Use of an Artificial Neural Network in determination of iron ore pellet bed permeability

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Abstract

The thermal processing of iron ore pellets in pelletizing plants is a decisive stage regarding final product quality and knowledge of its characteristics has a fundamental importance in its process optimization. This study evaluated the variable sensitivity involved in pellet bed formations and their permeability using the artificial neural networks method. The model stated that standard diameter deviation, sphericity and pellet bed height mostly affect bed permeability. The computational model was able to predict pellet bed backpressure by means of pellet geometrical features, thus allowing improving green pellet generation, in order to ensure fuel and energy consumption reduction, final quality improvement and better productivity.

Keywords: pellet, artificial neural networks, iron ore.

1. Introduction

The agglomeration of iron ore appeared with the necessity to optimize the production process of raw materials connected to the steel industry, using the fines portion generated during the mining process and subsequent ore processing, thus transforming it into an iron-rich material, which until then would be process waste, thus becoming a marketable product with a higher value (Thella and Venugopal, 2011). The iron ore pellet is a cluster of approximately sphere shaped particles with some remarkable properties as: particle size distribution between 9 mm and 15 mm, high iron content (around 66%), uniform mineralogical properties, and high mechanical strength, along with a uniform, low tendency to abrasion and good behavior during transport (Meyer, 1980). The iron ore pellet production process comprises several steps, such as the separation of raw material, grinding, classification according to particle size, agglomeration, drying processes, burning and cooling.

For traveling grate kilns, herein presented, 90% of the heat transport in thermal processing is done by convection. Thus, the gas flow through the pellet bed is of fundamental importance (Meyer, 1980).

The gas flow is dependent on the strength and gas permeability of the bed, and highly influenced by the physical consistency of the pellets. The most adopted equation to solve gas flow through packed beds is Ergun's equation (Hinkley *et al*., 1994; Luckos and Bunt, 2011; Trahana *et al*., 2014; Koekemoer and Luckos, 2015; Erdin *et al*., 2015):

$$\frac{\Delta P}{L} = A\,\frac{(1-\varepsilon)^2}{\varepsilon^3}\frac{\mu U}{D_p^2} + B\,\frac{1-\varepsilon}{\varepsilon^3}\frac{\rho U^2}{D_p}$$

Where: ΔP - pressure drop of packed bed; L - height of packed bed; ε - void fraction; U - superficial bed velocity; μ - dynamic viscosity of the fluid; D_p - particle diameter; A and B – empirical coefficients.

The pressure variation is substantially high as there is a large variation in pellet diameters, the presence of fines, (Hollands and Sullivan, 1984) and according to Ergun's equation, varies linearly with the increase of bed height. The pressure drop is also responsible for the operation of the fans that drive the air heated by the various stages of the firing process.

Pellets with diameters distributed in a narrow band, with spherical shape and good mechanical strength, and low generation of fine particles, produce a bed in the drying step with high permeability, thus lowering production costs, improving productivity and increasing the quality of the final product (Matos, 2007).

It is therefore evident that the resistance encountered by the air flow through the pellet bed can be understood as a measurement of the quality factor of the raw pellets, providing an opportunity for energy savings in the overall process as well as a point which offers final product quality improvement.

The complexity of the equipment, the large amount of interrelated factors in the process and the difficulty of developing manufacturing condition experiments lead us to the mathematical modeling that has a broad application in metallurgy (Timofeeva *et al.*, 2013).

The method of artificial neural networks has shown great reliability and quick responses in several areas, proving to be a suitable choice when you want to get a general predictive analysis that includes a lot of variables (Dwarapudi *et al.*, 2007). Neural networks have the ability to capture nonlinear and highly complex relationships between inputs and outputs of the process. They are computationally efficient and do not require prior knowledge of the process to be modeled (Haykin, 2009).

2. Material and method

A sequence of 1000 industrial data collected from the pelletizing process have been used to create an artificial neural network (ANN) with the Multilayer Perceptron (MLP) architecture, feedforward type, with a seven neuron input layer composed of process variables. The data was processed with Multiple Back Propagation software (Lopes and Ribeiro, 2003). Table 1 shows the process average values, minimum, maximum and standard deviation.

The hardware used was a regular personal computer (Intel i3 chipset, 4GB RAM).

RNA	Variable	Mean	Min.	Max.	Std Dev.	Unit
	Inputs					
E 1.1	Raw pellets production	699.79	291.32	753.85	53.52	ton/h
E 1.2	Diameter mean size	11.87	4.14	12.71	0.705	mm
E 1.3	Diameter standart deviation	2.32	0.77	2.64	0.147	mm
E 1.4	Pellets between 10-16 mm	76.29	26.59	80.91	4.98	%
E 1.5	Pellets above 16 mm	3.74	0.88	11.85	1.13	%
E 1.6	Pellets below 10mm	16.36	5.36	31.69	2.5	%
E 1.7	Esphericity	79.34	28.36	80.26	4.62	%
	Output					
S 1.1	Bed Backpressure	-239.01	-282.64	-78.81	27.21	mBar

Table 1
Date set description.

The neural network is then followed by a hidden layer with 15 neurons defined by the Kolmogorov expression (Hetch-Nielsen, 1989):

$$N = 2n+1$$

Where: N-Number of neurons in the hidden layer; n-Number of inputs.

The output layer of a single neuron related to the back pressure of drying chamber, which leads us to the bed permeability.

We used the error backpropagation training algorithm, the learning function of gradient descent and the Round mean squared error (RMSE) as the performance function.

The transference functions were respectively hyperbolic tangent for the hidden layer and logistic for the output layer.

The sensitivity analysis was conducted to infer the relative importance of each variable. This contribution was measured by the RMSE degradation after the application of a 2%, 5% and 10% noise on each variable.

The neural network modeled for this application is summarized in Figure 1.

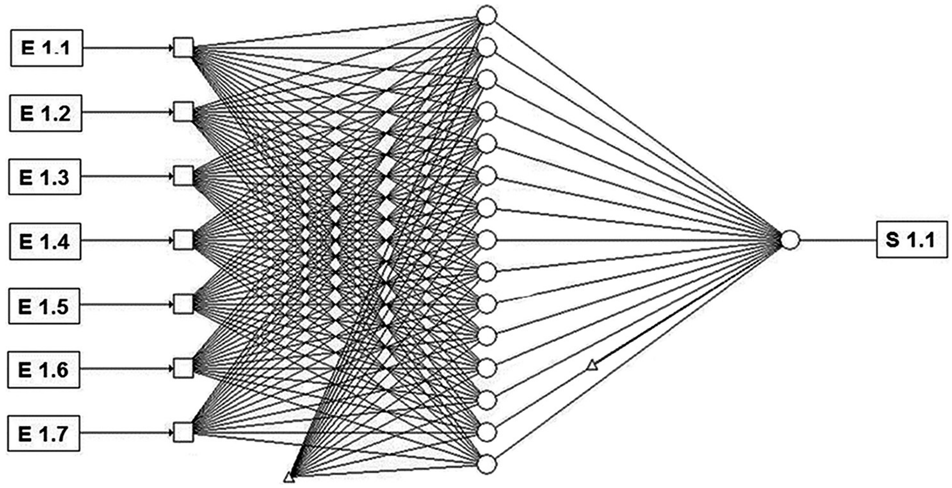

Figure 1
Artificial Neural Network, 7-15-1.

3. Results and discussion

After the artificial neural network validation with industrial data, there was a convergence as shown in Table 2 with the mathematical model.

Table 2
correlation coefficients $R^{2.}$

	Training	Test
R^2	0.870159	0.865757
RMSE	0.036486	0.0329154

Regression between the target and the Artificial Neural Network predicted outputs is plotted in Figure 2, pointing to a good convergence considering a factory scale experiment.

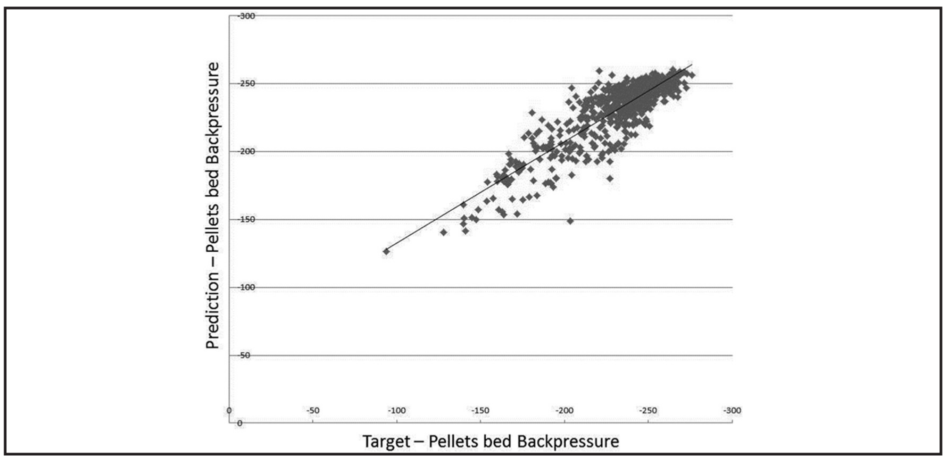

Figure 2
Regression for testing data.

The sensitivity analyses of the input variables were made exhibiting indexes in Figure 3. It was observed that the variables of highest influence on the drying chamber pressure and consequently in pellet bed permeability was the diameter standard deviation, followed by pellet production and pellet sphericity.

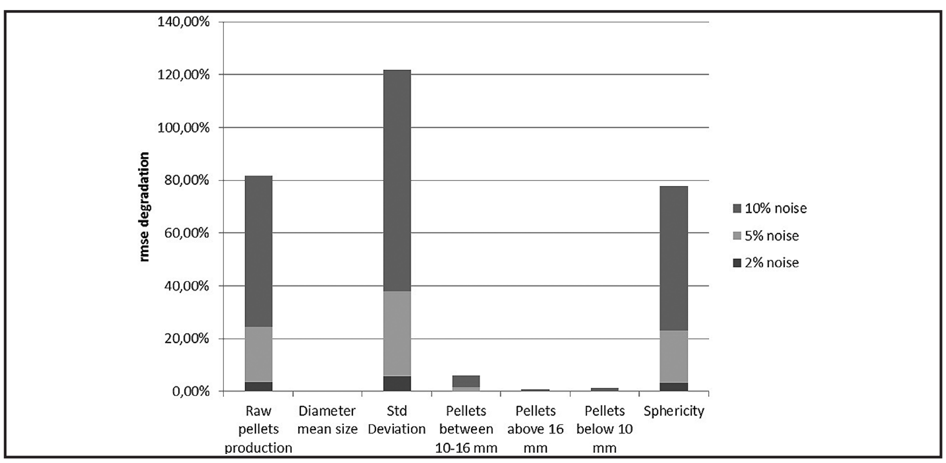

Figure 3
Variable sensitivity.

Particle size distribution, which has a direct relationship with the standard deviation of the pellet diameter, has a main role in bed permeability, since smaller pellets occupy interstitial sites among bigger pellets, decreasing bed voiding (Koekemoer and Luckos, 2015). In his way, a wider diameter distribution and/or the presence of fines block the air flow through the bed (Yazdanpanah *et al.*, 2010), causing a drying deficiency on the opposite side. A better control of diameter distribution can only be performed during the pelletizing step, showing the importance of control parameters during this phase.

According to the presented Ergun equation, bed height has a direct proportion on bed permeability, but controlling this factor in order to reduce back pressure will result in productivity reduction. In this case, despite a great influence in the final result, bed height should not be the parameter to be controlled.

Sphericity also affects permeability, since the pellet shape is decisive for bed formation and pellet packaging. The particle size and shape influence on bed formation is the object in several studies (Al-Raoush and Alsaleh, 2007; Li and Ma, 2011; Allen *et al.*, 2013; Kruggel-Emden and Vollmari, 2016). It is possible to infer that low compression strength green pellets tend to deform easily in contact with other pellets and/or in contact with a traveling grate kiln, forming a single block that chokes the air flow through the bed. Studies performed to check shape influence on bed formations have so far considered rigid particles. Such characteristic may be caused by a poor control of raw material and excess of water in the pulp.

Permeability is also connected with other aspects, such as, particle roughness, tank to particle ratio, and gas flow speed (Trahana *et al.*, 2014).

Mean size and pellet diameter ranging above 16mm and below 10mm show minor influence on the final result, proving that diameter distribution and particle shape modulations have a higher influence on bed permeability. Pellets distributed in a narrow diameter with spherical shape lead to a better bed formation.

The prediction model for backpressure in the drying chamber has its results plotted in Figure 4, presenting a good correlation considering the factory conditions where the data where obtained.

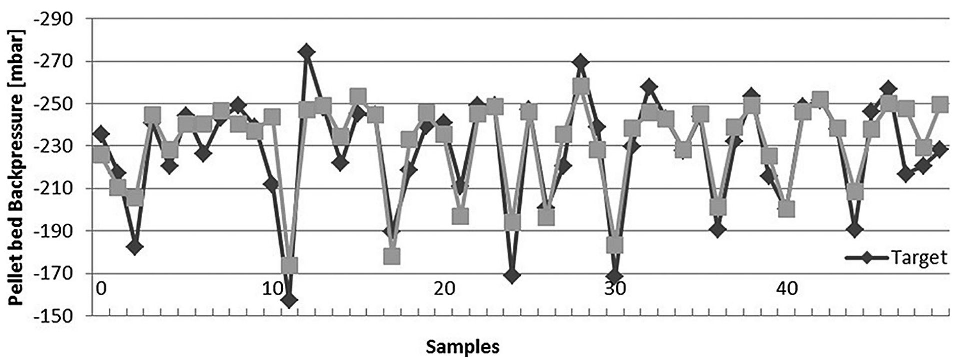

Figure 4
Pressure prediction, Target / Output.

4. Conclusions

The model pointed out variables that significantly affect the bed permeability in the drying stage of iron ore pellet production. Diameter standard deviation, pellet production and sphericity were identified as the main effective input variables that affect bed permeability during the drying stage and consequently, final product quality.

The artificial neural network method showed a suitable option in mathematical modeling of a complex process involving a lot of variables under a real production site environment. The computational model was able to predict optimizations in the preparation, production and quality control of pellet production, despite all the interrelated factors of a production plant.

A higher diameter standard deviation and the presence of fines negatively affect the back pressure inside a travelling grate kiln (Luckos and Bunt, 2011), since smaller particles occupy interstitial sites among bigger pellets.

Sphericity has an important role in bed formation, but its aspects should be better understood, since iron ore green pellets are subject to plastic deformation during their generation process.

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