Neural network application to mine-fire diesel-exhaust discrimination

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ABSTRACT: A series of seven underground-coal-mine fire experiments was conducted in the Safety Research Coal Mine at the National Institute for Occupational Safety and Health, Pittsburgh Research Laboratory. Coal and styrene-butadiene-rubber conveyor belting were burned upwind of two sensor stations, 18 m and 148 m from the fire source. Exhaust from a diesel locomotive flowed over the fire sources in six of the tests. Metal-oxide-semiconductor (MOS), CO, and optical-path-smoke sensors were positioned at both stations and found to be an optimum set of sensors for the fire discriminations. A representative set of 7,679 samples of CO data and data from the smoke and diesel-exhaust MOS sensors were used as inputs to train a neural network (NN). By testing 42,538 data samples from the seven experiments, all fires were detected by the NN within 9.67 min from the onset of significant changes in the MOS voltages without any false alarms.

1 INTRODUCTION

If diesel engines are present in underground mines, the presence of diesel exhaust can interfere with the early detection of hazardous combustion in flammable materials such as coal and conveyor belting. To discriminate the hazardous combustion from the diesel exhaust, it was decided that a collection of commercial sensors would be tested to determine what set of sensors would be most appropriate. These sensors included both fire and environmental sensors. A neural network algorithm was chosen as the function approximator in the analysis of the sensor data mainly because of the many possible independent and dependent variables involved. Earlier work included neural networks applied to the discrimination of coal combustion from water vapor and shot firing fumes (Brinn & Bott 1994) and to the discrimination of coal, diesel-fuel, conveyor-belting, electrical-insulation, and metal-cutting products of combustion (POC) from each other (Edwards et al. 2000). To determine what commercial sensors were appropriate and what neural network algorithm was best to process the data from the sensors, a series of seven underground fire experiments was undertaken in the Safety Research Coal Mine (SRCM) at the National Institute for Occupational Safety and Health (NIOSH), Pittsburgh Research Laboratory, Pittsburgh, PA, USA.

2 EXPERIMENTAL METHODOLOGY

Figure 1 shows a schematic diagram of the underground SRCM experimental entries. In each of four

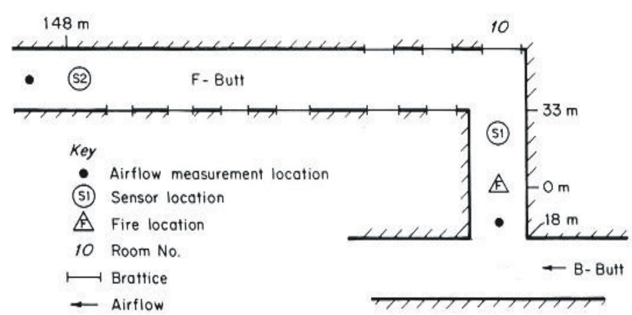

Figure 1. Schematic diagram of a portion of the SRCM.

experiments, about 14 kg of coal was ignited in a 61-cm-square steel pan placed on the floor in the middle of Room 10. Five electrical strip heaters were spaced evenly inside the pan under a layer of coal lumps of size less than 5-cm equivalent diameter and of depth sufficient to cover the heaters. About a kilogram of coal fines was sprinkled on top of the coal to thermally insulate the coal and decrease the time to ignition. The larger specific surface area of the coal fines compared to the coal lumps also provided more CO during the smoldering combustion stage. The coal was heated for about 40 min with power ranging from 1.3 kW to 2.4 kW in

10-V increments from 130 V to 170 V every 10 min. This rate of heating was selected to generate copious quantities of CO during the coal smoldering combustion stage. Usually, intense smoking of the coal occurred near 30 min after the start of heating with flaming near 40 min. In another three experiments, a 53-cm-square piece of styrene-butadiene-rubber, conveyor belting about 1.1 cm thick was clamped to the top of a steel plate. The belting was heated by the five strip heaters next to and spaced evenly below the steel plate. A nonflammable insulating board was placed under the heaters to level and protect the heaters from the damp mine floor. The belt was heated for about 40 min with power ranging from 1.1 kW to 3.3 kW in 20-V increments from 120 V to 200 V every 10 min. Usually, intense smoking of the belt occurred near 30 min after the start of heating with flaming after 40 min. In three of the coal and all of the conveyor belt experiments, an idling diesel locomotive was positioned in the entry, B-Butt. The air quantity through B-Butt was about 15 m^3/s. For the three coal combustion experiments with diesel exhaust, the diesel locomotive was located upwind of the Room-10 split from B-Butt. In the first coal experiment, diesel exhaust was absent. For the three belt combustion experiments, the exhaust pipe from the locomotive was attached to a 10-cm-ID, 4-m-long pipe that directed the exhaust into Room 10 and downwind toward the fire source. Room 10 had an average height and width of 2.0 m and 3.9 m, respectively. Collections of duplicate fire sensors at two locations, stations 1 and 2, were placed 18 m and 148 m, respectively, downwind from the fire source in six of the experiments and shown as S1 and S2 in figure 1. In the first coal experiment, when diesel exhaust was absent, only the data from the sensors at station 2 were used in a subsequent neural network analysis. The location of station 2 was in F-Butt, which had an average height and width of 1.9 m and 4.5 m, respectively. For the experiments conducted, the average air quantity near the fire source was 2.66 m^3/s and at the end of F-Butt was 4.73 m^3/s. The increase in air quantity downwind of the fire source was caused by leakage into F-Butt around cloth brattices blocking crosscuts connecting F-Butt with parallel airways.

At each of the two stations, a point CO diffusion-mode sensor was suspended from the roof with the inlet of the sensor 40 cm down from the roof. Concentration of CO was measured by this type of sensor in parts per million (ppm). A point, diesel-engine-exhaust-gas, MOS sensor was also suspended from the roof with its inlet about the same distance down from the roof. It was found that the MOS sensor output voltage responded bi modally. The voltage increased above its clear-air value when oxidizable gases such as CO and organic compounds were present. When only diesel exhaust in air was present, the MOS sensor voltage decreased below its clear-air value. This decrease in voltage was in response to the nitrogen oxides in the diesel exhaust gas. In all seven experiments, the onset of smoldering combustion released enough oxidizable gas to cause the MOS voltages to increase above their clear-air average values. Two other types of MOS sensors, designed for hydrogen and carbon monoxide detection, were placed at both stations but were subsequently found to be inferior to the diesel-exhaust MOS sensors in discriminating the diesel-engine and flammable material POC. An optical-path smoke-sensor assembly consisting of a pair of modules was placed approximately diagonally across the airway at each station with a path length between the modules of about 10 m. These modules consisted of an infrared emitter and an infrared collector mounted on two steel posts. The presence of infrared absorbing or scattering particles in the path of the infrared beam caused the sensor signal to decrease. An ionization smoke sensor placed at these two stations was also found to be inferior to the three sensors described above in discriminating the combustion of coal or conveyor belting from diesel exhaust. All the sensor data were collected from the sensors by a mine monitoring system above ground that polled the sensors every two seconds. These sensors and the mine monitoring system are more completely described in (Edwards et al. 2001).

3 DESCRIPTION OF NEURAL-NETWORK CLASSIFICATIONS

A computer package of a collection of neural networks named NeuroSolutions, (reference to specific products does not imply endorsement by NIOSH), from NeuroDimension, Inc., was applied to sets of inputs derived from the sensor data. The multilayer, perceptron neural network (NN) from this package, described in some detail in (Principe et al. 2000), was found to yield the best discrimination between the diesel exhaust and hazardous combustion. This NN was comprised of a set of inputs, hidden layers of nodes called process elements (PEs), and an output layer of nodes representing the probabilities of the possible events. In order for the NN to discriminate between two combustion sources, the NN had to be trained on data similar to data that would be routinely collected from underground mine sensors. Two sets of experimental data at station one, one coal and the other belt smoldering in the presence of diesel-engine POC, were combined into one data file of 7,679 temporal samples that was used to train the NN. From trial-and-error calculations, it was determined that two hidden layers in the NN yielded the best discrimination with 10 PEs in the first hidden layer and 5 PEs in the second hidden layer. Each PE used a hyperbolic tangent (tanh) activation function that operated on the sum of inputs to the PE. The three output PEs used softmax activation functions–functions that operated on the sum of inputs from the second hidden layer and classified outputs by assigning probabilities to each output. The output layer of the NN was divided into the three classifications–clear air, diesel exhaust, and a combination of diesel-exhaust and hazardous-combustion products. A desired value for an output was a value of one for a correct classification and zero for each of the two other possibilities. A classification of the outputs from a sample of the inputs occurred when the softmax activation function applied to the NN outputs indicated that the probability of one of the outputs was greater than each of the probabilities of the two other outputs. During training 105 weights were varied by the NN. These weights were coefficients of the outputs from the PEs and were initialized randomly in a range that depended on the structure of the neural network. The weights were then varied to make the mean sum of the squares of the differences between desired outputs (zero or one) and predicted outputs, named the mean square error (MSE), approach a small value. Acceptable training, also determined by trial-and-error, occurred after as few as 100 epochs or iterations through the entire training file. The exemplar (sample) weight changes were averaged over each epoch and the average weight changes were applied only after completion of the epoch. Changing the weights after each exemplar did not improve the classifications. The weight changes were calculated using a gradient descent method in the backpropagation-of-error part of the NN algorithm. A numerical term called momentum, having a default coefficient of 0.7, was added to the backpropagation expression for calculating each weight change. The momentum term used the value of the weight from the previous iteration to sometimes accelerate the convergence of the MSE. No compelling advantage was found for using other than the value of the default momentum coefficient.

4 APPLICATION OF THE NEURAL NETWORK TO DISCRIMINATIONS

Criteria were established to determine boundaries between the clear air, the diesel exhaust, and the combined diesel exhaust and hazardous combustion data. Because the MOS voltage responded differently to diesel exhaust gas than to hazardous combustion gas with relatively little noise in its value, it was selected to separate the three periods. The mean and standard deviations of the output voltages from the MOS sensors were calculated for each of the periods of clear air at the sensors. When 10 standard deviations decreased from the mean of the MOS-sensor voltage for more than two time-sampling increments, it was decided that the diesel exhaust had reached all the sensors at the station with the MOS sensor. If the noise superimposed on a constant signal is normally distributed, 10 standard deviations from the noise mean occurring within two consecutive samples of the signal would indicate almost certain confidence that the signal was being changed by something other than noise.

To determine the accuracy and responsiveness of the NN, the time interval between the time of arrival of hazardous POC at a station and the time the NN detected the hazardous POC was approximated. Since electrical heating of the flammable solids (coal or belting) occurred soon after the diesel locomotive was in position, the MOS sensors were affected by the thermal off gassing of volatile oxidizable compounds from the solids. This off gassing caused the MOS voltages to slowly increase before the start of combustion caused a more rapid rate of increase. This period of a slow rate of MOS voltage increase was often complicated by a slow decrease in the slope of the MOS voltage curve as the rate of emission of volatiles decreased. For these reasons, a visual decision was made on each set of MOS data when combustion was being sensed. The period between the time of visual indication of hazardous combustion in the MOS data and the time predicted by the NN computer algorithm from the 13 data sets ranged from 2.13 min to 9.67 min with the mean period being 5.57 min and the standard deviation of the periods being 2.51 min.

After the boundaries were determined for the three temporal periods of each experiment, the MOS data were digitized to improve the NN classifications of the three periods. In the clear-air period, the MOS input to the NN was set to 0. In the diesel-exhaust period or when the MOS voltage was less than ten standard deviations from the clear-air mean, the MOS input to the NN was set to -1. In the combination, diesel-exhaust and hazardous-combustion period or when the MOS voltage was more than ten standard deviations from the clear-air mean, the MOS input to the NN was set to 1. Only sensor data for the periods ranging from initial clear air to smoldering combustion were needed in the NN to discriminate the hazardous combustion from the diesel exhaust, since hazardous combustion detection was achieved in all of the data sets without considering the periods of flaming combustion. The total time intervals tested from each of the 13 data sets ranged from 1.36 hr to 2.21 hr with the mean time interval being 1.82 hr and the standard deviation of the time intervals being 0.32 hr.

To remove the effect of the different initial values of the smoke sensors from experiment to experiment, the initial smoke sensor data was normalized to a mean value of one during the clear-air periods of each experiment yielding a nominal experimental signal range from zero to one. The clear-air, mean background concentration of CO was subtracted from the CO data to yield a nominal clear-air CO concentration of zero. The CO data, the processed data from two sensors (the digitized MOS and the normalized, optical smoke sensors), and the product of the CO and the normalized smoke sensor data (COXSmoke in figures 3 to 7) were used as the NN input layer. The selection of the product of the CO and the normalized smoke sensor data was determined by trial-and-error from various combinations of the sensor data in order to minimize the time intervals from onset of combustion to hazardous combustion detection and the number of false alarms.

The robustness of the classifications was demonstrated in one of the belt experiments when a mistaken increase of about 50% in the ventilation velocity occurred during the diesel idling period and just before combustion of the conveyor belt began. The only difference between this experiment and the other belt experiments was a smaller percentage of samples (56%) during the belt combustion period from station-2 data that were detected by the NN as being belt combustion. Even with this relatively low percentage, when the belt combustion was detected, the probability was much above 0.5, the minimum certain-detection probability, and remained well above 0.5 for the rest of the test period. In other words, when the alarm for hazardous combustion started, it remained in alarm until the test was terminated. This pattern of the NN alarm remaining in an alarm state during the rest of the test period occurred in all of the 13 tests. Also, since the probabilities were consistently less than a third, the minimum probability for a false alarm, during the initial periods of the experiments before hazardous combustion began, no samples were detected as being hazardous combustion during these periods or there were no false alarms. No false alarms occurred even though the diesel exhaust was not cleaned and during one of the tests the diesel exhaust produced a peak concentration of 38 ppm of CO at the station closest to the diesel locomotive. Figure 2 shows a typical plot of the probabilities of detection of hazardous combustion during a coal experiment, the second coal experiment from station-1 data, and during a belt experiment, the third belt experiment from station-2 data. The probabilities in figure 2 are representative of the probabilities generated from the other 11 test data sets–meaning the values ranged from less than 0.2 initially to greater than 0.8 when the hazardous combustion was detected.

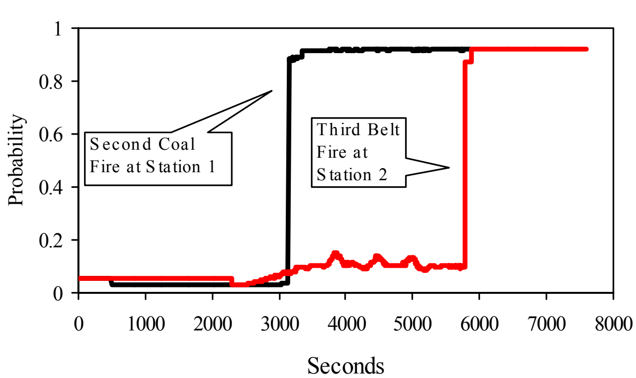

Figure 2. Probability of hazardous combustion from second coal fire at station 1 and third belt fire at station 2.

The NN input variables from the coal experiment without diesel exhaust are shown in figure 3 as a function of time from the start of the experiment. The plot of the continuous MOS data, which was not used as an input, is shown only for comparison with the digitized MOS (dMOS) data. Sets of inputs from stations 1 and 2 for the third and second coal experiments with diesel exhaust are shown in figures 4 and 5, respectively. The sets of inputs from stations 1 and 2 for the third belt experiment are shown in figures 6 and 7, respectively. The times of the NN

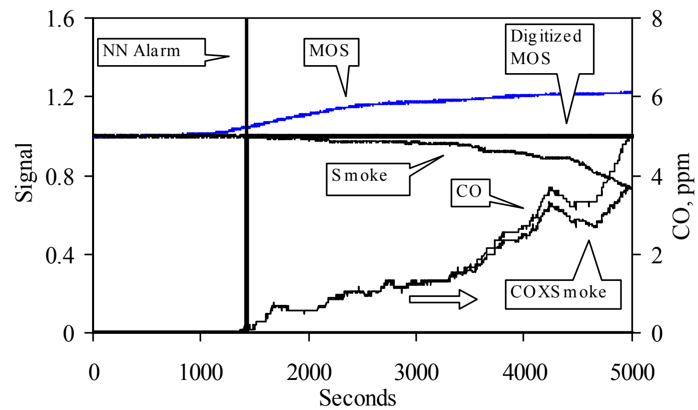

Figure 3. Inputs to the NN from station-2 data from the first coal fire without diesel exhaust.

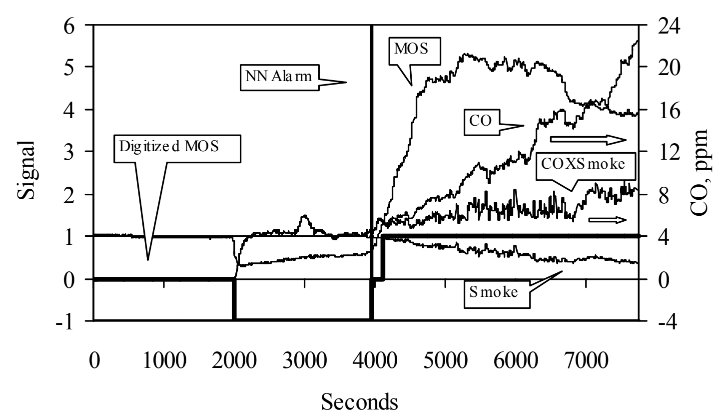

Figure 4. Inputs to the NN from station-1 data from the third coal fire with diesel exhaust.

predicted fire alarm are indicated as vertical lines on the figures. When the dMOS data responded to the hazardous combustion, a temporary plateau formed as the data returned to within the range of ten standard deviations from the clear-air mean. Even with these temporary, clear-air, digitized-MOS values of 0, the responses of the other sensors together were sufficient to prevent the NN from classifying as clear air these small time intervals.

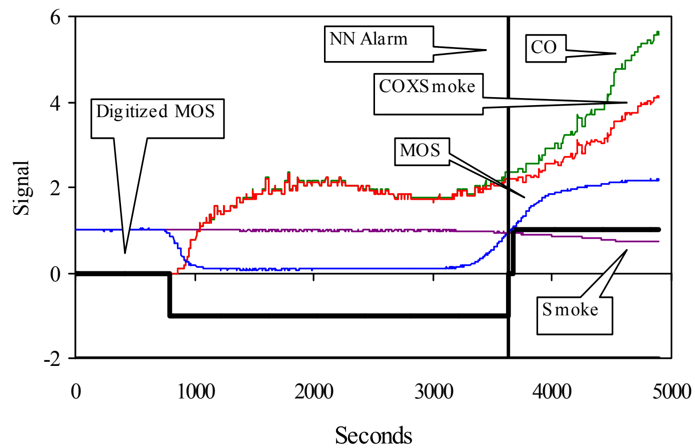

Figure 5. Inputs to the NN from station-2 data from the second coal fire with diesel exhaust.

All of the 13 sets of data collected were tested by the trained neural network–which also included the two data sets constituting the training file. A combined total of 10,359 temporal samples was collected from the sensors for the periods when clear air occurred. During these periods, all samples within the data sets were correctly classified as being from clear air. A combined total of 17,185 temporal samples was collected from the sensors for the 12 periods when only diesel exhaust and air were flowing over the sensors. During these periods, all samples within the data sets were correctly classified as being from a diesel-exhaust-air mixture. The main

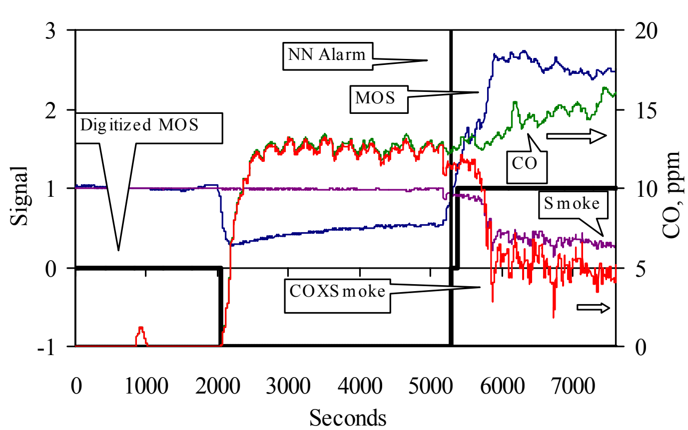

Figure 6. Inputs to the NN from station-1 data from the third belt fire with diesel exhaust.

reason that no diesel exhaust data were classified as clear air in all 12 data sets was because the change in the dMOS values dominated the other sensor changes at the start of the detection of the diesel exhaust. A somewhat similar effect occurred later in the experiments. At the time the dMOS values temporarily returned to a value of 0, the NN signaled hazardous combustion in all 12 of the diesel tests. The period between the first temporary dMOS value of 0 and the value of 1 when the MOS sensor detected hazardous combustion from these 12 data sets ranged from 32 s to 210 s with the mean period being 88 s and the standard deviation of the periods being 53 s. If the heating rate had been slower, these periods would have been larger. More volatile oxidizable gas would have been dissipated over a longer

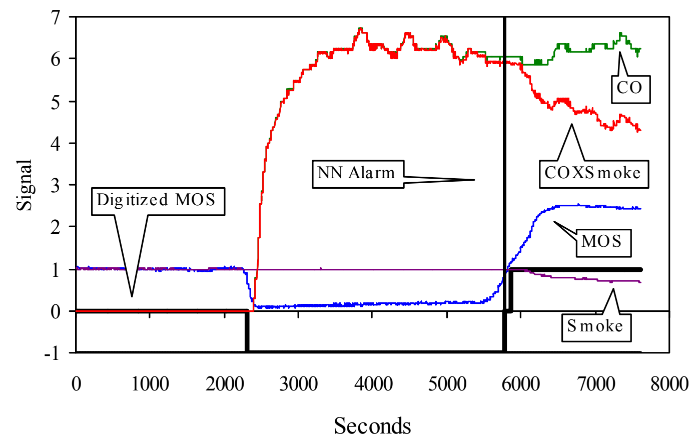

Figure 7. Inputs to the NN from station-2 data from the third belt fire with diesel exhaust.

heating period causing the time interval from smoldering combustion to flaming to also increase. Without the CO and smoke sensors, the MOS sensor would not have detected the smoldering combustion until later with the lag in detection depending on the rate of heating of the flammable material. In the first coal test, without diesel exhaust, only at the time the dMOS values became 1 did the NN signal a coal fire. A combined total of 12,485 temporal samples was collected from the sensors for the 12 periods when air mixed with diesel-exhaust and hazardous-combustion products was flowing over the sensors. During all of these latter periods, percentages ranging from 5% to 44% of the samples were classified initially as being from diesel exhaust with the mean percentage being 18% and the standard deviation of the percentages being 11%. The NN classified the first 6% of 2,509 temporal data samples from the hazardous combustion period of the first coal experiment as being from clear air.

5 CONCLUSIONS

1. A two-layer, perceptron neural network (NN) with 10 process elements in the first layer and 5 process elements in the second layer was superior to other neural networks investigated at discriminating diesel exhaust from coal and belt smoldering combustion without any false alarms.
2. Digitized MOS-sensor data, CO-sensor data, optical-path smoke-sensor data, and the product of the CO and smoke-sensor data were the best inputs found for the discriminations.
3. All clear-air and diesel-exhaust data were recognized by the NN from 13 sets of inputs from four coal and three belt combustion experiments with two collections of sensors 18 m and 148 m from the fire sources.
4. Smoldering combustion was detected by the NN within 9.67 min from the first visual indication from the MOS sensor at a station that hazardous combustion products were present for all of the 13 sets of inputs.
5. The applicability of a neural network to the discrimination of hazardous underground-mine combustion from diesel-engine exhaust was determined to be viable.

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