

Adjustment of the Minimum Spouting Velocity in a Conical Spouted Bed from Artificial Neural Networks

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The minimum spouting velocity is one of the fundamental parameters in the application of the conical spouted bed pyrolysis, gasification and combustion, therefore it is necessary the adequate calculation and the use of a correlation with good adjustment, for this an artificial neural network has been applied, in order to improve the correlations of the literature. Six variables that involve different geometrical parameters and operation of the bed have been used. With the purpose to compare the results of the model with the experimental data and those predicted by the empirical equations, the quadratic error has been used. Although there is a complex relationship between the input variables and the output variables, and despite numerous of available data, the training and test steps of the network show a good adjustment with respect to the experimental values. This shows that an artificial neural network is an agile method to predict the minimum velocity of the bed at the pump, especially when the relationship between geometric parameters, operating parameters and minimum speed is complex and difficult to define.

1. Introduction

The spouted bed reactor can achieve an intensive gas-solid contact, an important factor for the valorisation of biomass from thermochemical processes. Likewise, it operates stably in a wide range of gas flow due to the properties of mass and heat transfer. In this, you can process materials of different types of particle diameter and geometry. The most recent applications of the spouted bed reactor are many and varied, standing out in the industrial physical processes: drying of seeds, pharmaceutical powders and biomaterials (Konopka et al., 2008), granulated (Borini et al., 2009), materials coating (Rocha et al., 1995), and solid mixture (Hao et al., 2008). Applications in industrial chemical processes include gasification (Spiegel et al., 2010), combustion (Rasul, 2001) and pyrolysis (Olazar et al., 2001).

Different modifications of spouted bed reactor in the original have been proposed in the literature with the aim of improving its performance. These are mainly the geometry of the contactor and the gas input to the bed, this in order to increase the handling capacity of the coarse particles, decrease the pressure drop, improve the cyclic movement of the particles and keep the operation stable in a wide range of gas flow velocities (Olazar et al., 1992). In the same way, the operation can be carried out in a spouted bed reactor with very short gas residence times (as low as milliseconds) (Olazar et al., 1992).

According to Altzibar et al. (2013a), a crucial parameter that limits the scaling of the spouted bed is the relationship between the inlet diameter and the particle diameter, likewise, they argue that the inlet diameter should not be 20 or 30 times larger than the average particles diameter in order to reach the condition of spouted bed. The usual solution for this drawback is the use of a suction tube. Different configurations of the aspiration tube have been developed: solid, porous and open (Altzibar et al., 2013b) and are especially suitable for vigorous contact.

The minimum spouting velocity is an essential variable in the operation of a conical spouted bed and is one of the parameters required for design and scaling. Saldarriaga et al. (2016) calculated the minimum spouting velocity for different types of biomasses and configurations of both the contactor and internal devices, generating new correlations for irregular particles (biomass) because those provided in the literature did not have

considered this type of materials. The adjustment of these correlations was made from statistical analysis and development of algorithms in the Scilab tool.

Currently, other types of methodologies are being implemented for the calculation and adjustment of these equations, as in the case of Hosseini et al. (2017) that applied the networks to the calculation of the minimum spouting velocity, with results that were able to predict a model consistent with experimental values, with an error of 11.87 %.

Artificial neural networks can be an effective alternative as far as they can represent highly complex and non-linear processes. In addition, they are quite flexible and robust against input noise and, once developed and their coefficients determined, can provide a rapid response for a new input. The works available in the literature compare neural networks with mechanistic/empirical models (Silva et al., 2015). In this study, an artificial neural network was developed in order to predict the minimum spouting velocity at the spouted bed, for a wide range of experimental data (300 points for adjustment and 38 points for tests).

2. Experimental

In this work five types of biomass have been used, all of them selected for being susceptible to energy recovery by combustion, because they have physicochemical properties compatible with a combustion system of particulate solid materials, because they are representative of a set of materials on the that the proposed technology can be applied and be complementary to guarantee a constant and non-seasonal supply of a future biomass combustion plant.

The types of biomass used include waste from the *pinus insignis* sawdust industry, food industry residues such as rice husk and olive bones, herbaceous species such as *rumex tianschanicus* and poseidonia as *poseidonia oceanica*, a very common residue in the cleaning of Mediterranean beaches.

The moisture content has been measured following the ISO-589 standard, using a halogen moisture analyzer (HR83, Mettler Toledo). The particle density has been measured by mercury porosimetry (Saldarriaga et al., 2014) and the average particle size (average reciprocal diameter) according to the following expression:

$$\overline{d_p} = \frac{1}{\sum \frac{X_i}{d_{p_i}}} \quad (1)$$

Table 1: Physical properties of the different biomasses used in this study.

Biomass	d_p , mm	ρ_s , kg m ⁻³	ρ_b , kg m ⁻³	ϕ	Geldart
<i>Pinus insignis</i>	0,76	496	189	0,52	D
Rice husk	1,48	975	127	0,24	D
Olive	2,33	1220	650	0,73	D
<i>Rumex tianschanicus</i>	0,93	406	121	0,40	B
Poseidonia	1,02	702	119	0,20	B

In the physical properties, the irregularity of all the biomasses studied is evidenced showing that only the olive bone has a more spherical shape than the others, which influences its possible good fluid dynamic behavior as shown by different studies (Altzibar et al., 2013b) made with particles of spherical type, while the poseidonia, has a greater irregularity, presenting lower value of sphericity and that can influence its fluid dynamics remarkably. Likewise, it is observed that three biomasses belong to group D of Geldart and two to group B (Table 1) (Geldart, 1973).

The pilot plant consists of a blower that supplies a maximum airflow of 300 Nm³ h⁻¹ at a pressure of 1500 mm.c.a. The flow measurement is made with two mass flow meters controlled by computer and used in the intervals of 2.5-50 Nm³ h⁻¹ and 50-250 Nm³ h⁻¹ respectively. The air flow is set by opening or closing a butterfly valve actuated by an electric motor that sends the excess air to the outside. When the required flow is less than 50 Nm³ h⁻¹, the air passes through the first meter being regulated in the second by means of another solenoid valve. The precision of this control system means that the error in the measurement is always lower than 0.5 %. Four conical contactors of polymethyl methacrylate have been used, whose geometric characteristics are summarized in the scheme of Figure 2. The dimensions are total height (conical section more cylindrical), 1.16 m; diameter of the cylindrical zone, D_c , 36 cm; diameter of the base, D_i , 0.068 m. The unit allows to operate with different cone angles, γ , having evaluated the contactors of 28 °, 33 °, 36 ° and 45 °, corresponding to a height of the conic section, H_c , 0.60, 0.51, 0, 47 and 0.38 m respectively. The values of the inlet diameter of the gas, D_o , tested are 0.03, 0.04, 0.05, 0.06 m. The stagnant bed height values, H_o , are 0.05, 0.10, 0.15, 0.20 and 0.30.

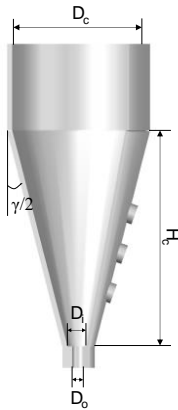


Figure 2. Geometric factors of the contactors used in the hydrodynamics study

Artificial neural networks are processing structures that imitate the human brain, that is, they are made up of several processing units, called artificial neurons, that can correlate databases with each other. Figure 3 shows a typical structure of a three-layer neural network:

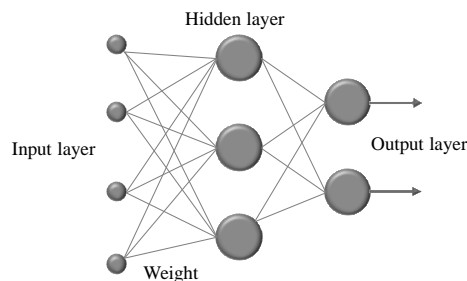


Figure 3. Layer of three neural networks

The first step in the design of a neural network is to select its basic structure, with the number of neurons and hidden layers between the input and output. A typical input/output relationship of a neural network is given by the following equation:

$$y = b_2 + LW \cdot \text{tansig}(b_1 + IW \cdot x) \quad (2)$$

where y is an output vector, x is an input vector, LW is the connection matrix of the corresponding weights of all the arcs from the output layer to the hidden layer, respectively, b_1 and b_2 are the bias vectors for the hidden and output layers, respectively.

In a neural network of compensation, the signal received by the intermediate layer (hidden) goes to the neurons of the output layer. In the hidden layer, in turn, each unit (y_j) adds its weighted inputs and applies the activation function to generate the output signal according to Equation 3.

$$y_j = f_{\text{act}} \left(\sum_{i=1} W_{ij} X_i + b_j \right) \quad (3)$$

where W_{ij} is the weight of the connection between the i -th input and the j -th neuron of the hidden layer and b_j is the weight of the bias of unit j . The activation function used in this work is the extreme tangential, given by Equation 4.

$$f_{\text{act}}(X) = \frac{1}{1 + e^{-x}} \quad (4)$$

The output of the neuron y_j is sent to all the units in the output layer. Each output neuron O_k adds the weighted input signal and applies the activation function according to Equation 5.

$$O_k = f_{\text{act}} \left(\sum_{j=1} V_{jk} Y_j + b_k \right) \quad (5)$$

The W_{ij} weights of each connection between neurons in adjacent layers are determined during the network learning process. The learning process uses non-linear optimization algorithms to update the weights and, once a network has been trained, can provide an answer with simple calculations, which is one of the advantages of using a neural network instead of fully differential models mechanistic. The learning step consists of iterations that often start with small random numbers as the values of the weights in the network. The inputs of the training

set are provided to the network and the resulting outputs are calculated. The error between the outputs of the network and the known values (objectives) is calculated and an optimization algorithm is executed to change the weights appropriately. The iterations are terminated when the value of the calculated error begins to increase with special care to avoid local minimums.

Like any data adaptation technique, the neural network is also evaluated in the ability to adjust training data and predict outside the training set. An appropriate neural network must show a good generalization for new data and computational efficiency, which means that the smaller the network, the fewer parameters and data are required and the shorter the identification time involved. In this work, a network of 7 neurons in the hidden layer (Figure 4) proved to be the most appropriate.

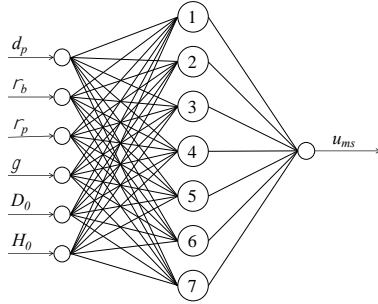


Figure 4. Multilayer neural network, a simple output layer (u_{ms}), with seven neurons in the hidden layer, and 6 inputs (d_p , ρ_p , ρ_b , γ , D_0 , H_0).

An artificial neural net of compensation type was designed with the help of the Neural Networks toolbox of Matlab 2013, with the Levenberg-Marquardt optimization algorithm to determine the weights and the subsequent propagation method for the training. The choice of a neural network with a single hidden layer, the most common in most applications in chemical processes (Aghbashlo et al., 2015), was to maintain the simplest possible input/output ratio given by Eq(2).

3. Results

In this work, an artificial neuronal network of seven neurons in the hidden layer was used in order to predict the minimum spouting velocity for different types of biomass with different types of sphericities in a conical spouted bed reactor. Similarly, there are six neurons in the input layer and a neuron in the output layer. The number of data points used was 349, in which different bed heights, contactor angles and five types of biomass were evaluated, as mentioned in the experimental section. For the training of the network, 311 data were taken and 38 data were used for the verification.

The number of neurons in the hidden layer was chosen by trial and error, starting with a neuron and adding more neurons until the performance of the network in the estimation of the output data (u_{ms}) was correct. The ultimate goal is to create a neural network with the smallest number of neurons. In the limit where the number of weights is equal to the number of data points, the regression coefficient (R^2) reaches the value of 1, but the neural network loses its ability to generalize, becoming too specific for the training set.

For the analysis of the data, a reasonable number of neurons has been found, which are around seven. According to Patel et al. (2007) the neural network cannot be over-trained due to an overfitting called overfitting. This process can cause an excess of equipment, or a local minimum can be achieved with excessive training. In the training process, as the number of iterations in the optimization step increases, the error in the predictions for the training set is decreasing due to an improved adaptation of the data to artificial neural networks. Accordingly, the following procedure was used to estimate a reasonable number of iterations: (i) the neural networks were trained using a given number of iterations of optimization; (ii) the model's ability to predict data outside of the training range was stopped and verified; (iii) in the case that the prediction was not satisfactory, the number of iterations was increased, and the prediction capacity was evaluated again. This cycle continued until the network forecast was satisfactory, which in turn provided the number of optimization iterations required. Based on equation (2) the weights and biases for the analysis were (Eq(6)):

$$IW = \begin{bmatrix} 6,5593 & -1,3419 & -4,3402 & -0,0544 & 9,9647 & -1,5974 \\ -13,8555 & -7,7386 & -6,3521 & 8,3734 & 4,1567 & 1,1103 \\ -14,5586 & -8,9439 & -8,8187 & -2,0427 & -11,3634 & -2,1752 \\ -0,3189 & 0,7244 & -0,7032 & -0,0926 & -0,2370 & -0,4143 \\ -4,1799 & -6,2517 & 9,6324 & 0,0326 & 2,1521 & -0,2634 \\ -5,3905 & 1,7093 & -3,4705 & 0,0395 & 0,2816 & 0,5730 \\ -4,5547 & 2,2591 & -3,4014 & -0,2339 & 1,8000 & 0,9086 \end{bmatrix} LW = \begin{bmatrix} -0,3075 \\ 0,0724 \\ 0,0642 \\ -1,9483 \\ -0,1589 \\ 0,4099 \\ 0,2935 \end{bmatrix} b_1 = \begin{bmatrix} -13,4106 \\ -4,7533 \\ -17,34 \\ 0,9637 \\ 0,2576 \\ -5,2778 \\ -2,4946 \end{bmatrix} \quad (6)$$

Figure 5a shows the verified data of the artificial neural network. The figure compares the predicted values of the minimum spouting velocity and also shows the best linear fit corresponding to the predicted results, with an R^2 of 0.942 (with an experimental range between 0.843 and 0.942), very similar to that found by Hosseini et al. (2017), analysis performed for particles of regular sphericity, confirming with this that the estimated networks are reasonably good in a wide range of operating conditions. Likewise, the good fit of the data is observed and coincides with the adjustments made by Saldarriaga et al. (2016), in which they compiled different correlations of the literature and adjusted the experimental data of different types of biomass with irregular sphericities to a new equation with a better fit.

In order to verify the artificial neural network, the predictions obtained from u_{ms} for the trained model with 311 data, this was compared with 38 data, which are shown in Figure 5b, in which the comparison of the values of the u_{ms} is observed predicted by the proposed neural network with the points of the experimental data. As it is observed, the data predicted by the network are consistent with the measured data (equality line). As shown in the figure, the linear adjustment is quite good and the same as Figure 6, which shows that the proposed network is quite good for a wide range of conditions and geometric parameters.

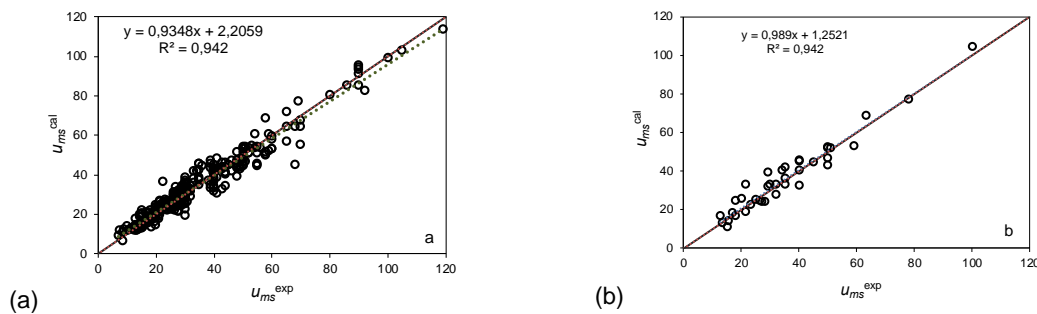


Figure 5. Comparison of the u_{ms} predicted by the neural network with the experimental data used, a. trained model and b. test model

As mentioned above, few correlations involving irregular particles have been reported in the literature and only one equation that takes into account only those particles (Saldarriaga et al., 2016), to calculate the minimum velocity of the spouted bed. In the present study, it was possible to verify the correct fit of the correlation made by Saldarriaga et al. (2016), which significantly improves the adjustment of irregular particles as is the case of biomasses that always have irregular geometries and which are also difficult treatment in fluidized bed systems and that must be treated in other types of systems such as the static or bubbling bed, where it has presented better results. With these results, it could be verified the good behavior of the conical spouted bed with respect to irregular particle systems, and those reported by other authors that recommend the use of this system for the thermal treatment (pyrolysis, gasification and combustion) of waste from biomass in order to value and generate energy from these (Altzibar et al., 2014).

4. Conclusions

An artificial neural network has been developed in order to estimate the minimum spouting velocity (u_{ms}) in a spouted bed system. According to this, six dimensionless modules involving the entrance diameter, the cone angle, the static bed height, the particle and bed density and, finally, the particle diameter, have all been taken as an input for the model. 349 experimental data were made to five types of biomasses (rumex, pine sawdust, olive bone, rice husk and poseidonia), which were divided into 311 and 38 data for training and validation of the neural network model, respectively, which means that the model is based on a large number of experimental data.

Likewise, this work shows that it is possible to use artificial neural networks (ANN) to estimate the minimum velocity of the bed at the pump. Similarly, although artificial neural networks and empirical models such as those applied by Saldarriaga et al. (2016) share the same parameters adjustment principles to match the experimental data observed, this study has shown that their adaptation characteristics are different. In the sense that RNAs achieved a reasonable performance by decreasing the base adjustment correlation for large databases with respect to empirical models.

Nomenclature

d_p Average particle diameter, m
 D_o Gas inlet diameter, m

Greek letters

γ Cone angle, rad
 ϕ Sphericity

D_b	Top diameter of the static bed, m	ϵ_o	Fractional void volume of static bed
D_c	Column diameter, m	ρ	Density of the gas, kg m^{-3}
D_i	Contactor base diameter, m	ρ_b	Bed density, kg m^{-3}
H_o	Static bed height, m	ρ_s	Particle density, kg m^{-3}
H_c	Height of the conical section, m		
Re_{msi}	Reynolds number for minimum spouting, referred to D_i , $\rho u_{ms} D_p \mu^{-1}$		
u_{ms}	Minimum spouting velocity measured at the inlet orifice D_o , m s^{-1}		

Acknowledgments

This work was carried out with the financial support of the Department of Civil and Environmental Engineering and FAPA of the Universidad de los Andes.

References

- Aghbashlo, M., Hosseinpour, S., Mujumdar, A.S., 2015. Application of artificial neural networks (ANNS) in drying technology: a comprehensive review, *Drying Technology*, 33, 1397–1462.
- Altzibar, H., Lopez, G., Bilbao, J., Olazar, M., 2014. Operating and peak pressure drops in conical spouted beds equipped with draft tubes of different configuration, *Ind. Eng. Chem. Res.*, 53, 415–427.
- Altzibar, H., Lopez, G., Bilbao, J., Olazar, M., 2013a. Minimum spouting velocity of conical spouted beds equipped with draft tubes of different configuration, *Ind. Eng. Chem. Res.*, 52, 2995–3006.
- Altzibar, H., Lopez, G., Bilbao, J., Olazar, M., 2013b. Effect of draft tube geometry on pressure drop in draft tube conical spouted beds, *Can. J. Chem. Eng.*, 91, 1865–1870.
- Borini, G.B., Andrade, T.C., Freitas, L.A.P., 2009. Hot melt granulation of coarse pharmaceutical powders in a spouted bed, *Powder Technology*, 189, 520–527.
- Geldart, D., 1973. Types of gas fluidization, *Powder Technology*, 7, 285–292.
- Hao, H., Guoxin, H., Fengchao, W., 2008. Experimental study on particles mixing in an annular spouted bed, *Energy Conversion and Management*, 49, 257–266.
- Hosseini, S.H., Valizadeh, M., Olazar, M., Altzibar, H., 2017. minimum spouting velocity of draft tube conical spouted beds using the neural network approach, *Chem. Eng. Technol.*, 40, 1132–1139.
- Konopka, I., Markowski, M., Tańska, M., Żmojda, M., Małkowski, M., Białobrzewski, I., 2008. Image analysis and quality attributes of malting barley grain dried with infrared radiation and in a spouted bed, *International Journal of Food Science & Technology*, 43, 2047–2055.
- Olazar, M., Aguado, R., San José, M.J., Bilbao, J., 2001. Kinetic study of fast pyrolysis of sawdust in a conical spouted bed reactor in the range 400–500 °C, *J. Chem. Technol. Biotechnol.*, 76, 469–476.
- Olazar, M., San Jose, M.J., Aguayo, A.T., Arandes, J.M., Bilbao, J., 1992. Stable operation conditions for gas-solid contact regimes in conical spouted beds, *Ind. Eng. Chem. Res.*, 31, 1784–1792.
- Patel, S.U., Jeevan Kumar, B., Badhe, Y.P., Sharma, B.K., Saha, S., Biswas, S., Chaudhury, A., Tambe, S.S., Kulkarni, B.D., 2007. Estimation of gross calorific value of coals using artificial neural networks, *Fuel*, 86, 334–344.
- Rasul, M.G., 2001. Spouted bed combustion of wood charcoal: performance comparison of three different designs, *Fuel*, 80, 2189–2191.
- Rocha, S.C.S., Taranto, O.P., Ayub, G.E., 1995. Aerodynamics and heat transfer during coating of tablets in two-dimensional spouted bed, *Can. J. Chem. Eng.*, 73, 308–312.
- Saldarriaga, J.F., Aguado, R., Altzibar, H., Atxutegi, A., Bilbao, J., Olazar, M., 2016. Minimum spouting velocity for conical spouted beds of vegetable waste biomasses, *Journal of the Taiwan Institute of Chemical Engineers*, 60, 509–519.
- Saldarriaga, J.F., Atxutegi, A., Aguado, R., Altzibar, H., Bilbao, J., Olazar, M., 2015. Influence of contactor geometry and draft tube configuration on the cycle time distribution in sawdust conical spouted beds, *Chemical Engineering Research and Design*, 102, 80–89.
- Saldarriaga, J.F., Pablos, A., Aguayo, A.T., Aguado, R., Olazar, M., 2014. Determination of particle density by mercury porosimetry for biomass fluid dynamic study in moving beds, *Avances en Ciencias e Ingeniería*, 5, 63–71.
- Silva, B.G. da, Fileti, A.M.F., Taranto, O.P., 2015. Drying of Brazilian pepper-tree fruits (*Schinus Terebinthifolius raddi*): development of classical models and artificial neural network approach, *Chemical Engineering Communications*, 202, 1089–1097.
- Spiegl, N., Sivena, A., Lorente, E., Paterson, N., Millan, M., 2010. Investigation of the Oxy-fuel gasification of coal in a laboratory-scale spouted-bed reactor: Reactor Modifications and Initial Results, *Energy Fuels*, 24, 5281–5288.