U.S. DOE

Federal Assistance Program DE-FC26-03NT41846

**“Sensor for Individual Burner Control of Firing Rate,
Fuel-Air Ratio, and Coal Fineness Correlation”**

Technical Progress Quarterly Report 3

For Quarter 1 JAN 05 to 31 MAR 05

Issued April 2005

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ABSTRACT

A no-cost time extension was requested, to permit additional laboratory testing prior to undertaking field data collection. This was received in this reporting period. To minimize program cost, this additional testing is planned to be performed in concert with EPRI-funded testing at the Coal Flow Test Facility. Since the EPRI schedule was undecided, a hiatus occurred in the test effort. Instead, a significant effort was exerted to analyze the available laboratory test data to see whether the source and nature of noise behaviors could be identified, or whether the key flow information could be extracted even in the presence of the noise. One analysis approach involved filtering the data numerically to reject dynamics outside of various frequency bands. By varying the center frequency and width of the band, the effect of signal frequency on flow dynamics could be examined. Essentially equivalent results were obtained for all frequency bands that excluded a neighborhood of the transducer resonance, indicating that there is little advantage to be gained by limiting the experimental frequency window. Another approach examined the variation of the dynamics over a series of 1-second windows of data, producing an improvement in the prediction of coal flow rate. Yet another approach compared the dynamics of a series of 1-second windows to those of a series of 5-second windows, producing still better results. These results will be developed further in the next reporting period, which should also include further laboratory testing at the Coal Flow Test Facility.

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EXECUTIVE SUMMARY

The project's overall objective is to develop a commercially viable sensing system to infer the flow rate and fineness of pulverized coal flows using the dynamic signature from a pipe-mounted accelerometer. The preliminary calibration data for this effort are to be obtained using a Coal Flow Test Facility built and operated by our subcontractor, Airflow Sciences Corporation, in support of an EPRI program. Additional operational data are to be collected in field testing at coal-fired power plants to fine-tune the calibration.

Analysis performed on the laboratory data collected to date has produced encouraging results, considering the limitations of the available data. Careful examination of each data file disclosed that various types of noise are present in many data files, in many cases of such a type that it would be easy to identify by a straightforward analysis built into the instrument system. Through extensive analysis of the data sets that appeared to be noise-free, it was discovered that some data sets still suffer from some form of noise that is as yet unidentified. The cases not suffering this noise produce extremely good flow correlations, while the noisy cases are essentially uncorrelated to coal flow. This led us to decide that additional laboratory testing was needed to identify potential sources of noise and to obtain additional data to serve as the basis of the instrument calibration. It is possible that this testing can be performed in concert with testing for an EPRI-funded program, significantly reducing the cost to this program. In this reporting period, we requested and received a no-cost time extension to accommodate this additional testing.

The EPRI test schedule was undecided in this reporting period, so no testing was done. Instead, our efforts centered on further analysis of the data collected to date. One analysis approach that was pursued was to digitally filter the raw data to eliminate behaviors outside of various frequency bands. Dynamical Instruments analysis was then performed on the filtered data. Interestingly enough, all frequency bands away from the sensor resonance produced similar results, indicating that all frequency bands contain dynamics related to the flow conditions and that noise is present in all frequency bands as well.

A second approach examined the statistics of the Dynamical Instruments signature quantities over a series of one-second data windows. By using the standard deviation of each signature quantity over time as new signature quantities, the quality of the correlations improved significantly. This implies that flow information is spread out over multiple-second periods. An additional analysis was performed to extend this approach, by comparing the signature quantities obtained for 1-second windows with those obtained for 5-second windows. This analysis produced even better results. This supports the results of the previous analysis, and indicates that additional analysis examining the temporal variation of the flow dynamics is warranted.

EXPERIMENTAL

Additional laboratory testing will be performed in the Coal Flow Test Facility prior to moving on to field testing. The purpose will be to collect additional data to identify potential sources of noise that have plagued the data collected in the laboratory so far. This testing preferably will be performed in concert with testing by EPRI, providing a significant cost reduction for this program. A no-cost time extension was requested and granted in this reporting period to accommodate this testing.

Planning of the EPRI testing was not completed during this reporting period, so no experimental work was performed. In the event that EPRI testing cannot be scheduled to accommodate the needs of this program, a limited test effort will be performed using program funds, possibly reducing the scope of the field test effort.

RESULTS AND DISCUSSION

During the previous reporting period, a bimodal correlation of the dynamic signature with coal flow was obtained for cases where the sensor was magnetically mounted at the elbow outlet, excluding those that had been identified as objectively noisy. Approximately half the cases had exhibited a near-perfect correlation of 0.994, while the other half were essentially uncorrelated with coal flow. The entire collection of cases yielded an overall correlation of 0.78 as displayed in Figure 1 below. As this suggested that an additional noise source was obscuring the dynamics, the focus at the start of the current reporting period was the identification of noisy data, with an eye towards locating measures less sensitive to noise. Using Particle Swarm Optimization, neural networks were trained on Dynamical Instruments signature quantities to distinguish the two sets of cases, those that were well correlated with coal flow and those that were not. Using just two inputs, the noisy cases could easily be distinguished from the others with a 100% success rate. However, examining pairs of signature quantities that were used as inputs to achieve this separation, little insight was gained towards qualitatively distinguishing the two sets of cases or identifying the noise source. Figure 2 shows typical behavior of a signature-quantity pair that distinguishes those cases where coal flow is well-predicted from those where it is poorly predicted. The data does not fall cleanly into two distinct clusters. Rather, there is a cluster of cases with intermediate signature-quantity values where information related to coal-flow could not be extracted.

Figure 1. *Bimodal correlation obtained with all elbow-outlet magnetically mounted cases after removing identifiably noisy cases*

Figure 2. *Separation of cases where coal flow is well predicted from cases where it is poorly predicted*

Based on the earlier observation that band pass filtering had produced better results than merely low pass filtering, the noise problem was now approached from the point of view of optimizing the window of frequency values that were passed in filtering. Focusing on the elbow-outlet magnetically mounted cases, again excluding those that were identifiably noisy, each raw data file was filtered six different times to allow a comparison of the results obtained when each of the following frequency ranges were passed:

- 20-40 kHz.
- 30-50 kHz.
- 40-60 kHz.
- 50-70 kHz.
- 20-60 kHz.
- 40-80 kHz.

As before, each filtered data file was broken up into 30 one-second windows of data, with signature quantities computed for each window. Again, only the median value of the signature quantities for each data file was used in an effort to reduce the inaccuracies due to noise spikes. The resulting median signatures from each frequency window were then trained thirty times using Particle Swarm Optimization with five inputs and three hidden nodes. Repeated training is needed to optimize the performance of the neural net due to the fact that success is highly dependent on initial training conditions. Certainly, the most important result is the highest r^2 value obtained. However, from a practical point of view, accessibility of information can ultimately have a major impact on the best value achieved. The results of this analysis are summarized by Table 1 below.

Table 1. Comparison of Results in Passing Different Frequency Ranges

Frequency Range in kHz	Highest r^2 value obtained	Number of runs with $r^2 > 0.70$
20-40	0.77	6 out of 30
30-50	0.75	1 out of 30
40-60	0.76	2 out of 30
50-70	0.78	4 out of 30
20-60	0.76	4 out of 30
40-80	0.69	0 out of 40

Overall, the highest r^2 value obtained was not all that different for the different frequency ranges, with the exception of the 40-80 kHz range. Likely, the latter range achieved poorer results due to noise related to transducer resonance. Beyond that, for some of the frequency ranges the information was more accessible, with more runs resulting in the higher end r^2 values. However, overall most frequency windows contain comparable information and comparable noise

interference as well, as is indicated by Figure 3 below. Further analysis was restricted to the data filtered to band pass 50-70 KHz, the frequency window that yielded the highest correlation value.

Figure 3. Comparison of r-squared values achieved for different frequency windows

An examination of the signature-quantity values for individual one-second windows as compared to the median value revealed significant differences in the temporal variation from case to case. This is illustrated in Figure 4 below for a particular signature quantity, sdADuSize. That observation in turn raised the question of whether the temporal variation might itself be related to coal flow or whether it was a reflection of the noise in the system.

Figure 4. Temporal variation of sdADuSize over each 30-second file

A simple measure of temporal variation is the standard deviation, which quantifies the magnitude of this variation. In order to address the above question, the training procedure that had been applied previously was now repeated with the median of each signature quantity replaced by the standard deviation of each signature quantity over the 30 one-second windows for each case. This training resulted in a significant improvement of results, attaining a maximum r^2 value of 0.85, as compared to a previous maximum of 0.78. Figure 5 below displays two histograms, providing a comparison for the correlation results based on the median of each signature quantity with those based on the standard deviation. Clearly, more information is extracted when the analysis is based on the standard deviation. Combining both dynamic signatures did not improve the analysis further.

Figure 5. Histograms comparing correlation results based on median of each signature quantity to standard deviation of same

The fact that the temporal variation of the dynamic signature over a case run provided more information concerning coal flow than the median value suggested that one-second windows of data are inadequate for extracting coal flow values and that the use of longer windows was warranted. Therefore, the one-second windows of data were replaced by five-second windows. Consecutive windows had starting points separated by one second and therefore overlapped by four seconds, once again resulting in a total of 30 windows for each data run. Training was now attempted as before, but this time using the median of the five-second windows of each signature quantity over each file. The results were not significantly different from those obtained based on the one-second windows. A maximum r^2 value of 0.79 was achieved as compared to that of 0.78 using one-second snippets. Both these results were based on the data filtered to band pass 50-70 kHz. Figure 6 below compares the histograms for 30 trainings based on the one-second windows to 30 trainings using five-second windows. At best, a modest improvement is attained with the longer windows.

Figure 6. Results based on one-second windows vs. those based on five-second windows

In short, the longer snippets of data produced lesser results than the simple measures of the standard deviation of each signature quantity over time. A comparison of the medians of the one-second signature quantities to the median of the five-second signature quantities revealed that there were two types of signature quantities. While all of the median signature quantities displayed similar behavior for the one-second windows and the five-second windows, for some signature quantities the values were essentially independent of the window size while other signature quantities displayed subtle variations in value between the two different window sizes. Figures 7 and 8 display representative examples of each of these two types of signatures.

Figure 7. *An example of a signature quantity for which the median value is independent of window length*

Figure 8. *An example of a signature quantity for which the median value varies somewhat with window length*

Given the fact that the standard deviation of the signature quantities had better captured temporal variation than the signature quantities over longer intervals, the question arose whether the difference between the median values of the one-second signatures and the five-second signatures might in fact be more sensitive to coal flow than the values of the signature quantities themselves. Training was repeated once again, this time replacing the medians of the one-second signatures by the differences between the medians of the five-second signatures and the medians of the one-second signatures. This time, the results improved dramatically, achieving maximum r^2 value of 0.97. These results are displayed in Figure 9 below. Note that a “perfect” result would place all data points on the diagonal. Referring back to Figure 1, the best results obtained at the conclusion of the last reporting period, the level of improvement is quite striking. Previously, the best neural net yielded no information at all about the coal flow for a substantive percentage of the data, namely, that mapped to the horizontal line at height 6212 in Figure 1. In contrast, the current analysis performs reasonably well on the entire collection of data.

Figure 9. Best neural net prediction of coal flow, based on difference between median of one-second signatures and median of five-second signatures

CONCLUSIONS

The results displayed in Figure 9, although not yet of precision instrument quality, gives rise to a fair amount of confidence that coal flow information can be extracted with the techniques at hand. It should be noted that the number of cases involved, 31, is still quite small and the quantity of data was insufficient to permit a test set. Still, the fact that the number of inputs times the number of hidden nodes was less than 50% of the number of cases precludes the

possibility of the neural net simply “memorizing” the data. These cases included all pipe arrangements described in earlier reports.

Two possibilities come to mind to explain the improved predictions in using the difference between median signatures for the longer and shorter windows over using the median signatures for a single window length,. We already know that noise has been a major problem with this data. It is possible that subtracting one median from the other effectively subtracts off an effect of the noise, with the remaining measurement a better reflection of the dynamics of the flow systems. A second possibility is that the degree to which a one-second window of data effectively populates a state space as well as the five-second window may in some way be dependent on the coal flow. The analysis of the additional data to be collected at the Coal Flow Facility should allow us to determine the extent to which the improvement in the analysis is due to reduced noise sensitivity and the extent to which the current algorithm has pinpointed those aspects of the dynamics that vary with coal flow. Once this is accomplished the signature quantities themselves can be fine-tuned to better capture the temporal variation of the dynamics to create a more incisive algorithm.