hybrid Model Results

This subsection is devoted to illustration of some results of the hybrid model for different input parameters. For the sake of simplicity \( \Delta t_{up} = 50 \) s and \( \Delta t_{d} = 110 \) s were fixed in the simulations. Table 4 reports the parameters of the examples.

5.2.1. Reference Case

As a reference case, the model was applied to predict the evolution of the stock level, stockrods and layer thickness using values of the parameters determined in Sec. 5.1. The hybrid model was first evolved through a sufficient number of sequences to make the effect of the initial values of variables vanish. The top panel of Fig. 11, which shows the simulated stockrod signals for a period of 1 hour, illustrates the way in which the model has been able to capture the overall behavior of this variable (cf. Fig. 2). The lower panels show the simulated stock level and layer thickness for one pass through the ten-dump sequence. Also these two simulated variables agree well with the observed values (cf. Table 1).

5.2.2. Effect of Movable Armor Setting

The model is next applied to study the effect of the movable armor settings. The armor settings of two dumps, number 5 and 10, were increased from 6 to 8 (cf. Table 4). All other parameters were set as in the reference case. As expected.
expected, the local effect of the change is a decrease in the layer thickness of these dumps, as depicted in Fig. 8. However, since the change also affects the stock level, practically all other layer thicknesses in the program change. Figure 12, which shows the stock level and layer thickness (dotted lines) and the corresponding values of the reference case (solid lines), clearly illustrates the coupling of $\Delta z$ and $z$.

5.2.3. Effect of Stock Level Set-point
The impact of the stock level on the burden distribution has been stressed in the preceding sections. The effect of $z_{set}$ was studied by changing the value by $\pm 0.20$ m. Figure 13 illustrates that the layers for $z_{set}=2.9$ m are thick enough (under the rods) to keep the time constraint inactive most of the time, i.e., the rods are practically always elevated at $z_{r}=z_{set}$ (resulting in $z=3.0$ m at the moments of charging). For $z_{set}=2.5$ m, in turn, the time constraint is active for all dumps but those following after the thickest dumps (number 4 and 9). The fact that practically all layer thicknesses grow with an increase in $z$ is in conflict with the volume balance of the dumps. This could possibly be ascribed to radial redistribution of the layers during the time between the dumps. A more likely reason is, though, a possible bias in the model introduced by inaccurate thickness estimates at very high or low stock levels, as discussed in Subsec. 4.2.1. However, in conclusion, the example clearly shows the importance of a proper dimensioning of the skip transportation and charging system to prevent loss of stockline.

5.2.4. Effect of Burden Descent Rate
The burden descent rate is known to play an important role for the burden distribution. In cases where the rate increases suddenly, e.g., when the hearth is drained rapidly (cf. Fig. 10) or if there is an increase in the rates of reduction and smelting, loss of stockline may occur. The influence was studied by carrying out simulations at $w=0.09$ m/min and $w=0.14$ m/min. As depicted in Fig. 14, the higher descent rate has resulted in a $0.10-0.15$ m loss of stockline, which, in turn, has increased some layer thicknesses. Figure 15, which depicts the simulated stockrod evolution around the point $(t=1\,500$ s) where the sudden change in the descent rate was implemented, illustrates the considerable change that results in the appearance of the stockrod signals.

6. Conclusions
Neural networks have been used to model the thickness of burden layers measured by stockrods in the blast furnace. With a relatively simple recurrent network it was possible to capture the general dynamic behavior of the burden layer formation. The neural model has been included in a hybrid model, which also considers the effects of practical con-
straints in the charging process on the stock level. By comparing its predictions with the average layer thicknesses for the data period studied, the hybrid model was found to be very accurate. The “off-line” use of the hybrid model was finally illustrated by examples, where the effect of changes in some important variables was studied. In the forthcoming work, more extensive data sets from periods with different charging sequences will be used in developing the neural model. This is expected to increase the required complexity of the model (e.g., in terms of more input variables) but will contribute to improved generalization capabilities of it. The hybrid model will also be applied to study the effect of process disturbances, such as hangings and slips, and more realistic variations in the variables (e.g., stochastics in the burden descent rate). Moreover, different schemes will be devised for maintaining a stable stock level while charging layers of different (local) layer thickness. It is of special interest to develop programs of stock-level setpoints for operation under high productivity, where the frequent charging required is a problem. Attempts will also be made to correlate the estimated burden layer thicknesses with results from theoretical burden distribution models. In future work, it is also possible that the stockrod signals used as the main source of information will be replaced by signals from a radar that is being installed at the blast furnace studied.

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