Learning and Nonlinear Models (L&NLM) – Journal of the Brazilian Neural Network Society, Vol. 9, Iss.4, pp. 256-265, 2011.

ON THE APPLICATION OF FUZZY LOGIC CONTROL IN PNEUMATIC CONVEYING SYSTEMS

Paulo Roberto Barbosa
Instituto Federal de Educação, Ciência e Tecnologia de São Paulo – IFSP, Campus São Paulo
Rua Pedro Vicente, 625, CEP 01109-010, São Paulo, SP, Brazil
barbosapr@gmail.com

Paulo Seleghim Jr.
Universidade de São Paulo – USP, Escola de Engenharia de São Carlos
Av. Trabalhador Sãocarlense, 400, CEP 13566-590, São Carlos, SP, Brazil
seleghim@sc.usp.br

Abstract- The pneumatic conveying of solids in a gas stream is a recurrent process in petrochemical industries as well as in agricultural, food and mining. However, due to practical limitations the majority of existing systems have capacities ranging from 1 to 400 tones per hour over distances less than 1000 m, mainly because of high power demand per transported unit mass. A safe circuit with reduced power demand can be designed using non-conventional control techniques. This work describes a fuzzy controller implementation for a 45mm i.d. pneumatic conveying system used to transport *Setaria italica* seeds over a distance of 21 m. Data obtained in a previous study about gas-solid flow regime identification through a self-organizing neural network were used in the controller design. Two types of accidents were induced to qualify the controller performance in an imminent blockage situation. The results show a safe operation and a reduction in power demand when compared with classical non controlled transport.

Keywords- Fuzzy logic, control, energy savings and pneumatic conveying.

1 Introduction

The pneumatic conveying of solids in a gas stream is a recurrent process in petrochemical industries as well as in agricultural, food and mining. The main advantages of this transport are: flexibility, security in the transport of high valued products, ease of automation/control and low maintenance costs. The range of material that can be pneumatically transported is extensive: powders and rocks of up to 50 mm in size to finished manufactured parts such as electronic components for instance. However, due to practical limitations the majority of existing systems have capacities ranging from 1 to 400 tones per hour over distances less than 1000 m and average particulate size less than 100 mm. Among these limitations probably the most important one refers to a high power demand per transported unit mass.

More specifically, to avoid the formation of dense structures such as dunes and plugs which may cause a violent pressure surge or a possible line blockage the system is preferably operated at homogeneous dispersed flow (depending on the characteristics of the material and on the availability of a pressure head from the carrier phase). To sustain such a flow regime, high velocities are needed (15 to 20 m/s for instance) and, accounting for the resulting higher pressure drops, higher power demand is required. Another important problem associated with the increase in the transport velocity is the abrasion of the equipment and degradation of the transported particulate.

From a phenomenological point of view, pneumatic transport can be seen as a special application of gas-solid flows which can be described with the help of the so called state diagram, i.e. the curves of specific pressure drop in function of the gas superficial velocity. It is also possible to define a state diagram by plotting mass flow ratios in terms of the Froude number, which is a more general and convenient representation of the phenomenon. Either way, gas-solid flow state diagrams indicate that the transition from dispersed (or light) type flows to dense phase flows is associated to a minimum in the specific pressure drop, which would be an ideal operating condition if the above mentioned problems could be avoided. More specifically, the problem of operating the transport line near transition velocities lies on the hysteretic behavior of the transition. This can be better understood through a test on a horizontal line where the velocity of the carrier phase is slowly varied between zero and a maximum value, above which the flow regime is dispersed and does not change. The different stages of this experiment which also were observed at the circuit considered in this work are indicated in Figure 1, where the velocity of flowing particles U_p is plotted against the gas velocity U_g.

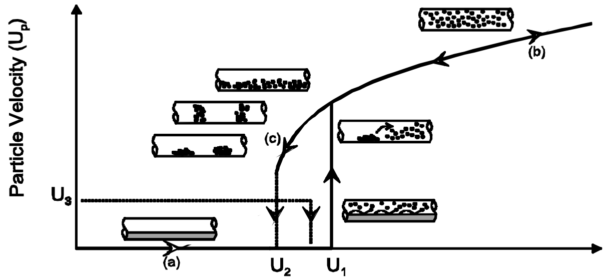


Figure 1: Schematic representation of the different flow regimes in horizontal gas-solid flow when varying the carrier velocity. (Adapt from Savage et al., 1996)

In stage (a) U_g is not sufficiently high to levitate the particles so $U_p = 0$ until a critical value is reached ($U_g = U_1$). After this, in stage (b), $U_g > U_1$, the particles are entrained by the gas flow and fully dispersed regime is asymptotically reached ($U_p \rightarrow U_g$). From a maximum gas velocity value, U_g is decreased in stage (c) of the experiment and different flow regimes may appear, such as stratified flow, intermittent flow and dune flow, until another critical value $U_g = U_2$ is reached. At this point particles are no longer sustained in the core, some of them will segregate and stop and others will roll and bounce over the fixed particle layer at $U_p = U_3$. Operating the transport line near the light-dense transition means setting U_g between U_1 and U_2 and handling a strong hysteretic behavior of U_p as well as of the pressure drop and other relevant flow variables. Therefore, the safe operation within these conditions requires special control strategies, which is one of the main objectives of this work. Considering this task, we look to Artificial intelligence techniques. Artificial intelligence can eliminate many of the common pitfalls in operations and designs (Klinzing, 2001) and a fuzzy system can be a suitable solution for a hysteretic behavior (Hai-chu et al., 2010). Searching for the ideal point considering the security and the energy saving, a preliminary study about the regime identification through self-organizing neural network were done (Barbosa et al.,2004) in order to produce data for the design of the control strategy proposed in this article.

2 Fuzzy systems

Fuzzy logic was originally proposed by Lofti Zadeh in 1965 with the work “Fuzzy sets” (Zadeh, 1965) and then developed as a tool for manipulating and processing vague information in uncertain conditions. One of the main characteristics of this approach is the element partial membership which allows smooth transitions from one rule to another (Yager and Filev, 1994). In this context, the production of the membership functions, i.e., functions that define the membership degrees for each input and output of the system is called “fuzzyfication”. All fuzzy set representing the crisp (physics) variables related by membership functions are the so called “knowledge basis”.

The knowledge basis has uncertain information however significant for the system modeling. Although this uncertain is completely solved as the input and output fuzzy sets and the knowledge manipulation strategy are defined.

A fuzzy algorithm processes the membership functions for each one of the fuzzy sets and the results are aggregating through instructions or rules, producing the so called “rule basis”. Often, in order to establish a truth degree for the rules each fuzzy output is multiplied by an appropriate scale factor.

There are basically two types of fuzzy system models differentiating in the ability of representing different kinds of information, i.e, in the form of representing the rule basis. The first include the linguistic models based in collections of IF-THEN rules with vague attributes and have fuzzy reasoning. In this type of model, fuzzy quantities are associating with linguistic labels and a fuzzy model is essentially a qualitative expression of the system. The second type of model is based in the Takagi-Sugeno-Kang reasoning method (Sugeno, 1985). These models are constructed by logic rules which are combination of fuzzy and crisp models (Yager and Filev, 1994). This work adopts the first type of fuzzy system.

A set of inference rules is adopted to manipulate the knowledge basis. The most used method to represent the human knowledge is through natural language expressions as:

IF (antecedent) THEN (consequent)

Since decisions are based on the testing of all of the rules in the inference system, the rules must be combined in some manner in order to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set.

One of the most used is the Mamdani implication method for inference in which the aggregated output is:

$$\mu_{B_n^k}(\alpha(i),\alpha(j)) = \max[\min[\mu_{A_{n1}^k}(\alpha(i)),\mu_{A_{n2}^k}(\alpha(j))]], \qquad \text{for } k = 1,...,r \tag{1}$$

where A_{n1}^k and A_{n2}^k represent antecedent fuzzy sets, μ represent membership functions, B_n^k represent the consequent fuzzy set for inputs $\alpha(i)$ and $\alpha(j)$.

Often the output of fuzzy process must be a scalar quantity and not fuzzy sets. A crisp value for the system output is obtained by the defuzzyfication of the fuzzy output set. In the literature there are some defuzzyfication methods as, for instance, centroid, bisector, middle of maximum (the average of maximum values of the output set), largest of maximum, and smallest of maximum. Perhaps the most popular defuzzification method is the centroid calculation, which returns the center of area under the curve. This was the method used in this work and the crisp value is obtained by the center of area given by the gathering of the output membership functions as

$$y^* = \frac{\int \mu_{B_n^k}(y)\,y\,dy}{\int \mu_{B_n^k}(y)\,dy} \tag{2}$$

where y^* is the value obtained by the defuzzyfication and B_n^k are the consequent fuzzy sets.

3 The test facilities

The validation tests were done at the experimental facilities of the Thermal and Fluids Engineering Laboratory of the University of São Paulo at São Carlos (NETeF-USP). The pneumatic transport loop, drawn schematically in Figure 2, has a transparent 45 mm inner diameter test section, extending horizontally through 12 m and vertically through 9 m. Air is supplied by a 43 kW screw compressor (1), capable of generating air speeds up to 40 m/s in the transport line. The air flow rate is controlled with the help of a servo-valve (2) and measured by an orifice plate (3), instrumented with temperature and pressure transmitters (differential and absolute; range = 0-500 mbar). The particulate is introduced in the transport line through a Venturi feeder (4), which receives the particulate from a screw conveyor (5). The solids flow rate is controlled by imposing the rotation of the screw conveyor with a frequency converter (6). A cyclone separator (7) is placed at the exit of the test section, from where the particulate may be returned to a separated storage container (8) for batch operation or, alternatively, to a rotary airlock (9) connected to the feeding silo (10) for continuous operation.

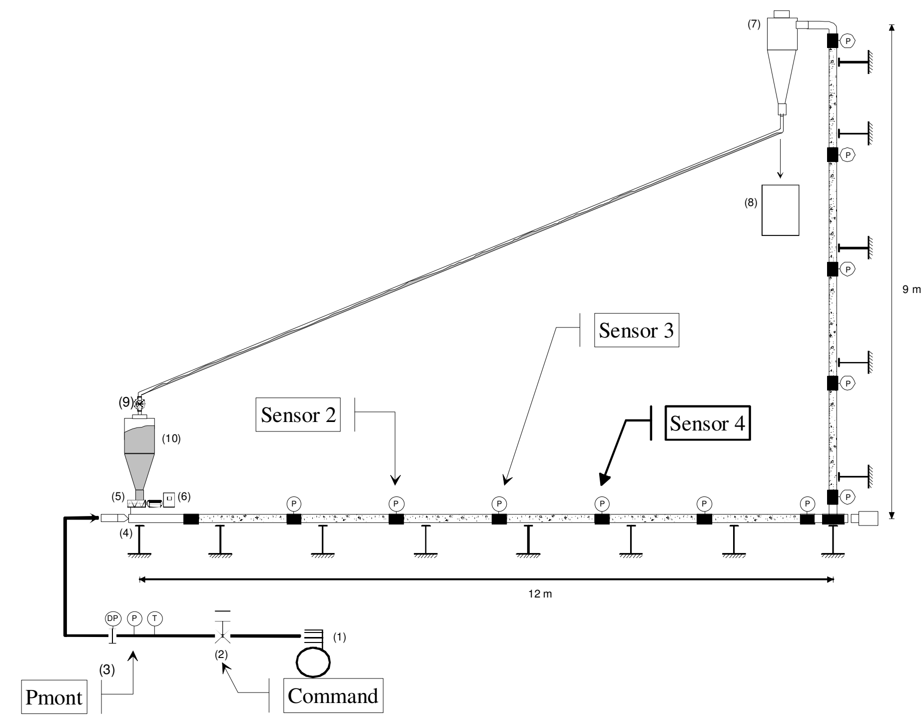


Figure 2: Schematic representation of the pneumatic transport test loop at the NETeF - USP

Besides the pressure transmitters, the circuit has a National Instruments acquisition system constituted by a PXI-1000B chassis, Multifunction I/O 6025E acquisition module and PXI8170 processing module, which allows the communications with the control computer.

4 Controller design

Fuzzy controllers have been successfully used for solving control challenges. Some examples of these applications can be found in Watano et al. (2001); Junhua (2010); Alghamdi et al. (2009) and Reddy et al. (2009). Specifically in multiphase flow area we can point out recent important works as Karppanen (2000); Huang et al. (2010); Navale and Nelson (2010) and Bhatt et al. (2009).

The controller structure proposed in this article is drawn in Figure 3 where the three calculations steps of a fuzzy controller is showed as described in section 2.

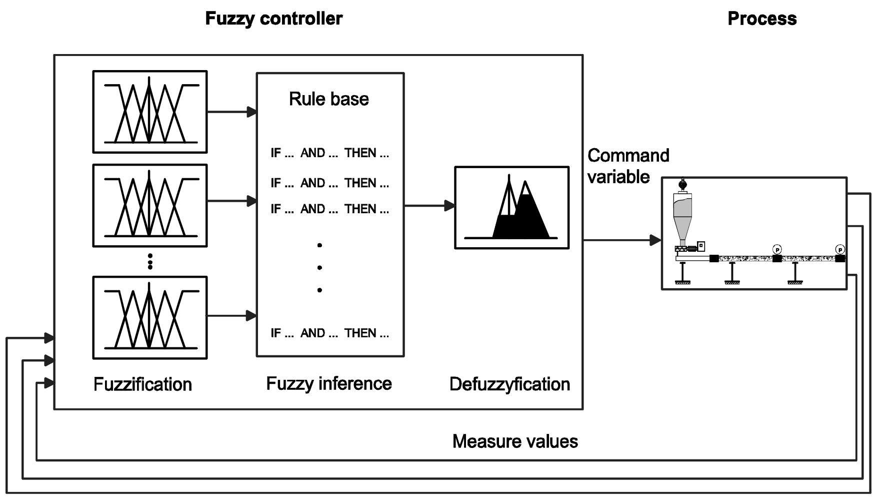
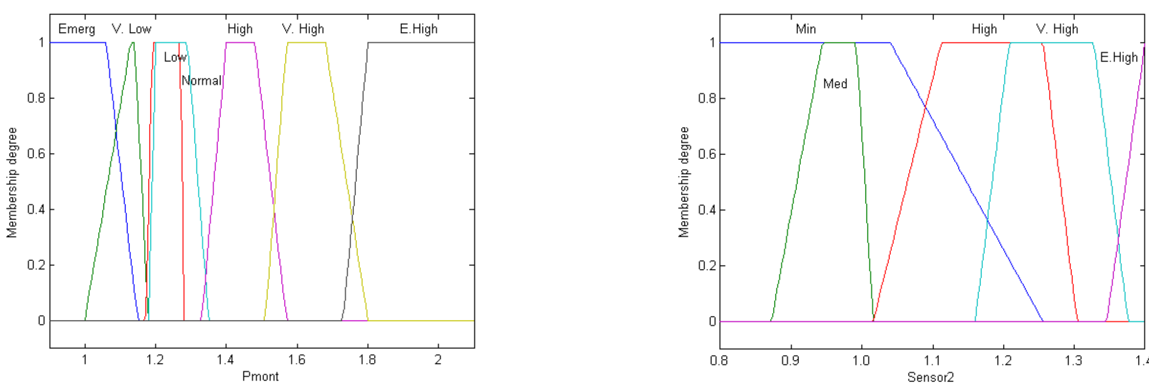


Figure 3: Structure of the fuzzy controller

This structure, perhaps the most basic if compared with the ones cited before, uses signals from the process sensors as a controller input signals and the controller output as a command value to drive the process actuator. The input variables were defined as pressure values from three sensors in the central part of the horizontal section and the absolute pressure in the orifice plate (see Fig. 2). In this work the four input variables were called Pmont, Sensor2, Sensor3 and Sensor4. The output variable, called Command, represents the command signal (volts) for the valve in the air pipe.



(a) (b)

Figure 4: Membership functions for the input variables Pmont (a) and Sensor 2 (b).

The units in Figures 4 and 5 are volts. In Figure 5 the variable Command is ranging from 3 to 4 volts. The pressure transmitter ranges are mapping into a voltage range of 1-5 volts, through a 250 Ω shunt resistor. Still in these figures is possible to verify that many fuzzy sets were defined in order to represent quantities as small, normal, big, very big, low, high etc.

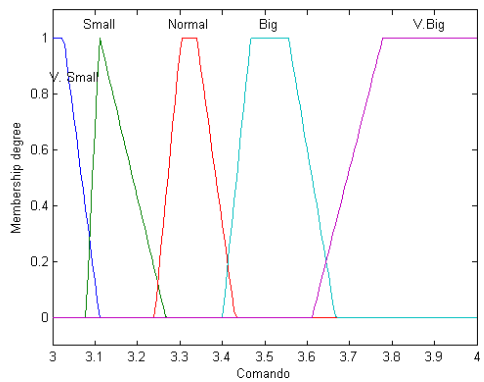


Figure 5: Membership functions for the output variable Command.

The main idea for the rule base design was as discussed before: search a velocity which could be lower as possible to improve the power demand and, by other side, high enough to avoid the pipe blockage. In this context and considering that the controller must be more severe in operating points near the transition region for the dense phase 24 rules were implemented with high weights in more instable situations. The data for this design were collected previously in steady state tests with *Setaria italica* seeds (average diameter of 2.5 mm and approximately density of 800 kg/m^3) as plotted in Figure 6 for a constant solid flow rate of 0,0739 kg/s.

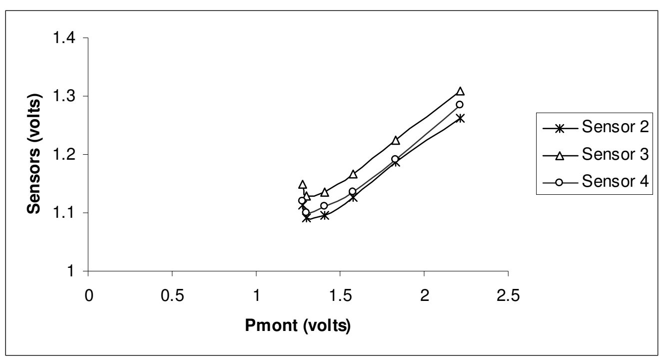


Figure 6: Input variables behavior when increasing the air flow rate and solid flow rate of 0,0739 kg/s.

This behavior suggest that for values labeled high in anyone of the three sensors and if the Pmont variable presents low values the circuit is operating at the decreasing part of the curves and because of this the Command variable must receive a big value (increase the air flow rate). By other side, if Pmont presents high values too the circuit is operating at the increasing part of the curves and in view of this the value Command can be reduced. Two examples of rules developed according this reasoning are

IF (Pmont is Low) AND (Sensor2 is High) THEN (Command is Big)
IF (Pmont is High) AND (Sensor3 is High) THEN (Command is Normal)

The fuzzy sets were chosen in this work exactly because they represent this uncertainness or imprecision when mapping the measured values in categories like Low, High, Small, Big etc. This uncertainty is involved in the considered system and it can be verified through Figure 7 that shows the same test as Figure 6, however by decreasing the air flow rate.

This behavior agrees with the phenomenon described at introduction section. At this point we find maybe the most important advantage of this application, i.e., the controller solves this situation of imprecision, eliminating a problem previously unsolved for the classical control techniques. Although it produces an unfamiliar shape (see Fig. 4) for a view out of this context, this is exactly a very practical feature of the proposed methodology once dispenses any type of processing to solve this intrinsical characteristic.

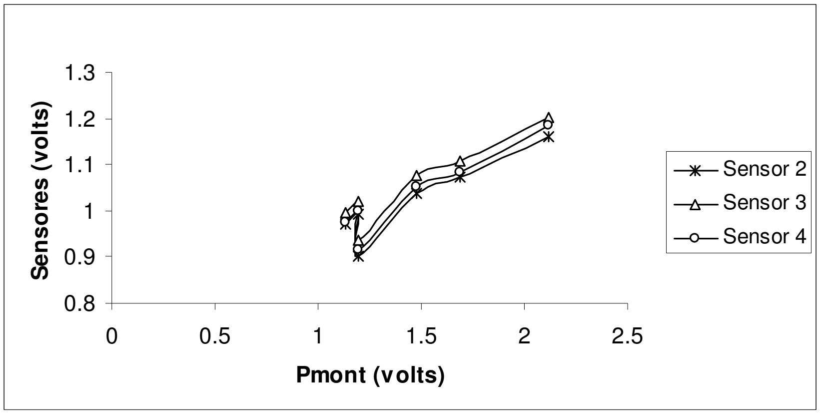


Figure 7: Variables behavior when decreasing the air flow rate and solid flow rate of 0,0739 kg/s.

.

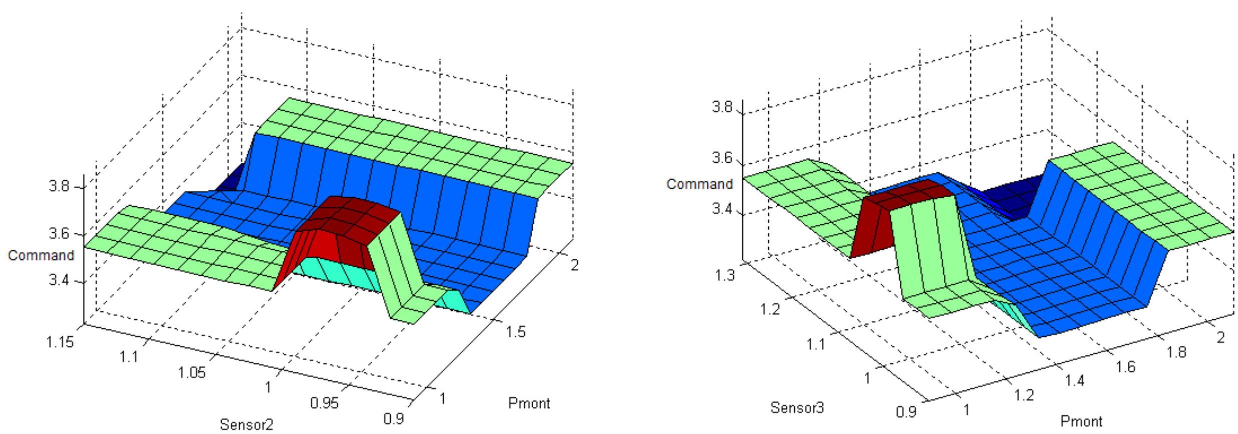


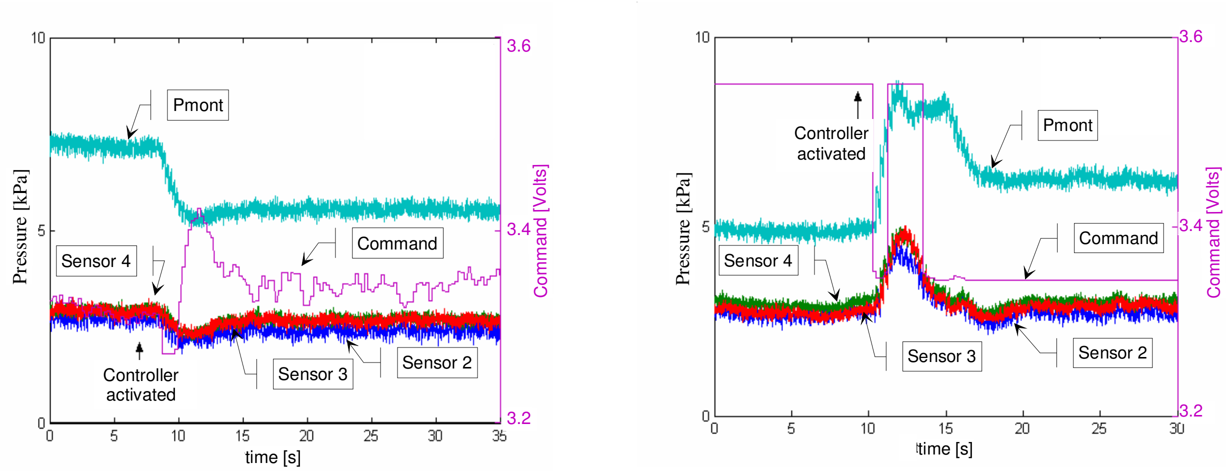
Figure 8: Rules surfaces.

The Figure 8 presents two output surfaces, i.e., the mapping considering Pmont, Sensor 2 and Command; and Pmont, Sensor 3 and Command. From these surfaces it is possible to identify critical regions where the Command has a high values and more usual regions where Command assumes low values.

5 Experimental tests

At first moment, the data acquisition was started in different operational points (different solid and air flow rates) and then the controller was activated to demonstrate its ability of setting the circuit according to the fuzzy inference result, without oscillations. Two pressure histories of these tests can be seen in Figure 9 where the command value (Command) is placed on right vertical axis.

The initial air flow rate, final air flow rate and solid flow rate were called $Q_{air\text{-}in}$, $Q_{air\text{-}fin}$ and Q_{sol} respectively. In these tests the controller stabilized the flow in a certain air flow rate (approximately 0.014 kg/s) that can be changed by the fine setting of the output surface. This can be made through the modification of the membership functions. Although, as discussed before, this flow rate represents the trade off between security and energy saving.



$Q_{air-in} = 0.017$ kg/s , $Q_{air-fin} = 0.015$ kg/s and $Q_{sol} = 0.0739$ kg/s $Q_{air-in} = 0.013$ kg/s, $Q_{air-fin} = 0.016$ kg/s and $Q_{sol} = 0.1228$ kg/s

Figure 9: Histories of pressures and commands.

In order to analyze the controller output in an imminent blockage situation two types of accidents were considered: The first, indicated by "Type 1" on Figure 10 consists of leakage in air pipe simulated by opening intentionally an emergency valve. This emergency valve was placed between the orifice plate and the feeding section. The second type of accident indicated by "Type 2" on Figure 10 consists of suddenly increasing the solid flow rate for values over the design operation conditions.

Figure 10 is a state diagram sketch which represents the relationship among pressure drop, superficial air velocity and the solid flow rate (each line represents a constant solid flow rate). The dotted line represents the minimum pressure line. According to the figure both types of accident take the circuit to the region of instability (dense).

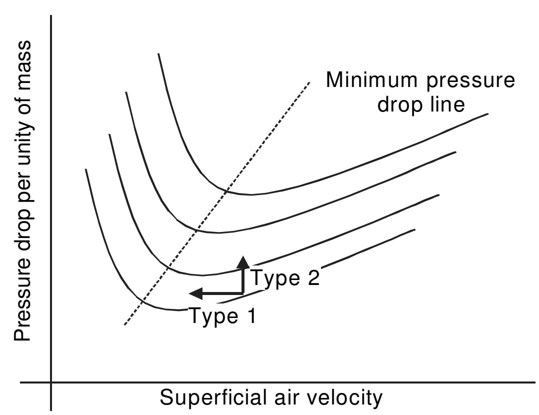
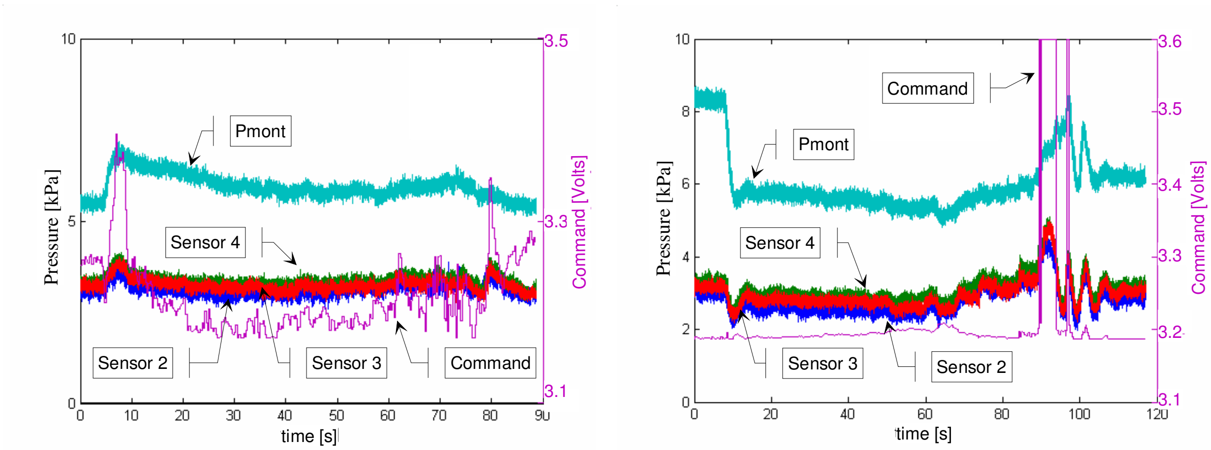


Figure 10: State diagram and the two types of accidents.

The pressure histories and the command signal for the type 1 tests are shown in Figure 11 with two different solid flow rates.

In Figure 11(a) the initial air flow rate was 0.013 Kg/s, i.e., slightly lower than the "ideal" according the controller (fuzzy inference). The correction for the ideal flow rate can be identified by the initial behavior of the curves, once that controller was activated at 3 seconds. Then starts the leakage and it was slowly increased. The effect of this in terms of pressure curves was the decreasing behavior contrasting with the increasing behavior of the command curve showing that the controller decided to compensate the leakage.

In Figure 11 (b) the test was done with a higher solid flow rate and the behavior was similar, however the emergency valve was opened and closed again. The effect of this can be seen in the final seconds of the test showing that the controller stabilizes the flow as the valve is closed.



(a) $Q_{sol} = 0.0739$ kg/s (b) $Q_{sol} = 0.1437$ kg/s

Figure 11: Histories of pressures and command signal for type 1 accidents.

The type 2 tests produced results as the showed in Figure 12 where the solid flow rate ranged from 0.0739 kg/s to 0.16 kg/s. The increase of pressures caused by the solid segregation that occur as the solid flow rate is suddenly increased is clearly observed. This situation continues until a certain moment (approximately 110 seconds) where the controller produces air pulses trying to clean the pipe.

In this situation and in the others showed in type 1 tests the circuit would be certainly damaged by the blockage without the controller. This demonstrates that the proposed fuzzy controller offer a safe operation of the circuit.

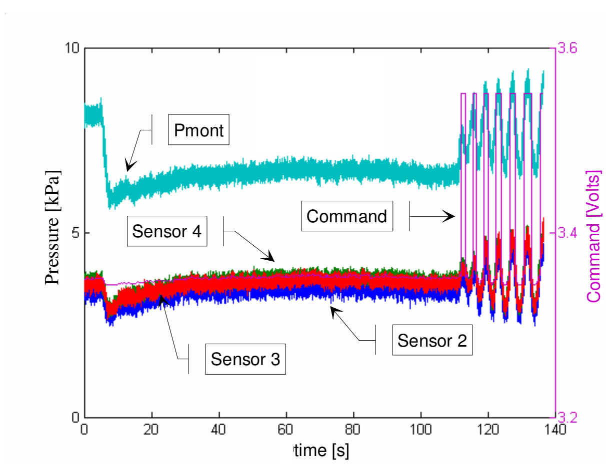


Figure 12: Histories of pressures in case of accident where the solid flow rate increases over the transport capacity in disperse phase – the system produce air pulses as it was coughing.

6 Improving the power demand

The necessary power (Taylor, 1998) using the controller was measured to verify the reduction percentage. These powers were calculated by assuming isothermal flow (RT = constant) and imposing energy balance for a pipe stretch, that is

$$W = Q_{ar}\ R\ T \ln\left(\frac{P_1}{P_2}\right) \tag{3}$$

where P_1 is the pressure at the inlet of the test section (1.5m downstream from the solids feeder), and P_2 the pressure at its outlet (1.5 m upstream from the cyclone)

The average saving was calculated considering the transport with 18 m/s of air velocity, according technical recommendations for *Setaria italica* seeds. The difference between nominal and controlled situations is showed in the following table.

TABLE 1: NECESSARY POWER (KW) WITHOUT AND WITH THE FUZZY CONTROLLER.

Q_{sol} (kg/s)	**0,0739**	**0,1037**	**0,1228**	**0,1343**	**0,1395**	**0,1437**
Without control	1,707	1,871	1,893	1,798	1,704	1,510
With control	1,04	1,171	1,011	0,984	0,995	0,908
Reductions	39,1%	37,4%	46,5%	45,2%	41,6%	39,8%

According to Table 1 if we consider a solid flow rate of 0,0739 kg/s, for example, in nominal conditions, a power of 1,707 kW would be necessary for the system operation. For this same test, if we consider the methodology proposed in this work a power necessary for the system operation decreases to 1,04 kW producing a reduction of 39,1 %. If we continue this reasoning for the others solid flow rates, the last line of table 1 will be fulfilled. As a global indicator it is possible to assert that the results show an important average saving of 41% .

In the literature it's possible to find other kinds of applications of fuzzy control with similar energy savings as, for instance, the 48% of energy saving in a water source heat pump system (Li et al., 2009) and the 50% of energy saving in a tunnel lighting system (Yang et al., 2011).

7 Conclusions

A technique for the control of gas-solids flow occurring in pneumatic transport system was proposed in this work. The control algorithm is based on a fuzzy structure. The controller inputs were defined as pressure values measured in four different locations and the controller output were defined as the command for the valve in the air pipe.

The controller was designed to allow a safe operation and improve the power demand. More specifically, the controller allows an air flow rate reduction resulting in an energy saving. At the same time it guarantees the security of the system once the operation point is closer the transition for the dense phase.

In order to analyze the ability to keep the system operating in hard situations and to avoid a pipe blockage, two types of accidents were simulated. In the first type a leakage was simulated in the air pipe by opening an emergency valve. In the second type of accident the solid feeding was increased abruptly causing a situation above the transport capacity in disperse phase. In both cases the controller kept the system operating safely and avoided the blockage. In particular in the second type of accident, the controller behavior was similar to a choke situation in which air jet are produced aiming to clean the transport line as occurs when a person chokes and coughs.

Experimental tests with *Setaria italica* seeds using the proposed methodology in a 45 mm i.d. pneumatic conveying line showed an important average saving of 41% in power demand for the same amount of solids transported.

These results show that the application of fuzzy logic reasoning may solve complex industrial problems, specifically in multiphase flow area.

8 Acknowlegments

The authors would like to acknowledge the financial support provided by FAPESP through grant 02/00472-5, and by CNPq through grant 62.0012/99-4.

9 References

Alghamdi, A. S., Eren H. and Mansour A. (2009). Application of fuzzy logic control in automated transport systems. Proceedings of Sensors Applications Symposium. Ireland. p. 216-219.

Barbosa, P.R., Crivelaro, K.C.O. and Seleghim JR, P. (2004). Identification of flow regimes in pneumatic conveying systems through self-organizing neural networks. III Congresso Nacional de Engenharia Mecânica, Belém-PA, Brazil.

Bhatt, T.U., Madala, K.C., Shimjith, S.R. and Tiwari, A.P. (2009). Application of fuzzy logic control system for regulation of differential pressure in Liquid Zone Control System. Annals of Nuclear Energy 36: 1412–1423.

Hai-chu, C., Hui, Y., Hua, Z. and Rui-Hua, Z. (2010). Study of proportion and fuzzy control method upon Precision Micro-flow Valve. Proceedings of 2nd International Conference on Future Computer and Communication. China.V3:581-585.

Huang, H.P., Yan,J.L. and Cheng, T.H. (2010). Development and Fuzzy Control of a Pipe Inspection Robot. IEEE Transactions on industrial electronics 57 (3): 1088-1095.

Junhua, G. (2010). Development of fuzzy control system for frozen food environment. Proceedings of the International Conference on Biomedical Engineering and Computer Science. China. p. 1-5.

Karppanen, E. (2000). Advanced control of an industrial circulating fluidized bed boiler using fuzzy logic. Academic dissertation. University of Oulu. Finland. 134 p.

Klinzing, G.E. (2001). Pneumatic conveying: transport: solutions, pitfalls, and measurements. In: Handbook of Conveying and Handling of Particulate Solids, Levy, A. and Kalman, H. (eds.). Elsevier. The Netherlands. 870 p.

Li, L., Xiang-long, L., Xiao, C., Ming, L., Zhu, L.H. (2009). The utilization of fuzzy control in energy saving control system of water source heat pump. Proceedings of the International Conference on Energy and Environment Technology, p. 471-474.

Navale, R.L. and Nelson, R.M. (2010). Use of genetic algorithms to develop an adaptive fuzzy logic controller for a cooling coil. Energy and Buildings 42: 708–716.

Reddy, N.P., Mathur, G. and Hariharan, S.I. (2009). Toward a fuzzy logic control of the infant incubator. Annals of Biomedical Engineering 37(10): 2146–2152.

Savage, B.S.; Pfeffer, R.; Zhao, Z.M. (1996). Solids transport, separation and classification. Powder technology 88:323-333.

Sugeno, M. (1985). Industrial applications of fuzzy control, Elsevier Science Pub. Co.

Taylor, T. (1998). Specific energy consumption and particle attrition in pneumatic conveying. Powder technology 95:1-6.

Watano, S., Numa, T., Miyanami, K. and Osako, Y. (2001). A fuzzy control system of high shear granulation using image processing. Powder Technology 115:124–130.

Yager, R.R. and Filev, D.P. (1994). Essentials of fuzzy modeling and control. New York, John Wiley & Sons.

Yang, C., Fan, S., Wang, Z. and Li, W. (2011). Application of fuzzy control method in a tunnel lighting system. Mathematical and Computer Modelling. Article in press. doi:10.1016/j.mcm.2010.11.018.

Zadeh, L. (1965). Fuzzy sets. Information and control 8: 338-353.