Control of Pneumatic Conveying Using ECT

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Abstract *- The control of dense-phase pneumatic conveying systems is notoriously difficult. Specifically, achieving sufficiently low air velocity to ensure efficient power utilisation, low product degradation and plant wear, whilst ensuring that blockage of the pipeline does not occur, is the greatest challenge. ECT could potentially offer a cheap, durable and potentially effective method of visualising solids movement within conveying pipelines and ultimately act as a primary sensory input to an optimal control system.*

A pneumatic conveying rig has been designed and constructed in order to simulate the slug flow of plastic pellets when using air as a transportation media. Twelve electrode ECT sensors have been placed on a test section of the rig to measure variations of slug flow and to further investigate any potential for control. A pre-requisite paper [1] details the successful time-based "animation" of solids flow through the pipeline, the analysis of these flow patterns and the potential of this work for the control of pneumatic conveyors. This "bolt-on" *paper will describe two parallel control strategies, which may be employed in association with an ECT system for the optimisation of pneumatic conveyors. One technique will utilise parametric modelling of conveying systems, while the other will be based on a fuzzy logic approach, where the membership functions will be optimised by the use of genetic algorithms.*

Keywords: ECT, pneumatic conveying, control, parametric modelling, fuzzy logic.

1. INTRODUCTION

Pneumatic conveying is defined as the transport of various granular solids and dry powders using an air (or other inert gas) stream as a transportation media. Pneumatic conveying offers many advantages over other methods of granular solids transport, factors such as low routine maintenance and manpower costs, dust free transportation and flexible routing. The main disadvantage is the reliance upon empirical procedures for conveyer design, which in effect limits the design to a specific solid material. Relatively minor changes in pipeline layout or operating conditions can often result in unpredicted blockage problems. In addition, power consumption, wear rate, product degradation and particle size separation can be major problems.

Dense phase pneumatic conveying systems are categorised as such by the solid particles not being fully suspended and therefore moving at low velocities. As such, these systems have the relative attributes of a low air requirement and hence energy demand, low pipeline erosion and low product degradation. However, the *control* requirements of such a transportation system are clearly far more acute in respect to the maintenance of flow regime and the prevention of blockage. As a safety measure and to accommodate future changes in the system, most dense phase systems are operated at a much higher air velocity than necessary, thereby reducing the potential benefits of this mode of operation.

The flow regime within a pipeline, for a given particulate material, can often be controlled by variation of the air velocity. It would normally be expected that industrial scale pneumatic conveyors would operate with discontinuous dense-phase flow regimes. This may take the form of discrete plugs of material, rolling dunes or a combination of the two. In reality, a pneumatic conveying system may simultaneously exhibit several flow regimes throughout its length. If unstable flow occurs it can result in violent pressure surges which will increase both plant wear and product degradation problems. In addition, the identification of the flow regime at critical sections of the pneumatic conveyor is fundamental to any void fraction estimate, upon which many standard measurements, such as solids mass flow rate, will depend.

Assuming that the particulate material in question is suitable for pneumatic conveying, blocking within such systems is normally caused by insufficient air velocity. Once blocking has occurred, it can be extremely difficult to remedy. Cross-sectional imaging of the pipeline therefore offers potential benefits in both the control and fault monitoring of pneumatic conveying systems.

Feedback control systems have, broadly speaking, the advantage of reducing the sensitivity to parameter changes and disturbances control of the air flow rate by such a system therefore offers the potential benefit of operating the plant at lower air rates without compromising reliability. The implementation and design of such a control system is not an easy task. The various aspects of this procedure are discussed within this paper.

Electrical Capacitance Tomography (ECT) [1], optical tomography [2] and ultrasonic tomography [3] have been used to visualise the particle distribution across a given cross section of a pneumatic conveying pipeline. The increases in computer power has made it possible to analyse such images on-line and extract information that may be used to achieve better control of the plant.

A problem arises for control strategies which are model based. Pneumatic conveying systems, and the dense-phase type in particular, have so far not been successfully modelled in a way that would make those models applicable to control design. There are new types of models and control systems emerging that might offer a solution to this problem [4]. The use of Neural Network Models [5] is discussed in this paper. Novel ideas are presented as to how tomographic data can be integrated with conventional measurements, such as flow rate and pressure drop, to act as sensory input to a pneumatic conveying control system. It is argued that robust and reliable control of a dense-phase conveyor should be achievable provided the best use of available data is made.

2. EXPERIMENTAL CONFIGURATION

A pilot plant scale vacuum conveying rig has been designed and constructed to allow different types of plug flow (with air and plastic pellets) to be generated and controlled in a repeatable fashion. A schematic of this conveyor is shown in Figure 1. The flow loop consists of a 15m length of 50mm diameter plastic pipeline, with two stainless steel right angle bends. The conveying power is provided by a *PIAB MLL 800 MK* 1 pneumatically driven vacuum pump and *Georg-Fisher* 24-V electrically actuated valves are used throughout the conveyor. The solids hopper loading section was custom made for the purpose. Instrumentation is provided by a differential pressure transducer across the inlet section and a load cell which is positioned to monitor the mass of returned solid material. These are interfaced to a personal computer via custom made signal conditioning circuits and a proprietary 12-bit A/D interface card. The complex start-up procedure and system control during operation is performed by the computer which runs *Labview*-based on a graphical programming language.

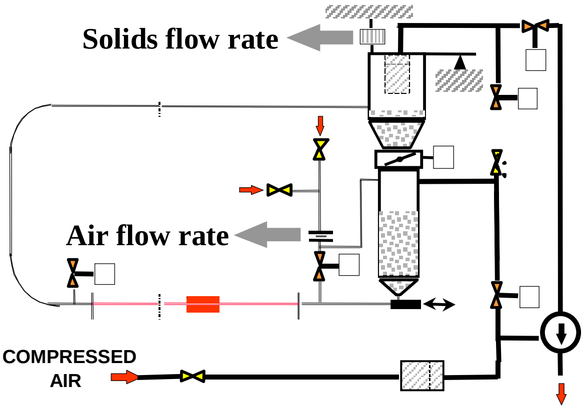

Figure 1: Schematic Diagram of Pneumatic Conveyor Experimental Rig

3. PARAMETRIC MODELLING

Modelling of dense-phase pneumatic conveying is inherently difficult, and, in such a situation, parametric models are a suitable choice for control applications.

A parametric model of a pneumatic conveying pipe-line must satisfy a number of requirements in order to form a useful basis for the control of such a system. These include:

- Cover a wide range of operating conditions
- Contain a small number of parameters
- Identification of the parameters must be feasible using available measurements

A generic model takes the form

$$Y = F_A(X) \tag{1}$$

where (in this particular case)

Y Outputs (pressure drop)
A Parameter vector
X Inputs (air and solid flow rates)

3.1. The State Diagram

A wide range of pneumatic conveying systems can be described by a state diagram [6], linking pressure drop with the air flow rate and the solids flow rate. A typical state diagram is shown in Figure 2.

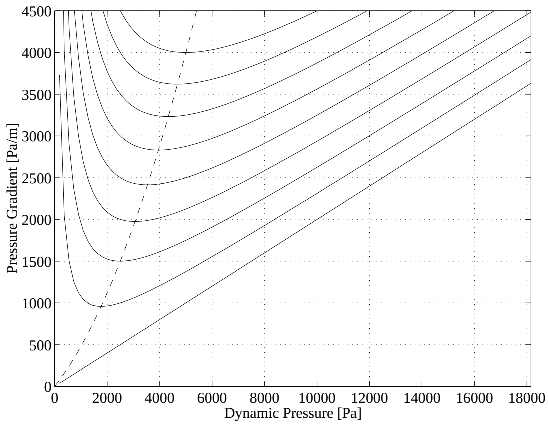

Figure 2: State Diagram

It is hoped that two parameters are sufficient to parametrise the state diagram to suit a wide range of systems. The following form is suggested:

$$\frac{\Delta p}{\Delta x} = aG\left(b + \frac{m_0}{\rho v^2}\right) + \frac{\rho v^2}{m_0} \qquad (2)$$

where

a,b	parameters
p	pressure
x	spatial co-ordinate
G	solids flow rate
v	superficial air velocity
ρ	density of air
$m_0 = 2D/\lambda_L$	parameter dependent on pipe diameter D and friction coefficient λ_L

The last parameter on this list depends on the pipe only but not the solids to be conveyed. It can either be calculated or determined experimentally.

The use of such a model for control is

- Serve as a model for control design procedures
- Predict consequences of control actions
- Determine desired region of operation
- Estimate the location of danger areas on the state diagram (regions where blockage is likely to occur)

For the last point, information in addition to the state diagram is required: The type of flow regime. The underlying assumption here is that the knowledge of the distribution of the various flow regimes allows a good estimate of where (in the state diagram) blockage is likely to occur.

The type of flow regime cannot easily be determined by use of pressure and flow rate measurements alone. This is where tomographic measurements are very useful.

3.2. Flow Regime Map

Preliminary studies have shown that just one simple tomographic signal, namely the void fraction, is sufficient to determine the flow regime.

This can be done in different ways:

- Spectral Analysis + Rule Base
- Statistical Analysis + Rule Base
- Neural Networks (recurrent or delay type)

Generally, the first two methods require more design skills to set up, whereas the third method is very easy to automate. While all methods worked with the test data, it was found that the neural networks exhibit a significantly faster response to changes in the flow regime.

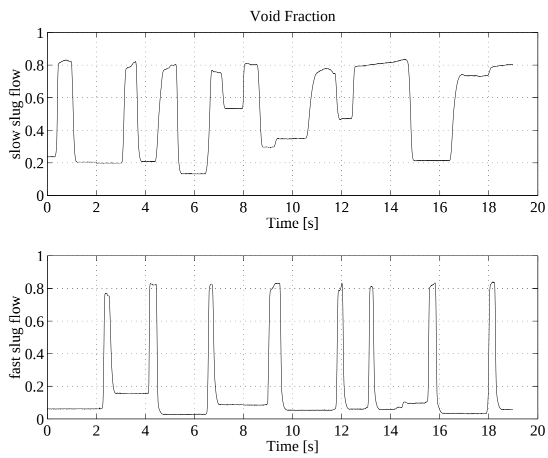

Figure 3: Two Flow Regimes

Some initial studies have been carried out to determine the best network architecture and also the number of neurons required. It has been found that a delay network is far superior to a recurrent (Elman) network. This is reflected by clearer flow regime separation as well as faster learning times. Figure 4 shows the output of a delay network with 6 delays and 10 neurons in the hidden layer. The test (input) data was a signal of two stretches each of two flow regimes A and B, arranged as a sequence ABAB. The void fraction signal of the two flow regimes, namely slow and fast slug flow, is shown in Figure 3. It can be seen the each flow regime is represented by one of the outputs of the neural net. This is shown in Figure 4. The response can be improved further by filtering the output signal using a low-pass filter (Figure 5).

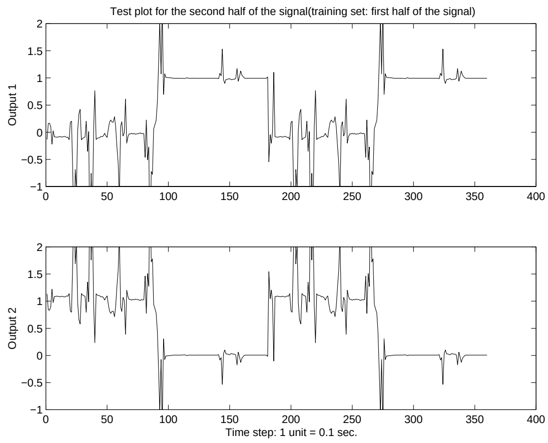

Figure 4: Neural Network Output

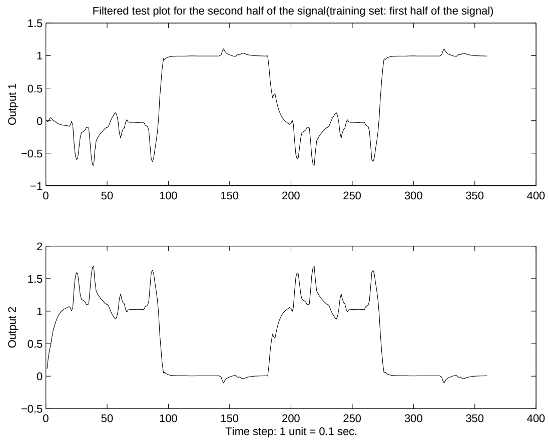

Figure 5: Neural Network Output (filtered)

3.3. Control Strategy

The adaptive control scheme we propose has two levels:

Low-level control: Adjust bypass valve setting based on flow-rate and pressure information. The objective it to counter any blocking tendencies very quickly. It is for this reason that this loop must be fast and can only rely on fast sensors.

High-level control: Slowly adapt the conceptual model and the flow regime map to compensate for changes in the plant (wear) and the operating conditions. This includes an update of the flow regime map.

The basic structure of the control system is shown in Figure 6. The inner loop is the faster of the two, using a bypass valve bank as an actuator. The outer loop identifies the flow regime.

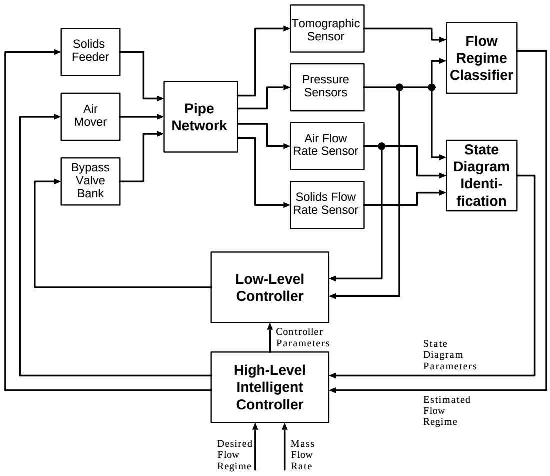

Figure 6: Parametric Modelling: Overall Control Scheme

4. FUZZY-LOGIC CONTROL

4.1. Motivation

Fuzzy logic is now an accepted technique in computer science for modelling the human ability to apply experience and knowledge to a wide variety of complex decision making processes involving unclear, vague or incomplete information

To date, it is probably a fair comment to state that no automated control system applied to a pneumatic conveying system, has outperformed experienced human operators. Pneumatic conveying systems are, by their very nature, complex in their flow dynamics and highly sensitive to operational changes. The human attributes of instinct and adaptability are essential for successful control of these systems. Hence, there is a clear justification for attempting to model these attributes using fuzzy-logic techniques.

4.2. Fuzzy-Logic Control Strategy

The remit of the control strategy is to utilise the void-fraction / time information derived from an ECT system (Figure 3) as a primary sensory input, with a view to minimising the power consumption of the conveyor. This data is to be monitored over a discrete period of time, at the end of which *mean void fraction* and *mean slug frequency* are both statistically estimated. These parameters are then *fuzzified*, using the *fuzzification windows* of Figure 7.

The input membership functions have been designed such that no input value should cause more than two *hits*. In addition the use of linear triangular membership functions allows the *membership (confidence) index* of each *hit* to be easily quantified. It is assumed that the conveyor blower nominally runs at half its maximum airflow output. (This is assumed for the purposes of symmetry and to allow the maximum range of control).

Figure 8 shows the *rulebase matrix*, where each cell contains the nominal percentage variation from the 50% figure. (These figures will be changed by the optimisation process)

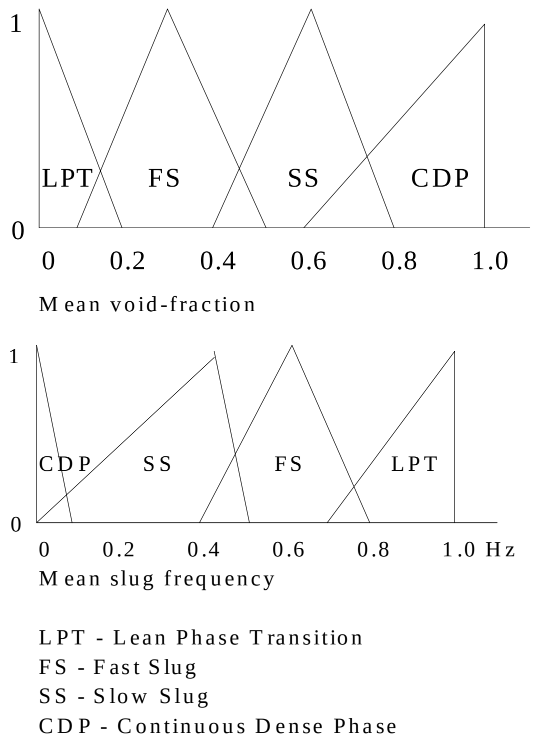

Figure 7: Input Fuzzification Windows

Mean slug frequency \ Mean void-fraction	LPT	FS	SS	CDP
LPT	-35	-10	+5	+15
FS	-10	0	+10	+20
SS	+5	+10	+25	+30
CDP	+15	+15	+30	+35

Figure 8: Rule-Base Matrix

An output window is constructed, showing the range of membership indexes for individual blower settings. The output window is subsequently *de-fuzzified* by use of the *centre of area method*.

4.3 Algorithm Operation Example

Consider a test sample giving mean void-fraction and slug-frequency values of 0.48 and 0.45 Hz respectively. By reference to Fig. 7, the following *hits* for the input memberships can be observed:

Parameter	Membership	Membership Index
Mean Void Fraction	Slow Slug (SS)	0.52
Mean Void Fraction	Fast Slug (FS)	0.18
Mean Slug Frequency	Slow Slug (SS)	0.3
Mean Slug Frequency	Fast Slug (FS)	0.3

All four possibilities have to be allowed for when determining the fuzzified output. With reference to the central four cells of Figure 8 therefore:

(i) If mean void fraction = slow slug and slug frequency = slow slug, then output set to +25 with a membership index μ = min(0.52, 0.3) = 0.3

(ii) If mean void fraction = fast slug and slug frequency = fast slug, then output set to 0 with a membership index μ = min(0.18, 0.3) = 0.18

(iii) If mean void fraction = slow slug and slug frequency = fast slug, then output set to +10 with a membership index μ = min(0.52, 0.3) = 0.3

(iv) If mean void fraction = fast slug and slug frequency = slow slug, then output set to +10 with a membership index μ = min(0.18, 0.3) = 0.18

Using this data, an output window can be constructed as shown in Figure 9

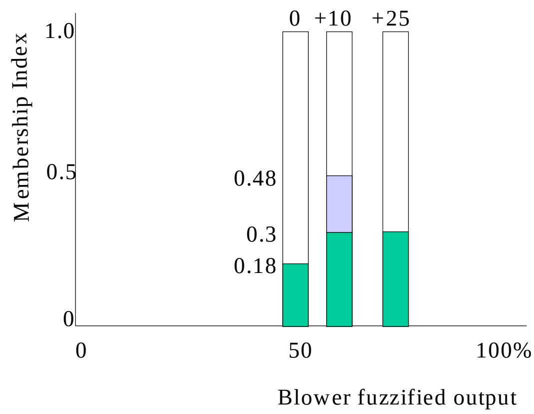

Figure 9: Output Fuzzy Window

Defuzzification of the output window can be achieved by the centre of area method.

$$d_{blower} = \frac{\sum_{0}^{100} d_i m(d_i)}{\sum_{0}^{100} m(d_i)} \tag{3}$$

where

δ = Rulebase matrix cell value
μ = Membership index

In this case therefore:

$$d_{blower} = \frac{(+25x0.3) + (10x0.48) + (0x0.18)}{(0.18 + 0.48 + 0.3)} \tag{4}$$

= 12.8%, i.e., blower air velocity is increased from 50% to 62.8% of maximum value.

4.4. Optimisation

The cell values shown within the rulebase matrix of Fig.8 are nominal values. Some degree of adaptability will be required due to the high disturbance susceptibility of pneumatic conveyors. For optimisation purposes, each cell value is represented by a six bit binary number, known as a *chromosome.* The rulebase therefore constitutes a population of 16 chromosomes, each having six *genes*. These 16 chromosomes are subsequently manipulated by the three standard *genetic algorithm* operators of *reproduction, crossover* and *mutation.* The fitness of each solution can be easily quantified by measurement of the solids delivery and energy expenditure, with quantification being expressed in terms of kWh / Tonne of solid material.

5. CONCLUSION

It has been shown that, in principle, flow regimes can be distinguished reliably using tomographic measurements, particularly when neural networks are employed. More experimentation and on-line implementation of both described control systems are required in order to evaluate performance in real world conditions.

For the parametric modelling approach, the neural network will be implemented using a DSP board with the appropriate I/O facilities. This system will be closely linked with the image processing of the tomographic data.

Provided these experiments prove successful, the information obtained in this way will be used by an intelligent control system. This will also be implemented using the same DSP board as the neural network. The control system can be relatively simple fuzzy controller provided the state diagram and the flow regime can be identified reliably.

Implementation of the Fuzzy Control Scheme using a DSP board should be numerically less demanding than the scheme based on the Parametric Model, as all the processing power of the DSP can be devoted to the fuzzy rule-base.

A comparative study of the two control strategies will show which one is more promising for industrial applications.

ACKNOWLEDGEMENTS

This work was supported by the European Coal and Steel Community (ECSC) under Contract No.7220-ED/083 B.9.

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