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Size Differentiation Of A Continuous Stream Of Particles Using Acoustic Emissions

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Abstract. Procter and Gamble (P&G) require an online system that can monitor the particle size distribution of their washing powder mixing process. This would enable the process to take a closed loop form which would enable process optimisation to take place in real time. Acoustic Emission (AE) was selected as the sensing method due to its non-invasive nature and primary sensitivity to frequencies which particle events emanate. This work details the results of the first experiment carried out in this research project. This experiment involved the use of AE to distinguish between the sizes of sieved polyethylene particle (53-250microns) and glass beads (150-600microns) which were dispensed on a target plate using a funnel. By conducting a threshold analysis of the impact peaks in the signal, the sizes of the particles could be distinguished and a signal feature was found which could be directly linked to the sizes of the particles.

1. Introduction and Problem Statement

Procter and Gamble (P&G) have certain quality standards that need to be upheld before their washing powder product can be sold. These checks comprise of a wet chemistry test to determine solubility properties, inspect the chemical properties of the powders and physical inspection to determine the particle size distribution. These methods are slow and reliant on human error and as a result this has given rise to the need for in-process monitoring sensors which would help apply a control loop to the process. This research will focus on the use Of Acoustic Emission (AE) sensors to estimate the size distribution of the powders online. Due to the size ranges of the particles being monitored (63-1000microns) and noisy production workspace, acoustic sensors in the ultrasonic region are used in this research as they are primarily sensitive to frequencies which particle events occur. [1]

2. Related Works Summary and Knowledge Gap

AE has been used previously to monitor the sizes of particles and in some case was used to estimate the overall flow rate of the particles.[1][2] Leach et al conducted pioneering studies using an ultrasonic microphone and a rotating drum, and he was able to establish a linear correlation between particle size and AE.[3] Buttle et al used a quantitative sizing technique that comprised of a deconvolution technique to estimate the sizes of particles falling on a target plate due to the deconvolution required the technique would struggle to work in real-time.[4] Ivantsiv et al designed a model capable of estimating particle size and mass flow rate, although his system was designed to work offline. [1] Papp et al investigated offline the relationship between the changes in size of particles with the change in

AE occurring during a granulation process. Her results showed that an inverse relationship existed between the AE frequency and particle size. [5] Neural networks were used by Bastari et al and Chen et al to classify different sized particles online, despite being able to perform a classification on the particles no indication of the physical behaviour of the process can be deduced with this system. [6][7] Hu et al designed an online model that linked the AE output voltage to particle size, his model was unable to detect particles smaller than 90microns and this was attributed to the overall signal noise in the process. [8] Ren et al used the wavelet transform to estimate the respective energies of differently sized particles and used this approach to estimate the mass fraction of the various particles in a mixture. [9] Although using Ren's model to estimate the size distribution of a mixture with different particle sizes, would lead to a very large and complex algorithm thereby slowing online computation time.

Comparing this signal processing architecture to the existing systems in literature, Bastari et al and Chen et al designed online particle classification systems using a data driven approach, this method would not suffice in this research problem as further information about the process behaviour cannot be inferred from a data driven system.[6][7] In terms of a more hybrid signal processing approach, Ren used the wavelet transform to identify particle size distribution online, but due to the algorithm complexity, a high model computation time would be required which would not be acceptable for a process which is aimed at being optimised online.[9]

In this research we would be looking to design for the first time, a hybrid signal processing model capable of identifying particle size distribution online. The work carried out in this report details the first experiment taken to design an online particle size distribution estimation model.

3. Research Methodology

The design space approach is being employed as the research methodology as it helps in the understanding of how a product behaves under various process conditions.[10] A designs space approach is a useful tool used to help comprehend the interaction between input variables and process parameters, and how they influence final product quality. [10] It is also useful in developing a versatile process which can comfortably deal with variability in input materials and process parameters. [10] A supporting statistical method used in conjunction with the design space approach is the Design Of Experiment (DOE).[12] Supporting the experiments with statistics helps in tracing root causes of variability and also distinctions between causal and correlative relationships. [11]This research problem would be investigated with the Design Space Approach and supported with the DOE technique.

4. Experimental Details

The washing powder compound comprises of an array of different particles types, so in order to simplify the problem a single experimental particle type was chosen and sieved into different seizes. This experiment detailed here involved the differentiation of particles of various sizes using their AE signal. This experiment would serve as the first stage in helping to solve our research problem of identifying the size distribution of a compound that comprises different sized particles. For this experiment, Medium Density Polyethylene and acid washed glass beads were used as the experimental particles.

4.1. AE Sensors

The sensor used was the PCI-2 Physical Acoustic sensors by Mistras. The sensor bandwidth spans from 100K-1MHz and a sampling rate of 1Ms was used during the acquisition. Figure 1 shows the block diagram of the signal processing chain. The acquired signal goes through a preamplifier before being sent through a band pass filter. This filtered signal is sent to the Analogue to Digital Converter where this signal is digitised and passed to a Field Programmable Gate Array(FPGA) where sampling and signal averaging takes place. The final digitised waveform is continuously streamed to the hard-disk of the computer. [13]

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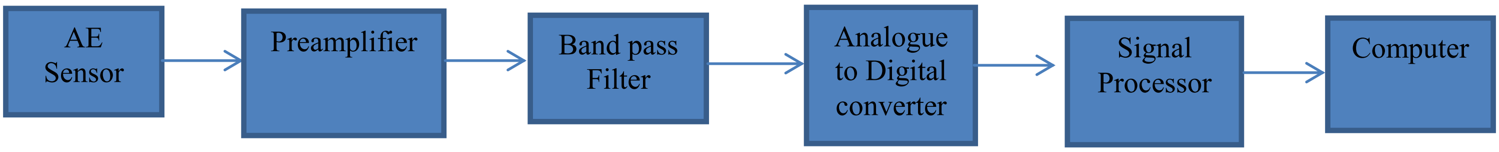

Figure 1: Block Diagram Of The Signal Processing Chain

4.2. Experimental Setup

Figure 2 shows an image of the experimental setup used here. It comprises a funnel of dimensions 8x11x18mm^3 and an Aluminium sheet of 0.7mm thickness with the sensor attached at the back of the plate using beeswax adhesive as this ensures a secure but gentle coupling between sensor and surface. A funnel was selected as part of the experimental setup in to ensure repeatability in the dispensation rate of the powders. The funnel exit was blocked using a finger while a measured mass of powder was poured into it. Then the finger was removed and the full powder mass was dispensed on the target plate through the funnel and the acoustic emissions were recorded. Assuming there are no sources of interferences,(through humidity, temperature and electromagnetic sources) by having a repeatable source, maintaining a constant height, and keeping the plate thickness constant throughout the experimentation, the variable being measured becomes the mass/size of the particles of interest. [2]

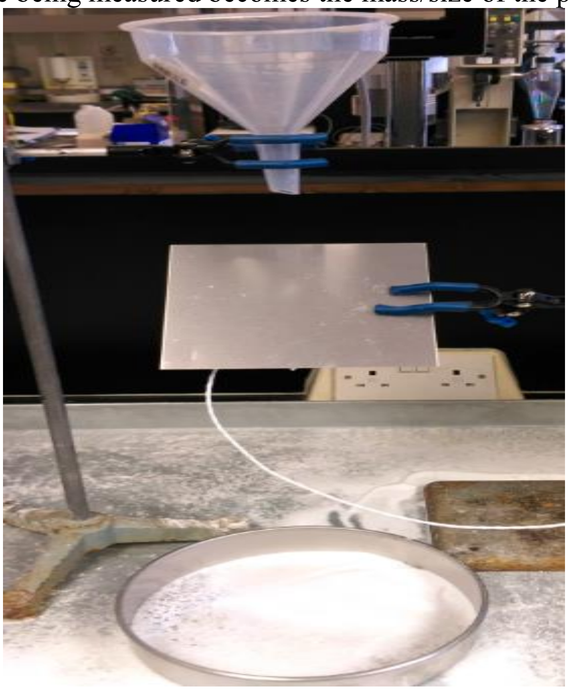

Figure 2: Final Experimental Setup

4.3. Powder Sieving

To further reduce experimental variability, the polyethylene powders were sieved into narrow size distribution bands by means of dry sieving as shown in Table 1 using an Endecotts layer sieve with an aperture size range from 53-1000microns. The glass beads came in pre-sieved classes so further sieving was not required for the particles.

Table 1: Particle Class Information.

Particle Type	Particle Class	Size Distribution	Average Mass In Grams(g)	Bulk Density In g/cm^3
Polyethylene	Class1	151-250microns	0.0047	0.3435
	Class2	126-150microns	0.00053	0.2522
	Class3	64-125microns	Particles could not be separated	0.2158

	Class4	53-63microns	Particles could not be separated	0.2113
Glass Beads	Class1	150-212microns	0.0049	1.5850
	Class2	425-600microns	0.1578	1.5938
	Class3	212-300microns	0.0091	1.5910

4.4. Environmental Scanning Electron Microscope Images
To produce the size distribution of each particle class, 10mg was taken from each class and viewed under the electron microscope .This was repeated six times and each time five particles were isolated and their dimensions(length and width) were measured.

4.4.1. Polyethylene Particles
Figures 3 show Environmental Scanning Electron Microscope (ESEM) image of the class 4 polyethylene particles. It can be observed that the polyethylene particles are highly irregular shaped.

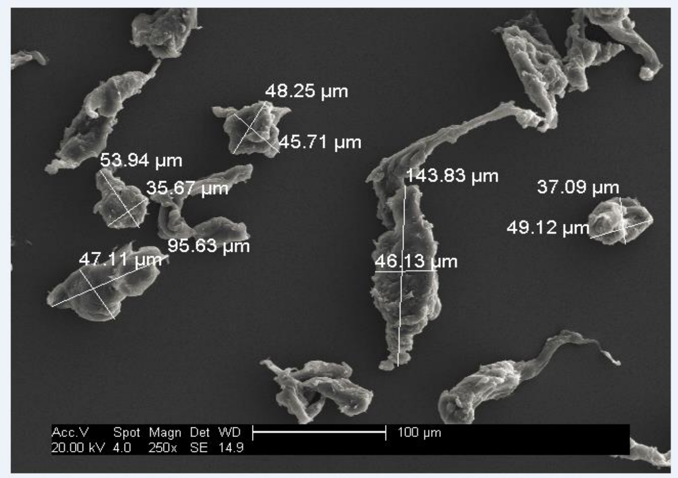

Figure 3: Class 4 Particles (53-63microns)

Due to the apertures of the sieves being square and the particles being irregular, a generalised mean was calculated by way of the Root Mean Squared (RMS) to the acquired dimensions to produce the histogram in figure 4.

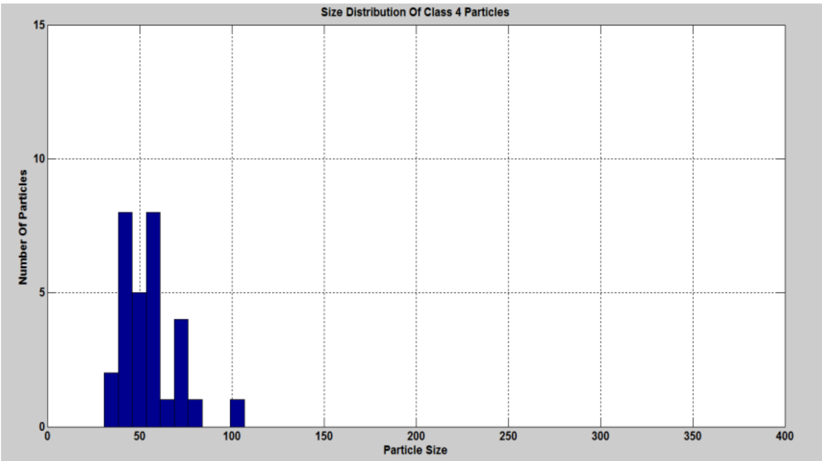

Figure 4: Size Distribution Of Class 4 Particles

4.4.2. Glass Beads

The ESEM image of the class1 glass beads can be seen in figures 5. And unlike the PE particles the glass beads have a tighter distribution and a spherical geometry.

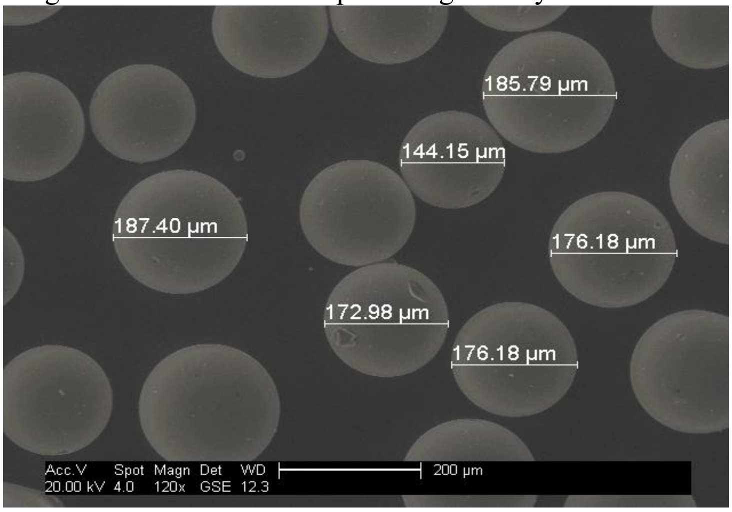

Figure 5: Class1 Glass Beads (150-212 microns)

A respective histograms of the glass bead particles can be seen in figures 6, and in comparison to the PE particles the distribution of the glass beads are within their sieved bands thereby limiting the number of outliers present.

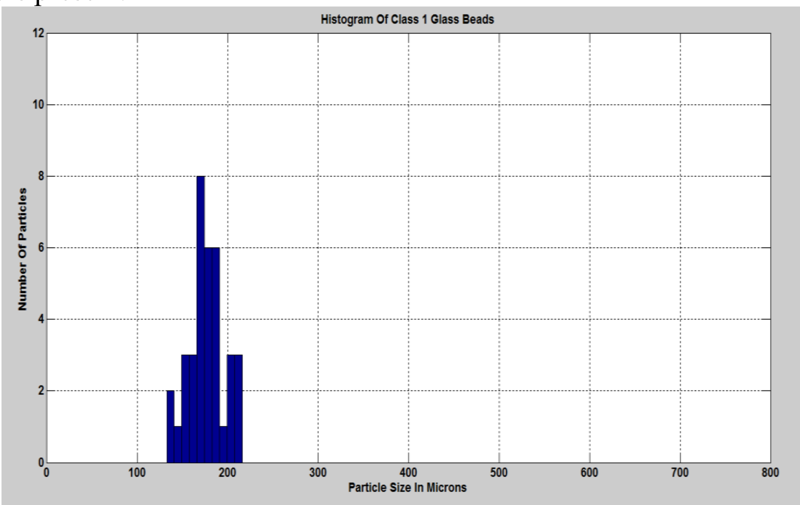

Figure 6: Histogram Of Class 1 Glass Beads

5. Experimental and Data Analysis Procedure

For each particle group, 2g was weighed and dispensed into the funnel while the exit was blocked using a finger as the measured mass of powder was poured into it. This procedure was repeated four times for each particle class. The acquired data was analysed using a thresholding method. This method was used by Hu et al to differentiate particle sizes and also by Ivanstiv et al to not only differentiate particle sizes but also measure flow rate, the thresholding method was chosen due to its simplistic and effective nature [1] [8]

The thresholding method works with the signal shaping chain which can be seen in figure 7, it states that a linear relationship exists between particle size and output sensor voltage. The signal shaping chain was from the pioneering work carried out by Leach et al and validated by Buttle et al. [3] [4] It shows that a convolution between the source function, wave propagation function and instrument response function yields the AE Voltage Signal.

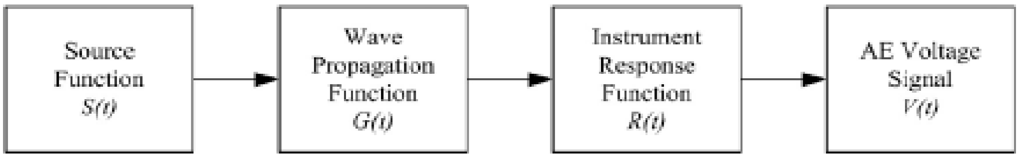

Figure 7: Signal Shaping Chain [8]

When a particle of a certain size drops on a target medium, it gives off an impulse which is related to the size of the impinging particle. This impulse is represented by a peak in the time domain and with a suitable threshold capable of detecting these peaks; particles can be identified and differentiated using their impact peaks.

5.1.1. Designed Threshold Method and Particle Sizing Approach

A varying threshold method was implemented and details of each step can be seen below;
-Step1: Take absolute values of signal to eliminate non-negative signal values.
-Step2: Identify maximum peak from experimental repetitions of the same size particles.
-Step3: Reduce threshold by a factor of 10% each time and take arithmetic mean of peaks above the threshold level.
-Step4: Calculate linear correlation co-efficient for each threshold level (e.g 90%,80%)
-Step5: Select threshold which provides best linear correlation for data

With the dispensation of the particles being through a funnel, this caused the amplitude of the acquired AE signal to vary, this can be seen by the highly varying amplitude of the AE signal in figure 8. So for the data analysis procedure, 20,000 data points were extracted from a section of the data where the flow rate was maximum and constant.

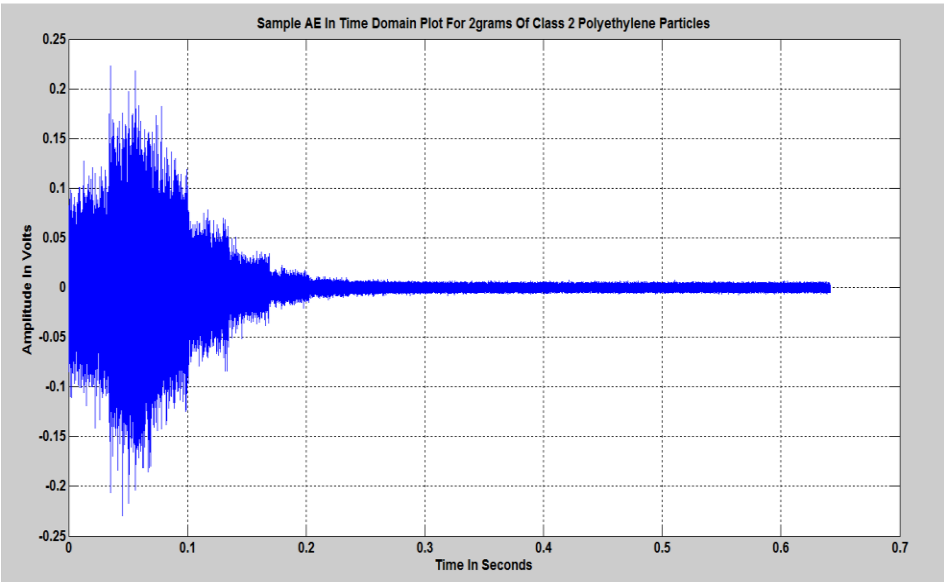

Figure 8: Acoustic Emission Plot Of Class 2 Polyethylene Particles

The plot in figure 9 shows a simple example of an isolated constant segment of 20,000 data points along with an example of how a 60% threshold would work.

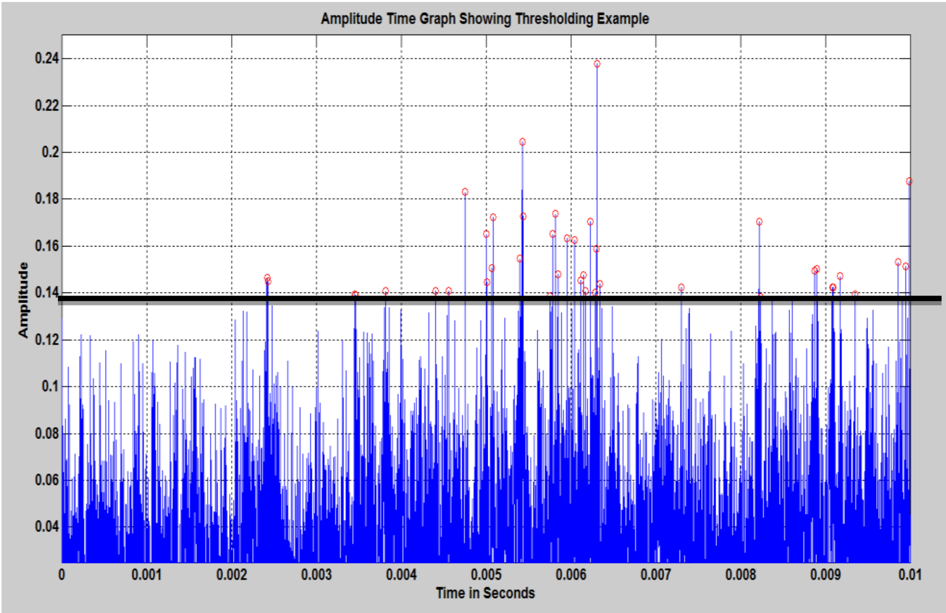

Figure 9: Amplitude-time Graph with a threshold level of 60% (peaks above 0.138)

6. Results

6.1. Polyethylene results

Once the data sections were isolated, the threshold method was applied and the linear correlation coefficient was calculated for each threshold level. The thresholding exercise began with a 90% threshold this reduced by a factor of 10 each time and stopped at the 10% threshold. The threshold varying stopped at the 10% level because below this threshold we would enter the sensor noise region and in order to ensure the best data quality, the selected threshold should be selected to be greater than the noise level. Although for this simple experimental setup, setting the threshold to include the noise would still give a good correlation (greater than 0.90) due to the negligible noise contribution and high signal to noise ratio. But in a more practical rig setup where there may be greater noise contribution, the selected threshold would need to be above the noise level in order to ensure maximum signal to noise ratio.

Figures 10 and 11 show correlation figures of particle size against mean of threshold peaks for 90% and 10% threshold levels, with their respective correlation co-efficient being 0.87 and 0.97. From the correlation co-efficient score, it can be seen that the deepest threshold level(10%) provides the best linear correlation. A possible reason for this could be that the linear correlation increased with the higher number of data points considered.

An explanation for the outliers at the zero mark on the x-axis in figure 10 is due to the maximum peak identification method. For each particle class, the experiment was repeated four times. The maximum possible peak value was identified by inspecting all four repetitions of the experiment, this meant for the high threshold there was the possibility of the particle sizing algorithm to identify zero peaks for some experimental data set.

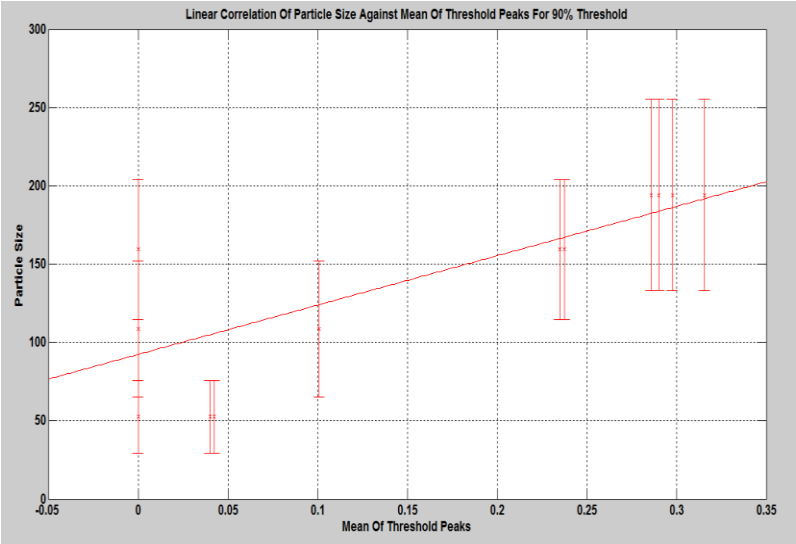

Figure 10: Linear Correlation of Particle Size against Mean of Threshold Peaks For 90% Threshold (correlation factor 0.87)

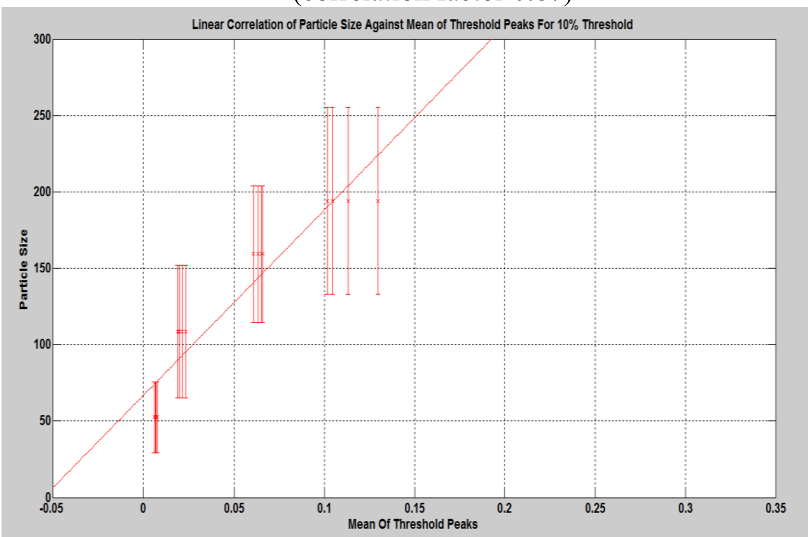

Figure 11: Linear Correlation of Particle Size against Mean of Threshold Peaks For 10% Threshold (correlation factor 0.97)

It can be noted that the mean of threshold peaks showed some variability for the bigger particles, this was due to the wider distribution in the particle class due to sieve sizes. For example, the particles in class 4 ranged from 54-63microns accounting for a variation of 9microns. Whereas the class 1 particles ranged from 151-250microns,which equals a variation of 99microns.

The plot in figure 12 was obtained using the 16 collected data points and it illustrates how the linear correlation between the particle size and mean of threshold peaks increases with the lowering of the threshold level.

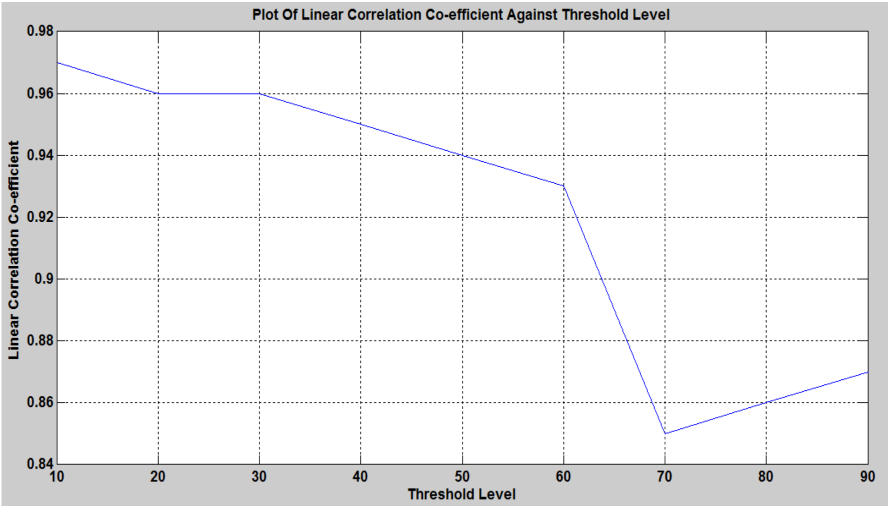

Figure 12: Plot Of Linear Correlation Co-efficient Against Threshold Level

6.2. Glass Beads Results

The threshold analysis was tested with glass beads as validation that the technique can work for more than just one particle type, as the washing powder compound comprises of different types of particles, so it was important to make sure that this technique was not unique to just one particle type. Figure 13 shows a sample AE plot for class 2 glass beads and unlike the polyethylene, the glass beads produced more constant amplitude when the flow was constant.

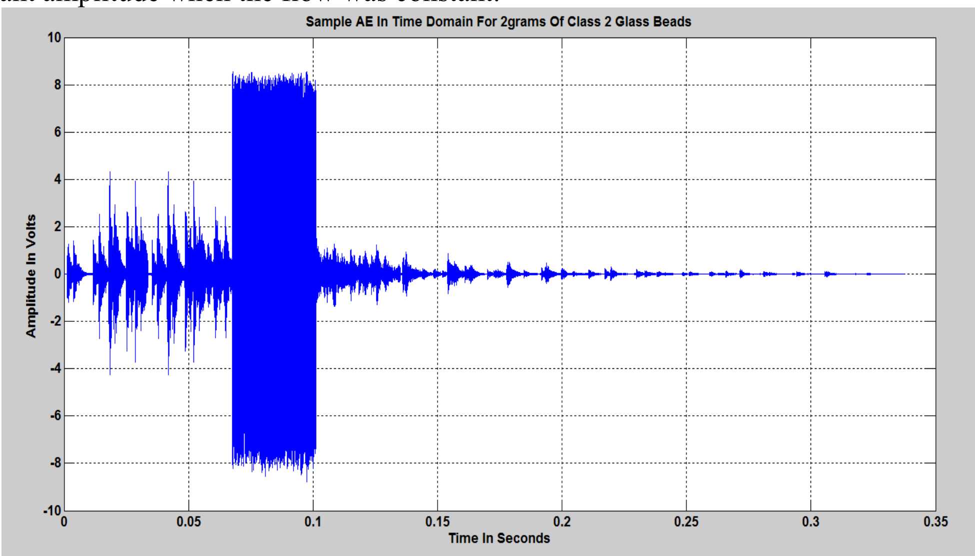

Figure 13: Sample AE In Time Domain Plot For 2g Of Class 2 Glass Beads

The glass beads sizes were classified using the same signal processing method used for the polyethylene and with a 10% of maximum threshold. For each class of glass bead, the dispensation exercise was repeated 5 times each giving a total of 15 data points. For all 5 experimental runs from each particle class and with a 10%, the AE amplitudes were averaged to obtain a representative value for each particle group. A correlation between these values and the median particle size of each class of glass bead was calculated and can be seen in figure 14.

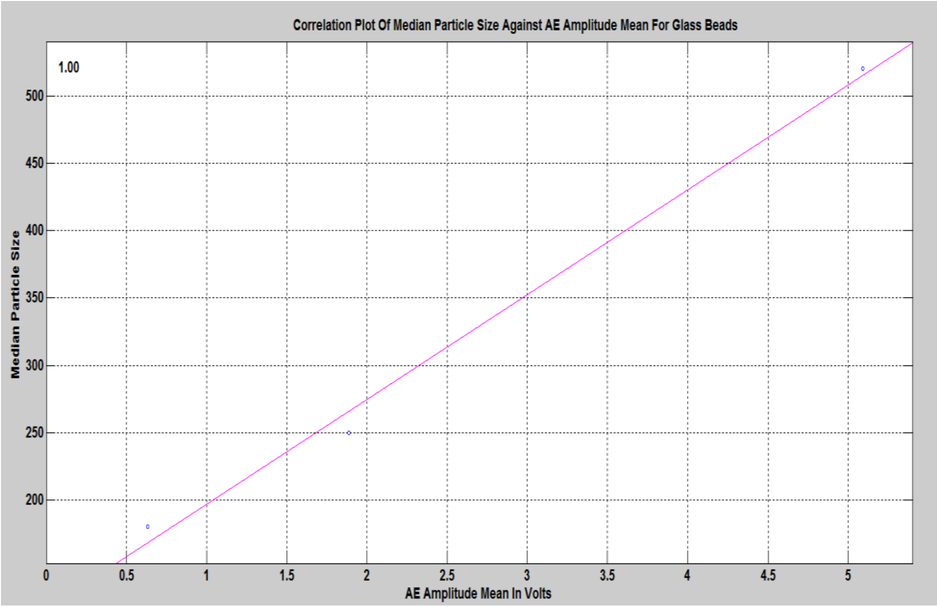

Figure 14: Correlation Plot Of Median Particle Size Against AE Amplitude Mean For Glass Beads(R=1)

From figure 14, it can be seen that a good correlation exist between the median particle size and AE amplitude mean. This would suggest that the signal processing technique can be used to effectively differentiate between particles of various sizes under the same condition used in this experimental setup.

7. Conclusion

From the literature, enough evidence exists to support the assumption that particles sizes can be monitored online. The experiment carried out in this work was aimed at the determination of the particle sizes from their acoustic emissions using sieved sets of polyethylene powder and glass beads. The objective was to successfully differentiate particles of different sizes using their AE and to find a signal feature which was could be directly correlated with particle size. In this experiment, a known mass of particles were dispensed into a funnel which released a continuous stream of particle unto a target plate which an acoustic emission sensor was placed on. By implementing a threshold and evaluating the amplitude of the peaks on each threshold, the particle sizes were distinguishable and the amplitude mean of the threshold were able to be correlated to the various particle sizes. A linear correlation was seen to exist between the AE and particle size, thereby validating the results obtained in previous literature. The next experiment would now involve the mixing of particles of various sizes to see how they interact when in a mixture.

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