Real-time neural network application to mine fire – nuisance emissions discrimination

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ABSTRACT: : The National Institute for Occupational Safety and Health (NIOSH) implemented a real-time neural network system which can discriminate mine fires from nuisance diesel emissions as part of an atmospheric mine monitoring system in NIOSH's Safety Research Coal Mine. The real-time response of a neural network to fire sensor outputs was demonstrated for coal and belt combustion in the presence of diesel emissions. The fire sensors consisted of an optical path smoke sensor, a carbon monoxide (CO) sensor, and two types of metal oxide semiconductor (MOS) sensors. The real time neural network was trained with coal, wood, and belt fire experiments with and without diesel emissions background. The trained neural network successfully predicted mine fires with these combustibles in the smoldering stage prior to the onset of flames.

1 INTRODUCTION

The discrimination of mine fires from nuisance signatures such as emissions from diesel equipment, flame cutting and welding operations, and battery charging operations is an ongoing problem for early and reliable mine fire detection. Currently most in-mine fire detection systems use thermal or CO sensors. Thermal sensors are useful in the proximity of flaming combustion. CO sensors are subject to false signals from CO diesel equipment nuisance emissions and H_2 cross-interference from battery charging operations. Multiple type fire sensors and statistical methods, including neural network, have been used for mine fire detection and the elimination of nuisance emissions in non-mining applications (Ishii et al., 1994, JiJi et al., 2003). As discussed previously (Edwards et al , 2002, Friel and Edwards, 2002), a set of three sensors and a neural network was determined to predict the occurrence of a mine fire in the presence of diesel emissions. These sensors were: a carbon monoxide sensor; an optical path smoke sensor; and a MOS sensor with bimodal response to products-of-combustion (POC) from mine fires and NO_x from diesel equipment. These evaluations were based upon coal and conveyor belt combustion experiments in the presence of diesel emissions. Subsequent to that research, additional experiments included wood combustion. A new neural network (NN) was constructed based upon an optimum choice of sensors. These included the previous three sensors and a second MOS sensor. The new NN uses directly the CO sensor, optical smoke sensor, and bimodal MOS sensor output, the product of the CO sensor and optical smoke sensor outputs, and the product of the outputs from the bimodal MOS sensor, labeled 2105, and a MOS sensor, labeled 2600, which is more responsive to H_2 than CO. The utility of the program can only be successful for underground mining applications if predictions can be made accessible to the mine personnel in real-time. This required the implementation of a real-time sensor data interpretation program for the NN executable file. The objective of this research was to demonstrate how this could be accomplished.

2 SENSOR TYPES

For mine fire detection the available sensor types include gas, smoke, and thermal sensors. Although thermal sensors are widely used, their range is limited to the immediate proximity to a fire in its flaming combustion stage. A sensor commonly deployed when belt entry air is used at the mine working face is a CO sensor. An advantage of a CO sensor is its capability to quantify a fire in terms of the molecular concentration of a product gas species. A CO sensor is especially useful for early detection of a deep seated spontaneous coal heating where smoke concentrations are low. Disadvantages are its response to emissions from diesel equipment, flame cutting, welding, and its susceptibility to interfering gases, such as H_2 from battery charging operations. Smoke sensors, which are either optical or ionization, are responsive, stable, and easy to check. The ionization smoke sensors are usually based upon the decay of an alpha emitter such as Am^{241} or a beta emitter such as Kr^{85}. A disadvantage of an ionization smoke sensor is the requirement for a license for the radioactive source dependent upon the strength of the source. Optical smoke sensors can be either a point or a path type. The point type sensor is based upon optical scattering, and the path type is based upon optical obscuration. An advantage of the path sensor is its ability to probe the cross section of an entry. A disadvantage for a path optical smoke sensor is the optical path distance which can create a problem for its installation in a mine. Nuisance emissions which can affect smoke sensors include dust, water vapor, and particulate emissions from diesel equipment and flame cutting, and for the case of an optical path sensor the potential blockage by personnel and equipment. Optical smoke sensors, which are generally in the infrared optical range, are very responsive to larger smoke particulates produced by smoldering combustion, and ionization smoke sensors are generally more responsive to smaller smoke particulates produced by flaming combustion. The demarcation size is about 0.3 micrometer. Because of the optical sensor's response to larger particulates, it will be less responsive to smaller diesel particulate emissions.

Another class of sensors which respond to mine fire gases are MOS sensors. These sensors are very responsive, but not very selective in their response. Their responsiveness can be ordered in terms of their resistance change to various oxidizing and reducing gases. Methods to vary their selectivity include the addition of a catalyst, sensor element grain size selection, heating of the sensor, and filters. Another advantage of the MOS sensor is its compact size. Its cylindrical structure has a height and diameter of about 1.3 cm. A disadvantage of a MOS sensor is the high temperature, 250 to 380 ° C, of the sensing element. A MOS sensor which is sensitive to NO_x has an increase in its electrical resistance associated with adsorption of oxygen due to electron transfer from the surface element to the oxygen and the buildup of a positive space charge on the element surface. The presence of deoxidizing POC gases will remove the adsorbed oxygen and result in reduced resistance. To be useful, the MOS's sensitivity to NO_x must be sufficient to overcome its sensitivity to CO in diesel emissions, otherwise the discriminating capability of the sensor will be compromised. Generally there are gas concentration ranges over which the sensor's resistance element will respond with a power dependence upon the adsorbed target gas concentration. For an extended range of concentrations this nonlinear logarithmic dependence makes the prediction of the net effect problematic, and direct experimental verification is required.

In a refueling area where rapid flaming combustion most likely will occur, optical spectral emission sensors could be useful. In this case the distance between the source fire and sensor will be relatively short, and infrared signal attenuation by smoke will initially be minimal.

The ordinary use of fire sensors depends upon defined alarm values. Fire sensors for in-mine use have established alarm values (Code of Federal Regulations, 2001). These include a CO alert value of 5 ppm above ambient, a CO alarm value of 10 ppm above ambient, a smoke optical density of 0.022 m^{-1}, and a temperature of 165 ° F.

3 MINE FIRE DETECTION METHODS

There are three approaches for utilization of sensors for mine fire detection in the presence of nuisance emissions. One approach is to increase the sensor alarm and alert values to compensate for nuisance emissions. Without an exact knowledge of the nuisance emissions' gaseous and particulate concentrations, which will be variable in response to the operation of the emissions producing equipment under variable power loads, early and reliable fire detection will be compromised. For example, this approach would be expected to miss early smoldering stages of a mine fire. A second approach is rule making. This approach would rely upon an understanding of the generation of emissions from nuisance producing sources and combustion sources. For example, this approach could examine rates of change in a measurable emission, such as CO, so as to differentiate CO emissions from a diesel and from a mine combustible. However, the rate of change of a fluctuating time variable quantity will fluctuate considerably and can produce indistinguishable events. Another example is to rely upon the measured historical relationship between two emission components, such as NO and CO from a diesel engine. This approach can depend upon the growth rate of the fire (Edwards et al., 1999). A third approach is information processing. This approach is useful when multiple type sensors with nonlinear responses to various POC are used. In this approach a relationship between the classification of an event and the sensors' inputs can be established with a method which recognizes patterns for known data sets. An advantage is that a number of mine fire-nuisance emission experiments can be conducted to establish the functional relationships. One such information processing approach is a NN approach. Based upon these relationships classifications of unknown events similar to those for which the relationships are developed can be made. These classifications can be quantified with a probabilistic interpretation.

4 NN PROGRAM

A NN program named NeuroSolutions developed by NeuroDimension, Inc[1] was applied to fire prediction. The trained perceptron NN which was implemented was composed of thirty eight processing elements that produced three output classifications in response to five inputs. The NN program had two-hidden-layers with 20 processing elements (PE) in the first layer and 10 PE in the second layer. A hyperbolic tangent function was used as the activation function which operated on the linear combination of inputs to the PEs in the hidden layers. The output classification is a result of the application of a softmax function to the inputs to the PEs in the output layer. The softmax function is a probability function based upon exponential weights. Applications of the NN method require the determination of the internal weights between the input layer of sensor data and the first hidden layer, between the sequential hidden layers, and between the last hidden layer and the output layer. A backpropagation method for the errors associated with the feedforward of the input training is used to determine the weights for the PEs during the training stage. The testing stage or predicting stage uses a forward propagation method. The five inputs consisted partially of the responses of the CO sensor, the optical path smoke sensor, and the bimodal MOS sensor, all normalized by their ambient values. In addition two product functions of sensors were included. These were the product of the responses of the CO and optical smoke sensor, and the product of the bimodal MOS sensor and a MOS sensor responsive to H_2 and CO. A trained NN executable file was constructed by iterating on the training data set with known output classifications. Based upon a training data set which consists of six in-mine combustion experiments in the presence and absence of diesel emissions, an optimum set of sensor type inputs was determined which would detect the test fires and yield the minimum number of false alarms. The combustion fuel sources were coal, conveyor belt, and wood.

[1] Mention of any company or product does not constitute endorsement by NIOSH.

5 DATA EVALUATION

Each sensor's analog output voltage is converted into a digital signal by an accessor card for processing by the mine monitoring system. The range of the analog signal is subdivided into 255 subdivisions associated with the 8 bits of electronic information available for data representation. The subdivision represents the minimal signal variation that can be processed. For example, if the sensor's output signal range is 0 to 5 volts, then the minimum signal change which can be processed is 19.6 mV. As part of the mine monitoring system, an applications computer program was prepared which managed the real-time sensor data for inclusion into the NN executable file. To process the input data for the NN, the background average is computed for each sensor's response based upon a specified time increment. This time was generally selected to be about 5 minutes prior to start of the experiment. After the average values were determined for the sensors, the program proceeded to normalize the subsequent input by the average values. For all sensors exclusive of the CO sensor, this data normalization was accomplished by a division of the sensor output by the sensor's average ambient value. For the CO sensor, the ambient value was subtracted. The normalized values were found to yield more consistent input data for the NN than the actual signal values, since changes relative to ambient are important for characterization of the event. The program also developed the appropriate multiplicative combinations from the sensor data as inputs for the NN. The NN output was displayed on a monitor as columns of probability values for clear air, diesel emissions, and fire POC. When a fire was identified the monitor displayed a box with a fire alert message. This system was successfully evaluated not only with previously acquired data, but also in real-time while a mine fire detection experiment was in progress.

6 EXPERIMENTAL METHOD

Figure (1) shows a plan view of the section of the Safety Research Coal Mine (SRCM) in which the experiments were conducted. To establish a sensor atmosphere which contained diesel emissions, a diesel locomotive was positioned in B-Butt either upwind of the split formed by 10-Room, or at the entrance to 10-Room. In the latter case a tube was

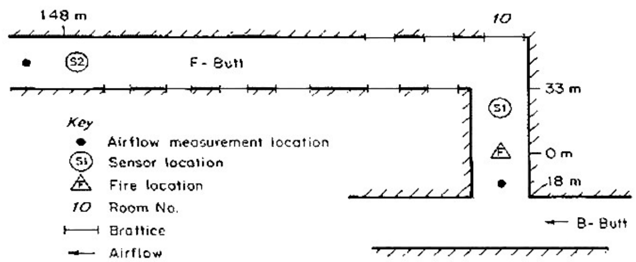

Figure 1. Plan view of the SRCM section

connected to the locomotive's exhaust port to direct the emissions directly into 10-Room. Identical fire sensor types were located at S1 and S2, which were 18 m and 148 m downwind of the fire zone. The average height and width of 10-Room were 2.0 m and 3.9 m, and the average height and width of F-Butt were 1.9 m and 4.5 m. The average air flows for the experiments were 3.0 m^3/s in 10-Room and 4.4 m^3/s in F-Butt. Table 1 lists the measured airflows for the experiments. The flow ratio refers to the airflow increase in F-Butt compared to 10-Room. The higher airflow in F-Butt was due to the leakage around brattices which block the crosscuts from parallel airways into F-Butt. The dual sensor stations with gas and smoke signature dilution between stations S1 and S2 provided a method to define two experiments for one mine fire combustion event. There was an average 47 pct increase in the ventilation between the two sensor stations.

The fires were contained in a 0.61-m square tray. In order to provide a slow heating of the solid fuels which would transition through a smoldering stage prior to a flaming combustion stage, a controllable heating source was maintained with the use of electrically powered strip heaters. For the coal fires the heater elements were embedded in approximately 14 kg of Pittsburgh Seam Coal with a diameter less than 5 cm. About 1 kg of coal fines was distributed over the coal. For the conveyor belt combustion experiments about 0.5 m square samples of belt 1.1 cm thick with a 3 kg mass were attached to a steel plate which was heated from below by the electrical strip heaters. For one combined coal and belt combustion experiment a belt sample about 0.3 m by 0.5 m was positioned on top of the coal. The wood combustion experiments utilized twenty eight oak sticks, 0.46 m long and approximately 1.6 cm square cross section, cut from mine support timber arranged in a two-layer crib set with an approximate total mass of 2 kg. The wood crib was placed upon five electrical strip heaters. The identification of the experiments is provided in table 1.

7 RESULTS

The training data set for the NN consisted of experiments T71S2, T75S1, T79S1, T81S1, T82S1, and T85S1. This data set includes coal, conveyor belt, and wood fires in the presence and absence of diesel emissions. The trained neural network was used to evaluate the experiments previously conducted, and used in a real-time mode for fire prediction in experiments T87S1, T88S1, and T89S1. A conservative fire alert was marked by the probability exceeding 0.5 even though a probability of a fire near 1/3 could exceed the probabilities of the other two events.

Figure 2 shows the response of the sensors and NN probability at station S1 to a developing primary coal fire and secondary belt fire in the presence of diesel emissions as part of experiment T88S1. The power supplied to the heater elements varied from

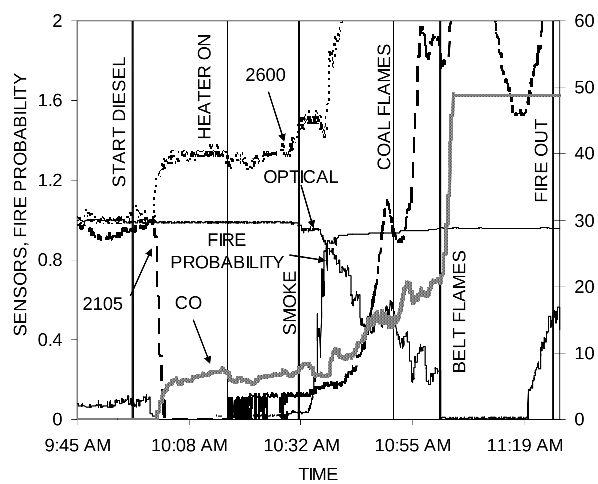

Figure 2. Sensor responses at station S1 and NN fire probability for coal and belt combustion in presence of diesel emissions.

1.6 kW to 2.9 kW over a 20-min time period. The presence of diesel emissions results in a significant response of the two MOS sensors, an increase of the CO concentration above the 5-ppm alert concentration, and an insignificant response of the optical path smoke sensor prior to heating the combustibles. Associated with the visual observation of smoke results was a rapid increase in the 2600 sensor's response, and less rapid rates of response for the CO, optical smoke, and 2105 sensors. The onset of flaming coal combustion resulted in visually obscuring smoke which saturated the optical smoke sensor's response. The identification of a fire with the NN probability curve occurred 5 min after the visual observation of smoke, and 16 min prior to coal flaming combustion. The flaming belt combustion occurred 10 min after the flaming coal combustion. When the NN identified the fire, the optical density was 0.012 m^{-1}, which is less than the 0.022 m^{-1} smoke optical density alarm value specified in 30CFR75.344 and 30CFR75.340 (Code of Federal Regulations, 2001). The maximum temperature measured at the roof above the fire was 98 ° F, which occurred during the belt flaming stage. This temperature is less than the thermal alarm temperature of 165 ° F. In this particular example, the clear advantage of the NN approach is its ability to discriminate the false CO alert value associated with the diesel emissions, and identify the incipient smoldering coal combustion stage prior to its flaming combustion, and the subsequent flaming belt combustion.

Figure 3 shows the response of the sensors at station S1 and the NN probability curve to a belt fire in the presence of diesel emissions for experiment T78S1. In this case the ventilation was adjusted to

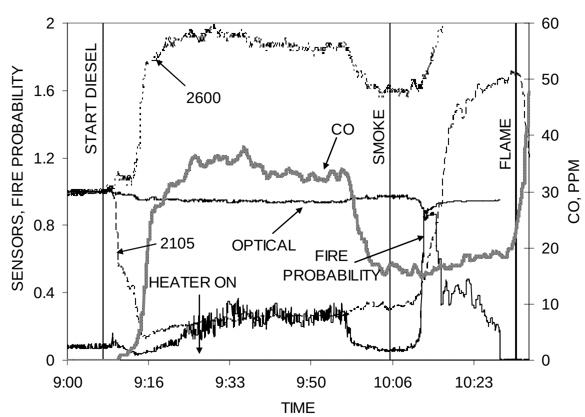

Figure 3. Sensor responses at station S1 and NN fire probability for belt fire in presence of diesel emissions.

produce CO concentrations from the diesel exhaust in excess of 30 ppm prior to heating of the belt. This exceeds the 30CFR75 defined 10 ppm alarm value. Smoke emissions were observed when the temperature of the belt surface in contact with the heated plate reached approximately 560 ºF, and flaming combustion commenced when the temperature reached approximately 870 ºF. The electrical power applied to the heaters varied from 1.1 kW to 3.3 kW over a 40-min time period. The NN probability curve identified the fire 7 min after the visual observation of smoke, and 19 min prior to belt flaming combustion. At the NN identification of the fire the optical density was 0.0061 m^{-1}. A comparison of the maximum CO concentration for the experiments in figures 2 and 3 prior to heating of the fuel show measured CO values of 8 and 36 ppm respectively. In figure 2 a CO concentration of 36 ppm, which was an average of two CO sensors at the station, was not reached until flaming coal combustion occurred. This illustrates the uncertainty in increasing a fire sensor's alarm alert and alarm value. Although there will be a scaling of the CO concentration with ventilation change, this scaling provides one more parameter which would need to be known with certainty prior to identification of a fire produced CO alarm concentration.

To evaluate the effectiveness of the NN for identification of a variable quantity nuisance emissions source, the trained NN was used to identify a nuisance event which consisted of a diesel locomotive moving along B-Butt past the air split of 10-Room. Figure 4 shows a minimal deviation of the optical smoke sensor to the diesel emissions, and the relatively sharp responses of the CO and 2105 sensor to

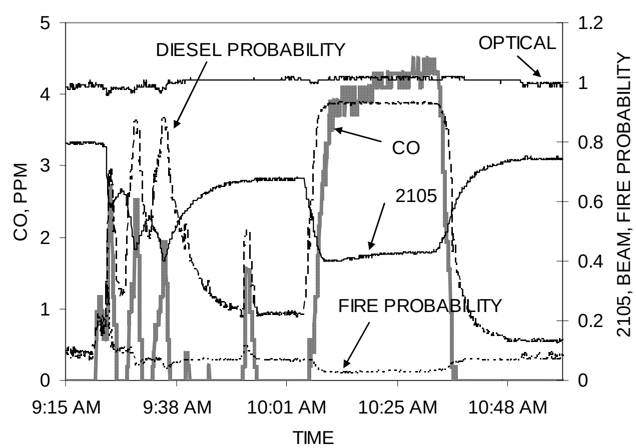

Figure 4. Sensor responses at station S1 and NN fire probabilities for diesel locomotive variable emissions

the emissions. The NN probability curve correctly identifies the diesel emissions signature. Its response is coincident with the CO and 2105 responses. The fire probability curve shows that in no case is there a significant indication of a fire. The advantage of a probability display is the presentation in real-time of a continuous source of information which mine personnel can use to make decisions. For example, the continuous fire probability curve can be subdivided into regimes of low, medium, and high fire alarm. The current application program provides a real-time visual display of the probability values for fire, diesel emissions, and clear air conditions.

A listing of all the mine fire experiments by combustible, presence or absence of diesel emissions and airflows is shown in table 1. For the experiments conducted, the NN prediction of a fire is evaluated in terms of the prediction of the fire relative to the first visual observation of smoke and flames. Figure 5 shows the NN prediction of a fire based upon the fire probability exceeding 0.5 as a lag time relative to the time of first observation of smoke. (Notation T in table 1. is omitted from experiment number on coordinate axis in figure 5.)

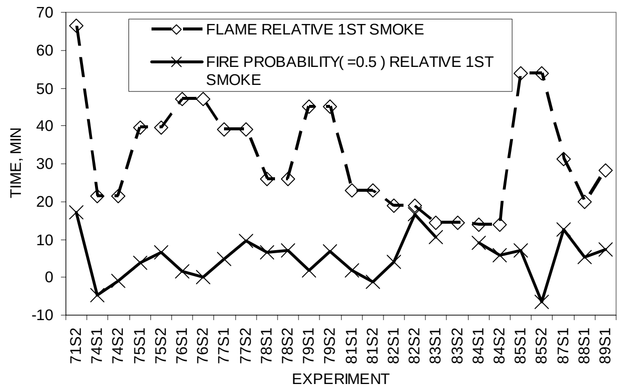

Figure 5. NN prediction of fire relative to first observation of smoke, and flaming combustion relative to smoke for each experiment

Also shown in the figure is the lag time of the flaming combustion relative to first smoke. For example, for experiment T71S2 the fire probability is 17 min after the first observation of smoke, and flaming combustion occurs 67 min after smoke production. Although for experiments T74S1, T74S2, T81S2, and T85S2 the fire is identified prior to the first observation of smoke, its occurrence is after the heating of the combustible was initiated. For 25 of the 26 experiments the NN successfully predicted the occurrence of a fire. Only for one experiment, T83S2, did the NN fail to identify the fire, and that was due to a relatively small wood fire with dilution of the POC at S2. For the experiments listed in table 1, the average optical density at which the NN predicted a fire was 0.0059 m^{-1} with a standard deviation (SD) of 0.0050 m^{-1}. This average value is more than three SD s less than the minimum smoke alarm value of 0.022 m^{-1} specified in 30CFR75.

Table 1. Mine fire detection experiments listed by combustible, presence or absence of diesel emissions, and airflows.

Test No. And Sensor Station	Combustible	Diesel Emissions	Flow, m^3 / s	Flow Ratio
T71S2	Coal	no	4.3	1.7
T74S1	Coal	yes	2.7	
T74S2	Coal	yes	5.4	2.0
T75S1	Coal	yes	2.0	
T75S2	Coal	yes	3.9	1.9
T76S1	Coal	yes	3.3	
T76S2	Coal	yes	4.2	1.3
T77S1	Belt	yes	3.3	
T77S2	Belt	yes	5.7	1.7
T78S1	Belt	yes	1.9	
T78S2	Belt	yes	3.8	2.1
T79S1	Belt	yes	2.8	
T79S2	Belt	yes	5.4	1.9
T81S1	Wood	no	1.7	
T81S2	Wood	no	3.5	2.1
T82S1	Wood	yes	2.1	
T82S2	Wood	yes	4.8	2.3
T83S1	Wood	yes	2.9	
T83S2	Wood	yes	2.8	1.0
T84S1	Wood	yes	3.1	
T84S2	Wood	yes	4.5	1.4
T85S1	Belt	no	3.1	
T85S2	Belt	no	4.2	1.4
T87S1	Coal	yes	5.6	
T88S1	Coal\Belt	yes	4.2	
T89S1	Coal	no	3.7	

The most sensitive sensor for fire detection in the selected set of sensors is the optical path smoke sensor. This is illustrated with a simple test in which a rag was ignited upwind of sensor station S1 in the SRCM.

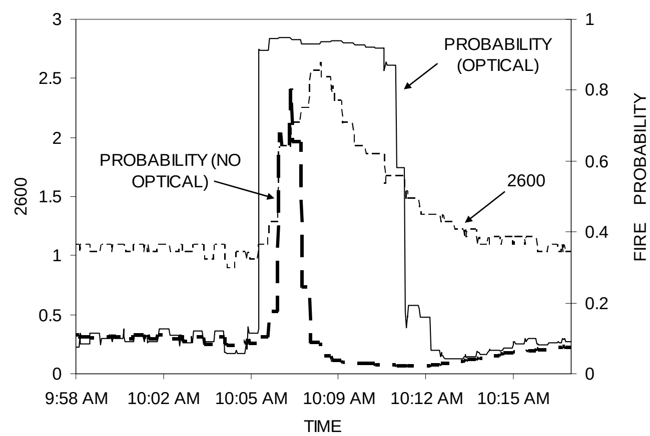

Figure 6. NN prediction of rag burn with and without optical path smoke sensor

Figure 6 illustrates the response of the 2600 MOS sensor to the burning of the rag. The duration of this sensor's response defines clearly the combustion duration. The fire probabilities with and without the response of the optical path sensor are shown in figure 6. It is seen that the fire probability determination with the inclusion of the optical path sensor correctly envelopes the fire duration. The NN calculation which excludes the optical path sensor results in a much shorter indication of the fire duration.

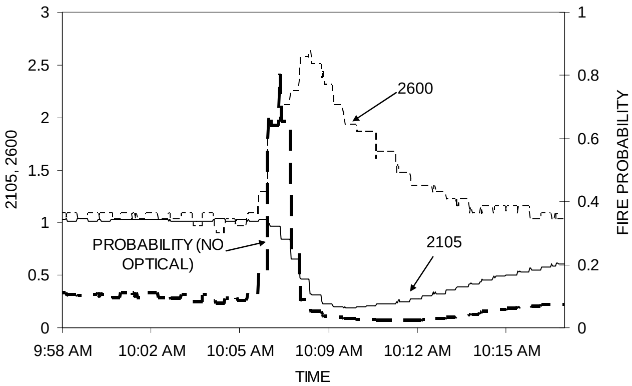

Figure 7. Comparison of NN fire prediction with response of 2105 and 2600

Figure 7 illustrates the reason for this result. The 2105 MOS sensor responds to the NO_x compounds generated by the burning rag. There appears to be unknown nitrogen additives in the cloth. As the NO_x concentration increases, the fire probability evaluation in the absence of the optical smoke sensor incorrectly identifies the combustion as a nuisance event.

8 CONCLUSIONS

A NN was trained to discriminate a mine fire from background diesel emissions based upon the response of a multiple sensor array consisting of a CO sensor, an optical path smoke sensor, and two MOS sensors, one of which has a bimodal response to NO_x emissions and reducing gases. An interactive computer program was developed that can accept real-time data from the data acquisition system and evaluate with the NN the probability of a fire. It was demonstrated from applications to coal, conveyor belt, and wood combustion experiments in the presence and absence of diesel emissions that a smoldering fire prior to flaming combustion could be predicted for 25 of 26 fire detection experiments conducted.

REFERENCES

Code of Federal Regulations, 30 CFR, Parts 75.340, 75.344, and 75.351, 2001. Office of the Federal Register, National Archives and Standards Administration, U.S. Government Printing Office, Washington, D.C., July 1, 2001.

Edwards, J.C., Franks, R.A., Friel, G.F., Lazzara, C.P., and J.J. Opferman. Mine Fire Detection in the Presence of Diesel Emissions. In J.C. Tien (ed), Proc. 8th U.S. Mine Ventilation Symposium, The University of Missouri-Rolla, June 11-17, 1999, (University of Missouri-Rolla Press, Rolla, MO), pp. 295-301.

Edwards, J.C., Franks, R.A., Friel, G.F., Lazzara, C.P., and Opferman, J.J. In-Mine Evaluation of discriminating Mine Fire Sensors. In E.DeSouza (ed), Proc. 1st North American & 9th U.S. Mine Ventilation Symposium, Ontario, Canada, June, 2002, (A.A.Balkema, Lisse, 2002) pp. 527-532.

Friel, G.F., and J.C. Edwards. Neural Network Application to Mine-Fire Diesel-Exhaust Discrimination. In E.DeSouza (ed), Proc. 1st North American & 9th U.S. Mine Ventilation Symposium, Ontario, Canada, June, 2002. (A.A.Balkema, Lisse, 2002) pp. 533-538.

Ishii, H., Ono, T., Yamauchi, Y., and S. Ohtani. Fire Detection System by Multi-Layered Neural Network with Delay Circuit, Fire Safety Science-Proc. of the Fourth International Symposium, pp.761-772, 1994.

JiJi, R.D., Hammond, M.H., Williams, F.W., and S.L. Rose-Pehrsson. Multivariate Statistical Process Control for Continuous Monitoring of Networked Early Warning Fire Detection (EWFD) Systems, Sensors and Actuators B vol. 93, pp.107-116, 2003.