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Metallurgical limestone shaft kilning neural network model development

Introduction

Nowadays metallurgical limestone, used as a fluxing agent in iron manufacturing, kilning process monitoring is based on traditional PID control regulation systems. Such monitoring systems can be valid in limited conditions only, as any introduced by the system insignificant alternation implicates all the regulation characteristics reconfiguration.

In consequence of unregulated alternations multiplicity, metallurgical limestone kilning process is specified by, an importance of adaptive to varied technological conditions new monitoring system development has become evident. The development procedure supposes two research stages: a shaft kiln model development (identification) and control algorithm design in accordance with the obtained model [1]. It should be noted that control quality will significantly depend on the shaft kiln model achieved at the identification stage.

The following work is aimed at metallurgical limestone kilning process neural network model elaboration. Neural network methods use will allow to update the model parameters according to variable conditions and thus to improve technological process monitoring quality.

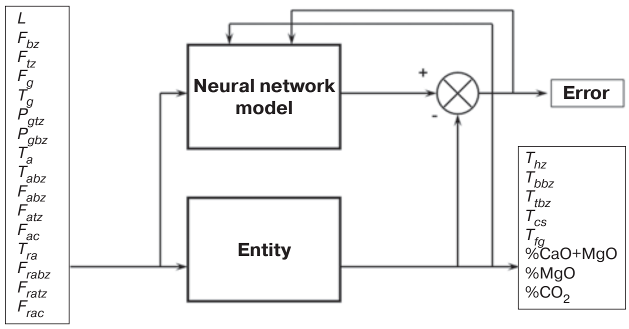
The matter of study characteristics and neural network modeling task statement

The process of metallurgical limestone kilning takes place in shaft kilns directly. Shaft kilns are the ones of continuous-motion. They correspond to a high freeboard equipped with special devices for the materials charging and outloading; cooling fans as well as outgoing gas exhaust blowers and fuel burner. When active, a shaft kiln is fully charged with lump material going down by gravity, being successively heated, and torrefied and cooled. After the finished stock outloading through a discharging device in a shaft bottom, the rest material column falls down and a new portion of raw material is added to a blank space on top. Counterflow principle is kept inside a shaft, therefore in zones of heating and torrefying raw material moves towards combustion-product gas, whereas towards air current in a cooling area.

Heated up whilst raw material cooling air current reaches burning zone of kiln and takes part either in a fuel combustion process or intermingles the fire gases in case a fuel is burnt in special combusters outside a kiln. While carrying-gut of the described process analysis [2] input and output parameters of the developed model have been estimated; 16 input and 8 output ones all in all.

The following parameters have been chosen as the input data: ore level inside the kiln (L), gas rate in the bottom zone (F_{bz}), gas rate in the top zone (F_{tz}), gas rate for cooling (F_g), gas temperature (T_g), the bottom zone gaseous pressure (P_{gbz}), the top zone gaseous pressure (P_{gtz}), an induced air temperature (T_a), the bottom zone induced air temperature (T_{abz}), the bottom zone air-flow rate (F_{abz}), the top zone air-flow rate (F_{atz}), air-flow rate for cooling (F_{ac}), recirculated air temperature (T_{ra}), the top zone recirculated air-flow rate (F_{ratz}), the bottom zone recirculated air-flow rate (F_{rabz}), recirculated air-flow rate for cooling (F_{rac}). As the output data the parameters listed below have been chosen: temperature in the heating zone (T_{hz}), temperature in the bottom burning zone of kiln (T_{bbz}), temperature in the top burning zone (T_{tbz}), temperature in the cooling section (T_{cs}), flue gases temperature (T_{fg}), CaO+MgO content (%CaO+MgO), MgO content (%MgO), CO_2 content (%CO_2).

Metallurgical limestone kilning process modeling scheme is represented on figure. The main task of the neural network modeling is estimation of output parameters with provision for current data-in.



Metallurgical limestone kilning process modeling scheme

Theoretical framework of the process neural network modeling development

There is a sequence of four procedures [3] which is involved in the process neural network modeling development. This sequence is as follows: data reduction, choice of network structure, parameter optimization and model verification.

The objective behind the data reduction procedure has been to obtain the most relevant information and to organize data in the way providing good results at the neural network modeling development.

The following steps can be distinguished in the data reduction procedure. First comes scaling, followed by data cleaning and further deletion of the superfluous data and signal emission. Unfortunately no precise rules of some method application are derived for the process under consideration. That's why it is worth testing the efficiency of the method application at this stage. It must be admitted that the neural network development must be preceded by this efficiency estimation. To take an example, Lipshchits' constant has been chosen as a criterion in one paper [4] and the coefficient of the stationary state as well as data consistency has been offered as a criterion in the other one [5].

As a result, the set has been obtained assuming the procedure of the data reduction. It represents the process considered in its full working range and gives the optimum criteria of data reduction efficiency.

$$Z_N = \{[u(t), y(t)], t = \overline{1, N}\} \qquad (1)$$

u(t), y(t) — system inputs and outputs respectively, N — the number of discrete samples.

The stage of the network structure choice provides the following problems solution. They are the choice of the both input vector (a regressor) of the neural network modeling and the internal structure of the neural network. The first problem turns out to be solved easily enough. The problem of the regressor choice can be approached from the priori knowledge of the system and it depends on the tasks completed at the simulation process. The contrary is the case of the internal structure determination that appears to be much more complex and ambiguous.

The capacity of restriction of the maximum quantity of latent layers containing neurons results from Kolmogorov's theory [6]. If the continuous function transforming N-dimensional set of the input data x in the M-dimensional output vector d is considered to be a limit it is possible to prove, that approximation of such type is certain to be made using the network with one latent layer. If N is the number of the input neurons, the latent layer having (2N 1) neurons will be enough for this function realization.

The stage of network parameter optimization concerns the network weight coefficient setting as a result of the testing procedure based on a number of examples. Testing appears to be representation of the set of experimental data to the set of neural network modeling parameters. The back propagation of error is known to be one of the most popular techniques.

The traditional main question behind the model verification procedure has been "To what extent is the optimized model valid?» At present the most useful techniques of the given stage carrying out are the following: model estimation from the perspective of misfit (research of correlation functions of various combinations of misfits and data) as well as simulating modeling (k steps forward preceding) and an estimation of an average generalization error.

So far there are no precise rules of technique application at each of those stages. Therefore the process neural network modeling development can be approached by various method combinations followed by making a choice of the most effective ones.

The neural network modeling of the metallurgical limestone roasting in shaft kilns

The data of the shaft kiln operation monitoring have been regarded as initial ones. Training and testing samples have been chosen with reference to these data.

The data reduction procedure results in the set of data (Lipshchits' constant is 136, stationary state coefficient is 0,81):

$$Z_N = \{[u(t), y(t)], t = \overline{1,1648}\},$$

$$u(t) = [L, F_{bz}, F_{tz}, F_g, T_g, P_{gbz}, P_{gtz}, T_a, T_{abz}, F_{abz}, F_{atz}, F_{ac}, T_{ra}, F_{ratz}, F_{rabz}, F_{rac}]^T$$

$$y(t) = [T_{hz}, T_{bbz}, T_{tbz}, T_{cs}, \%CaO{+}MgO, \%MgO, \%CO_2]^T$$

The neural network having three latent layers has been chosen to solve the problem required. There are twelve neurons in the first latent layer, while six neurons in the second one and eight neurons in the third layer. (Kolmogorov's theory [8] has been taken into consideration while making this topology choice). The hyperbolic tangent has been used as the activation function in the internal layers. Besides, the linear functions of activation have been used as the activation function in the input and output layers. The algorithm of back propagation of error has been chosen for neural network testing.

The verification of the neural network development has been carried out by correlation functions research. The ratio of the correlation coefficients of the neural network in the training samples and testing ones is given in the table as an example.

The analysis of correlation coefficients has revealed the validity of the neural network testing (the least correlation coefficient value in the training sample is 0.9, while it is 0.69 in the testing sample).

Conclusion

It is concluded that the model developed within this research is capable enough of describing the process of metallurgical limestone kilning. The neural network using has allowed obtaining of the model that is simple but capable to function in changing process conditions.

Having extra training capacities and abilities of getting quick results this neural network modeling may be used at the development of the neural network system of metallurgical limestone kilning monitoring.

The results of neural network activity

Count of network yields	1	2	3	4	5	6	7	8
Correlation coefficients in the training samples	0.91	0.94	0.96	0.97	0.95	0.90	0.95	0.93
Correlation coefficients in the testing samples	0.71	0.74	0.70	0.94	0.69	0.76	0.84	0.87

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Small-volume blast-furnaces — the future of blast-furnace practice?

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New structural scheme of ferrous metallurgy

In the past century, the ferrous metallurgy developed towards constructing large volume aggregates. Outdated and small blast-furnaces were replaced by large volume blast-furnaces. The traditional pig-iron making technology remains the fundamental technique for various grades steel smelting and metal products manufacture. At the present time about 70 % of the world steel production is based on primary metal production, obtained by traditional technology. At least 95 % of the world pig-iron is obtained in blast-furnaces. That fact proves that blast-furnaces play a crucial role in ferrous metallurgy.

Under these conditions it is necessary to overestimate the use perspectiveness of large volume blast-furnaces.

The USSR was the world leader in large-volume blast-furnace manufacture. In the latter half of the past century blast furnaces with the working volume of 1386, 1513, 1719, 2002, 2300, 2700, 3200, 5014, 5580 m3 were manufactured. These aggregates increased the productivity and therefore proved the economic benefit of the blast-furnace working-volume increase. The in-depth analysis was carried out piecewise so that the existing political system and the industrial development course (at that time) would not be doubted.

Meanwhile, there are some disamenities of blast-furnace volume increase. These are:

1. Large-volume blast furnaces operate only when high quality burden material is used, therefore when operating large-volume blast furnaces the burden material preparation costs increase.

2. Considering the blast-furnace height limitations, the volume increase was generally performed by aggregate lateral dimensions increase. Under these conditions the basic blast-furnaces processes development was hindered along the furnace cross-section which eventually led to cast iron composition when tapped from different tap holes.

3. The lateral dimension increase led to oxidation zone decrease relative to furnace hearth radius. That led to coke packing performance difficulties. In 1980’s engineers once again started to use the term “dead man”.

4. Some difficulties occurred with facility management on integrated iron-and-steel works. Accidental and emergency shut-downs of large-volume blast furnaces could easily shut down the utilities and pig iron consumers since large-volume blast furnaces excluded the possibility of a maneuver available when using a small-volume blast furnaces. Along with that, large burden masses that were processed by blast-furnaces caused railway service functioning difficulties.

5. The environmental restrictions led to the end of large-volume blast-furnaces domination era.

It is widely known, that the major drawback of metallurgical branch (in terms of environmental impact) is its high concentration ratio. Comparing to other industrial branches, metallurgical branch is defined by high concentration per area unit of a metallurgical region. Based on environmental conditions and population health status, it is advisable to utilize 5 blast furnaces with the working-volume of 1000 m^3 spaced far apart than one 5000 m^3 furnace.

6. The world raw material market formation changes the views on metallurgical branch. For Third World Countries along with separate regions of large countries it is not necessary to produce large quantities of primary metal therefore it is not necessary to construct large volume aggregates.

7. In most cases, small volume blast furnaces have better working data (by energy resources consumption) and are more maneuverable in terms of manufactured products range. Finally the recycling process of technogenic and sanitary waste takes place primarily in small volume metallurgical aggregates.