Monitoring of Erosion in a Pneumatic Conveying System by Non-intrusive Acoustic Sensors – A Feasibility Study

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Abstract

This paper presents the results of a study where the feasibility of a non-invasive acoustic measurement method was tested for monitoring of erosion in a pneumatic conveying system during the dilute-phase conveying of sand. Measurements were collected by the acoustic method from a pipe bend in a test area of a pneumatic conveying system which were found in previous studies to be especially afflicted with erosion. Reference measurements of the loss of mass caused by erosion were obtained by removing a detachable piece from the test area and weighing it before reattaching it to the pipeline. Partial least squares regression was used to calibrate models relating the acoustic measurements to the response variable. Cross-validation techniques were used to evaluate the feasibility of the method for monitoring of erosion in the pipe bend and to investigate whether the method would be affected by noise and vibrations generated by the pneumatic conveying system.

Keywords: *erosion, pneumatic conveying, monitoring, acoustic sensors*

1 Introduction

Pneumatic conveying, the transportation of dry material through a pipeline in a gas stream, is a common method of transportation of particulate and granulate material in many industries. Advantages of the technology include flexibility in the conveying system with multiple pick-up and discharge points, clean and dust-free transportation of solids and easy automation of the conveying systems. Pipe erosion has been identified as one of the main challenges of the pneumatic conveying technology. Erosive wear is particularly significant in dilute phase pneumatic conveying due to the higher velocities used in such systems. Pipe bends are often exposed to severe erosion.

Erosion is defined as the removal of material from a surface due to impinging particles. Erosive wear can be influenced by multiple factors, including properties of the conveyed material such as particle size and hardness as well as flow properties like particle velocity and impact angle. The characteristics of the surface material can also have an effect on erosive wear (G. E. Klinzing et al. 1997). Material which is removed from the pipe walls can mix with the conveyed material and cause quality and safety issues. Contamination of the conveyed material can be highly problematic for example in food and feed production. In some processes, mixing metal particles with the transported powder materials can cause dust explosions. Also, equipment failure due to erosion can lead to system downtime and higher maintenance costs (Ratnayake et al. 2007).

In a study by (Vieira et al. 2017), a system of 16 non-intrusive ultrasonic devices attached to the outer wall of a pipe bend was used to measure erosion in a test rig during multiphase flow. The pipe wall thickness was monitored in 16 points under various conditions, and the measurements were used to investigate the resulting erosion rates and patterns. The ultrasonic method was found to be a useful tool for investigating erosion mechanisms and getting a better understanding of the erosive wear phenomenon. However, for monitoring of erosion in an industrial setting, a simpler and more practical monitoring system which require less equipment to be installed in the test area would be preferable.

Developed at the University College of South-Eastern Norway, acoustic chemometrics is an indirect monitoring method in which chemometric techniques are applied to relate acoustic measurements to a response variable. A recent, active version of the acoustic method was presented in (Haugland et al. 2019), where the method was used to monitor scaling in a pneumatic conveying system. Acoustic chemometrics is a non-intrusive technique utilizing easy to install "clamp-on" sensors.

This paper presents the results of a study conducted to test the feasibility of the active acoustic method to monitor erosion in a pneumatic conveying system transporting material in dilute phase. Measurements were obtained during powder transportation as well as during system shutdown periods to evaluate whether the performance of the method would be disturbed by noise and vibrations from the conveying system during powder transportation.

2 Materials and Methods

2.1 Pneumatic conveying test rig

Tests were conducted in a pilot-scale pneumatic conveying rig located in the powder research hall of SINTEF Tel-Tek (Porsgrunn, Norway). A schematic sketch of the rig, which makes up a closed system, can be seen in Figure 1. When the pneumatic conveying rig is operated, bulk material is dispatched from the storage tank and fed into the pipeline by a rotary feeder at a pre-set feeding rate. The pipeline (3.5-inch) consist of both horizontal and vertical sections as well as several bends. At the end of the line, the material is collected in the receiving tank, from which it can be transported back into the storage silo. The receiving tank is installed on top of three load cells. Readings from the load cells can be used to estimate the material flow of the conveying system. Transportation air is supplied by a screw-type air compressor (Ingersoll Rand R110i) combined with an air dryer (Ingersoll Rand D1300IN-A). The air flow rate is controlled manually by a ball valve and monitored by two air flow meters (Yokogawa, YF 108) situated at the start and end of the conveying pipeline, respectively. The pressure drops are monitored by nine pressure transducers (General Electric, UNIK 500 series) distributed along the pipeline.

In previous tests conducted in the pneumatic conveying rig, several areas where severe erosion occur were identified. One of these areas, the exit of a 90° bend, was selected as the test area for this study. The position of the test area is marked in Figure 1. In the test area, the pipe was fitted with a customized flange such that the outer wall of the pipe bend could be detached from the pipeline. The detachable part of the pipe bend will hereafter be referred to as the test piece. By removing and weighing the test piece, reference measurements of the erosion of this part of the pipe could be obtained. An image of the test piece can be seen in Figure 2.

2.2 Active acoustic monitoring method

A newly developed version of acoustic chemometrics, the active method involves exciting a system by an acoustic input signal. The acoustic signal will be changed by the system in a way that is affected by some of the systems physical properties. Thus, such altered acoustic signals contain latent information about system characteristics. Altered acoustic signals are measured as output signals from selected locations in the system. The measured and processed output signals are referred to as acoustic spectra. In order to extract information from the acoustic spectra, models which relates the measurements to the properties of interest must be calibrated.

Piezo elements (Murata, 7BB-20-6L0) were used both to send the input signal and to measure output signals in the study. The piezo elements (one transducer and two sensors) were attached to the test piece and their cables were taped to the same surface to avoid vibrations which could disturb the measurements. The set-up of the transducer and sensors can be seen in Figure 2.

A function generator (Escort ECG-3230) was used to create the input signals, which consists of a square waveform sweep function of linearly increasing frequency (0-200 kHz) and constant amplitude. Simultaneously, the frequency response of the sweep function was monitored as output signals by the two sensors. The output signals were amplified by a signal adapter (SAM, Applied Chemometrics Research Group, University of South-Eastern Norway) and then sent through a bandpass filter to avoid aliasing. Subsequently, A/D conversion was conducted by a DAQ-unit (National Instruments). The signals were filtered by a Blackman-Harris window to avoid spectral leakage and transformed from the time domain to the frequency domain by a Fast Fourier Transformation (FFT). A PC with specialized LabVIEW software (National Instruments) was applied for the data acquisition.

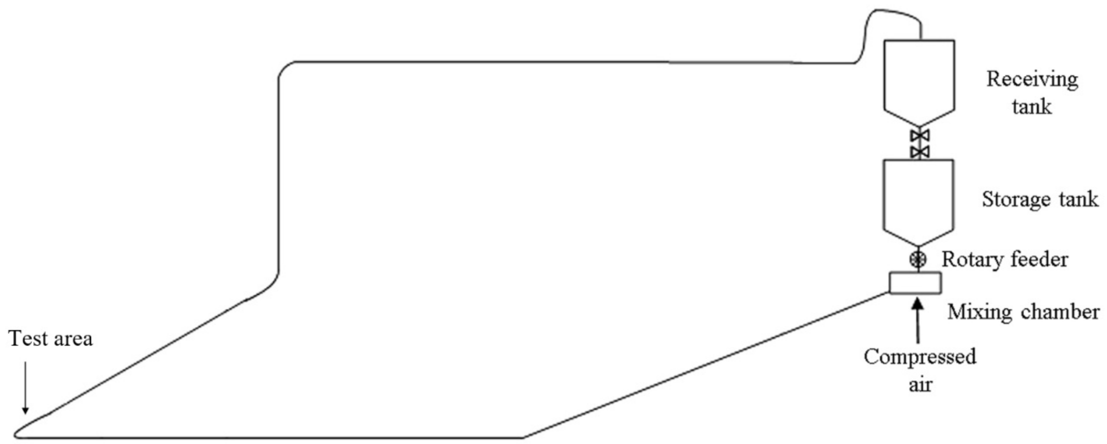

Figure 1. Schematic overview of the pneumatic conveying system.

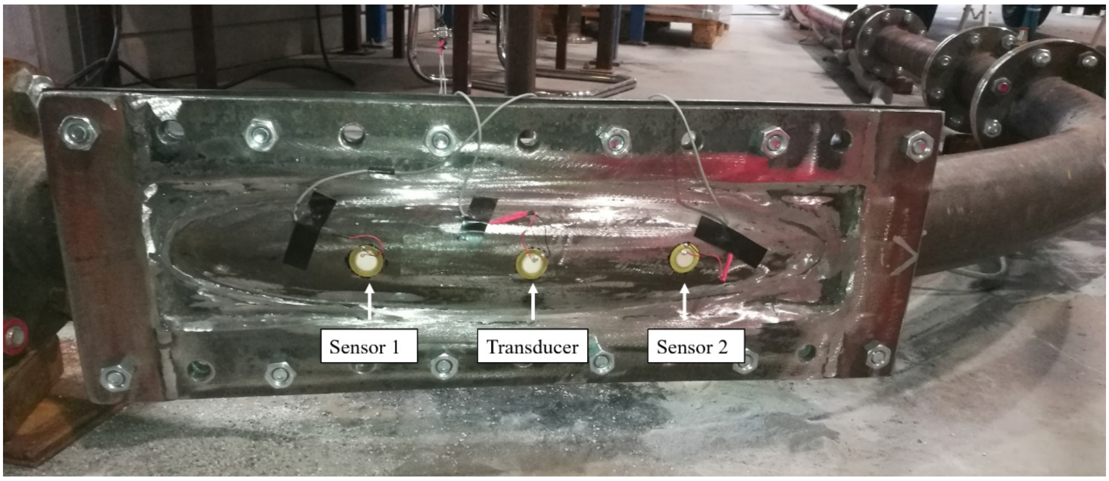

Figure 2. Photography of the test piece with transducer and acoustic sensors.

2.3 Test procedure

Due to its abrasive nature, sand was selected as the material to convey. A 50:50 mixture (approx. 550 kg) of two different sand qualities A and B (Sibelco Nordic AS) was added to the storage tank. The two qualities were mixed in order to get a steady flow through the pneumatic conveying system. The size ranges of the sand qualities are given in Table 1.

Table 1. Size ranges of sand qualities.

Sand quality	*Size range (mm)*
A	0.4-1.0
B	1.0-2.5

To operate the pneumatic conveying rig, the air inlet valve was opened to start air flow before sand was introduced from the storage tank to the pipeline through the rotary feeder. When the desired test conditions had been achieved and the dilute phase transportation of sand had reached steady state, three replicate measurements were obtained by the acoustic sensors. After all the sand had been conveyed from the storage tank to the receiving tank, the pipeline was flushed to remove any remaining material from the pipeline. Subsequently, the pneumatic conveying system was shut down and three additional replicate measurements were obtained by the acoustic method during the system downtime. Finally, the material was transferred back to the storage tank. The procedure was repeated multiple times. An overview of the test conditions is listed in Table 2.

Table 2. Overview of test conditions.

Inlet air flow rate [Nm^3/h]	300-320
Air temperature [°C]	15-20
Solid mass flow rate [kg/s]	0.2-0.3
Solid loading ratio	0.9-1.5
Reynolds number	$1.1*10^4$-$1.2*10^4$

Reference measurements of the erosion as the loss of mass from the test piece was obtained approx. for every 2 tons of sand transported past the test area. To get a reference measurement, the test piece was detached from the pipe bend and weighed. Then the test piece was reattached to the pipeline and pneumatic conveying of sand was resumed.

2.4 Data analysis

Two datasets were prepared from the measurements, one containing the acoustic spectra obtained during operation of the pneumatic conveying system and the other consisting of the measurements collected during system downtime. In each of the datasets, the acoustic spectra were arranged in a matrix **X**. In **X**, every row contains a measurement and every column represents a frequency of the acoustic spectra. The reference values associated with each spectrum were placed in the corresponding rows of a response vector **y**. The variables in the datasets were mean centered and scaled to unit variance prior to the data analysis.

2.4.1 Latent variable matrix decomposition

In many cases, multivariate data is colinear. That is, many of the variables the matrix **X** are related to and influenced by some common factors. Thus, the data in **X** can be expressed by a smaller set of components, sometimes referred to as latent variables. Each latent variable is represented by a score vector **t** and a loading vector **p** and can be constructed by linear combinations of the original variables in **X**. There are several different strategies which can be applied to decompose a matrix into latent variables, of which the NIPALS algorithm is the standard choice. This approach is based on an iteration process of successive orthogonal projections as described in Equations 1-3 (Kvalheim 1987).

First, a weight vector $\mathbf{w}_a$ is defined and a score vector $\mathbf{t}_a$ is calculated by projecting the rows of $\mathbf{X}_a$ onto the weight vector as described in Equation 1.

$$\boldsymbol{t}_a = \boldsymbol{X}_a \boldsymbol{w}_a \quad (1)$$

Next, the columns in $\mathbf{X}_a$ are projected onto the score vector to calculate the loading vector $\mathbf{p}_a$ as stated in Equation 2.

$$\boldsymbol{p}_a = \frac{\boldsymbol{t}_a^T \boldsymbol{X}_a}{||\boldsymbol{t}_a^T \boldsymbol{X}_a||} \quad (2)$$

Finally, the part of the $\mathbf{X}_a$ matrix which is described by the component represented by $\mathbf{t}_a$ and $\mathbf{p}_a$ is subtracted from $\mathbf{X}_a$ as described in Equation 3, for which $\mathbf{X}_1 = \mathbf{X}$.

$$\boldsymbol{X}_{a+1} = \boldsymbol{X}_a - \boldsymbol{t}_a \boldsymbol{p}_a^T \quad (3)$$

The steps expressed in Equation 1-3 are repeated for $a = 1,2, \ldots, A$, where $A \leq \text{rank}(\mathbf{X})$. Typically, **X** can be closely approximated by a model constructed from only a few components, that is $A << \text{rank}(\mathbf{X})$. Thus, the matrix decompositions can lead to a significant reduction of dimensionality and simplify interpretation of the data. Accordingly, the **X** matrix is decomposed into an information part (represented by the *A* components) and a noise part (the **E** matrix) as expressed in Equation 4.

$$\boldsymbol{X} = \boldsymbol{t}_1 \boldsymbol{p}_1^T + \boldsymbol{t}_2 \boldsymbol{p}_2^T + \cdots + \boldsymbol{t}_A \boldsymbol{p}_A^T + \boldsymbol{E} \quad (4)$$

2.4.2 Partial Least Squares Regression (PLS-R)

Partial Least Squares Regression (PLS-R) is a multivariate calibration method based on latent variable matrix decomposition. In PLS-R, the target is to find a matrix $\boldsymbol{\beta}$ which relates the predictor variables in **X** to the response variable **y** and minimizes the error $\boldsymbol{\epsilon}$ in Equation 4.

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \quad (5)$$

In PLS-R, the weights **w** are defined as stated in Equation 6.

$$\boldsymbol{w}_a = \frac{\boldsymbol{y}_a^T \boldsymbol{X}_a}{||\boldsymbol{y}_a^T \boldsymbol{X}_a||} \quad (6)$$

As a consequence of the definition of the weights **w**, the matrix decomposition in PLS-R is guided by a criterion maximizing the covariance between the predictor variables in **X** and the response **y**. Thus, the PLS components will contain relevant information to describe the relationship between **X** and **y** (Martens and Næs 1989).

2.4.3 Cross-validation

In cross-validation, the *n* measurements in a calibration dataset is split into *s* segments of similar or equal size, where $s = 2, 3, \ldots, n$. The distribution of measurements into segments can be done randomly or by some dedicated method. One by one, each of the segments are held out while a sub-model is calibrated based on the remaining measurements. The measurements in every left-out segment are used to test the corresponding sub-model. For the left-out measurements, $\hat{\mathbf{y}}$-values are predicted by the calibrated sub-model (Filzmoser 2009). The root mean squared error of cross validation (RMSECV) is calculated by comparing every $\hat{\mathbf{y}}$-value to the corresponding reference **y**-value as stated in Equation 7.

$$RMSECV_a = \sqrt{\frac{\sum_{i=1}^{n} \left(\hat{\boldsymbol{y}}_{a,i} - \boldsymbol{y}_i\right)^2}{n}} \quad (7)$$

A RMSECV value is calculated for every component *a* and can be used to evaluate how many components should be included in a model. There are several versions of cross validation, differing by the selected number *s* of segments applied.

The case where $s = 2$ is considered to be the ideal version of cross-validation and should only be used when the calibration set contains a high quantity of measurements. This method is somewhat similar to test set validation, the latter a validation method where an independently collected test set is used to validate a model (Esbensen et al. 2001). There are multiple ways of combining the *n* measurements into two segments. Thus, the model statistics resulting from using the 2-segmented version of cross-validation will vary to some extent depending on how the measurements in the calibration set are distributed into the two sections.

Leave-one-out (LOO) is another version of cross validation, for which $s = n$, meaning that every measurement in the calibration set is left out once while a sub-model is calibrated based on all other measurements. Although much used in the literature, this method is considered the weakest form of cross validation (Esbensen et al. 2001). However, since there is only one possible way of distributing the *n* measurements into segments for LOO, the model statistics resulting from using LOO will not vary based on sample selection as was the case with the 2-segmented version of cross validation. Consequently, the LOO cross-validation method is well suited for conducting relative comparisons of the performance of models calibrated from similar data obtained under different process conditions.

3 Results

In Figure 3, the measured values of loss of mass from the test piece are plotted against the mass of sand transported through the pneumatic conveying system.

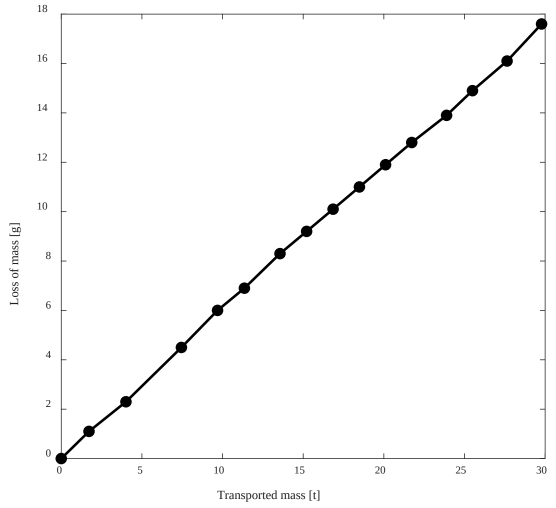

Figure 3. Erosion as loss of mass from test piece.

As can be seen from Figure 3, erosion of the test piece occurred by a steady rate throughout the study. Based on the data in Figure 3, reference values for every obtained acoustic measurement were calculated.

To evaluate the feasibility of the acoustic method for monitoring of erosion in a pipeline, the 2-segmented version of cross-validation was used when calibrating models from the measured data. Several plots describing one of these models, which was calibrated from the measurements obtained during powder transportation, are shown in Figure 4 to Figure 7.

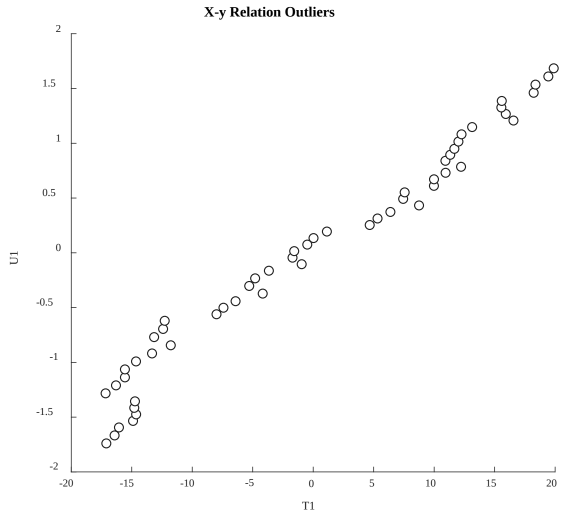

Figure 4. X-y Relation Outliers plot.

Figure 4 shows a X-y Relation Outliers plot which can be used for outlier detection. The measurement points should form a relatively straight line in a X-y Relation Outliers plot, and any points deviating significantly from the line can be considered as outlier candidates. In Figure 4, it can be seen that most of the points falls close to a straight line. A few points in the lower left corner of Figure 4 deviates from the rest to some extent. The deviating points correspond to some of the first measurements obtained in the study, when very little erosion had occurred. Thus, it is not so surprising that the points are somewhat different from the rest. Since it was assumed that the outlier candidates were correctly obtained measurements representing special conditions in the test area, they were not removed from the dataset.

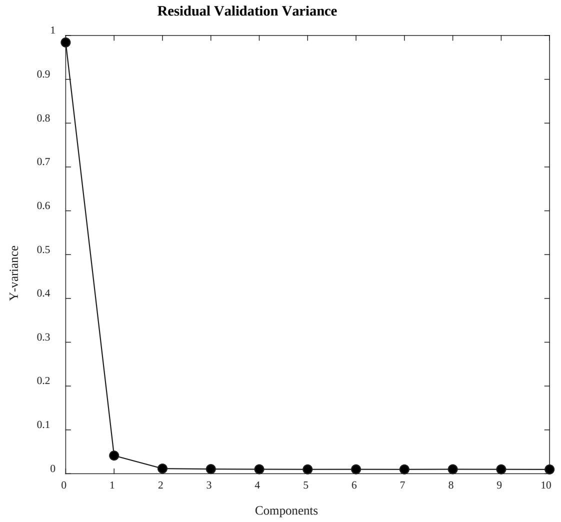

Figure 5. Residual Validation Variance plot.

In Figure 5, a Residual Validation Variance plot showing the variance in the response vector **y** which is explained by adding components to the model is shown. Such plots can be used to decide the number of components which should be included in a model to be able to describe the relevant variations in a dataset without overfitting the model. Based on the plot in Figure 5, it was decided to include two components in the model.

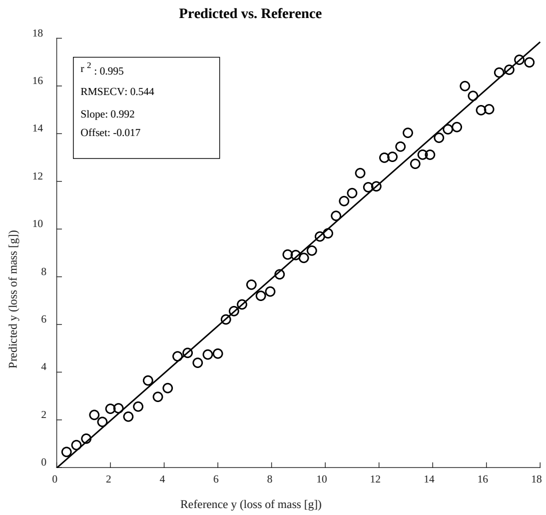

Figure 6. Predicted vs. Reference plot.

The measured reference values are compared with the corresponding values predicted by the calibrated model in Figure 6, which also include some model statistics describing the model. The RMSECV error has the same unit as the **y**-values. The relatively low RMSECV-value together with the r^2-value, slope and offset of the line fitted to the points in Figure 6 shows that the two sub-models calibrated as part of the cross validation could predict the held-out values with good precision.

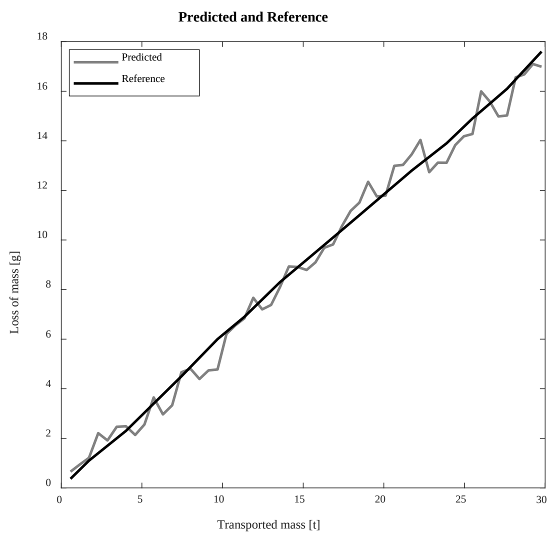

Figure 7. Predicted and Reference plot.

From Figure 7, in which the reference values are plotted together with the values predicted by the model, it can also be seen that there is generally a good correspondence between the predicted values and the reference values. After considering the plots in Figure 4 to Figure 7 together with the model statistics given in Figure 6, it can be concluded that the acoustic method holds good promise as a monitoring method for erosion in a pipeline. There is a clear structure in the measured acoustic data which can be related to erosion through calibrated PLS-R models. To estimate the magnitude of the prediction error which should be expected when the acoustic method is used to predict new values **y** based on new measurements **X**, test set validation against a new and independently measured dataset should be performed in future work.

In order to compare how well the acoustic method performed for monitoring of erosion while sand was transported through the pipeline with the case where the pneumatic conveying system was shut down, two additional models were calibrated. One model was based on data obtained during powder transportation and the other on measurements conducted during system shutdown. The leave-one-out version of cross validation was used in the model calibrations to facilitate objective comparison of the two situations. Model statistics describing the resulting models are listed in Table 3.

Table 3. Model statistics for LOO cross validated models.

Model	*Powder transport*	*System downtime*
r^2	0.991	0.996
RMSECV	0.485	0.439
Slope	0.979	0.981
Offset	0.180	0.162

From Table 3, it can be seen that the model based on the measurements which were obtained when the pneumatic conveying system was shut down gave slightly better model statistics and lower error than the model calibrated from data measured during powder transportation. However, the differences are minimal, showing that the acoustic method is not significantly affected by noise from the system during powder transportation.

Further work is needed to test the effect of factors like temperature changes, variating flow conditions, on the performance of the method. Model should be made from measurements obtained for conditions spanning/representing the range of conditions in a specific industrial site. Scaling, heat expansion

4 Conclusions

In this study, the feasibility of an acoustic measurement technique for monitoring of erosion in dilute phase pneumatic conveying was evaluated. Results indicated that the method holds good promise for monitoring of erosion in pneumatic conveying pipelines. A clear structure in the data which could be related to erosion through PLS-R models was found. Also, it was found that the acoustic method was not significantly affected by noise and vibration generated by the pneumatic conveying system during transportation of material through the pipeline.

Acknowledgements

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