

Mathematical Modeling of Cyclones - Dust Collectors for Air Pollution Control

Márcia Peixoto Vega*, Thiago Ferreira de Souza Ribeiro, Frederico Ribeiro Belfort Vieira, Cláudia Míriam Sheid

DEQ - UFRRJ, BR 465, km7 – CEP: 23890-000 – Seropédica – RJ – Brazil
 vega@ufrj.br

Cyclones are used in the field of air pollution control with small cyclones for ambient and source sampling and large ones for industrial particulate control. Their simple design, low capital and maintenance costs, and adaptability to a wide range of operating conditions have made cyclones one of the most widely used industrial dust collectors. The main objective of this paper is building a generalized mathematical model for describing cyclones, at laboratory and industrial environments, concerning Stairmand and Lapple families and also unusual configurations, covering a wide range of pressure and flow rates, cyclone diameters and particle sizes.

1. Introduction

A cyclone is a particle removal device without moving parts which spins a gas stream to collect entrained particles by centrifugal force. In fact the particle-laden gas enters the cyclone at the top of the cylinder and makes several revolutions due to the shape of the entry forming a vortex with a high tangential velocity which accelerates particles outward to the wall for collection. Below the bottom of the gas exit tube, the spinning gas gradually migrates inward, to a central core axially along the cylinder centerline, and from there up, finally out to the exit tube.

Cyclones are used in the field of air pollution control with small cyclones for ambient and source sampling and large ones for industrial particulate control.

Their simple design, low capital and maintenance costs, and adaptability to a wide range of operating conditions have made cyclones one of the most widely used industrial dust collectors.

Due to the complex three-dimensional fluid flow in cyclones the exact mechanisms of removing particulate are still not fully understood. In addition, different operating conditions such as temperature, pressure and flow rate add even more difficulties to the already complicated problem.

Therefore, most cyclone theories are based on a simplified model or depend upon empirical correlation equations. Although these theories are valid for certain cyclone operating conditions, none of them has been satisfactorily validated. Therefore, study on cyclones is still largely based on experiment methods and design of cyclones relies upon experience, trial and design guides.

Nonlinear system identification involves model parameters selection, determination of the forcing function which is introduced into the plant to generate the output response, estimation of model parameters and comparison of plant information and model predictions for data not used in model development.

All steps represent very challenging theoretical and practical problems, for a general theory is not available.

As a result, further investigation on systematic techniques for nonlinear model validation, characterization of the amount and type of process data required to build nonlinear empirical models with satisfactory predictive capability and the identification of nonlinear model structures which are capable of capturing a wide variety of process behaviors are future research issues that need to be explored. The neural network (NN) approach has proved to be a useful tool and is the most popular framework for empirical nonlinear model development (Vega et al., 2008).

The main objective of this paper is building a methodology for NNs construction, allowing the development of confident model identification procedure for use in the laboratory and industrial environments. NNs were validated in terms of the traditional methods, Pollard et al. (1992) and Srinivas et al. (1995), and in terms of their static and dynamic behaviour.

As observed through many examples, Vega et al. (2008), the use of traditional validation tests is not enough to guarantee successful use of NNs, as the complex dynamic behavior displayed by the model may be completely different from the one displayed by the plant, resulting in poor identification efficiency. Good identification performance can be detected using numeric simulation studies.

It is proposed here that standard static-dynamic analysis be used as an additional validation procedure for implementation of NN models. In order to illustrate this point, Stairmand, Lapple and unusual configuration families of cyclones, separating solid particles from gases, are taken as a case study.

The technique is used to allow the development of confident NNs, based on experimental data. Experimental data are obtained through an experimental unit that may employ different types of cyclones. It is shown that static and dynamic analysis of NNs may be very helpful for the appropriate development and implementation of model identification.

The specific NNs models were built in order to represent which specific family of dust collectors. In addition, a generalized NN modelling approach represented simultaneously Stairmand, Lapple and unusual cyclone configurations, using a single architecture, and also predicting accurately the particle efficiency of big and small designs.

2. The Process Analyzed

A cyclone is a particle removal device without moving parts which spins a gas stream to collect entrained particles by centrifugal force. Figure 1 shows a typical cone-under-cylinder cyclone design. In this design, particle-laden gas enters the cyclone at the top of the cylinder and makes several revolutions due to the shape of the entry forming a vortex with a high tangential velocity which accelerates particles outward to the wall for collection. Below the bottom of the gas exit tube, the spinning gas gradually migrates inward, to a central core axially along the cylinder centreline, and from there up, finally out to the exit tube.

Due to the complex three-dimensional fluid flow in cyclones the exact mechanisms of removing particulate are still not fully understood. In addition, different operating conditions such as temperature, pressure and flow rate add even more difficulties to the already complicated problem.

Therefore, most cyclone theories are based on a simplified model or depend upon empirical correlation equations. Although these theories are valid for certain cyclone operating conditions, none of them has been satisfactorily validated. Therefore, study on cyclones is still largely based on experiment methods and design of cyclones relies upon experience, trial and design guides.

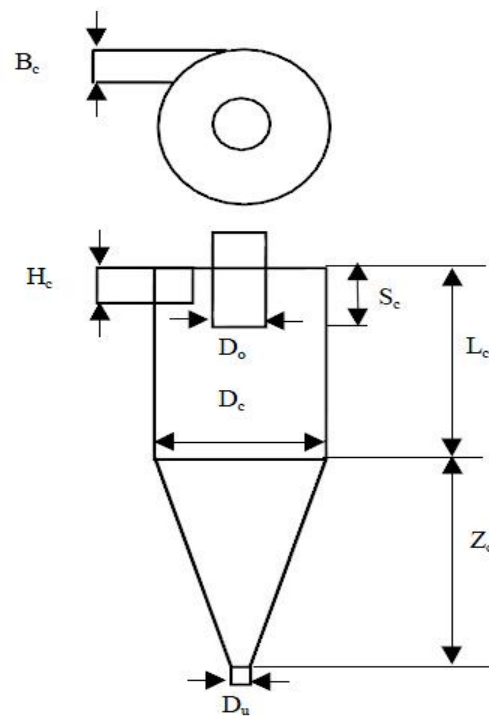


Figure 1: Typical cyclone design

3. Results and Discussion

Literature information provides that as the parameter D_c improves, the collection efficiency decreases. The increase of P produces a decrease in the collection efficiency. As Q , S_c , L_c , D_u and dp increase the collection efficiency increases. In addition, as B_c and D_o increases, the collection efficiency diminishes. Finally, it is well-known that the collection efficiency varies from zero to unity.

The NN models were a function of operational conditions [flow (Q), diameter of the particle to be separated (dp) and ratio between fluid viscosity and particle density (μ/ρ_p)], the equipment characteristic relations [(H_c/D_c) , (B_c/D_c) , (D_o/D_c) , $((L_c+Z_c)/D_c)$, (L_c/D_c) , (D_u/D_c) , (S_c/D_c)] and cylindrical section diameter, D_c . The lower and upper limit values for the parameters are reported in Table 1.

A three layer feedforward neural network, using hyperbolic tangent and linear activation functions at the hidden and output layers, respectively, was employed. Input NN data comprised the variables: D_c , P , Q and dp for predicting the particle collection efficiency (output information). In accordance with standard cross-validation procedures (Pollard et al., 1992; Srinivas et al., 1995), a hidden layer with an optimal number of neurons (5 neurons) was selected (Figure 2).

In order to build NN empirical models, two independent data (training and validation), containing different data sets, were used. A total of 3 neural models were built for representing each family ((Lapple, Stairmand and unusual configuration). The empirical model dynamic patterns were similar to the one shown by the literature for the analyzed configurations.

For generalized empirical model building purposes, a three layer feed forward neural network, using hyperbolic tangent and linear activation functions at the hidden and output layers, respectively, was selected. The architecture comprised, as input information, D_c , P , Q , H_c/D_c , B_c/D_c , D_o/D_c , S_c/D_c , Z_c/D_c , L_c/D_c , D_u/D_c and dp (Figure 3).

The NN predicted successfully the particle collection efficiency for various types of dust collectors, including Lapple, Stairmand and unusual configurations (Figures 4 and 5). It is important to mention that NN predictions are in agreement with cyclones standard behaviour reported by literature, which states that particle collection efficiency increases as Q , dp and solid density increases. In addition, particle collection efficiency decreases as D_c increases. Finally, it can be observed that generalized NN predictions distinguished Stairmand (higher efficiency) from Lapple (lower efficiency) configurations.

Table 1: Parameter range

parameter	big diameter cyclone		small diameter cyclone	
	lower limit	upper limit	lower limit	upper limit
D_c , m	0.18	0.4	0.01	0.05
$P \times 10^9$, m^2/s	4	80	4	80
$Q \times 10^3$, m^3/s	43	240	0.15	4.8
H_c/D_c	0.25	0.7	0.21	0.59
B_c/D_c	0.15	0.3	0.15	0.32
D_o/D_c	0.3	0.58	0.2	0.8
Sc/D_c	0.35	3.5	0.4	1.64
$(Lc+Zc)/D_c$	3	6	2.3	4.3
Lc/D_c	0.5	3.5	1.1	2.1
Du/D_c	0.38	1	0.3	0.69
dp , m	1×10^{-6}	1×10^{-4}	1×10^{-6}	1×10^{-4}

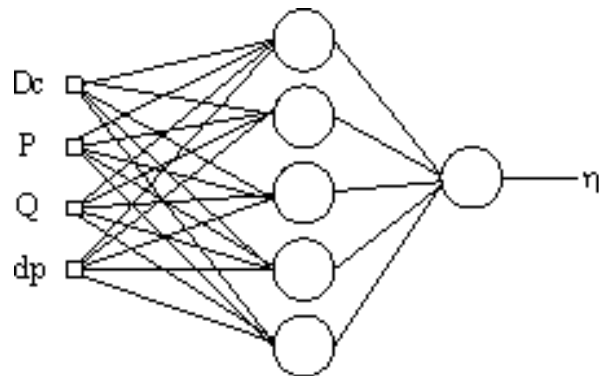


Figure 2: Specific NN architecture

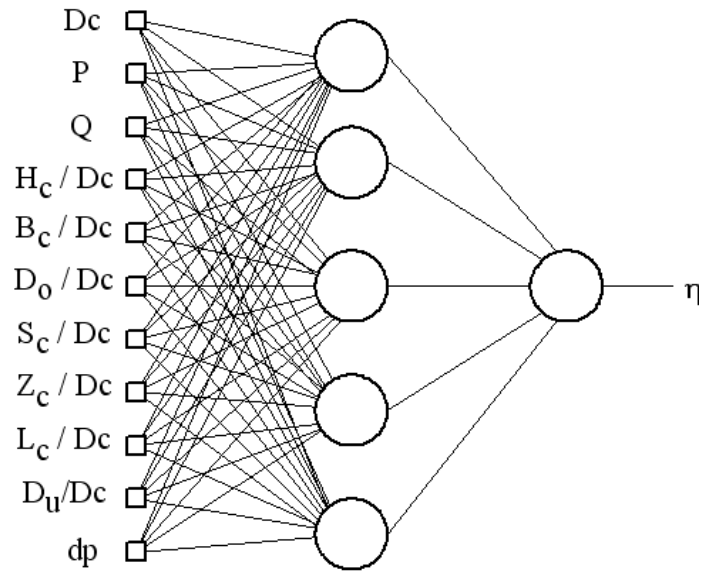


Figure 3: Generalized NN architecture

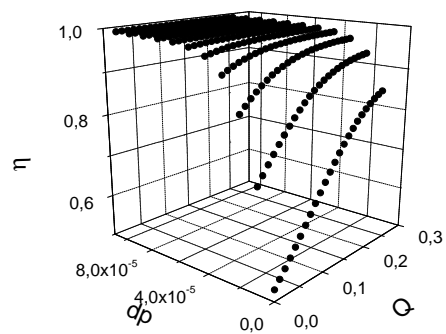
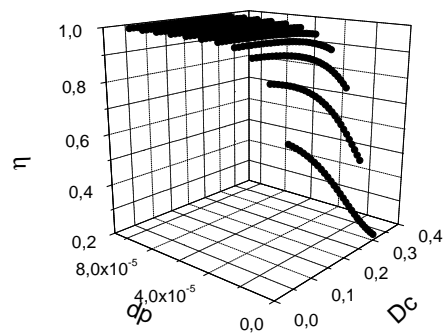


Figure 4: Generalized NN predictions Particle: quartz, configuration: Stairmand

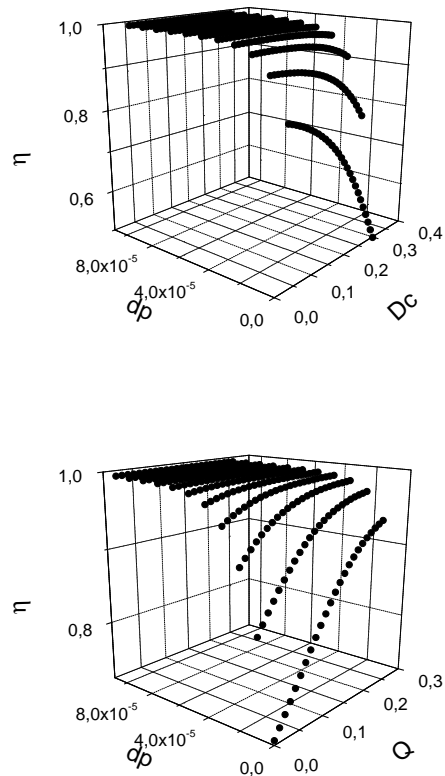


Figure 5: Generalized NN predictions Particle: quartz, configuration: Stairmand

4. Conclusions

Specific and generalized confident NN models were built for describing cyclones, using experimental data obtained from a multi-purpose plant, concerning Stairmand, Lapple and unusual families, covering a wide range of pressure and flow rates, cyclone diameters and particle sizes for describing calcium carbonate, baritine, coal, quartz and alumina particles.

References

- Pollard, J.F., Broussard, M.R., Garrison, D.B. and San, K.Y., 1992, Process Identification using Neural Networks, Computers and Chemical Engineering, 16, 253-270.
- Srinivas, G.R., Arkun, Y., Chien, I-L and Ogunnaike, B.A., 1995, Nonlinear identification and control of a high-purity distillation column: a case study, Journal of Process Control, 5, 149-162.
- Vega, M.P., Lima, E.L., Pinto, J.C., 2008, Use of bifurcation analysis for development of nonlinear models for control applications, Chemical Engineering Science, 63, 5129-5140.