NEURAL NETWORK MODEL OF BLAST FURNACE BURDEN DISTRIBUTION

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ABSTRACT: This paper presents an approach to estimate the burden distribution in the ironmaking blast furnace using stockrod measurements as the primary source of information. After preprocessing the stockrod signals, the local layer thickness of the charged burden materials can be estimated. The relation between the layer thicknesses and other process variables, which are known to exert influence on the distribution, has been modeled by neural networks. The results achieved when the technique was applied to data from a Finnish blast furnace indicate that the local layer thickness can be predicted quite accurately, given information about the “recent history” of the stock level. A preliminary approach is also made to analyze transient behavior in the charging sequence by recurrent networks.

KEYWORDS: Feedforward and recurrent neural networks, blast furnace, burden distribution

INTRODUCTION

In the operation of the ironmaking blast furnace, the distribution of the burden material is a crucial issue, since it influences the distribution of reducing agents and gas in the furnace (Omori 1987). The distribution directly affects thermal and chemical phenomena in the lumpy zone, and it also plays an important role for the formation of the cohesive zone, where the iron-bearing materials start to soften and melt. Since it is difficult to carry out direct measurements of the burden distribution, a variety of different techniques have been proposed for its indirect estimation. Many of the techniques are based on a combination of probe data with mathematical models (Nicholle et al. 1987, Iwamura et al. 1982, Nikus and Saxén 1996). The ideas presented in the present paper differs in the sense that an approach is made to estimate the local thickness of the burden layers on the basis of signals from the stockrods (see Figure 1), which measure the stock (bed) level. These signals were logged at “high ” frequency (1 s^{-1}) and processed to estimate the layer thickness. On the basis of these estimates, neural networks were used to study the influence of some central variables on the burden distribution. The findings of the study indicate that the (local) burden layer thickness primarily depends on, or, at least, can be characterized by, the stock level. Inspired by this fact a simplified dynamic model, implemented in the form of a small recurrent neural network, is proposed.

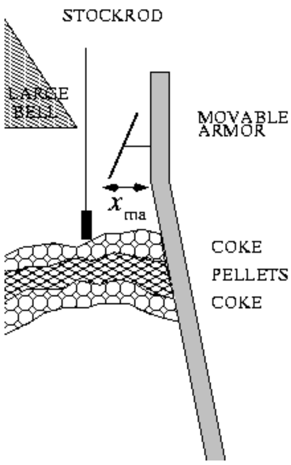

Figure 1: Upper part of the blast furnace

BACKGROUND INFORMATION

The treatment of the problem at hand relies on findings from previous studies of the burden distribution in a small Finnish blast furnace. In this furnace, a four-dump charging program is applied, with two dumps of coke and pellets, respectively. A schematic view of the burden distribution (Saxén et al. 1998) is given in Figure 2. First, the movable armors are applied (high x_{ma}) for the coke dumps (C^1 and C^2) to form a crest. Next, two pellet dumps enter without hitting the armors (low x_{ma}). The first one, P^1, is trapped outside the crest, while the second pellet dump, P^2, distributes mainly towards the center, since the previous dump has filled the pocket at the wall. A noteworthy fact is that pellet dumps, due to their high kinetic energy, might occasionally collapse the crest or the uppermost (partially fluidized) burden layers.

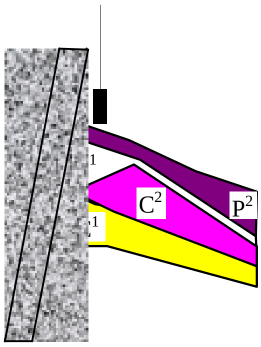

Figure 2: Schematic depiction of the burden distribution in the furnace.

The stockrods in the blast furnace measure the burden level almost continuously, but are elevated before each dump of burden is charged into the furnace. When the stockrod signals are processed, the first task is to detect whether the rods are on the burden surface or not. Here, it is important not to misinterpret the measurements from periods where the lead has “collapsed” because of lack of strain in the wires. The detection was accomplished by simple logical tests, considering the level, z, and the time elapsed since the maximum distance was measured (Hinnelä and Saxén 1997). After these tests, the stockline level and the burden descent rate can be estimated. By extrapolating the descent of the burden surface during the time when the stockrods are elevated a local layer thickness, Δz, can be estimated.

Table 1 shows the average values of the burden layer thickness of the four dumps ($P^1{\downarrow}$ $P^2{\downarrow}$ $C^1{\downarrow}$ $C^2{\downarrow}$) in the charging sequence, computed for a selected period of 88 consecutive dumps where the rod measurement were regular and no major slips or peaks occurred. Clearly, the first pellet dump is thickest below the rods, as expected (cf. Figure 2), and the results are also in agreement with earlier investigations (Saxén et al. 1998), where the findings have been compared with values derived on the basis of a simplified geometrical treatment of the problem.

1. Average values of the burden layer thickness under the stockrods.

Dump	Average Δz / cm
P^1	47.6
P^2	16.2
C^1	8.0
C^2	7.6

MODELING BY NEURAL NETWORKS

The effect of different factors on the burden distribution was examined by selecting a set independent variables and using these as inputs to neural networks that were trained to predict the layer thickness, Δz_t, where t is an index denoting the discrete time: The time between the dumps is on an average 4 minutes. In this study, networks of multi-layer perceptron type were used, implemented in a tool for neural network modeling (Saxén and Saxén 1994).

NETWORK TRAINING AND VALIDATION

In the analysis of feedforward networks, the input variables considered were the stock level and the burden descent rate prior to the dump (z_t and w_t, respectively), the movable armor position (x_{ma}: 0...600 mm, cf. Figure 1), the burden material type (M_1: 1 for coke and 2 for pellets) and order (M_2: 1 for the first dump and 2 for the second dump). However, since both pellet dumps entered with x_{ma} = 0 mm, and no changes in the armor settings for the coke dumps were made during the period studied, the input information can be compressed in that M_1 and M_2 together contain information about x_{ma}. As an alternative these three input variables were replaced by a counter, N, indicating the dump number in the sequence (N = 1...4 for P^1...C^2).

A large number of different combinations of input variables, also including lagged values of the above mentioned variables, and network sizes (i.e., number of hidden nodes) were tested. Because of a limited data set a cross-validation procedure was applied to find a suitable network complexity: An over-parameterized network (with too many hidden nodes) is likely to perform well on the training set at the expense of a poor prediction quality on novel observations. The available observations were divided into a training and a test set in different ways (e.g., first 60 used for training and remaining 28 for testing, first 28 for testing and remaining 60 for training, etc.). Using these results, the most promising networks among a set of potential candidates were selected. Their training and test errors, averaged over the different sets of data, have been reported in Table 2.

A simple network that exhibited promising results is a one with two hidden sigmoid nodes where the stock levels prior to the present and previous dumps, as well as the dump number are used as inputs (denoted by z_t , z_{t-1} and N). This network (reported as the first one in Table 2) showed an average error of about 8 cm. Since the stockrod signals in themselves are quite inaccurate, the approximation provided by the network, as illustrated in Figure 3, can be considered good.

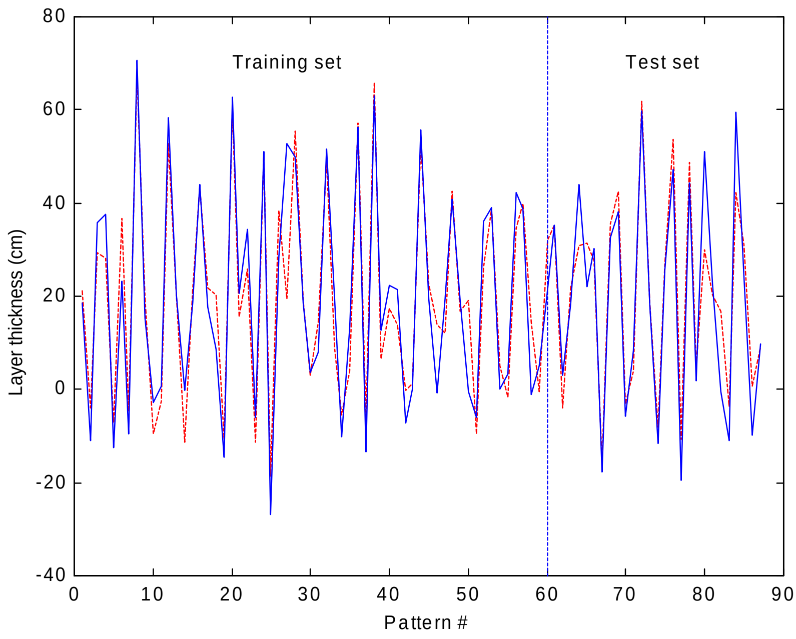

Figure 3: Measured layer thickness (———) and approximation (····) by the first network reported in Table 2.

An alternative, but slightly more complex model with input N replaced by M_1 and M_2, using three hidden nodes, can also be chosen (second network of Table 2). The input information content being essentially the same, the network can be expected to exhibit similar prediction accuracy as the previous model. This is in fact noted in the table. However, the higher model complexity yields a smaller training error. For the purpose of comparison, the results of a third potential model have been reported on the last row the table. This network exhibits inferior predictions because of the loss of essential input information contained in z_{t-1}, which is in line with both practical and theoretical findings that indicate that mainly the preceding burden surface level and shape play an important role for the burden distribution. Finally, it is interesting to note that models with previous layer thicknesses as inputs instead of previous stockline levels resulted in worse predictions. This can be ascribed to the obvious inaccuracy of the procedure for estimating the layer thickness, which results in a considerable noise term in Δz (cf. Figure 3).

2: Average errors for some feedforward networks predicting the burden layer thickness.

Network	Inputs	Training error ε / cm	Test set error ε / cm
(3,2,1)	z_t , z_{t-1}, N	8.2	9.4
(4,3,1)	z_t , z_{t-1}, M_1, M_2	7.6	9.4
(3,2,1)	z_t , w_t, N	8.3	10.1

ANALYSIS OF THE RESULTS

The general features of the resulting models were studied by analyzing numerically the way in which changes in the input signals affected the predicted layer thickness. For the purpose of brevity, only one of the models, the (3,2,1) network reported as the first one in Table 2, will be used to illustrate the models. As indicated in Figure 4, where the stock level and the dump number have been varied (keeping z_{t-1} constant on its average value of 2.95 m) the qualitative effect of the stock level is similar for all the dumps. However, the predicted thicknesses are of different magnitude. A reason for the successful performance of networks with the dump number, N, instead of M_1 and M_2, as an input now becomes clear: By chance, the average thicknesses of the four dumps (Table 1) vary monotonically with the counter N. Another notable observation in the figure is that the burden layer thickness increases with the vertical level of the stock. (Observe that z is defined as the distance between an upper reference level and the burden surface, so a low z corresponds to a high stock level.) A plausible explanation for this is that at a higher z the burden is more susceptible to bump towards the center of the furnace, after hitting either the wall (for pellet dumps) or the movable armors (for coke dumps). Finally, the model predicts a considerable change in layer thickness for $z_t \in$ [3.0 m, 3.1 m]. This, together with the decreasing trend discussed above, can be ascribed to an increased kinetic energy of the dumps, which makes the (possibly partially fluidized) stock column collapse or, for the pellet dumps, pushes the coke crest towards the furnace center (cf. Figure 2). The fact that the layer thickness estimates are close to zero on the right side of the “bump” in the figure also supports this explanation.

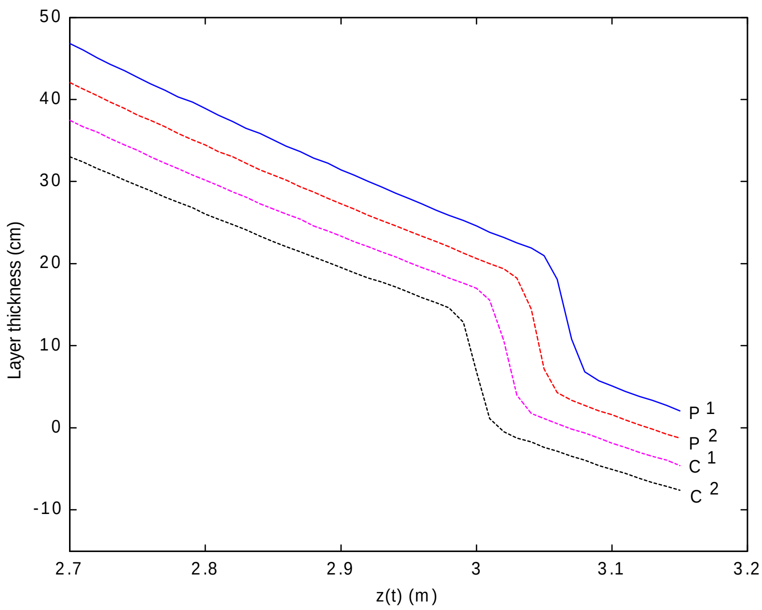

Figure 4: Relation between stock level (z) and burden layer thickness (Δz) predicted by a (3,2,1) network.

Figure 5 shows the relation between the two previous level signals, z_t and z_{t-1}, and the layer thickness, Δz_t, for the first pellet dump, P^1. The general characteristics are similar to those observed in Figure 4, the uppermost curve of which, in fact, is a cross-section of the present figure at z_{t-1} = 2.95 m. The largest Δz_t:s are obtained for cases with high stock level (low z_t) prior to the present dump and low level (high z_{t-1}) before the previous dump. This is explained by the altering (thin, thick, thin,...) layer thicknesses at the wall, which are characteristic for the charging program in question. For cases where the value of z_{t-1} was high, the abrupt change in the layer thickness disappears, and the model predicts a practically linear dependence between Δz_t and z_t.

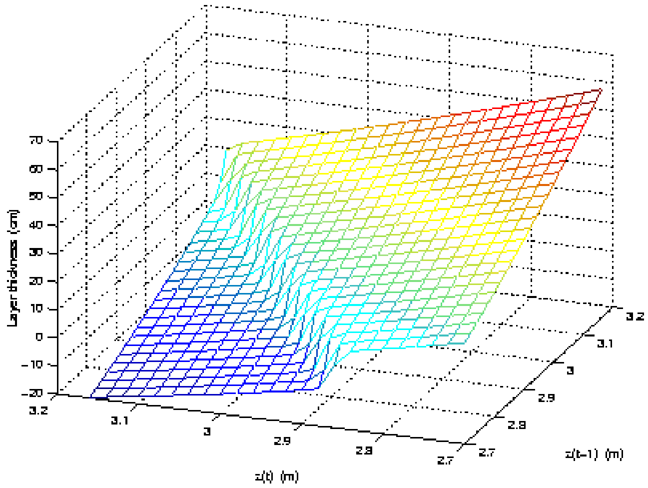

Figure 5: Relation between stock levels (z_t and z_{t-1}) and layer thickness (Δz_t) of the first pellet dump, P^1, predicted by a (3,2,1) network.

DYNAMIC MODELING

Finally an attempt was made to analyze the dynamics of the system by the use of recurrent networks. Limited tests of different architectures indicated that already a (fully) recurrent two-node network gave interesting results. This network used the present stock level (z_t) as its only input value. In spite of the fact that the network has to reconstruct both the effect of the sequence (N) and the previous dump height (z_{t-1}) it still performs quite well on the task, showing an average test error of about 11 cm.

In an attempt to illustrate the model, the average values of the stock level prior to the different dumps of the sequence were calculated on the available data. The resulting averages, $\bar{z}(\mathrm{P}^1) = 2.86\,\mathrm{m}$, $\bar{z}(\mathrm{P}^2) = 2.92\,\mathrm{m}$, $\bar{z}(\mathrm{C}^1) = 2.95\,\mathrm{m}$ and $\bar{z}(\mathrm{C}^2) = 3.03\,\mathrm{m}$ were next used as "artificial" input data to the trained recurrent network. The upper panel of Figure 6 illustrates the evolution of the signal, while the lower panel shows the layer thicknesses predicted by the network. The thickness of the first pellet layer is about 40 cm, while the remaining layers show thicknesses of about 10 cm under the rods. This constitutes a reference case for the analysis that follows below.

A test of the effect of a sudden change in stock level was carried out by perturbing the value of the stock level before the different dumps by ±30 cm. In Figure 7, a decrease in stock level (i.e., and increase in z) was introduced prior to each dump, and the effect was studied for some further dumps until the system returned to its periodic state. The figure illustrates the behavior when the stock level was lowered before the first and second pellet dumps (upper two panels) and first and second coke dumps (lower two panels). The position where the change was introduced has been indicated by an arrow and the solid lines denote the reference case while the perturbed case is depicted by dotted lines. The increased falling distance of the burden is seen to reduce the thickness of the dump that follows by 30...35 cm, while the thickness of the next dump instead increases by 30...40 cm. However, the system is damped so the offsets shown by the third and later dumps are only minor. The figure also indicates that the responses are quite independent of the position of the perturbation in the charging sequence.

Figure 8 shows in a similar way the effect of an increase in the stock level (i.e., a decrease in z). Here, the observed behavior is practically the opposite of the one reported in Figure 7; an increased stock level is seen to affect the layer thicknesses of the next two dumps, after which the system returns to its quasi steady state.

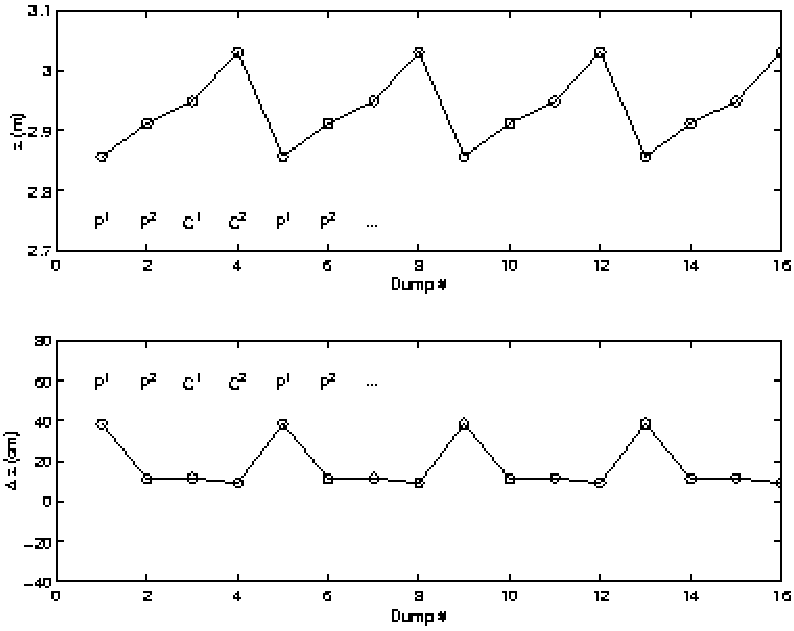

Figure 6: Vertical distance to the stock level, z_t, for the reference case and corresponding burden layer thicknesses predicted by a recurrent neural network. The only input to the model is the value of the stock level.

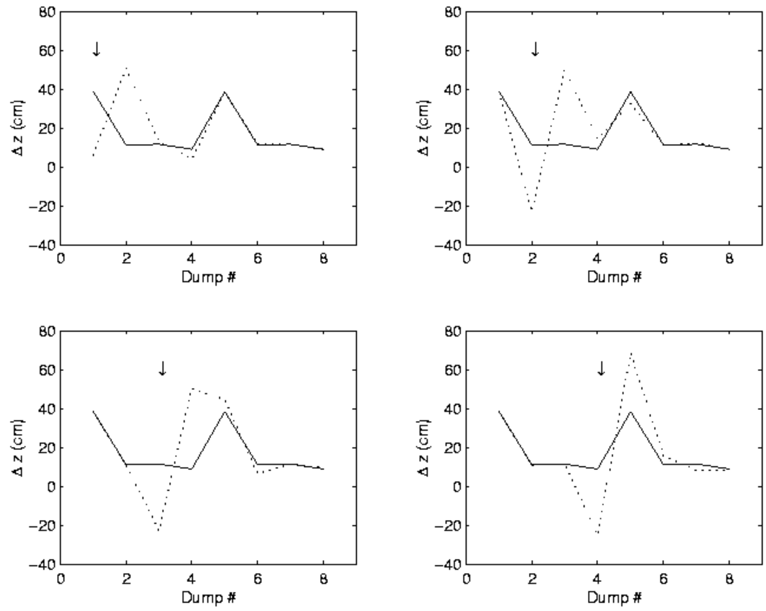

Figure 7: Burden layer thickness predicted by a recurrent network after an occasional lowering, indicated by downward arrows, of the stock level.

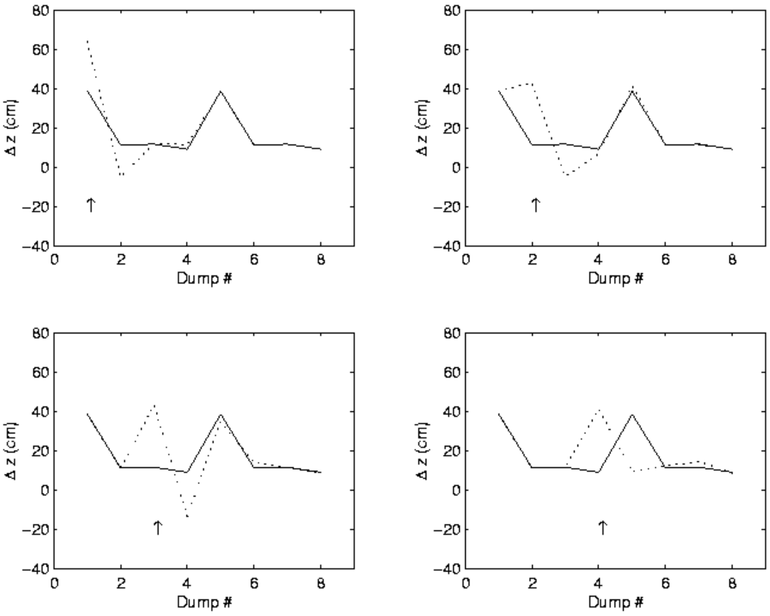

Figure 8: Burden layer thickness predicted by a recurrent network after an occasional elevation, indicated by upward arrows, of the stock level.

CONCLUSIONS

Neural-network models for burden distribution estimation on the basis of stockrod measurements in the blast furnace have been described. In the furnace studied, the effect of the "recent history" of the stock level on the burden distribution was observed to be considerable. Using two previous values of the stock level, it was possible to predict the local thickness of the burden layer relatively accurately using feedforward neural networks. An attempt to model the dynamics of the charging sequence using recurrent neural networks was also reported. The results of the models will be used to throw light on the complex behavior of the burden when charged into the blast furnace, and will be applied to improve the control of the burden distribution in the practical operation.

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