The Use of Acoustic Emission to Detect Fines for Wood-Based Composites, Part One: Experimental Setup for Use on Particleboard

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Wood-based composite panels continue to be important in the wood building industry. Particleboard is commonly used for non-structural applications, while oriented strand board (OSB) is commonly used for structural applications. For both types of boards, however, manufacturers are interested in minimizing the presence of small particles or "fines" in the panels. The presence of fines can cause an increase in the consumption of resins as well as an increase in the weight of the board. Fines can be produced when a refiner or chipper blade becomes dull or when the wood raw material becomes excessively dry. There is a need for manufacturers to simply and accurately monitor the presence of fines and control their presence. Acoustic emission (AE) is an elastic or plastic wave generated when a surface is deformed or has an external force exerted on it. This research showed the feasibility of using AE to monitor the presence and percentage of fines in particleboard furnish. The research also showed the effect of the experimental setup on the AE signal level.

Keywords: Particleboard; Fines; Acoustic emission; Process monitoring

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INTRODUCTION

The use of wood-based composites is continuing to grow. Particleboard (PB) competes with medium density particleboard (MDF) and plywood for use in kitchen cabinets, furniture, and other non-strength applications of panel products such as floor underlayment (Stokke *et al.* 2014). Oriented strand board (OSB) competes with plywood for strength applications such as roof sheathing. Newer products such as oriented strand lumber and laminated veneer lumber are beginning to compete with traditional lumber in critical strength applications as well. These composites use smaller diameter trees as well as material that in the past would have been considered a residue or by-product. Wood-based composites continue to improve both in performance properties as well as in their use of environmentally friendly or sustainable adhesives. Work has been conducted on the use of plant-based proteins as adhesives for the wood industry (Khrosravi *et al.* 2010, 2011). These adhesives perform similar to urea formaldehyde-based adhesives, which have limited moisture resistance. Additional research has been conducted into whether plant-based adhesives could have a moisture resistance similar to phenol formaldehyde (Liu *et al.* 2015). This work showed that the use of undecylenic acid (UA)-modified soy proteins resulted in an improved water resistance of 35 to 62% over the control soy-based adhesive. These types of improvements in environmentally friendly adhesives, plus the greater demand on wood fiber, suggest that wood-based composites are an important product category for the building industry.

Improvements have also been made in how panel products are made. Continuous pressing techniques and improved process monitoring/control sensors have resulted in an improvement in the consistency of the resulting panel products. In a wide array of wood-based composites, the size and shape of the fibers, particles, or flakes used is important, as these factors affect the properties and performance of the final panel product (Maloney 1993). Other factors affecting panels include wood species, type and amount of binders, and the presence of other additives. Parameters such as board structure as determined by mat forming, layering, and the pressing conditions also affect the board properties. As Maloney (1993) states, however, particle geometry is one of the main parameters in determining board properties. Considerable work has been conducted to understand the optimum processing parameters, such as knife angle, processing speed, and grain angle (Pfeiffer *et al.* 2015), and how they affect final chip geometry. Stiglbauer *et al.* (2006) found that as the blade angle decreased, additional small, broken chips, or flakes are produced. These small broken flakes or particles are called "fines". A decreased blade angle is consistent with blade wear. Nati *et al.* (2010) investigated the production of chips from both poplar and pine in the field for use as energy. They found that blade wear resulted in a reduction of chip quality and increased fuel consumption for the chippers. They also found an increase in the volume of fines generated when using small pine logs. In the Stiglbauer *et al.* (2006) study, fines were defined as the material falling through screens with 0.125-inch (3.125-mm) openings. The generation of fines is influenced by species, material temperature, moisture content, and machining parameters. Species that have a lower fracture strength will generate more fines, as will wood with a lower moisture content or temperature; thus, the generation of fines in a processing plant can be seasonal. An increase in fines in wood-based composites normally results in increased consumption of resins and final board weight and reduced overall panel strength (Stiglbauer *et al.* 2006). An increase of fines, however, is often desirable in the surface of some panel products to increase surface quality.

The techniques for separating out the size and shape of the furnish, however, remain mostly unchanged (Maloney 1993). Particles and flakes are typically separated by screens, air classification systems, or both. Periodic observations of the screens can help quality control personnel determine if the production of fines is increasing or not. Currently, the process monitoring tool used for the production of fines in a flake or chip manufacturing process is an ampere or power meter attached to the refiner or chipper. This approach is not very sensitive to slight blade wear but will detect major blade wear or blade failure. What is desirable is an on-line process monitoring technique that will allow the quality control personnel or production manager to determine the degree of production of fines in their process.

In a study by Hartmann *et al.* (2006), five different horizontal and three rotary screening devices were tested and compared along with different screen hole diameters. The screening results were measured by volume (length, width, and thickness) with a digital caliper and by weight. These measurements were also compared to the results from a commercially available continuous measuring image analysis device. The results showed that while the screening techniques were all comparable for some of the measurements, the length classifications by both the screening process and the image analysis system were often in error. The misclassification was due to long strands being able to go through screens lengthwise. The image analysis, while being more accurate than the manual techniques, was still sensitive to particle overlap. The gravimetric and the volume method are indirect methods where the particles are first separated into size categories, which are then converted into mass categories by weighing. These methods assume consistent density regardless of size, so any variation in density or even moisture content can affect the accuracy of the method. The optical method was not affected by density variations but, as mentioned before, can be affected by particle overlap when used continuously online. Igathinathane *et al.* (2009) showed that machine vision could yield a particle size distribution for wood and other biomass without the need to use screening when attempting to separate material based on length. While great advances have been made in machine vision in recent years, there is not a standard system in use to monitor the size of wood flakes or particles.

The need to classify and separate particles is not unique to the wood industry. One promising technique for monitoring the size of particles in the powder industry is acoustic emission (Leach *et al.* 1977). Acoustic emission (AE) is defined as the elastic energy that is spontaneously released when a material undergoes deformation (Miller and McIntire 1987). Acoustic emission consists of low intensity, high frequency (100 KHz to 1 MHz) elastic waves that propagate in all direction through a structure. When these elastic waves strike an AE sensor, which contains piezoelectric material, the mechanical energy is converted to electrical energy that can then be amplified, filtered, and processed. The decaying signal (Fig. 1) can then be quantified by a number of waveform descriptors such as energy, peak amplitude, and signal duration.

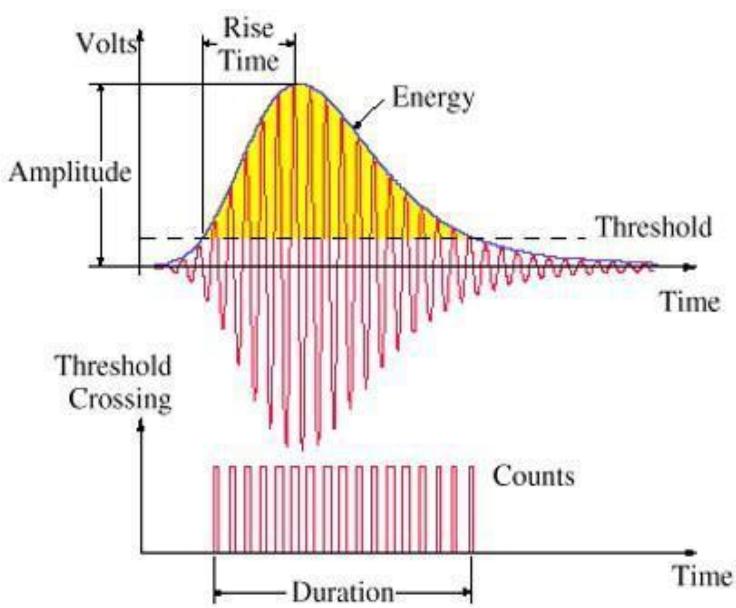

Fig. 1. Example of acoustic emission signal with common waveform descriptors (Ramasso *et al*. 2012)

The main disadvantage of AE-based techniques is that the defect or flaw must be active. Acoustic emission has been used extensively in the petrochemical and nuclear power industries to monitor cracks in pressure vessels. In the 1980s, considerable research was conducted on the use of AE monitoring techniques (Drouillard and Beall 1990). Though the technique showed promise in a number of areas in the wood industry, and a number of commercial products were marketed for the industry, AE monitoring never truly caught on in the wood industry.

Previous studies have shown that when a material such as powder or particles strikes an AE sensor, the signal generated is related to the material properties, including size, weight, and velocity. By keeping the velocity of the material striking the surface constant, an indirect descriptor of the material may be obtained. In early work by Leach *et al.* (1977), AE was used to determine particle size and distribution in powders of rigid particles. They compared spheres of the same diameter but different materials, spheres of different radii but of the same material, and spheres of different radii and different materials. Investigators in this study did not have the limitation of having to classify each individual sphere to demonstrate that each category of spheres had different AE signal characteristics. This work showed that the AE signals generated from a relatively large number of spheres were fundamentally similarly to the AE signals generated from individual spheres. As an erosion test, Droubi *et al.* (2015) used particles in a water slurry stream striking a material with an AE sensor to measure the energy dissipated upon striking the target. The results of this study, while showing differences in AE signal levels between water and slurry, showed lower than predicted energy striking the target. The AE energy was linear to particle concentration and scaled to the cube of particle size. An earlier study by Shen *et al.* (1997) used AE sensing and a neural network to determine the effect of cutting advancement in coal on the amount of coal dust (fines) produced. Though they found more classifiers were needed to build a reliable neural net model, it was determined that more fines were generated at slower cutting advancements than when advancing more quickly into the coal. In a study by Boschetto and Quadrini (2011), acoustic emission was used to measure particle size properties for steel, cast iron, and alumina powders. This study showed satisfactory results between AE signal levels and size (weight and diameter) for steel and iron powders. For alumina powders good trends were only observed for large particles and high-weight differences.

The work reported on here is a refinement of a study conducted previously by Lemaster (1994). In the original study, AE was used to classify wood particles and flakes. The study showed that more sample waveforms resulted in less variability in the resulting data. In this study, a small sample of the wood material was dropped onto a target that had the AE sensor attached. The sample was dropped either by placing it on a trap door and dropping it all at once or by sliding the material down a small slide onto the target. The current study used a target placed inside a cement mixer filled with the wood particles or flakes that rotated, allowing the material to fall onto the sensor and then slide off. This simulated flakes or particles coming down a conveyor or pipe. This allowed for a high number of samples, which reduced the variation in the technique. The study was conducted in two parts. The first part, which is reported here, optimized the experimental procedure by determining the best frequency of signal to use as well as the best AE signal descriptor to use. This study used particleboard furnish. The second part of the study (Edwards *et al.* 2018) evaluated the ability of the technique to characterize flakes and detect the percentage of fines in the mix.

EXPERIMENTAL

The objective of this study was to determine the feasibility of using acoustic emission (AE) for monitoring the percentage of fines in a mix of wood particles. Furthermore, the objective included determining the optimal experimental setup for such a study. The series of tests included: (1) the effect of sensor type (frequency and resonant versus wide band) and AE waveform descriptor, (2) the effect of the length of the data collection and collection exclusion window, (3) the effect of target angle to AE signal level, (4) the difference between core and surface panel material on AE signal, and (5) the sensitivity of system to percentage changes of fines in both surface and core material.

Materials

A simple homeowner-type electric cement mixer was used to tumble chips inside and allow them to fall onto a target with an AE sensor attached. Figure 2 shows a close up of the cement mixer with the AE target in position. The cement mixer used was a ½ hp Proforce™ electric mixer. The mixer had two shelves or fins inside the tub; for each revolution of the tub, there were two series of drops of chips onto the AE target. The tub rotated at 50 revolutions per minute.

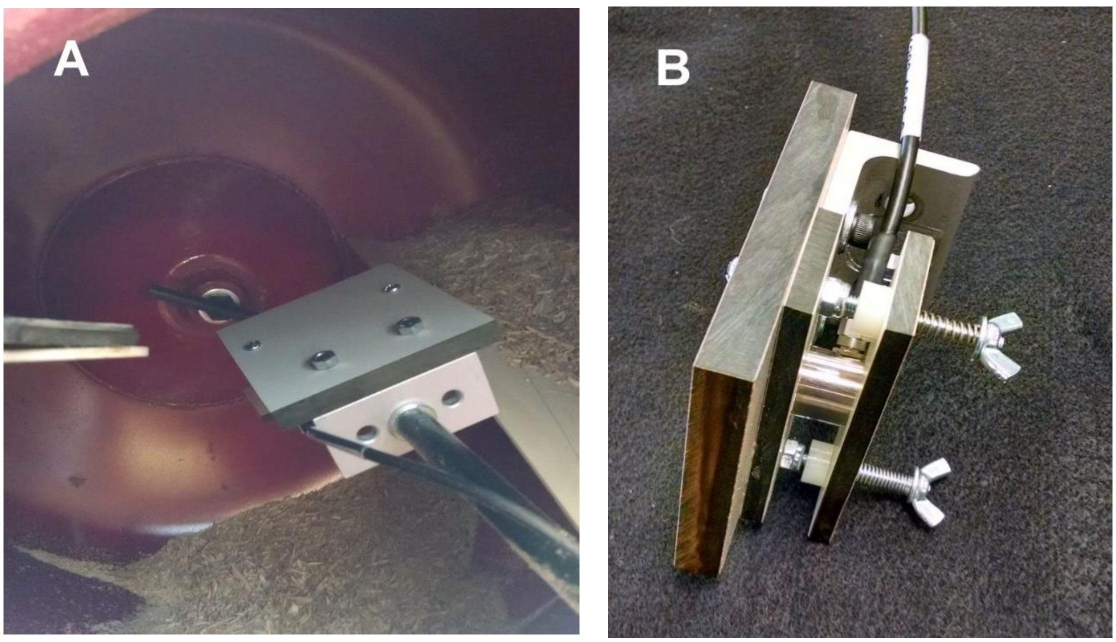

Fig. 2. (a) Inside of cement mixer used to tumble particles; (b) close up of AE sensor and target

Particles were obtained from Arauco N. A. in Moncure, NC. Particles were collected to be used for both the core and the surface of the particleboard. The particle material for both the panel surface and core was then screened using a Tyler vibrating screen system. The definition of "fines" for this study was anything that would pass through a 60 mesh screen (250-micron opening). The number 60 indicates the number of openings per inch in the screen. The mesh screen used was a U.S.A. Standard Testing Sieve by Fisher Scientific Company (Hampton, NH), and the machine used to screen the material was called a Shieve Shaker (W. S. Tyler Ro-Tap, Mentor, Ohio). The material was prepared so that all the fine material was removed from both the core and surface material. The core material was shaken for 2 min per batch, and the surface material was shaken for 3 min per batch due to the fact it contained significantly more "fines." The "fines" and "accepts" were collected separately. The fines could then be reintroduced into the mix as a percentage of the total weight of the particles.

During the initial setup of the system, various amounts of particles were placed in the tumbler to determine the minimum amount of material needed to get good particle coverage falling onto the AE target during tumbling. This was done to minimize the amount of particles needed per test series. It was determined that at least 460 grams (1.0 pound) of material was sufficient.

Methods

The acoustic emission setup was a Mistras USB AE Node (Princeton Junction, NJ, USA). This is a USB-based unit that allows for collection of the AE signal for up to 10 M of samples/sec as well as the extraction and recording of waveform feature descriptors. The software used for data acquisition, feature extraction, and recording was AEwin™ also by Mistras. The AE unit uses piezoelectric sensors with integral preamplifiers.

This study determines whether a resonant sensor of a particular frequency yielded better results than a broad band sensor, which has less sensitivity than a resonant sensor. In addition to the type of sensor selected, the AE waveform descriptor that was the most sensitive to changes in the composition of the particles was also determined. The first test used chips that had the fines removed and introduced a chip mixture composed of 15% fines by weight.

Three types of sensors were available for this type of AE amplifier. There were two resonant sensors with peak frequencies of 150 kHz and 500 kHz. These sensors are most sensitive to AE events that occur near their resonant frequency. The third sensor was a broadband sensor that is less sensitive than a resonant sensor but has a flatter frequency response or is sensitive over a larger frequency range. Though the AE unit had many waveform descriptors that could potentially be used, many were similar to each other, such as the various frequency descriptors. The AE waveform descriptors chosen were a representative set, including rise time to first threshold crossing, count (number of threshold crossings), energy (time integral of the absolute signal voltage), amplitude (peak voltage of the AE signal), average frequency of the signal (count divided by duration, divided by 1000 (thus, kHz)), and the RMS (root mean square voltage during the timeframe of the waveform).

A series of informal tests were conducted to determine the gain to use on the AE system to evaluate all three sensors. While a sample of particles was being tumbled and the particles were striking the AE target, the gain was adjusted, and the AE waveform was observed. What was desired was an AE signal that was not so large that the signal was saturating and the peaks of the signal were higher than the AE system could measure, and not so low that the AE system would not trigger a data acquisition. Values during these tests were not recorded, since a saturated signal is meaningless due to the fact it is not known how high the signal actual is. Similarly, the low values, where the signal is not triggering a data collection, is also meaningless. These tests were conducted for all three sensors with only “accepts” of the particle mix as well as a mix of 2/3 “accepts” and 1/3 “fines”. The gain that was the best compromise for these tests was 52 dB. The sampling speed was set at 1 M samples / sec for a waveform length of 1000 samples. This meant 1 waveform was being collected every 1 microsecond. Each test consisted of tumbling the particle mix for 60 seconds. This resulted in 50 revolutions of the tumbler or 100 drops of particles. Each drop of particles, however, would result in multiple AE waveforms being generated.

The next part of the study consisted of determining the data collection window to use for this type of experimental setup. Three AE timing parameters can be controlled for AE waveform collection. These include Peak Definition Time (PDT), Hit Definition Time (HDT), and Hit Lockout Time (HLT). In brief, a proper setting of the PDT ensures correct identification of the signal peak for rise time and peak amplitude measurements. Proper setting of the HDT ensures that each AE signal from the structure is reported as one and only one hit. With proper setting of the HLT, spurious measurements during the signal decay are avoided, and data acquisition speed can be increased. Chips with 15% fines were tumbled, the AE waveform collected, and the waveform features extracted. This was repeated for several sets of PDT, HDT, and HLT. The variability of the results was used to decide which set of timing parameters to use.

The AE target angle position was originally set by watching the chips fall on the target and adjusting the angle of the target empirically so that the chips struck the surface soundly but did not accumulate on the target. A target position that was too small of an angle allowed the chips to accumulate on the target surface which cushioned additional chips falling on the surface and lowered the AE signal. A too-large target angle meant that the chips would glance off the target surface and result in a lower AE signal. After the sensor frequency and waveform descriptor to use was determined, the angle of the target was varied to observe if more optimization of the test setup was possible.

The final series of tests were to determine the difference between core material and surface material as well as the percentage of fines in both types of materials. The details will be discussed below, but the system setup parameters, as determined above, were used to "optimize" the AE system. This included using a 150 kHz resonant sensor and the AE target at an angle of 59° relative to the horizon. The timing parameters were set at 500, 1000, and 12,000 for PDT, HDT, and HLT respectively. Three separate replications of each test were conducted, and the standard deviation between those three replications were determined.

RESULTS AND DISCUSSION

From the first series of tests, it was determined that the sensor to use was the 150 kHz resonant sensor and the waveform descriptor to use was the "energy" AE waveform descriptor. These results are shown in Fig. 3. An additional waveform descriptor was evaluated based on the experience of the authors in other acoustic emission research. When AE data were collected during an extended period of time, like the tumbler, there were occasions when a false signal was collected. The "error" signal was normally drastically different than the majority of the waveforms. In one study, the signal was low amplitude with a longer duration than normal. By dividing the energy of the signal by the duration of the signal, the spurious nature of some of the signal waveforms was minimized. In this study, however, the spurious signals that were observed tended to be a single spike with very little duration. This spurious signal normally showed up with an extremely high standard deviation of the waveform descriptors during a single data collection period compared to the other waveforms. The standard deviation of the AE waveform descriptors is calculated by the AE instrument, so they are easy to monitor. In this series of tests, the typical ratio of the standard deviation for the AE energy parameter to the mean of the AE energy was less than 2.0. One test, however, showed a ratio of over 22. This is easy to monitor online, and just requires excluding the data set from the analysis and recollecting the data. In a real-world scenario, a spurious signal could occur from a chunk of wood or metal getting past the screens or a spike in the supply voltage due to a large piece of equipment cycling on or off.

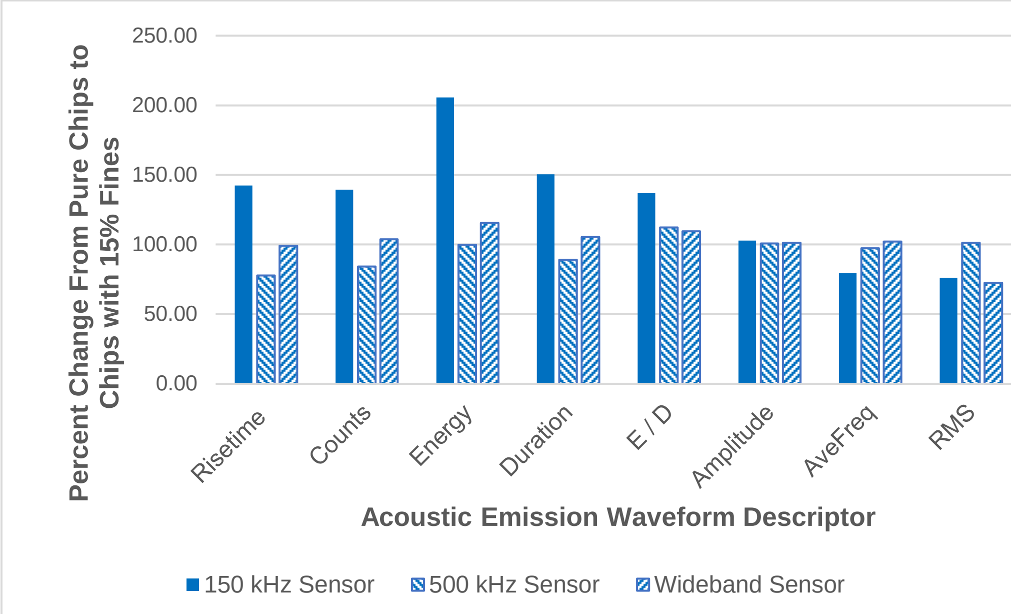

Fig. 3. Effect of acoustic emission sensor type and waveform descriptor

The same series of tests were used to observe the repeatability of the test setup. Only the "energy" waveform descriptor was used, as the results of the previous test showed that the "energy" waveform was the descriptor that changed the most when sawdust was added to the chips. Figure 4 shows that the "energy" waveform descriptor changed the most for the 150 kHz sensor and that the change was greater than one standard deviation. The wide band sensor and the 500 kHz sensor showed changes in the "energy" waveform descriptor that were within a single standard deviation of the data. Therefore, the 150 kHz resonant sensor was used for the remaining experiments. A series of preliminary tests were conducted to determine the best AE waveform timing factors. Table 1 shows the results of the varying PDT, HDT, and HLT. The PDT, HDT, and HLT values of 500, 1000, and 12,000 respectively, were used for the remainder of the tests.

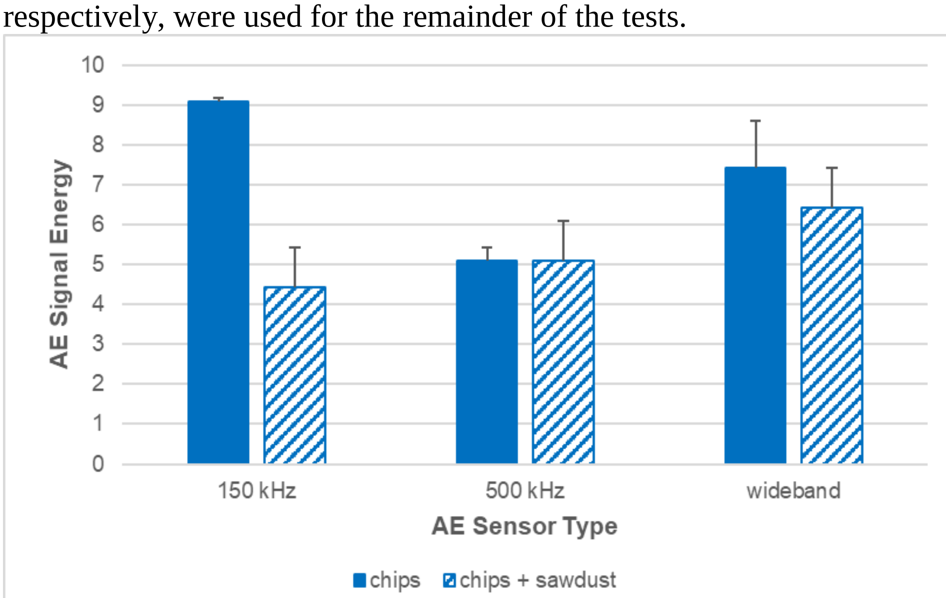

Fig. 4. Repeatability of "energy" waveform descriptor by sensor type (error bars = 1 standard deviation)

Table 1. Effect of AE Timing Parameters on the Variability of the AE Signal

PDT	HDT	HLT	Coefficient of Variation (Energy)
1,000	2,000	20,000	24.17%
500	1,000	10,000	20.83%
2,000	4,000	40,000	32.68%
500	1,000	12,000	19.73%

The preliminary study to determine the best target angle showed that the middle angles performed similarly but the largest angle tested was the best. Figure 5 shows that the best angle tested was a target angle of 59° relative to the horizon. A target angle of 22° had material that would stay on the surface of the target. It was believed that this would cause a padding effect and reduce the AE signal energy, as observed in preliminary tests but at an even flatter angle. However, this was not the case and the test with the target set at 22° had results comparable to the mid-angles.

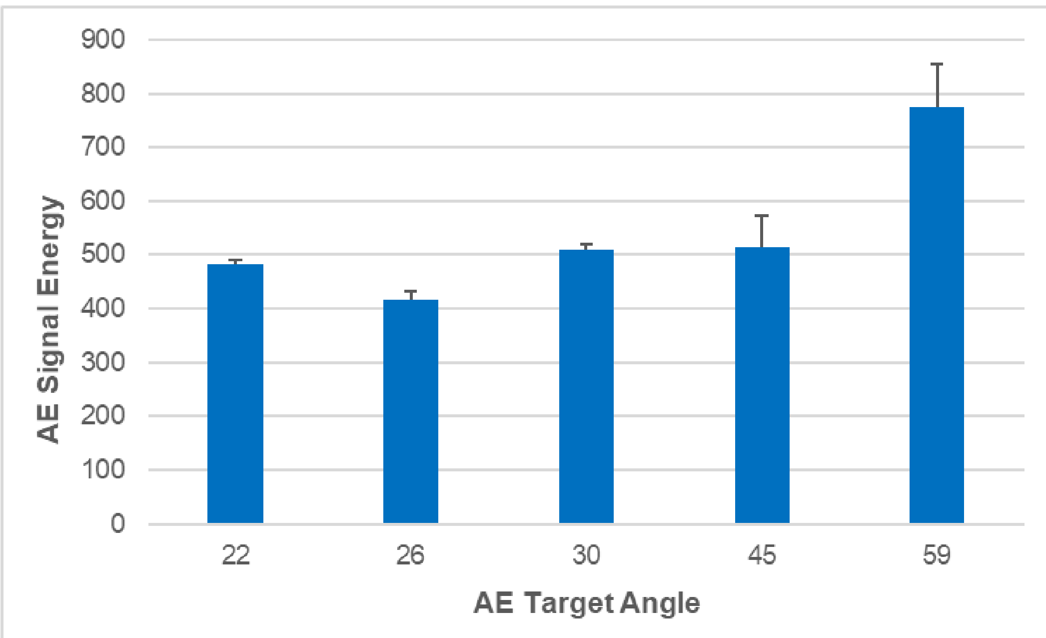

Fig. 5. Effect of AE target angle on AE signal energy (core material with 15% fines)

The final series of tests was used to determine how the "optimized" system could detect fines in an actual particleboard furnish at the percentage levels of interest to particleboard manufacturers. Figure 6 shows a plot of core material with 0% to 15% fines by weight. The AE system could detect differences between the percentages of fines at these percentage levels. In addition, the error bars (1 standard deviation) for these levels showed that the results were very consistent for the 1 min of data collection at 100 drops of chips onto the surface of the AE target per minute. Looking at the raw data for the 59° angle for the AE target, 100 particle drops resulted in 773 to 921 AE signals that were used to obtain the average energy of the AE signal. The length of sample time was not varied in this study. In a real-world situation, the chips would be falling on the AE target continuously, so an even smaller spread in the data is expected due to the larger sample size. For long term monitoring, spurious AE signals can be expected. This could be due to either a foreign object in the mix or to an electrical spike nearby. A way to eliminate the effect of spurious signals is to monitor the standard deviation of the energy for each sampling interval. If the standard deviation is extremely large, then that sampling sequence can be eliminated. In this current study, the standard deviation of a single data sample was up to 2 times greater than that of the mean. The only outlier in this study was when the standard deviation of the energy for the sample was 22 times greater than the mean. This data set was ignored in the analysis, and another data set was collected. The standard deviations of the energy shown in the plots are between sample data sets and not the standard deviation within a data set. The variation within a sample set was expected due to the fact that both large and small particles were generating AE signals.

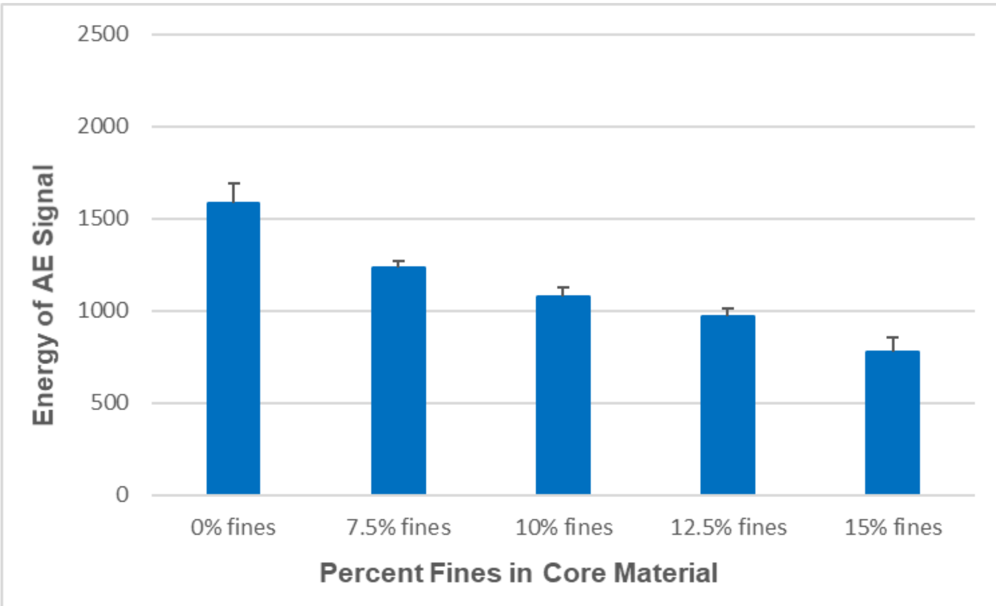

Fig. 6. Ability of the AE system to detect fines in core material (error bars = 1 standard deviation)

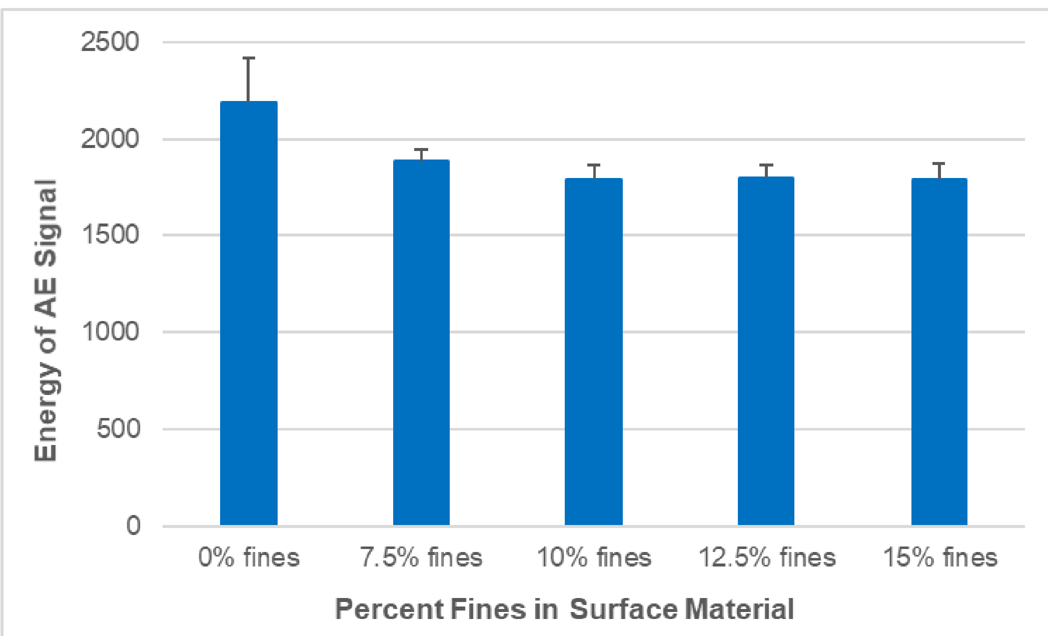

Fig. 7. Ability of AE system to detect fines in surface material (error bars = 1 standard deviation)

Figure 7 shows the ability of the AE system to detect changes in the percentage of fines of the surface material. The system was not as sensitive to changes in the percentage of fines for the surface material as it was to the core material. This was not unexpected, as the size of the particles in the surface material was smaller and closer to the size of the fines than to the core material. It was also not a concern because manufacturers typically do not mind the fines in the surface but want to control it in the core material. However, being able to monitor the generation of the fines is still desirable from a machine monitoring standpoint.

Future work would involve installing an AE system like this in a particle board manufacturing process. The AE target would be placed in a particle transport system (conveyor or duct) and the AE signals would be observed over time, as the manufacturer would know the history of the refiner or chipper blades, material source, moisture content, and species of particles as well as outdoor temperature. These parameters, along with the traditional, periodic particle furnish analysis, would then be used to set thresholds to sound alarms if the furnish consists of an undesirable proportion of fines or is approaching an undesirable condition. This data would also show if the alarm threshold needed to be adjusted based on season or raw material used.

CONCLUSIONS

1. The acoustic emission (AE) system was able to detect differences in the percentage of fines in the core material.
2. While the AE system could detect differences in the percentage of fines in both the surface and core materials, the system was not as sensitive to the percentage of fines in the surface material.
3. Of the ones tested, it was determined that the “energy” AE waveform descriptor was the best parameter to use.
4. For this type of AE system, it was determined that the 150 kHz resonant sensor yielded better results than a 500 kHz resonant sensor and a wide band sensor.
5. The position of the AE target was varied through a range of angles relative to the horizon. It was determined that the greatest angle (59° from horizontal) yielded stronger AE signals than the other angles tested.

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