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A low-error calibration model for an electrostatic gas-solid flow sensor fusion obtained via machine learning techniques with experimental data

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Abstract

Sensor fusion is the use of software that intelligently combines data from multiple sensors in order to improve overall system performance. This technique can be applied to measurement of mass flow rate of solids in a pipeline with non-intrusive electrostatic techniques. Data fusion from multiple heterogeneous/homogenous sensors can overcome limitations of an individual sensor and measured variable. It is shown that the output voltage of a ring-shaped electrode is predominantly a function of solids mass flow rate, air-solids ratio and particle velocity. By additionally incorporating measured flow velocity in a proposed mathematical model (obtained via machine learning), meter output voltage could be predicted/calculated with superior accuracy, for a range of different flow parameters from numerous experiments with a pneumatic conveying system. A transposed model utilised in software enables accurate mass flow measurement with velocity compensation. Accurate mass flow measurement facilitates enhanced monitoring and controllability of blast furnaces, power stations, chemical reactors etc. where there is a flow of solid fuel/reactant in pipelines. Optimisation of highly materially consumptive and energy intensive processes can yield significant reductions in waste and emissions (CO_2, NOx) and increased efficiencies in global production of energy and materials.

Keywords: sensor fusion, machine learning, electrostatic flow measurement, gas-solid flow, pneumatic conveying, non-linear regression

1. Introduction

Gas-solid flows as pneumatic conveying processes are commonplace in industry. They are utilised in coal-fired power stations, blast furnaces and cement, chemical, pharmaceutical and food production processes as a method to transport bulk solids - being a fuel, reactant or food or pharmaceutical constituent. Often, but not always, the gas phase is air. In order to optimise these processes, reduce waste and emissions or increase combustion efficiencies, it is desirable to be able to accurately measure the mass flow of bulk solids. There are various meters that are commercially available that do enable mass flow measurement of bulk solids [1]. Some are intrusive in nature, and are unable to conduct measurement without disturbing the flow stream.

This is undesirable and wastes energy which has been already invested in the transfer of material. Also, some intrusive sensor designs may be damaged over time by constant abrasion. Some commercially available non-intrusive meters based on electrostatic techniques have been deployed in power stations and blast furnaces. However, current systems do not perform as well as single phase systems, having a notable issue with regards to spatial sensitivity [2] and whilst they can offer flow assurance, they lack the accuracy to be utilised in reactor/furnace control loops – which limits the potential for process optimisation.

A main issue is that, unlike simpler measurement systems, the voltage induced in the electrode is related to not only the mass flow rate of solids, but also air-solids ratio, particle velocity, flow profile, humidity, particle size [3] and electrostatic properties of the bulk material itself. It is a complex relationship with many interacting variables resulting in the measured voltage signal. However we can assume that some of the latter variables remain sufficiently constant for a given system. Variables could be controlled/fixed under experimental conditions and from subsequent observation it was found for a system using the same bulk material, same grade or particle size, same humidity and temperature, the output (rms) voltage of a ring-shaped electrode around a conveying pipeline can said to be primarily a function of the mass flow rate Q_m, air-solids ratio R_{as} and particle velocity v_p. The meter function to be found is therefore;

$$V_{rms}(mV) \cong f(Q_m, R_{as}, \mathrm{v}_p) \tag{1}$$

Solids mass flow rate has proven difficult to measure directly. Therefore, this measurement challenge is still of research interest in a time when we have single phase gas/liquid flow meters (e.g. Coriolis) with accuracies of 0.05%. Current multiphase gas-solid flow meters are somewhat behind (±10%), but accuracy can be improved by utilisation of multiple homogenous/heterogeneous sensors and combining data in software to improve system performance in a method termed 'sensor fusion'. With electrostatic gas-solid flow measurement, this can be through the use of multiple ring-shaped electrodes at different positions on the pipeline. This can reduce the issue of sensitivity to flow profile and enable simultaneous determination of particle velocity using the cross-correlation technique, which is a well-understood technique described and demonstrated in the literature [4-6].

By obtaining an accurate model, when meter voltage and remaining variables are known/measured, a transposed model utilised in measurement system software, continuously updated with sufficient sensor data should then enable online measurement of mass flow rate. System performance, i.e. measurement accuracy should exceed that of current/existing designs.

2. Experimentation

The Teesside University pneumatic conveying rig shown in Figure 1 was used to collect data. A 40mm pipeline containing conveyed solids consists of a vertical and horizontal section with 4 electrostatic meters. The configuration enables simultaneous measurement of particle velocity using the cross-correlation technique. An inverter-controlled fan takes in air, which is mixed with solids (Fillite) introduced to conveying line via a screw feeder. The reference solids mass flow rate is obtained by mass differentiation. An additional inverter controls the speed of the screw feeder. Air flow rate is measured downstream and air exits the system via an exhaust.

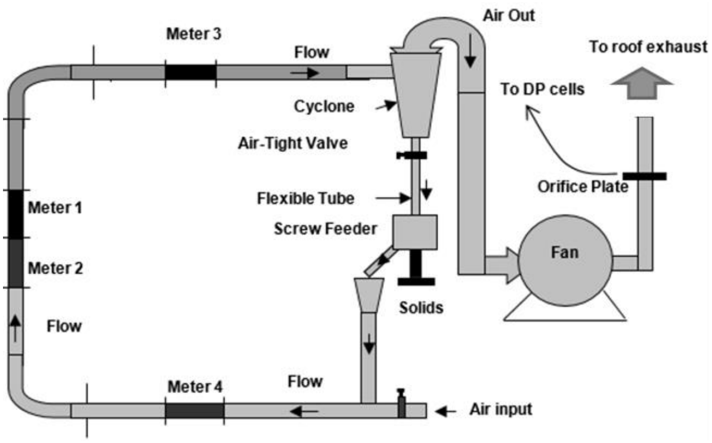

Figure 1 – Diagram of pneumatic conveying rig

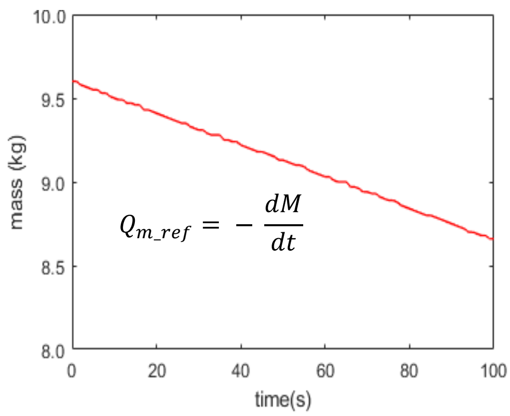

Figure 2 – Reference mass flow rate

The instantaneous root-mean square voltage from each meter, the mass of solids in the hopper, the air flow rate and solids velocity are all logged in software (Labview) every second during an experiment. Over 30 different experiments were conducted, all with different (controllable) mass-flow rates, solids velocity and air-solids ratio. These values were then used to form a split train/test data-set, to enable acquisition of system model via machine learning techniques.

3. Preliminary Model derivation with Machine Learning

Using the Regression Learner app in MATLAB, a variety of machine learning algorithms were deployed with the train data set (70% of overall data) and are ranked below in order of their respective model performance metrics; R^2 value and (root) mean (squared/absolute) error.

Table 1 – Machine learning techniques with model performance metrics (ranked)

Method	R^2	RMSE (mV)	MAE (mV)
Linear Regression	0.93	11.37	9.07
Linear State Vector Machine	0.93	11.48	9.10
Boosted Regression Tree Ensemble	0.89	14.69	10.86
Fine Regression Tree	0.87	15.86	12.46
Bagged Regression Tree Ensemble	0.84	17.30	13.15
Fine Gaussian State Vector Machine	0.74	22.39	15.00

As can be seen, the best-fitting model/technique of those tried is linear regression. This enables the derivation of a linear equation for meter output voltage;

$$V_{rms}(mV) \cong 3.3Q_m + 2.1\mathrm{v}_p + 8.3R_{as} - 48.2 \tag{2}$$

As well as having the best fit to test data, with this type of model there is less concern with regards to overfitting a because the data conforms well to a simple model rather than requiring say a complex regression tree, or state vector machine.

4. Model Refinement

An improved model should also encapsulate the slightly non-linear/curved nature of meter voltage with increased mass flow rate. This is seen in the data set when experiments with similar flows parameters are grouped in terms of air solids ratio and velocity to see the effect of altering each parameter and also mass flow rate in isolation. A higher order model which predicts zero output voltage for zero flow is preferable, because it corresponds to the reality of the system intended to be modelled. Although the initial linear regression model was deemed insufficient, it facilitated the derivation of the unknown coefficients for a second order polynomial model. A model with a structure similar to this this has been presented previously by Zhang [7]. This model expressed meter output voltage as a function of air-solids ratio and mass-flow rate, but did not incorporate particle velocity, and was of the form;

$$V_{rms} = (ARas\ + B)\ Q_m^2 + (CRas + D)Q_m + ERas + F \tag{3}$$

Where A, B, C, D, E and F are constants to be determined. This model was found to have a maximum relative error of around 7%. The newly proposed model has zero intercept and also incorporates particle velocity and has the form;

$$V_{rms}(mV) \cong \{a + bR_{as} +\ c\mathrm{v}_p\}Q_m^2 + \{d + eR_{as} + f\mathrm{v}_p\}Q_m \tag{4}$$

Where a, b, c, d, e and f are coefficients which have been determined as;

$$a = 0.047,\ b = -0.008,\ c = -\ 0.002,\ d = 0.111,\ e = 0.546,\ f = 0.136$$

This refined non-linear model was found to be more accurate at predicting meter output voltage than the linear model and also significantly more accurate than the model of equation 3 in the range shown. If then, for a given system, the meter voltage(s) and remaining predictor variables are known/measured, then the mass flow rate can be determined in measurement system software using the available data with the following transposed mathematical model;

$$Q_m = \frac{2V_{rms}}{\sqrt{4V_{rms}\left(a + bR_{as} + c\mathrm{v}_p\right) + (d + eR_{as} + f\mathrm{v}_p)^2} + d + eR_{as} + f\mathrm{v}_p} \quad (5)$$

5. Results and Discussion

The following table shows the root mean square meter voltage for a range of experiments conducted with particle velocity varying from 15 to 30 m/s, air-solids ratio ranging from 1.5 to 3.5 (which is typical of power station concentrations) and mass flow rate ranging from 10 to 40 kg/hr. The meter voltage is predicted using the aforementioned non-linear regression model and the relative error (%) of the prediction is also calculated. The model fit to steady state test data from numerous experiments is then shown graphically in Figures 3 and 4.

Table 2: Model fit to experimental data

v_p	R_{as}	Q_m	V_{rms}	V_{fcn}	e_r%
15.59	3.29	10.96	41.18	42.85	-4.06
15.56	2.83	12.64	45.47	46.64	-2.57
15.53	2.46	14.51	51.68	50.95	1.40
19.41	3.15	14.72	59.26	62.09	-4.79
19.38	2.84	16.18	63.91	65.77	-2.91
15.46	2.05	17.34	57.59	57.67	-0.14
23.14	3.27	17.40	81.65	80.06	1.95
19.27	2.46	18.57	74.50	71.84	3.57
23.07	2.85	19.86	86.66	86.75	-0.11
26.73	3.23	20.98	103.4	101.3	1.96
15.31	1.58	22.17	66.40	69.59	-4.81
19.23	2.00	22.67	82.02	82.74	-0.88
23.07	2.45	22.99	97.24	95.51	1.78
26.69	2.86	23.56	107.0	108.6	-1.53
22.95	2.03	27.46	111.2	107.8	3.06
26.69	2.43	27.56	119.3	120.0	-0.59
19.01	1.60	28.03	95.79	97.10	-1.37
30.00	2.48	31.43	136.0	141.8	-4.27
26.34	2.03	32.76	129.8	133.7	-3.04
22.50	1.62	34.04	124.3	125.3	-0.80
18.77	1.19	37.29	118.8	123.4	-3.90
29.78	2.03	38.17	159.5	159.1	0.21
25.91	1.62	40.45	153.9	153.7	0.10

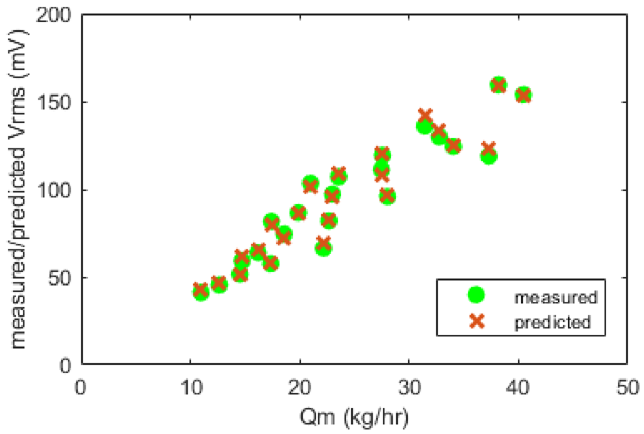

Figure 3: Model fit to Vrms with Qm

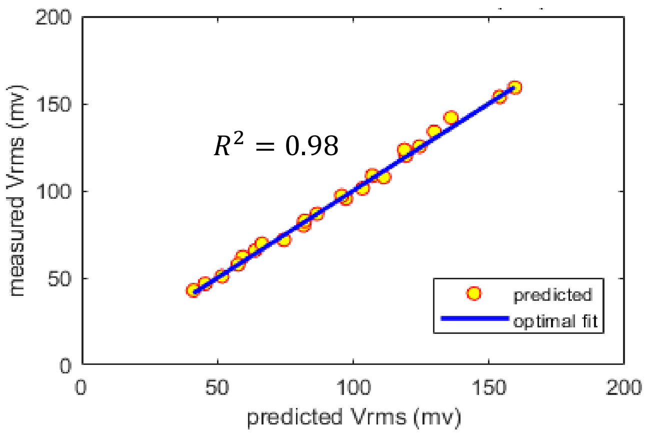

Figure 4: Predicted vs measured Vrms

As expected, the model shows an improved fit to steady state (moving) averaged meter voltage, as opposed to instantaneous values from the original sampled data. As can be seen, the mean relative error is less than 1% and the maximum relative error is less than 5%. This is more than acceptable for a multiphase flow meter and is constitutes a significant improvement to that of the previous model (eq. 3) from the literature, which did not incorporate particle velocity.

6. Conclusions and Future Work

With such a low mean relative error (less than 1%) when compared to test data, this well-fitting model provides the foundation for an accurate solids mass flow meter, capable of utilisation in furnace/reactor control loops. This could then enable process optimisation and reductions in waste and emissions for some of the most energy intensive and polluting industrial processes. Therefore, if widely adopted, even relatively slight resulting optimisations could globally constitute millions of tonnes of carbon prevented from being released into the atmosphere.

As in practice it is difficult to measure air-solids ratio, it is desirable to eliminate it from the model if possible. As both mass flow rate and velocity are both flow variables relating to air solid ratio, and it is thought that a model incorporating only V_{rms}, Q_m and v_p can exhibit sufficient accuracy to constitute a useful multiphase meter. Such a model would have the form;

$$Vrms(mV) = (\alpha + \beta v_p)\, Q_m^2 + (\gamma + \delta v_p) Q_m \qquad (6)$$

Preliminary results with such a model indicate a mean relative error of 1.4% and maximum relative error of less than 8.5% - this is acceptable for a multi-phase flow meter (though improvable) and can be achieved without need for new hardware, utilising multiple ring-shaped electrostatic meters as in Figure 1. Subsequent work will ascertain both a theoretical basis for the model and its potential practical performance and results will demonstrate non-intrusive online measurement of mass flow rate of bulk solids in a pipeline, with first-rate accuracy.

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