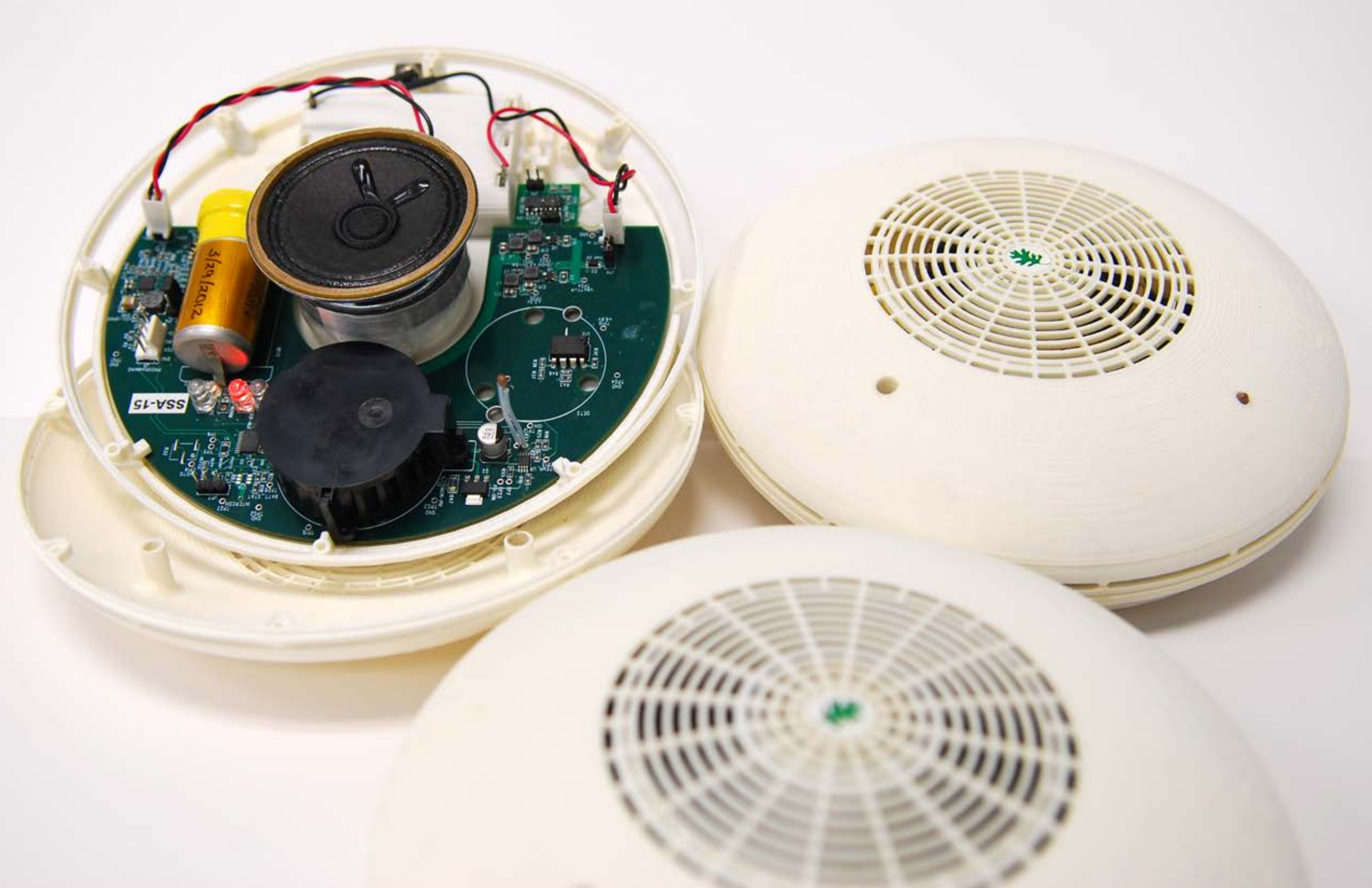
U.S. Fire Administration

Smart Smoke Alarm

Using Linear Discriminant Analysis

January 2015

FEMA



Smart Smoke Alarm

Using Linear Discriminant Analysis

R. J. (Bruce) Warmack
Dennis Wolf
Shane Frank

Oak Ridge National Laboratory
Oak Ridge, TN 37831

January 2015

U.S. Fire Administration | FEMA | United States Consumer Product Safety Commission | Oak Ridge National Laboratory

This work is sponsored by the U.S. Fire Administration (USFA) and the U.S. Consumer Product Safety Commission (CPSC) and prepared under DOE Contract # DE-AC05-00OR22725 between Department of Energy Oak Ridge Office and UT-Battelle, LLC.

Table of Contents

Executive Summary iii

Home Smoke Alarms 1

Classification Techniques and Discriminant Analysis 3

- Principal Components Analysis 3
- Linear Discriminant Analysis 3

Linear Discriminant Analysis With Multiple Sensors 5

Linear Discriminant Analysis Studies Using Fire Test Data 7

Prototype Design and Construction 11

Underwriters Laboratories Testing 12

- Calibration Testing 12
- Fire and Nuisance Test Setup 12
- Fire Test Results 12
- Nuisance Test Results 14
- Limitations 14

Future Directions 15

Acknowledgments 16

Appendix 17

Acronyms 31

This page intentionally left blank.

Executive Summary

More than 80 percent of all fire deaths in the United States occur in homes. While this percentage has remained fairly consistent for years, the overall number of fire deaths has declined significantly. The introduction and widespread use of smoke alarms in homes is considered to be a principal factor contributing to the decline in home fire deaths. As significant an achievement as this has been for the nation, there are persistent facets of fire hazards that have eluded solutions. Although socio-economic factors create obvious limits, low-cost technological approaches have markedly reduced and can continue reducing the impact of fire losses in residential occupancies.

An earlier publication, "Home Smoke Alarms — A Technology Roadmap," provided an overview of current and future technologies that could prove helpful in designing improved residential smoke alarms.[1] Few new sensor types were identified that could benefit fire detection, and their potential use is limited by cost and availability. In the report, the use of shorter wavelengths and multiple scattering angles were recognized as ways to improve existing photoelectric sensors, but such methods have yet to be implemented in residential systems. A powerful mathematical technique was briefly disclosed that uses data from one or more sensors to optimize the discrimination of hazardous and nonhazardous conditions. If this is properly implemented using microcontrollers commonly found in modern smoke alarms, nuisance alarms could be greatly reduced, thus relieving the temptation by the resident to disable the offending alarm.

Linear discriminant analysis (LDA) is a technique employed in advanced chemical detection for military and civilian systems. Applying LDA techniques to historical sensor data recorded in fire testing yields patterns associated with various types of fires and nuisance conditions. Modeling results on the same fire test situations show that smoldering fires can often be detected sooner than conventional alarms, even when using only a photoelectric sensor. The addition of a temperature sensor or a carbon monoxide sensor allows better discrimination between real fires and nuisance sources.

The Smart Smoke Alarm is a practical demonstration of a home smoke alarm using LDA. Combinations of sensors found in today's smoke alarms are analyzed in real time by an inexpensive microcontroller to determine whether to alarm or remain silent. Ten units were tested at Underwriters Laboratories (UL), and they alarmed during the existing UL-217 fire tests[2] as well as proposed flaming and smoldering foam tests. These units also performed well in limited nuisance tests and alarmed only when dangerous conditions were approached. We anticipate that the technology will be adopted by smoke alarm manufacturers to improve the performance of home smoke alarms without substantially increasing the cost to consumers.

---

1 Warmack, R. J., et al. (2012). "Home Smoke Alarms — A Technology Roadmap." http://www.cpsc.gov//PageFiles/93425/homesmokealarm.pdf.

2 "Standard for Single and Multiple Station Smoke Alarms." (2006). UL-217, Edition 6. UL, Northbrook, IL.

This page intentionally left blank.

Home Smoke Alarms

The introduction and widespread adoption of residential smoke alarms over the past four decades has been tremendously successful in saving countless lives by providing early warning for home occupants to potentially life threatening fires. Smoke alarms have been developed to be reliable in general and economical to employ, requiring occasional maintenance via testing and battery replacement. Nevertheless, there remain some shortfalls in operation. Nuisance or false alarms, which are triggered by nonfire-related sources, account for the majority of smoke alarm activations.[3] Additionally, construction methods and home furnishing materials have changed over the years, dramatically increasing the fire growth rate and reducing the time for safe egress. Rousing sleeping occupants in a timely manner can also be challenging, especially for children and the elderly. Given these concerns, improvements in residential smoke alarms could have a huge impact upon residential fire safety by reducing the number of injuries and deaths.

Nuisance alarms constitute a serious impediment to smoke alarm performance, as occupants sometimes disable the offending alarms, rendering them useless for alarming in genuine fires. One study found that in reported home fires in which smoke alarms were present but did not operate, almost half (47 percent) of the smoke alarms had missing or disconnected batteries.[4] Nuisance alarms were also found to be the leading reason for disconnected or unpowered smoke alarms. Thus, nuisance alarms are an indirect cause of home fire injuries and deaths.

In response to the problems caused by nuisance alarms, requirements for smoke alarms to have "resistance to common nuisance sources" have been added to the 2013 edition of NFPA 72, *National Fire Alarm and Signaling Code*,[5] effective Jan. 1, 2019. A current study[6] is underway by the Fire Protection Research Foundation to define just what constitutes "resistance to common nuisance sources." This study will supply information to the UL-217 task group to develop performance requirements to satisfy the NFPA 72 future requirements. Because of the current prevalence of nuisance alarms resulting from cooking, NFPA 72 changed the installation requirement for smoke alarms installed from 6 feet to 20 feet away from a fixed cooking appliance (range or stove). This requirement was made effective as early as Jan. 1, 2016.

Most residential smoke alarms are based solely upon the detection of smoke aerosol particles emitted by nearly all fires. Ionization sensors in smoke alarms are especially sensitive to dense small particles associated with flaming fires, while photoelectric sensors in smoke alarms are more sensitive to less dense concentrations of larger particles associated with smoldering fires. In either case, manufacturers set sensitivity thresholds to meet UL-217 fire detection requirements that include tests for both types of fires. Unfortunately, both types of sensors respond to other nonfire or nuisance aerosols, including cooking fumes, dust and steam fog. Additionally, other principal combustion products, including heat, carbon monoxide and carbon dioxide, have until recently been largely ignored as an auxiliary means for fire detection.

Gottuk and co-workers demonstrated that combination aerosol and carbon monoxide detectors using simple algorithms significantly improve fire detection and false-alarm rejection.[7] Cestari and

---

3 Ahrens, M. "Smoke Alarms in U.S. Home Fires." 2014, National Fire Protection Association (NFPA), Quincy, MA.

4 Greene, M. A., & Andres, C. (2009). "2004-2005 National Sample Survey of Unreported Residential Fires." U.S. Consumer Product Safety Commission (CPSC).

5 "2013 NFPA 72: National Fire Alarm and Signaling Code." NFPA, Quincy, MA.

6 Dinaburg, J., & Gottuk, D. (2014). "Smoke Alarm Nuisance Source Characterization — Phase 1." Fire Protection Research Foundation, Quincy, MA.

7 Gottuk, D. T., et al. (2002). "Advanced fire detection using multi-signature alarm algorithms." Fire Safety Journal 37: 381-94.

co-workers also found that carbon monoxide sensing alarms could respond to smoldering fires faster than photoelectric-type aerosol sensors and with better nuisance rejection.[8]

Fire detection technology must continue to evolve with advances in sensors, microcontrollers and alerting methods. Some integration is already beginning to be seen for commercial smoke alarms. Combination ionization and photoelectric smoke alarms have been available for some time, and they address the weaknesses of each type of sensor. Unfortunately, simple threshold programming can increase the propensity for alarming to nuisance sources.

Some models are beginning to appear with more sophisticated algorithms that adjust sensitivity dynamically according to the progression or rates of change of the aerosol sensor.[9] By this means, drifts due to changing atmospheric conditions and aging can be compensated and distinguished from more rapid changes that may be indicative of fire conditions. A few models have combined signals from carbon monoxide and temperature sensors in their fire detection algorithms. The presence of elevated levels of these signals by themselves does not necessarily indicate fire, but when appropriately combined with signals from aerosol sensors, it forms a strong corroboration. Even humidity sensors have been employed to signal the possible nuisance source of steam fog particles. Such techniques show an encouraging trend for improved performance in detecting fires and rejecting nuisance sources.

Microcontrollers allow the use of advanced discrimination techniques to be exploited, and they are particularly applicable for multiple channels of data from multiple sensors. Decisions must be made in real time to classify basic conditions such as "fire," for which the alarm is sounded or "nuisance" or "normal" conditions, for which no alarm is given. For systems that include a carbon monoxide sensor, a toxic gas alarm could be added to indicate the presence of that gas, according to UL-2034 specifications,[10] when a fire is not indicated. Approaches for smoke alarms based upon rules involving set concentration thresholds of multiple sensors are cumbersome for the design engineer and possibly inaccurate when in service.

This report presents the use of advanced statistical techniques that allow data from multiple channels to be classified for alarming. LDA, for example, involves a set of linear equations that can be readily evaluated on an inexpensive microcontroller in an advanced smoke alarm. The linear coefficients for the LDA are determined beforehand using training data from realistic fire scenarios. Fortunately, considerable data already exist in prior tests, and they can be used for training and validating the model. Statistical techniques also allow each sensor output and its rate of change to be included in the analysis. A smoke alarm employing one or multiple sensors and a suitably programmed microcontroller can provide faster response to real threats while rejecting conditions that would trigger false alarms in conventional smoke alarms.

---

8 Cestari, L. A., Worrell, C., & Milke, J. A. (2005). "Advanced fire detection algorithms using data from the home smoke detector project." Fire Safety Journal 40(1): 1-28.

9 Gonzales, E. V. "Dynamic Alarm Sensitivity Adjustment and Auto-Calibrating Smoke Detection." (2011). U.S. Patent Application 201110018726.

10 "Standard for Single and Multiple Station Carbon Monoxide Alarms." (2008). UL-2034, Edition 3. UL, Northbrook, IL.

Classification Techniques and Discriminant Analysis

The critical function of a smoke alarm is to determine whether observed conditions indicate that an alarm is warranted. For most existing alarms with a single aerosol detector, classification is simply to alarm for aerosol concentrations beyond a fixed threshold, which unfortunately can also be met by a sufficient level of nuisance aerosols from any source. Designing a smoke alarm based upon whether any one of several channels exceeds a certain threshold can lead to excessive nuisance alarms if the thresholds are set too low or false negatives if the thresholds are set too high. Pattern recognition or statistical classification couples the data channels so that the analysis provides the best discrimination for classification based upon sensor response to historic data.

Classification methodologies are types of mathematical techniques that determine class or group membership of an object of unknown membership according to rules derived from training data collected from all classes. These include discriminant analysis, tree-based modeling, neural networks and nearest-neighbor classification. Principal components analysis (PCA) is a useful technique for understanding the main characteristics of multiattribute data and how those characteristics may relate to class differences. Next, we discuss PCA and then focus upon LDA as a recommended technique to program alarms in residential smoke alarms.

Principal Components Analysis

One of the goals of PCA is to identify main characteristics of a data set containing a number of interrelated variables[11] (e.g., sensor data channels in a smoke alarm). PCA transforms the original variables into a new set of uncorrelated variables called principal components (PCs). The PCs are weighted sums of the original variables, where the weights are optimally chosen. The first PC is constructed so that it explains the most variation in the data, with the caveat that the source of the variation may or may not be due to differences among the classes. The second PC explains the next greatest amount of the variation and is uncorrelated with the first PC. Other PCs are constructed similarly. PCA is not a classification technique **per se**, but if the major sources of variation in the data are related to the class differences, then the PCs can be useful in a discriminant analysis. PCA has been used to develop fire detection algorithms that have shown improved performance for fire sensitivity and nuisance recognition.[12]

Linear Discriminant Analysis

Discriminant analysis is supervised pattern recognition,[13] and it can be used for optimal classification of conditions based upon any number of sensor channels. A set of discrimination rules is constructed from training data and then used to classify new observations into predefined groups. The basis for pattern recognition is supplied by actual field data of smoke, temperature and combustion products for stimulating prescribed sets of sensors to be incorporated in a system.

LDA is one approach that classifies an observation according to its (multivariate) similarity or closeness to a group. In LDA, the observed data variables, or their PCs, undergo a linear transformation into new, uncorrelated variables, called linear discriminant (LD) coordinates, in such a way as to maximize the differences among the predefined groups, as measured on these variables.

Unlike PCA, which does not take into account the differences between classes of events, the goal of LDA is to separate classes of events. LDA classifies each observation of all sensor channels, including rates of change, using a simple linear transformation to obtain the discriminant coordinates (i.e., the observation's position in discriminant space). The closeness of the discriminant coordinates to each

---

11 Joliffe, I. T. "Principal Component Analysis." (1986). New York: Springer-Verlag.

12 Cestari, Worrell, & Milke.

13 Mardia, K. V., Kent, J. T., & Bibby, J. M. (1976). "Multivariate Analysis." New York: Academic Press, Inc.

of the prescribed classes or groups (e.g., "normal," "nuisance," "fire," "toxic") can then be easily calculated and sorted — even by inexpensive microcontrollers.

There is a hierarchy of the discriminant coordinates. The first discriminant coordinate, LD1, accounts for the greatest separation among the groups; the second discriminant coordinate, LD2, accounts for the next greatest separation; and so forth. The maximum number of discriminant coordinates that can be extracted is one fewer than the number of groups.

Plots of combinations of the various discriminant coordinates are often used to visualize group separations. Clear group separations seen in two-dimensional plots will indicate success for those groups. Groups that appear to overlap in one plot (e.g., in the LD1 versus LD2 plot) may appear separated in another two-dimensional view (e.g., LD2 versus LD3). A discrimination rule can still be effective, even though there is no clear separation of groups in certain two-dimensional plots.

Linear Discriminant Analysis With Multiple Sensors

Scaling and Baseline Correction

Discriminant analysis begins by preprocessing or scaling data recorded by one or more sensors. Preprocessing is performed in the same way for training data and for real-time data collected by a smoke alarm. Changes and rates of change in sensor signals are important for indicating deviations from normal conditions. A convenient method is to offset signals by respective baselines x_{0i}, which can be determined by a modified moving average according to the following equation, where x_i are the scaled sensor signals:

$$x_{0i|new} = \frac{(n-1)x_{0i} + x_i}{n} \tag{1}$$

To eliminate slow offset drift in sensors, n can be very large, representing measurements over several hours or days. When n is a small number, representing a shorter average, then effective rates of change are calculated by the difference between the reading and the baseline. Sensor signals S_i are simply differences between scaled signals from various sensors and their respective baselines:

$$S_i = x_i - x_{0i} \tag{2}$$

Note that there can be more than one S from each sensor when baseline offsets with different values of n are used. For example, an aerosol sensor may be assigned two sensor signals if one has a long-term baseline subtracted to correct for drift associated with changing atmospheric conditions and aging, and if another has a shorter baseline that shows rapid changes associated with either a smoldering or flaming fire event. The sensor signals represented in (2) are based upon test data used as input to the LDA or are real-time data observed by a smoke alarm.

Classification

To build the LDA for application in a smoke alarm, each successive sensor signal S_i in time is assigned to a predefined group. Since training data generally begin with normal conditions, the early data is classified as "normal." As sensor data begin to change, the classification is appropriately changed. For example, normal cooking conditions may evoke sensor changes, so the assignment of "nuisance" is appropriate. Various types of fires can be defined as separate groups because the conditions for each type of fire can be rather different. Smoldering fires typically grow much more slowly with less observable temperature rise than fast, flaming fires. It is advantageous for classification to maintain separate grouping even though either condition would be cause for triggering an alarm. Further, because fires can also transition from one type to another, it is also advantageous to assign each observation to the appropriate group. Rules can be generated to qualify each observation into an assigned group. Observations that do not fit into predefined groups can be disqualified and omitted from the training data.

Given training data from a series of tests containing observations with scaled signals S_i along with their assigned groups, the LDA may be obtained with standard software packages, including "R," Mathematica, Matlab, SAS, SPSS and Stata. The output of the LDA includes a set of coefficients D_{ij} and offsets C_i to transform observations into LD coordinates. Given n_s signal channels S_i for each observation, the associated LD coordinates are calculated according to:

$$LD_j = \sum_{i=1}^{n_s} D_{ij}(S_i - C_i) \tag{3}$$

The LDA output also generates the LD coordinates G_{kj} for the mean or centroid of each group so that the LD coordinates of each observation in LD space can be compared to the centroid of each group. Given n_d dimensions in LD space, the Mahalanobis or Euclidian distance squared to each centroid k is given by:

$$R_k^2 = \sum_{j=1}^{n_d} (G_{kj} - LD_j)^2 \tag{4}$$

A simple criterion for classification is to select the group associated with the minimum R_k^2, although other selection criteria could be employed based upon the LD coordinates of the observation.

Once the LDA is formulated based upon extensive training data, implementation for classification in a modern microcontroller is straightforward. Sensor data are scaled and offset in the same manner as used in the LDA formulation to yield n_s signal channels S_i. The LDA coefficients D_{ij} and C_i stored in the microcontroller are used to transform S_i into LD coordinates according to (3). Classification may be assigned according to (4) or similar means.

Once the LD_j coordinates have been calculated, classification can be assigned by the microcontroller code based upon the Mahalanobis or Euclidean distance squared to each centroid using (4) or by other criteria. In effect, based upon training data and scaling, LDA optimizes the classification of observations by creating a coordinate map with regions associated with normal ambient, nuisance and various types of hazardous conditions. Once the LD coordinates of an observation are calculated, a decision can be made to turn on an alarm or to remain silent.

Linear Discriminant Analysis Studies Using Fire Test Data

Comparisons can be made between alarms based upon LDA classification and conventional alarms based upon smoke thresholds. Training data for LDA transformations were supplied by UL[14] during 18 fire tests in the UL-217/UL-268 Fire Test Room and by the National Institute of Standards and Technology (NIST),[15] which took data from historical tests of fire and nuisance situations in home dwellings. NIST data were recorded during 21 fires, each with multiple sensor locations (67 total) in a manufactured (mobile) and a two-story home, plus 25 nuisance tests that frequently triggered conventional ionization and/or photoelectric alarms for common cooking scenarios such as toast, pizza, bacon and hamburgers. The ceiling sensors common to both UL and NIST tests included photoelectric, ionization, temperature and carbon monoxide sensors, as well as commercial home smoke alarms.

First, a simple LDA was constructed using the UL fire data with events categorized as flaming or nonflaming fires. Data recorded prior to the onset of the fire was categorized as "normal." Only three channels of data were included in the analysis: (1) the long-term baseline-corrected ionization signal, (2) its rate of change with a 10-minute baseline, and (3) the rate of change of the temperature with a five-minute baseline. The conditions associated with normal, flaming and nonflaming situations appear in distinctive locations of LD space.

To illustrate the progression of a fire, Figure 1 shows the calculated LDA coordinates for the first two dimensions during two test fires. The coordinates start near the normal centroid and progress toward and beyond the centroids for both the flaming and nonflaming fires. Although the LDA coordinates can easily resolve the differences between the two types of fires, only one alarm sound would be produced for typical homeowner use.

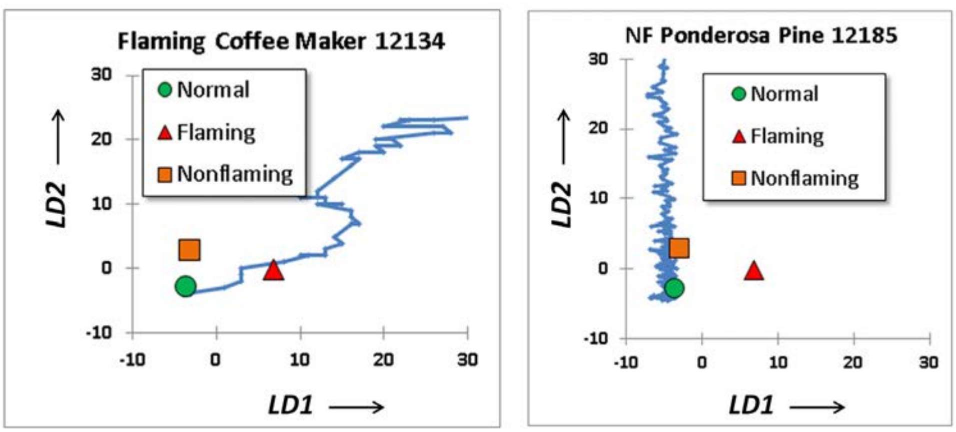


Figure 1. Illustrations of the LDA coordinate progression in an example of flaming fire **(left)** and nonflaming or smoldering fire **(right)**. The LDA centroids of the test conditions of normal, flaming and nonflaming are indicated.

In the flaming fire test shown in Figure 1, the commercial alarms sounded at 3.5 minutes for an ionization alarm and 7.3 minutes for a photoelectric alarm. The alarm based upon LDA coordinate proximity to each of the centroids would have triggered at 2.2 minutes or 37 percent faster than the commercial ionization alarm. In the case of the smoldering fire shown in Figure 1, the commercial alarms sounded at 45 minutes for photoelectric alarm and 48 minutes for the ionization alarm, while the LDA alarm would have alerted at 34 minutes or 24 percent faster. Obviously, early detection times are important to extend the time for safe egress in emergency conditions.

14 Fabian, T. Z., & Gandhi, P. D. (2007). "Smoke Characterization Project." Northbrook, IL: UL.

15 Bukowski, R. W., et al. "Performance of Home Smoke Alarms." (2008). Technical Note 1455-1, revision. This study is also known as DUNES II.

The NIST data include a variety of fires and nuisance sources so that response time and false-alarm rejection can be evaluated for various LDAs. Because the characteristics of the fires change during their evolution, groups were more narrowly defined according to sensor response. For example, data can be categorized as “Flaming” when the rates of increase in the temperature and aerosol signals are above set thresholds. Conversely, data can be categorized as “Smoldering” when the rates of increase in temperature and aerosol signals are below set thresholds. The category of “Grease” was added as a characteristic of vegetable oil that was heated to ignition.

An example of the progression of conditions for one test fire is shown in Figure 2 in three-dimensional LD space. In this LDA, ion, photoelectric, temperature and carbon monoxide sensors were included. As time moves forward, the conditions evolve from Normal to Nuisance and finally to Smoldering. The LDA would have alarmed at 53 minutes, while the conventional combination alarms actually alarmed at 90 minutes.

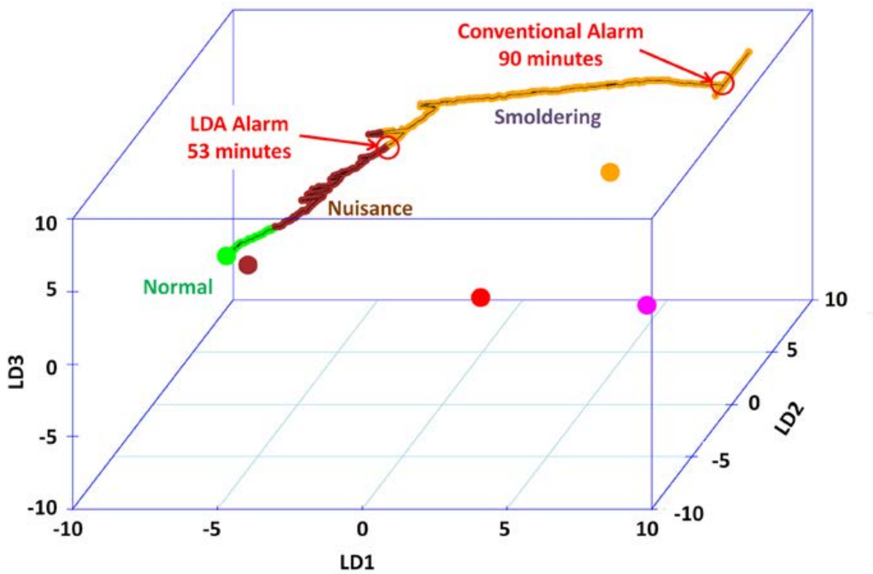


Figure 2. Progression in three dimensions of LD space for data recorded by NIST[16] during a smoldering chair test (SDC01A). Conditions are color coded: Normal (green), Nuisance (dark brown), and Smoldering (light brown). The colored circles represent the centroids of various fire conditions.

In Figure 3, the performance of LDA-based alarms using various combinations of sensors is compared to the commercial alarms used in the NIST tests. Using three sensors, photoelectric, temperature and carbon monoxide, the LDA alarm would have alerted to the smoldering fires an average of nearly 14 minutes faster than a conventional photoelectric-ionization combination alarm. Such an LDA alarm was also found to trigger more slowly than conventional smoke alarms and fully suppress half of the nuisances that triggered false alarms in conventional smoke alarms. In any case, the LDA-based algorithm would always respond more slowly to nuisances than conventional alarms. Even when only a conventional photoelectric sensor is used (not shown in Figure 3), LDA processing has improved the alerting to smoldering fires compared to a conventional photoelectric alarm, although there was only a very small improvement in false-alarm rejection over conventional aerosol-based smoke alarms.

Tests involving heated vegetable oil (not shown in Figure 3) show the tendency of conventional smoke alarms to trigger well prior to ignition due to the production of oil aerosols. Little carbon monoxide is produced until about the time of ignition. Because of the absence of carbon monoxide and insignificant temperature rise for the remote sensors used in these particular tests, the LDA

[16] Bukowski, et al.

algorithm classifies the event as a nuisance until the ignition point is approached. Since heated oil is frequently used in cooking, smoke aerosols involved could be considered a nuisance until the oil is heated well above normal cooking temperatures, at which point an alarm is desirable. Although oil temperature data is unavailable in the NIST tests, limited experimental tests of the LDA algorithm with heated oil at UL are presented in a subsequent section of this report.

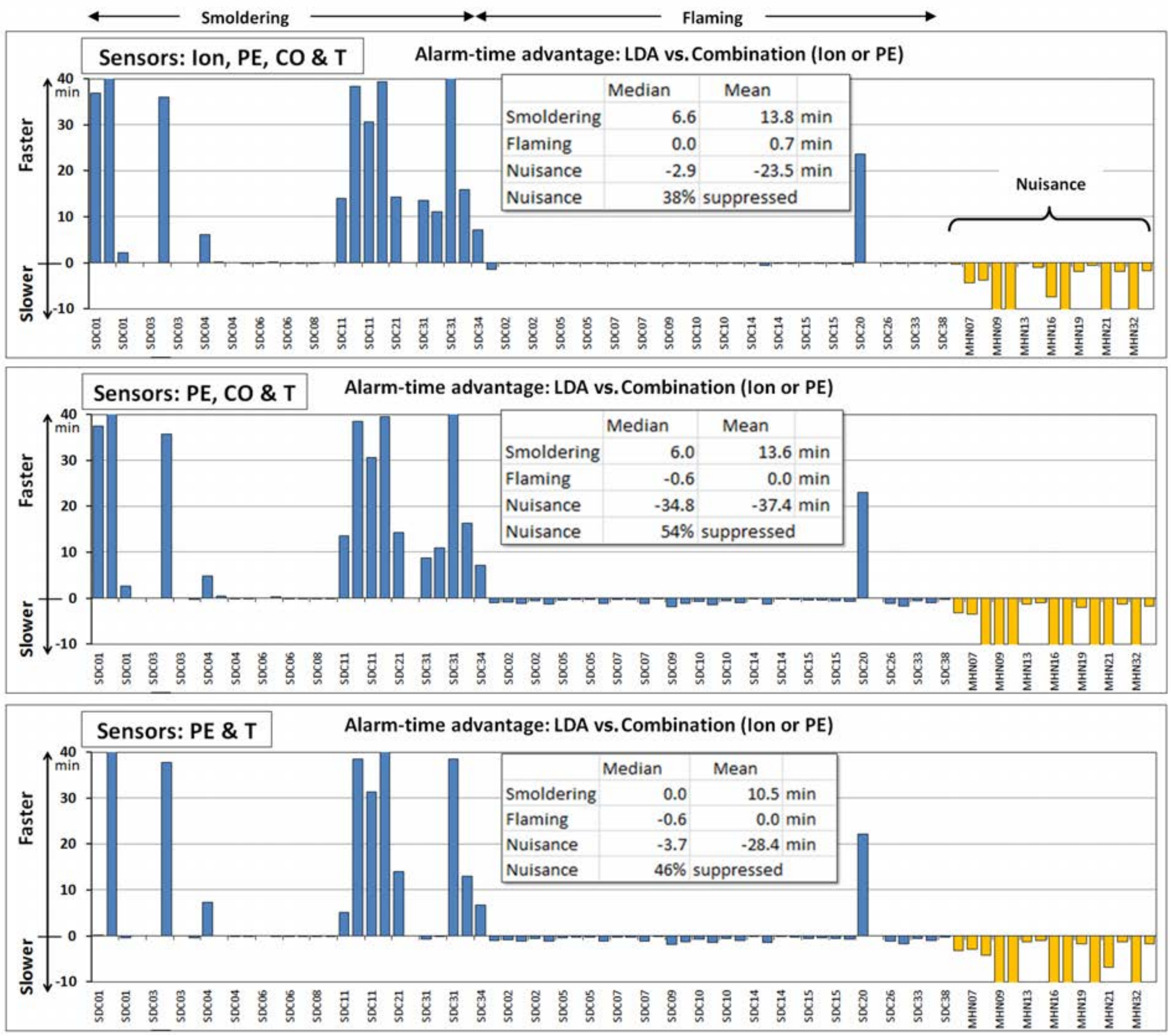


Figure 3. Comparison of alarm times for various LDA-based sensor sets against a combination alarm with an ionization and photo-electric sensor in which the most sensitive setting is used for both sensors. The bars represent individual tests segregated according to flaming, smoldering and nuisance situations. The median and mean times to alarm for the LDA algorithm are given in the insets.

The worth of each sensor to the overall performance of the LDA smoke alarm can also be inferred. Comparison of the alarm times with and without the ionization sensor in Figure 3 reveals that the alarm times for flaming fires are improved by about 30-40 seconds over systems that use a photo-electric sensor for aerosol detection. The well-known fact that ionization sensors in smoke alarms are more sensitive to flaming fires is reflected in these simulations. The addition of the ionization sensor has a slightly deleterious effect upon nuisance rejection in this LDA simulation, although alarming to the nuisances tested is always delayed over that observed using conventional smoke alarms. The addition of the carbon monoxide sensor improves nuisance rejection and smoldering fire performance, since the production of carbon monoxide is nearly always associated with combustion but not with nuisance sources.

The conclusion is that LDA processing alone can improve response time, at least for smoldering fires, while additional sensors can provide faster detection of fires and rejection of nuisance sources for false alarms. The benefit of the addition of carbon monoxide sensing is twofold: (1) acting as a toxic gas sensor and (2) acting in concert with smoke sensors for improved fire detection. A practical smoke alarm that combines commercial sensors with a microcontroller implementation of LDA processing is described next.

Prototype Design and Construction

Prototype home smoke alarms were constructed using multiple sensors integrated by an inexpensive microcontroller that costs under $1 in volume. An electronic circuit was designed to allow up to four sensors to be populated and used for discrimination, including ionization, photoelectric, carbon monoxide and temperature sensors. These sensors were taken from modern residential smoke alarms to demonstrate the immediate applicability of LDA with present sensor technology. Normal settings of biases and sensitivities were used on the aerosol sensors. An analog amplifier circuit was developed to allow the electrochemical carbon monoxide sensor to resolve concentration changes to ±1 parts per million (ppm) with a rise time of about 15 seconds, which is consistent with early fire detection needs. The thermistor circuit has a resolution of approximately ±1 C and protrudes through the enclosure to better sample changes in temperature. A low-frequency speaker was added for improved alerting, consistent with findings that a 520-hertz square-wave auditory signal is much more effective than the currently used 3,100-hertz T-3 alarm signal.[17] Figure 4 shows an assembled prototype with components mounted on a custom printed circuit board and enclosed in a custom shell that includes a battery chamber for three AA batteries.

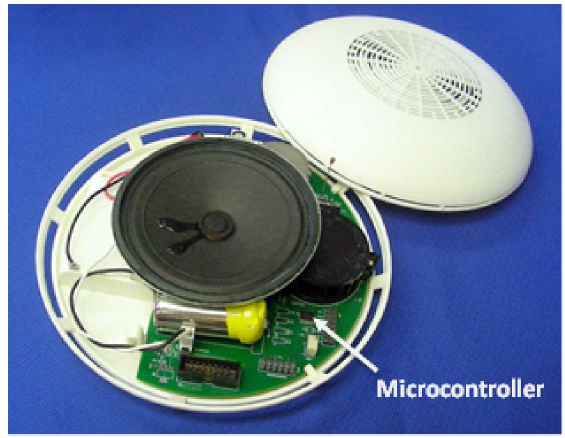


Figure 4. Assembled prototype incorporating multiple sensors, a microcontroller, power (three AA batteries), and a speaker for 520 hertz alerting. The enclosure is 6.5 inches in diameter and 1.7 inches tall.

The microcontroller is used to read the analog signals from each of the sensors and calculate the LDA signals and LD coordinates according to stored coefficients predetermined by LDA. The microcontroller then determines whether an alarm condition has been met and operates the alarm speaker and indicator lights as designed. Data from the LDA signals and the classification are also made available on a serial line for full recording of events during testing. Samples are taken at two-second intervals, between which the system sleeps to conserve battery life. The battery life of the prototype using three AA batteries was not tested, but it was calculated that the prototype smoke alarm would last six months or longer. Repackaging the prototype and carefully selecting the number and type of batteries and/or having the unit be powered on alternating current (AC) with battery backup could satisfy the power requirement in UL-217.

17 Thomas, I., & Bruck, D. "Awakening of Sleeping People: A Decade of Research." Fire Technology 46(3): 743-61.

Underwriters Laboratories Testing

In August 2014, 10 Smart Smoke Alarm prototypes were tested at UL in Northbrook, Illinois. Two types of units were tested; both included photoelectric, carbon monoxide and temperature sensors, and one type added an ionization sensor. LDAs were developed for each type of unit using fire and test data from the NIST study.[18] After calibration testing, both types were subjected to standard UL-217 fire tests plus flaming and smoldering foam tests. A limited set of nuisance tests were also performed (steam, oil, toast, bacon).

Calibration Testing

The Smart Smoke Alarms were initially tested in a standard UL smoke box for threshold sensitivity using a smoldering wick. The LDA software was disabled, and units were programmed to alarm at a specified photoelectric threshold. Calibration was adjusted until the photoelectric reading corresponded to the obscuration reading of the smoke box lamp at 0.5 percent/foot. The ionization sensor was similarly calibrated for units containing that sensor. Calibration factors for the carbon monoxide and temperature sensors had been previously determined at Oak Ridge National Laboratory (ORNL). The calibration factors of each sensor were programmed to be the same for all units and were not adjusted between individual units.

Fire and Nuisance Test Setup

UL-217 specifies a set of three alarms under test to be located on the ceiling of the fire test room and one to be on each of the side walls at a nominal 17.7-foot radius from the smoke source. The two types of Smart Smoke Alarms — five with photoelectric, temperature and carbon monoxide sensors and four with the same set of sensors plus an ionization alarm — were symmetrically positioned at the standard ceiling and wall positions. Units were rotated to allow the aerosol sensors to face the most presumably favorable draft inlet position, with aerosol sensors oriented toward the fire source.

Standard UL-217 fires were set up and conditions (lamp transmission and Measuring Ionization Chamber (MIC) current for the ceiling and two side walls) were recorded by UL personnel, while serial data from the alarms were recorded on the external computer. Between each test, the room was cleared and reset to standard ambient conditions according to UL standard practice, and the alarms were power cycled to restore baselines that would otherwise have been affected by previous tests.

Fire Test Results

The time to alarm for each Smart Smoke Alarm and for each fire test is given in Table 1. Each of the units responded well within the prescribed four minutes for the flaming tests. Test 12 was repeated since the beam obscurance had only reached about 4 percent/foot by the end of the test. Figure 5 shows the lamp obscurances and MIC readings during the repeated smoldering wood test. All units alarmed at beam obscurance readings between 0.5 percent/foot and 2 percent/foot, well below the required 10 percent/foot limit, except for Unit 11, which alarmed at about 10 percent/foot. The cause for the late alarm in this unit is unknown at present.

[18] Bukowski, et al.

Test number:	9	10	11	12	13	14	15
Unit	Flaming Liquid	Flaming Wood	Flaming Paper	Smoldering Wood	Flaming Foam	Smoldering Foam	Smoldering Wood
5 (Ion, PE, CO, T)	0.57	2.53	1.53	46.00	1.67	35.10	30.32
7 (Ion, PE, CO, T)	0.77	2.82	1.98	39.57	2.33	32.42	38.27
8 (Ion, PE, CO, T)	0.78	2.98	1.93	38.05	2.52	33.45	41.10
9 (Ion, PE, CO, T)	1.27	3.45	1.95	35.83	2.62	31.70	35.45
10 (PE, CO, T)	1.60	3.03	1.87	39.68	3.17	30.32	43.35
11 (PE, CO, T)	2.37	3.90	1.88	48.05	3.28	34.37	56.10
13 (PE, CO, T)	2.42	3.23	1.95	41.92	3.20	32.45	41.30
14 (PE, CO, T)	2.72	2.88	1.90	41.27	3.28	29.67	44.28
15 (PE, CO, T)	1.52	3.27	1.83	29.75	3.07	32.80	30.00
Units 5-9 average (with ion)	0.85	2.95	1.85	39.86	2.28	33.17	36.28
Units 10-15 average (w/o ion)	2.12	3.26	1.89	40.13	3.20	31.92	43.01
Overall average	1.56	3.12	1.87	40.01	2.79	32.47	40.02
Standard deviation	51%	13%	7%	13%	20%	5%	20%

Table 1. Alarm times and averages for each unit in minutes after the start of each fire test. Units 5 and 10 were located on the side wall; Units 9 and 15 were located on the opposing side wall; and the remaining five units were located on the ceiling.

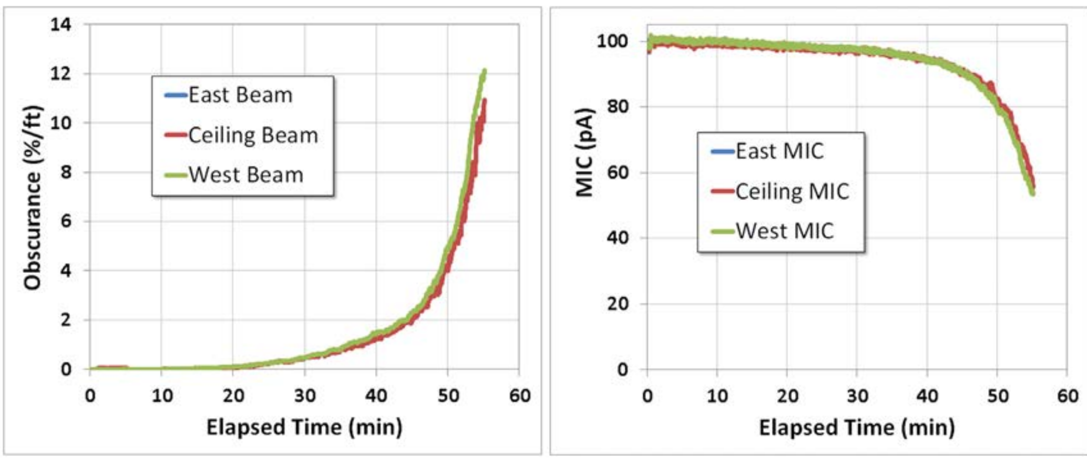


Figure 5. Lamp obscurance and MIC reading during Test 15 — Smoldering Wood.

Excluding the flaming liquid test, the alarm times were closely grouped within each test for both types of units. The units equipped with ionization sensors alarmed significantly sooner in the flaming liquid test, while units without ionization sensors required about one more minute to alarm. A similar pattern is seen in other flaming tests, although the differential advantage for units with ionization sensors is less than one minute. These observations are consistent with LDA simulations of flaming fires shown in Figure 3. For the smoldering tests, the ionization alarm typically adds little, if any, advantage for early alarming, if results from Unit 11 are excluded.

Details of sensor responses during each of the tests are shown in the appendix for a typical Smart Smoke Alarm (Unit 7). Both ionization and photoelectric sensors responded during each test, with the ionization sensor responding more to flaming tests and the photoelectric sensors responding more to smoldering tests. For the smoldering foam test, the response of the ionization sensor was very weak even after the obscuration had exceeded 10 percent/foot.

Nuisance Test Results

A series of nuisance tests were also performed with the same fire room and layout as the fire tests. None of the units alarmed until dangerous conditions or ignition was reached, at which point both types of Smart Smoke Alarms triggered. The time to alarm for each unit and for each test is given in Table 2.

Test number:	16	17	18	19	20	21
Test:	Oil (small skillet)	Steam	Steam	Oil (large skillet)	Toast	Bacon
Time to ignition:	7.87	-	-	25.83	-	22.48
Unit						
5 (Ion, PE, CO, T)	7.95	No alarm	No alarm	14.70	7.35	11.78
7 (Ion, PE, CO, T)	8.28	No alarm	No alarm	15.38	8.52	12.30
8 (Ion, PE, CO, T)	8.33	No alarm	No alarm	15.48	8.67	12.25
9 (Ion, PE, CO, T)	8.32	No alarm	No alarm	15.18	8.68	12.12
10 (PE, CO, T)	8.05	No alarm	No alarm	14.28	7.53	11.93
12 (PE, CO, T)	8.30	No alarm	No alarm	20.57	8.53	14.15
13 (PE, CO, T)	8.32	No alarm	No alarm	15.07	8.47	12.10
14 (PE, CO, T)	8.47	No alarm	No alarm	15.80	8.45	11.83
15 (PE, CO, T)	8.02	No alarm	No alarm	14.13	8.55	11.23
Units 5-9 average (with ion)	8.22	-	-	15.19	8.30	12.11
Units 10-15 average (w/o ion)	8.23	-	-	15.97	8.31	12.25
Overall average	8.23	-	-	15.62	8.31	12.19
Standard deviation	2%	-	-	12%	6%	7%

Table 2. Alarm times for each unit in minutes after the start of each “nuisance” test.

In Tests 16 and 19, a small or large skillet with approximately 3/8-inch of canola oil was located on an electric range that was set on high. The small skillet reached ignition temperature so quickly that the alarms sounded within seconds after ignition. In the case of the large skillet, the alarms typically sounded when the oil had reached about 310-320 C, which is above ordinary cooking temperatures but below the ignition point.

In Test 20, eight slices of toast were repeatedly toasted until heavily charred, accompanied by significant smoke emission and carbon monoxide evolution, at which point the alarms properly sounded to indicate dangerous conditions.

In Test 21, a pound of bacon strips covered the large skillet and was taken to ignition. The alarms typically sounded at about 250 C, which is above ordinary cooking temperatures but below the ignition point.

Limitations

The results of modeling studies (e.g., Figure 3) and the results from UL tests of prototype units are encouraging. More extensive testing, especially with a broader range of nuisance sources and in side-by-side tests with conventional smoke alarms, would be helpful for performance comparison with existing technology. Including a larger number of units in the tests would provide better statistical data on response predictability using manufactured sensors. Nevertheless, the UL tests demonstrated very similar responses for at least nine out of 10 units tested.

Future Directions

The LDA technology is applicable for any combination of sensors in residential and commercial smoke alarms for which data has been recorded during anticipated situations, including ambient, nuisance or alarming conditions. The NIST test data[19] that have been used in the prototype demonstration provide a good starting point. Additional field data can be added to bolster the appropriate responsivity to conditions found in specific consumer environments. In doing so, care must be taken to ensure that hazardous conditions are promptly recognized. Data recorded during UL tests of the prototypes can also be used, with appropriate calibration, to simulate how a particular set of aerosol, temperature and carbon monoxide sensors would act in UL tests. In fact, the UL data that was sampled by the detector units on wall and ceiling mounts would allow the performance of pairs of sensors, say ion and photo or photo and temperature, or even single sensors, to be fully simulated. Note that the performance of a single sensor can be improved by the LDA approach through the use of the baseline-corrected sensor output and one or more rates of change to provide additional channels of data.

Manufacturing always expects a certain level of variation in the sensitivity of ionization, photoelectric, carbon monoxide and temperature sensors. The effects of these variations could be simulated, for example, by determining the time to alarm for combinations of sensors for which calibration or sensitivity differs from the norm. In this way, the manufacturing tolerance can be determined for the desired performance in both the field and UL qualification.

In the long term, new sensors may be developed that could be advantageously employed, in addition to conventional ionization, photoelectric, carbon monoxide and temperature sensors.[20] Variants of existing sensors could be incorporated. For example, a photoelectric sensor using different or multiple wavelengths and scattering angles could extend its sensitivity or provide additional information about smoke (or nuisance) aerosols. The LDA approach provides a straightforward means for incorporating these sensors in an optimal algorithm.

[19] Bukowski, et al.

[20] Warmack, et al.

Acknowledgments

This work would not have been possible without the essential contributions of several people. Dennis Wolf laboriously distilled data from numerous fire tests and developed the mathematical algorithms that are at the heart of the Smart Smoke Alarm. Shane Frank designed the electronic circuitry and developed the embedded software. Danny Simpson and Don Hurst worked on the circuit layout.

This work was sponsored by the U.S. Fire Administration (USFA), the CPSC and the Technology Transfer Division of ORNL. Dr. Lawrence McKenna of the USFA has been especially supportive in providing guidance and connecting the authors with other active researchers in the field of fire detection and testing. Mr. Rohit Khanna of the CPSC has provided useful direction in the interest of consumers. We also thank members of the Technology Transfer Division for their support over the past year. Mr. Ben Miller provided marketing research and insights. Mr. Eugene Cockran has tirelessly contacted manufacturers to acquaint them with the technology and business opportunities. As Director of the Technology Transfer Division, Dr. Mike Paulus has very actively supported and greatly encouraged this work.

The authors appreciate UL for its support of fire and nuisance tests at UL's Northbrook, Illinois, facility. David Dubiel graciously and carefully arranged and managed the full set of standard UL-217 fire tests as well as foam and nuisance tests. David Mills was present throughout the tests and generously provided his support, expertise and guidance. Other staff and technical members worked hard to ensure that all tests were fully monitored and properly executed. The authors also express appreciation to Tom Fabian for early support and for sharing data, to Neil Lakomiak for supporting the testing, and to Pravinray Gandhi for his interest and comments.

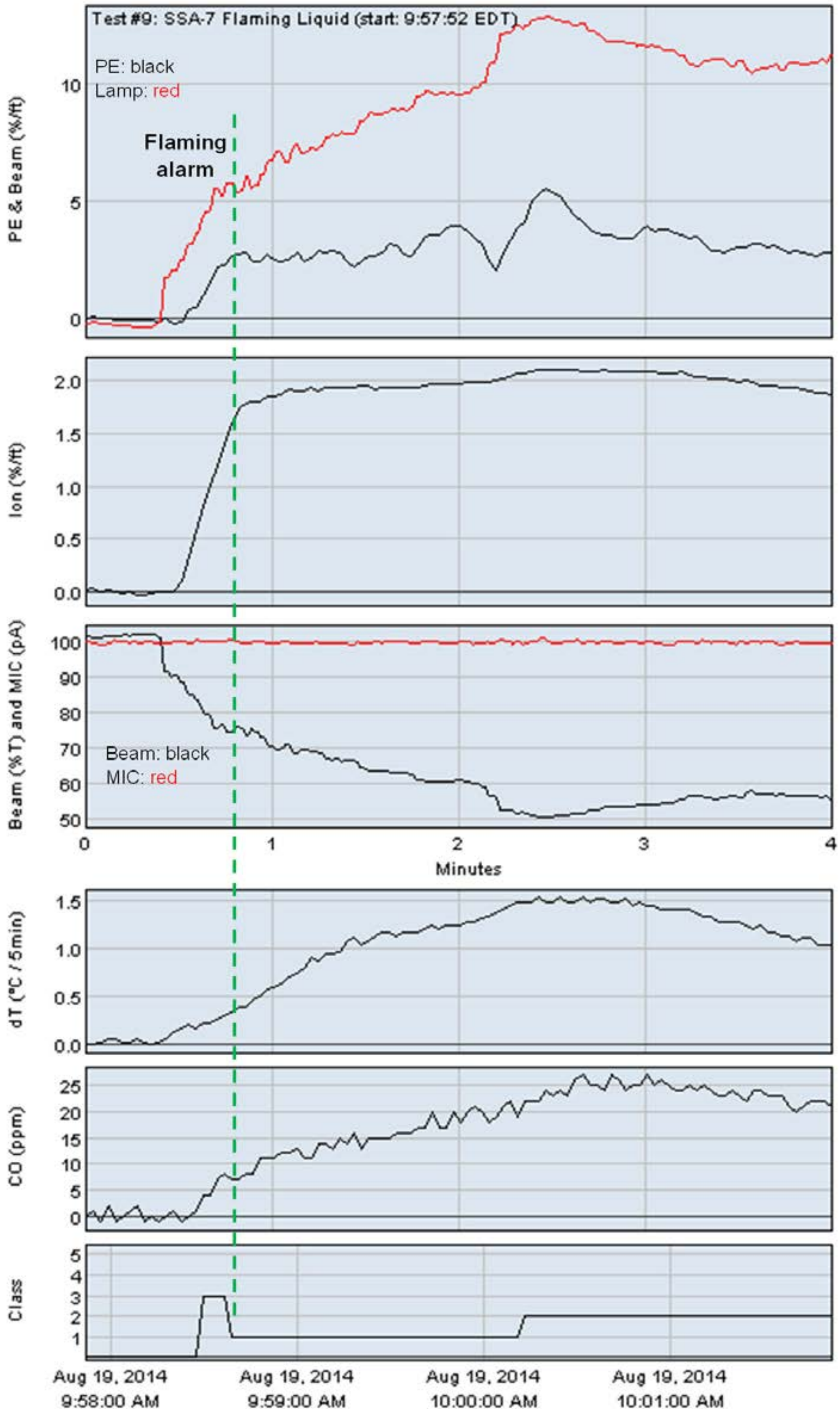
Appendix

The following graphs provide data taken during the fire and nuisance tests recorded during the UL tests by Smart Smoke Alarm (Unit 7), as a typical example, which was located on the ceiling of the fire room. The "PE" and "Ion" readings are scaled in obscurance units as previously calibrated. Lamp or beam obscurance is calculated from the adjacent UL beam-transmittance sensor. Also shown are data from the adjacent light beam transmittance and MIC current recorded in a time synchronized fashion by UL personnel. In some tests, the temperature of the oil, bacon or copper plate was recorded. The Smart Smoke Alarm thermistor reading is shown as change in temperature over a five-minute baseline correction (dT/5-min). Carbon monoxide from the built-in carbon monoxide sensor is shown in ppm. Finally, the algorithm in Smart Smoke Alarm determines the classification according to Table 3 as shown in the plots at the bottom of the graphs on Pages 19-31. A "Suppressed fire" category was added to indicate when the Smart Smoke Alarm determined that a fire condition existed, but the obscurance was not greater than 0.5 percent/foot as indicated by either the ionization or photoelectric sensors.

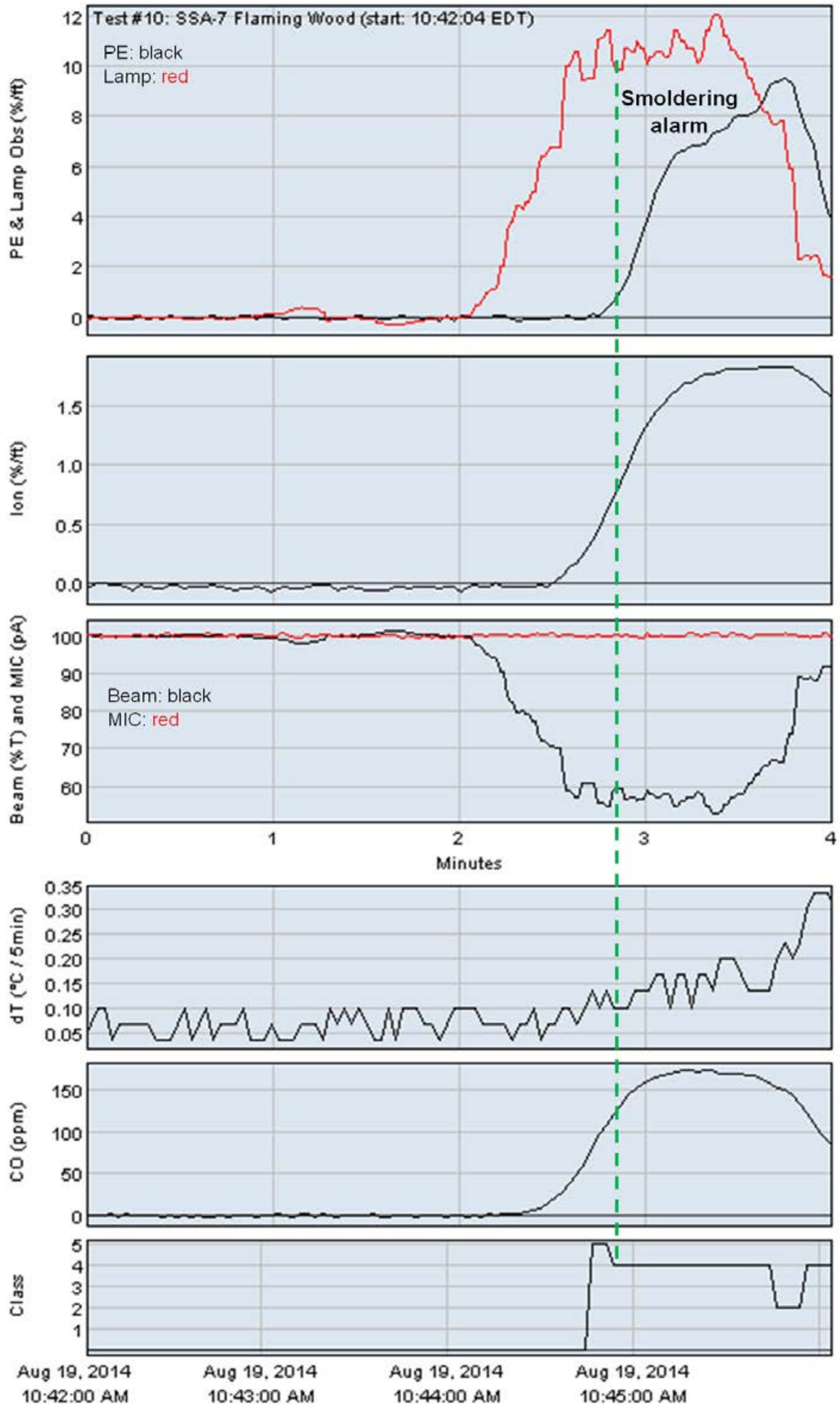
Code	Class
0	Normal
1	Flaming fire
2	Grease fire
3	Nuisance (no alarm)
4	Smoldering fire
5	Suppressed fire (< 0.5%/ft)

Table 3. Key for the classification codes determined by the Smart Smoke Alarm.

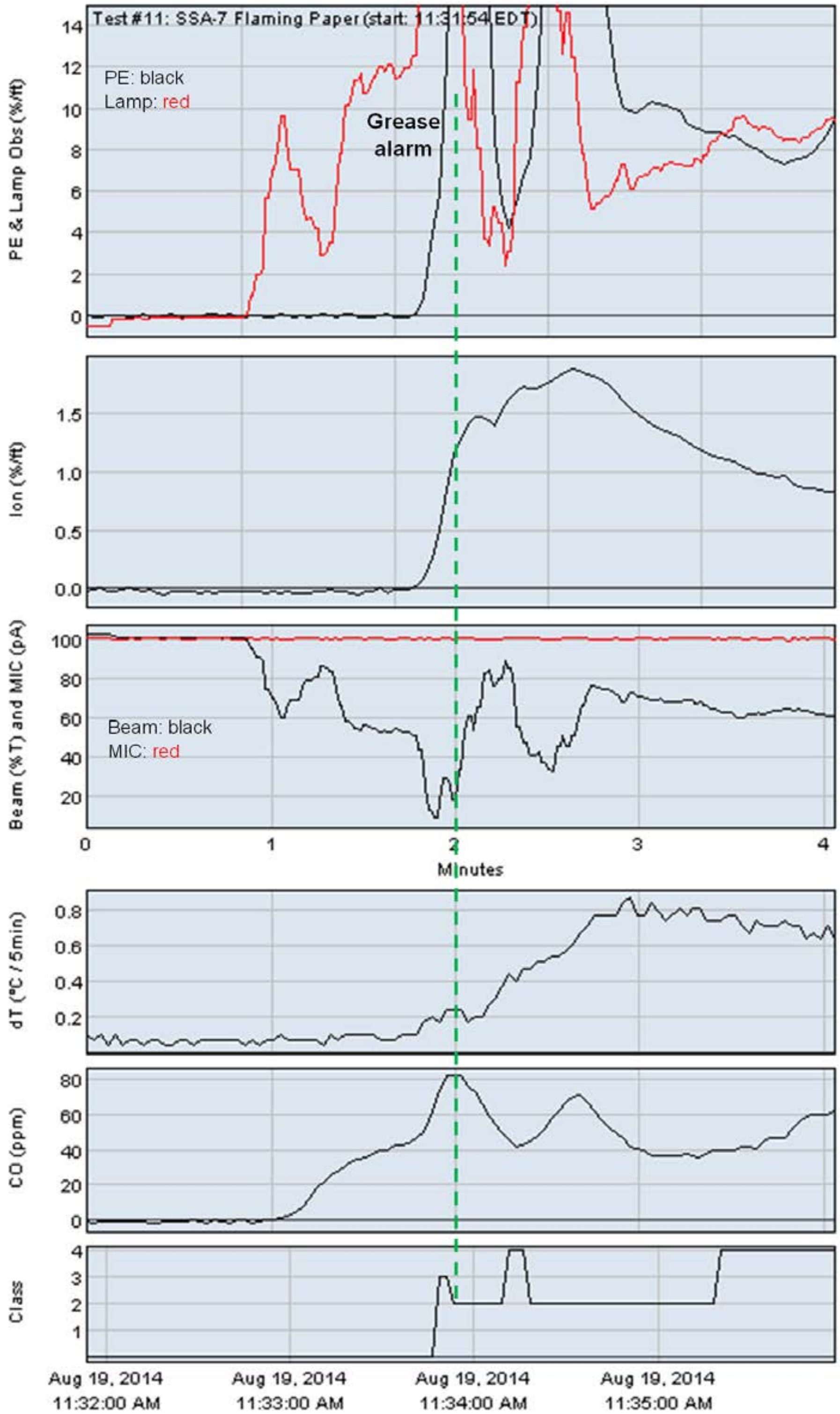
Test 9: Flaming Liquid (heptane/toluene)



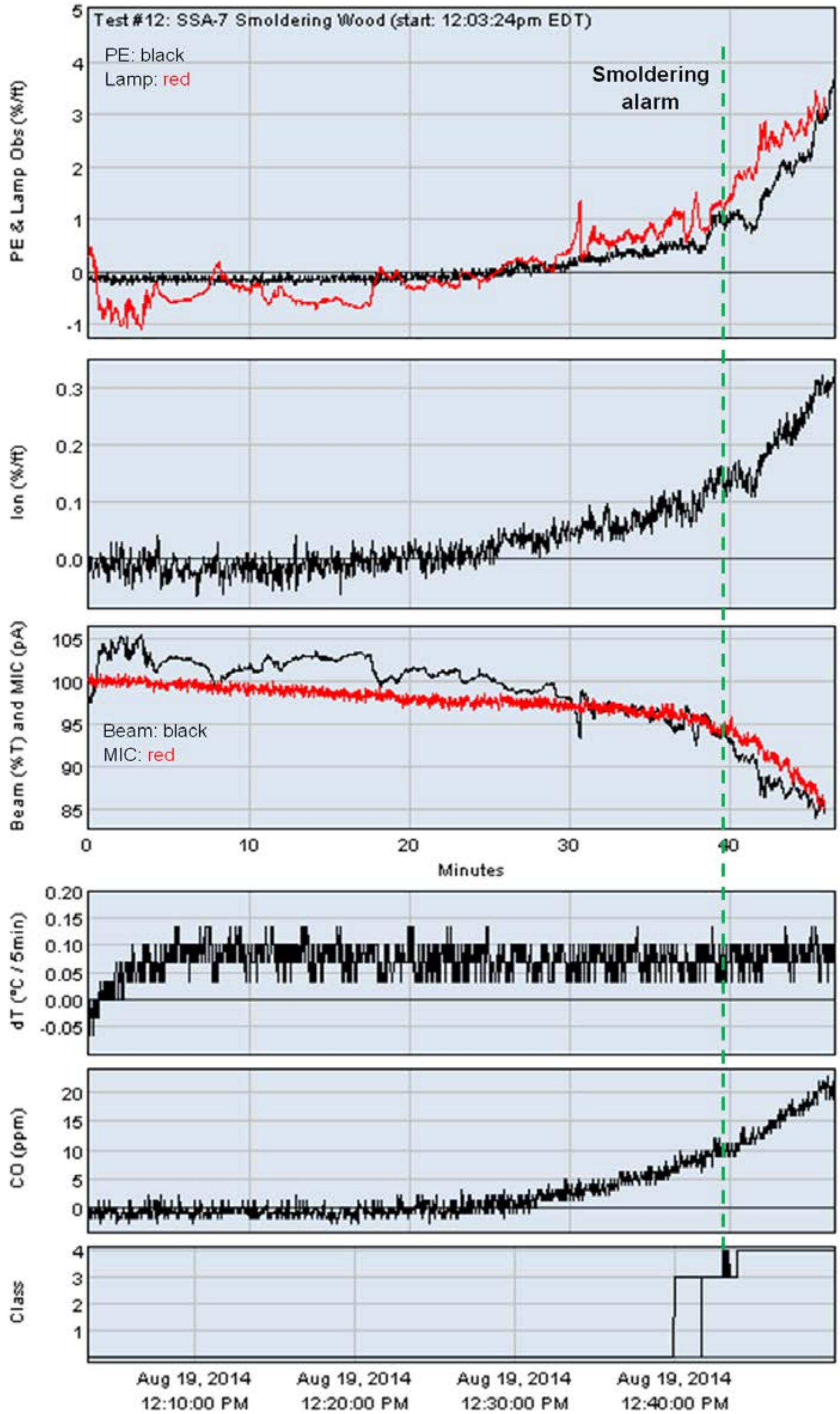
Test 10: Flaming Wood



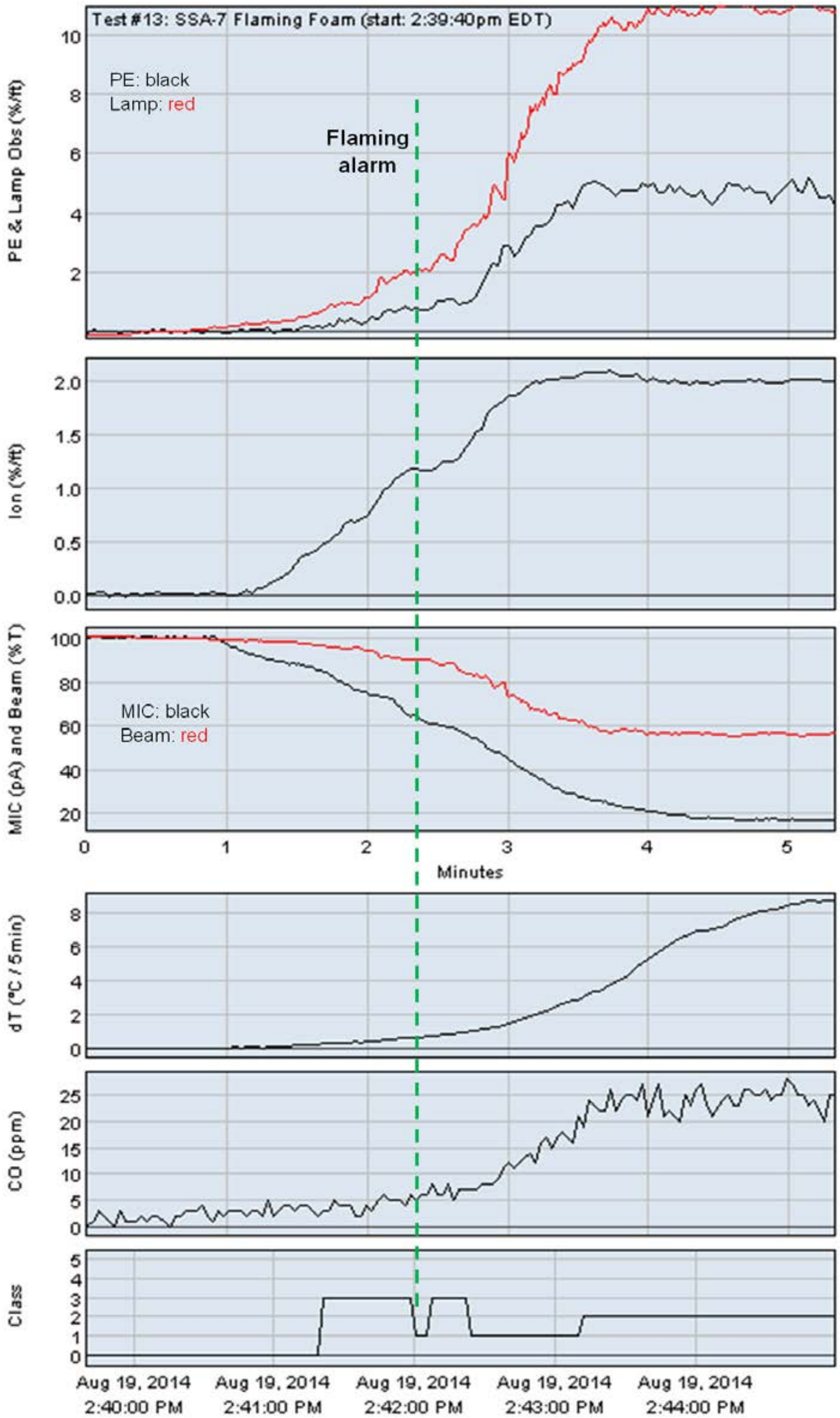
Test 11: Flaming Paper



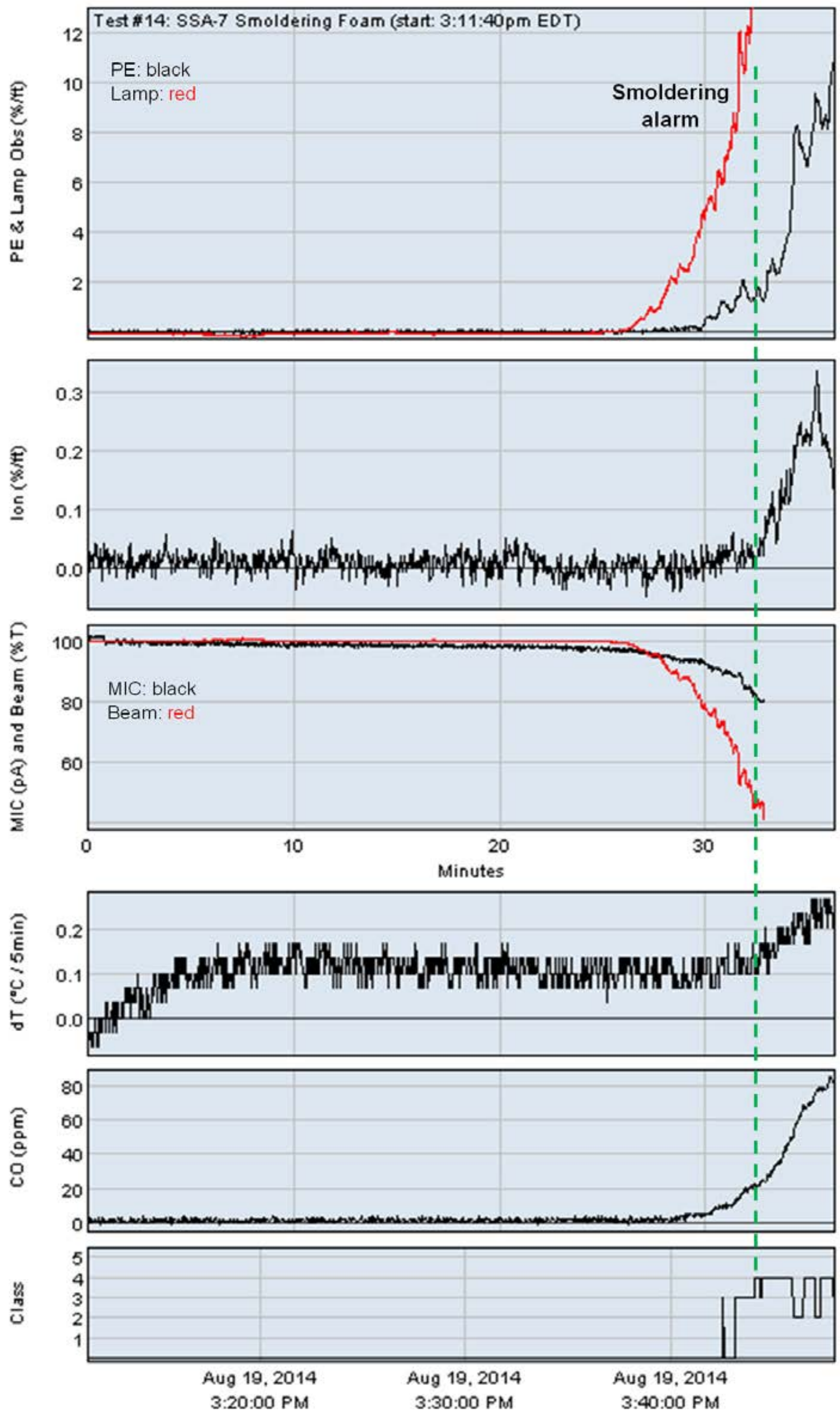
Test 12: Smoldering Wood



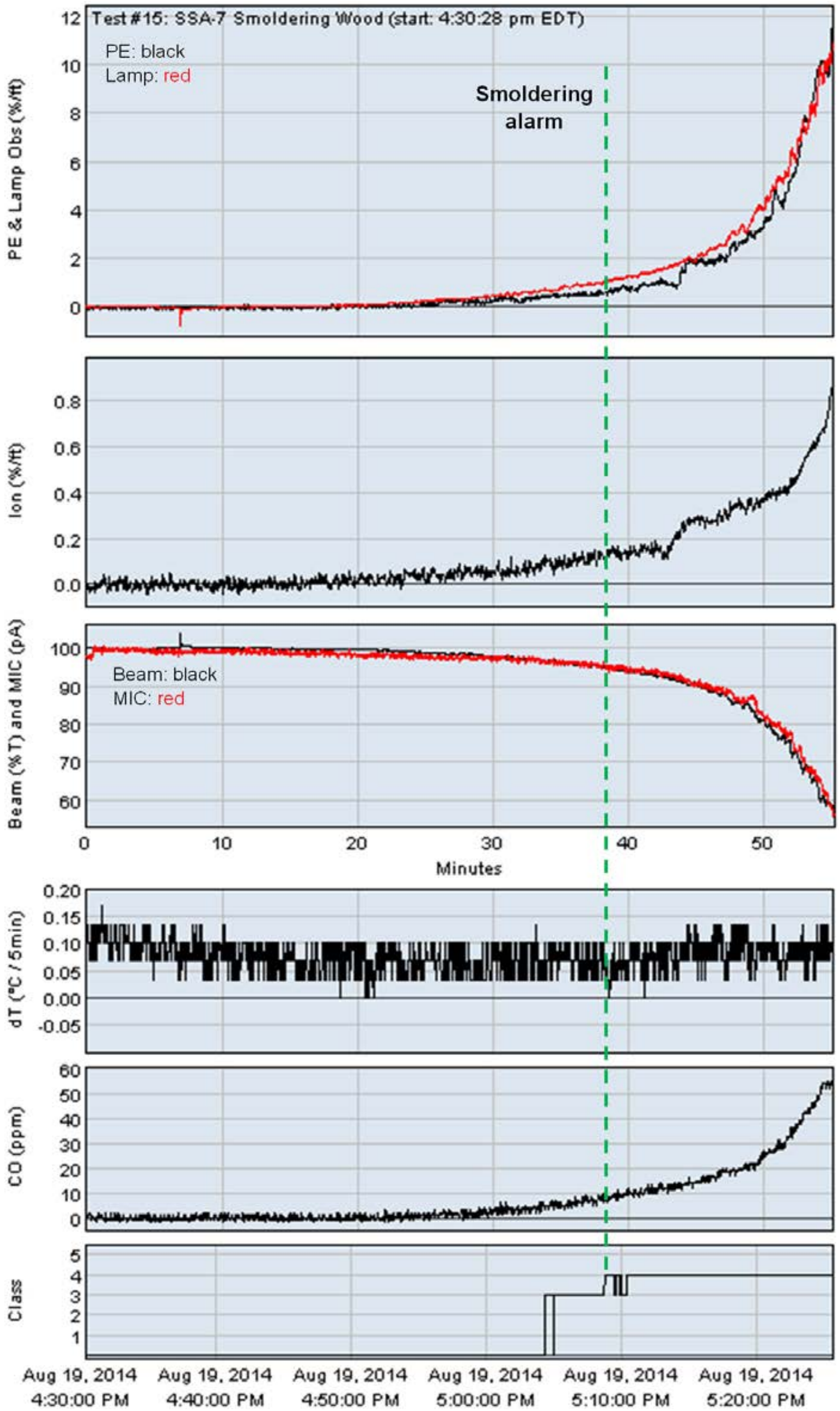
Test 13: Flaming Foam



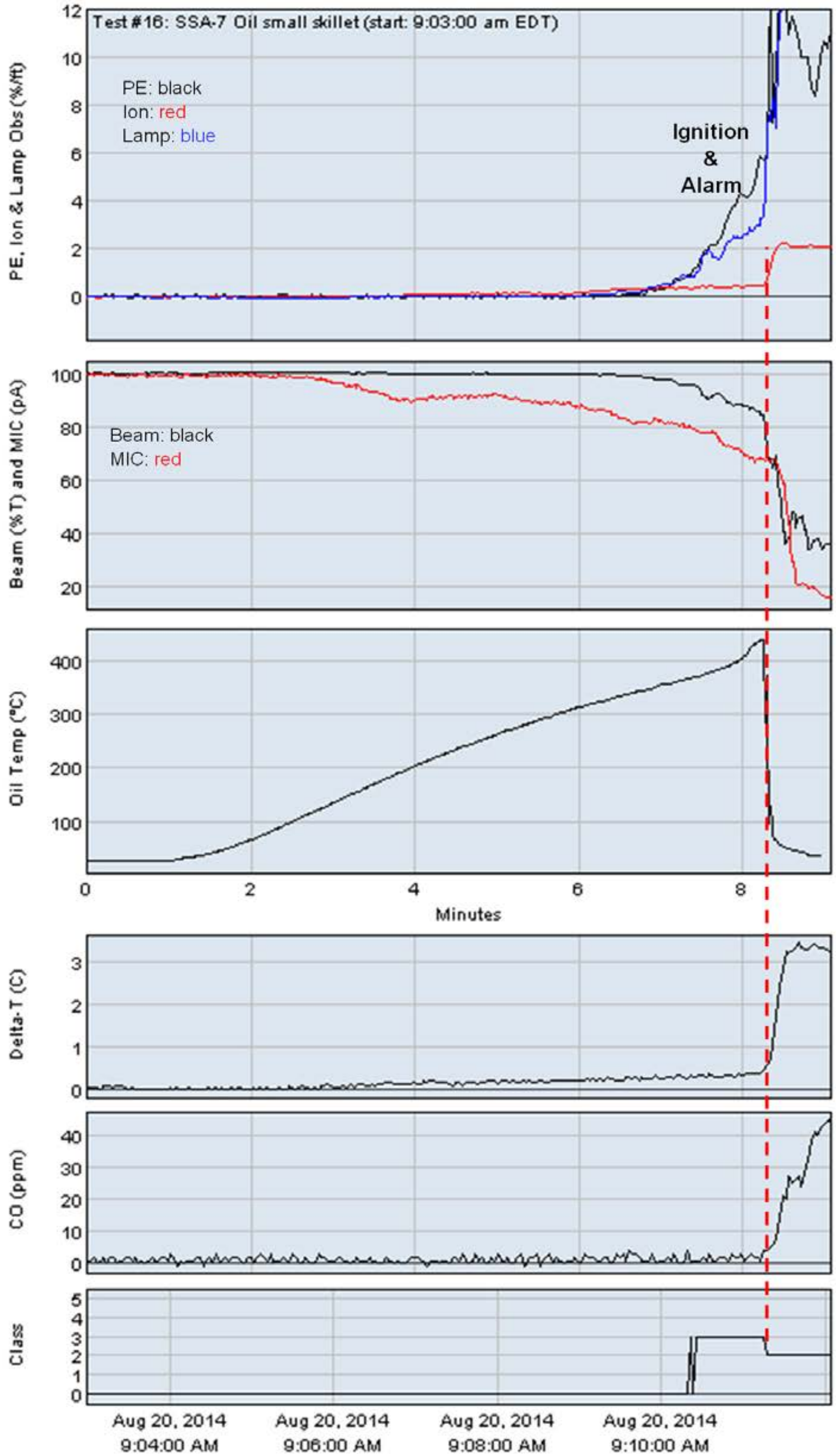
Test 14: Smoldering Foam



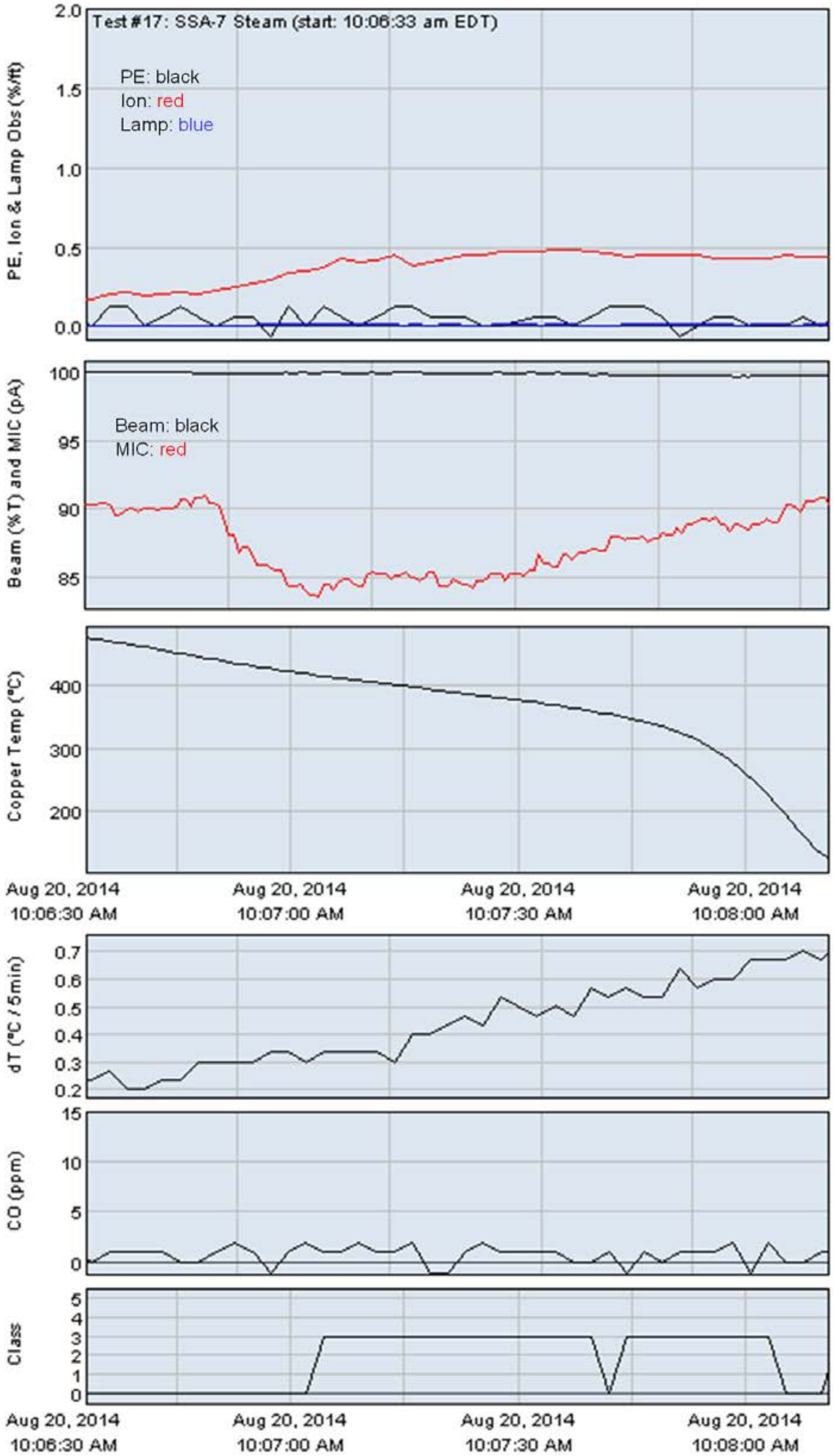
Test 15: Smoldering Wood (repeat)



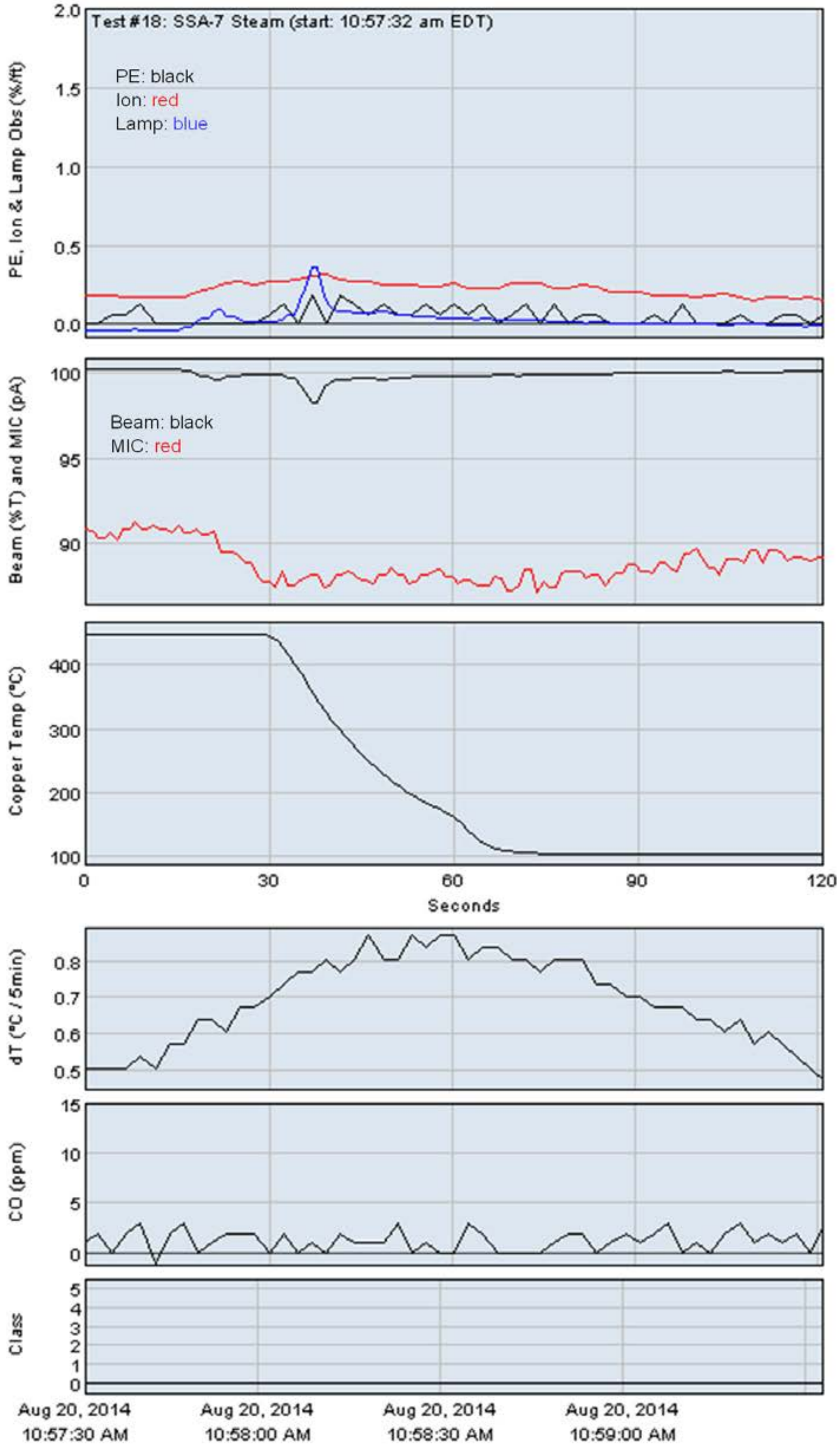
Test 16: Oil (small skillet)



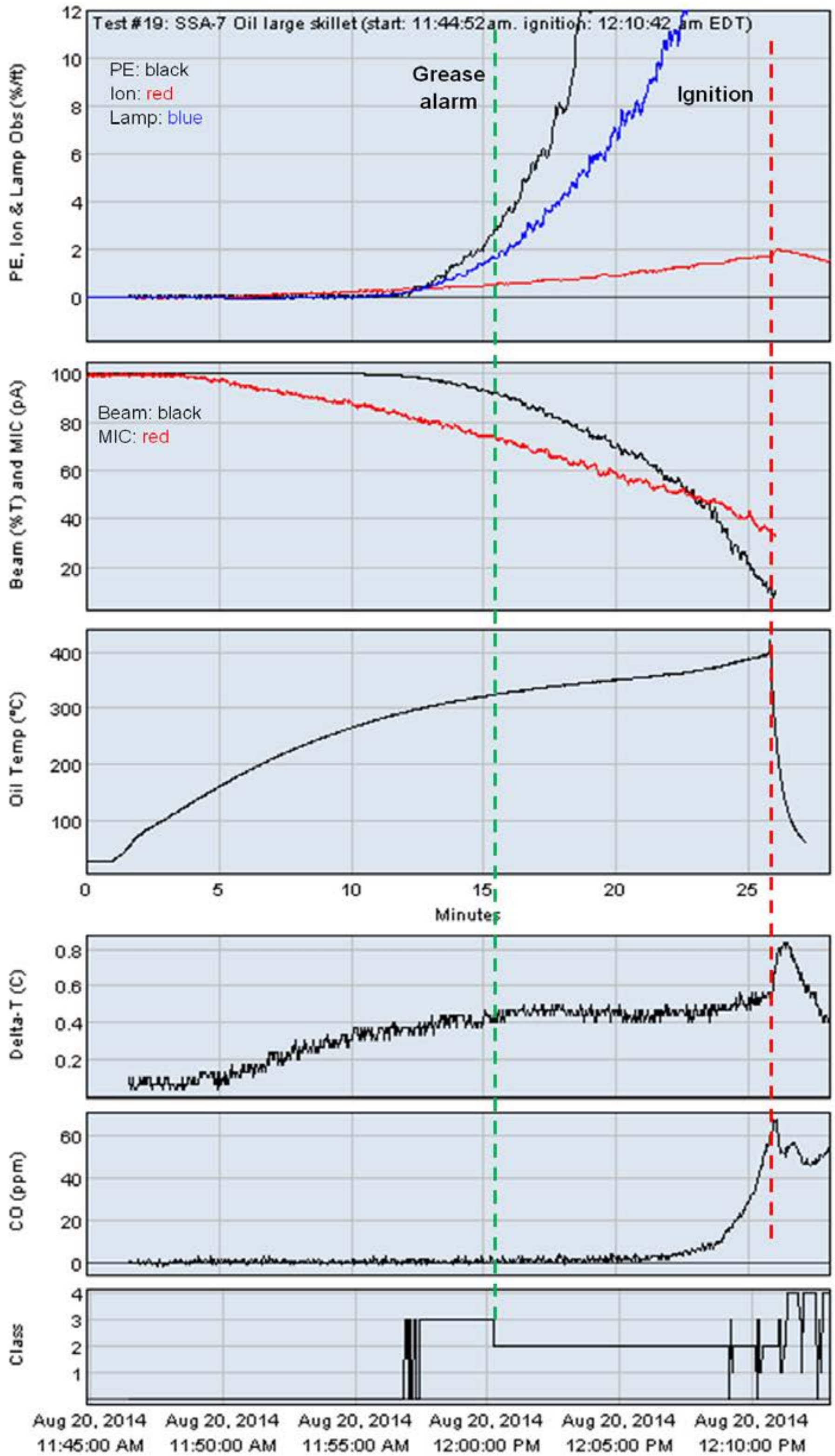
Test 17: Steam



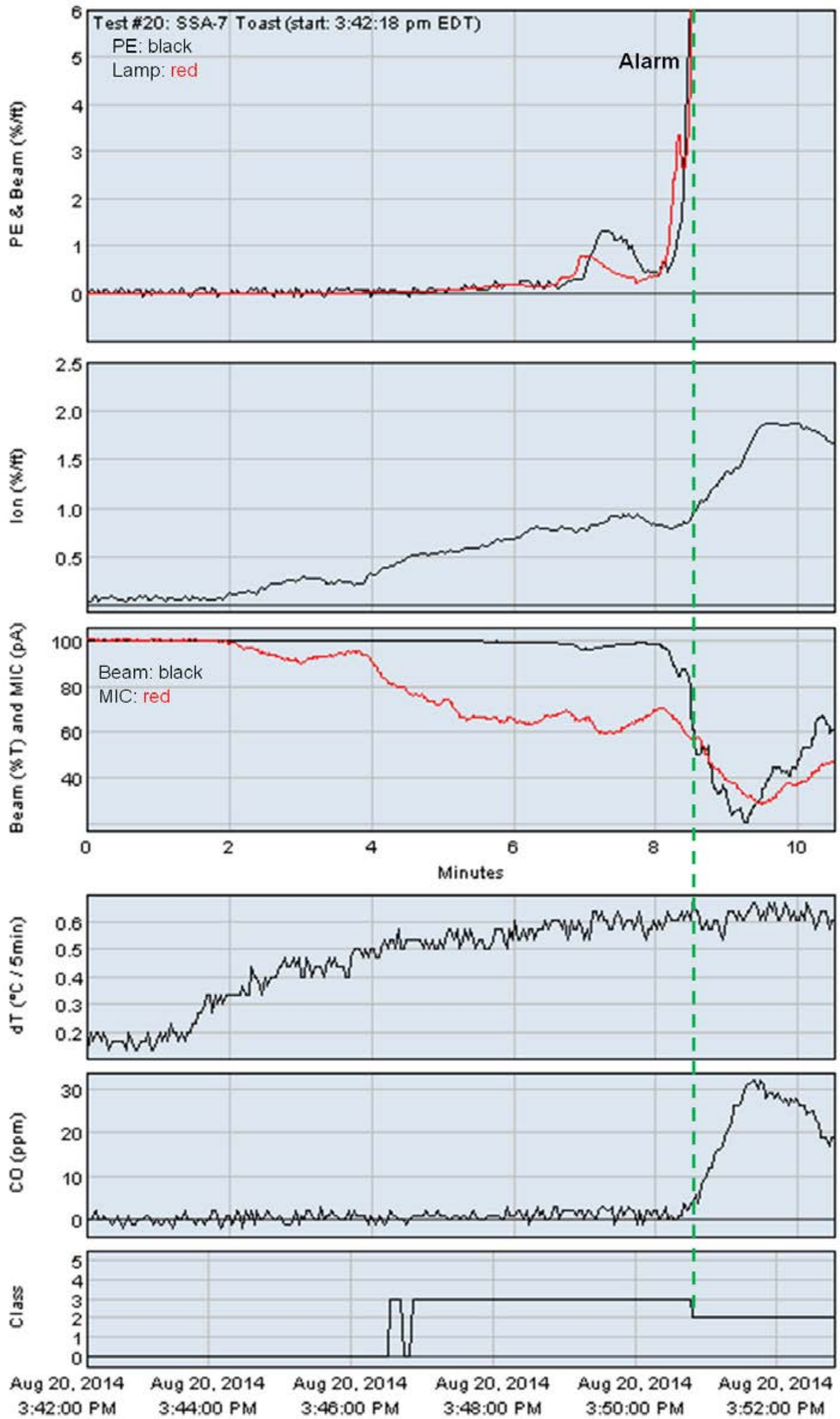
Test 18: Steam (repeat)



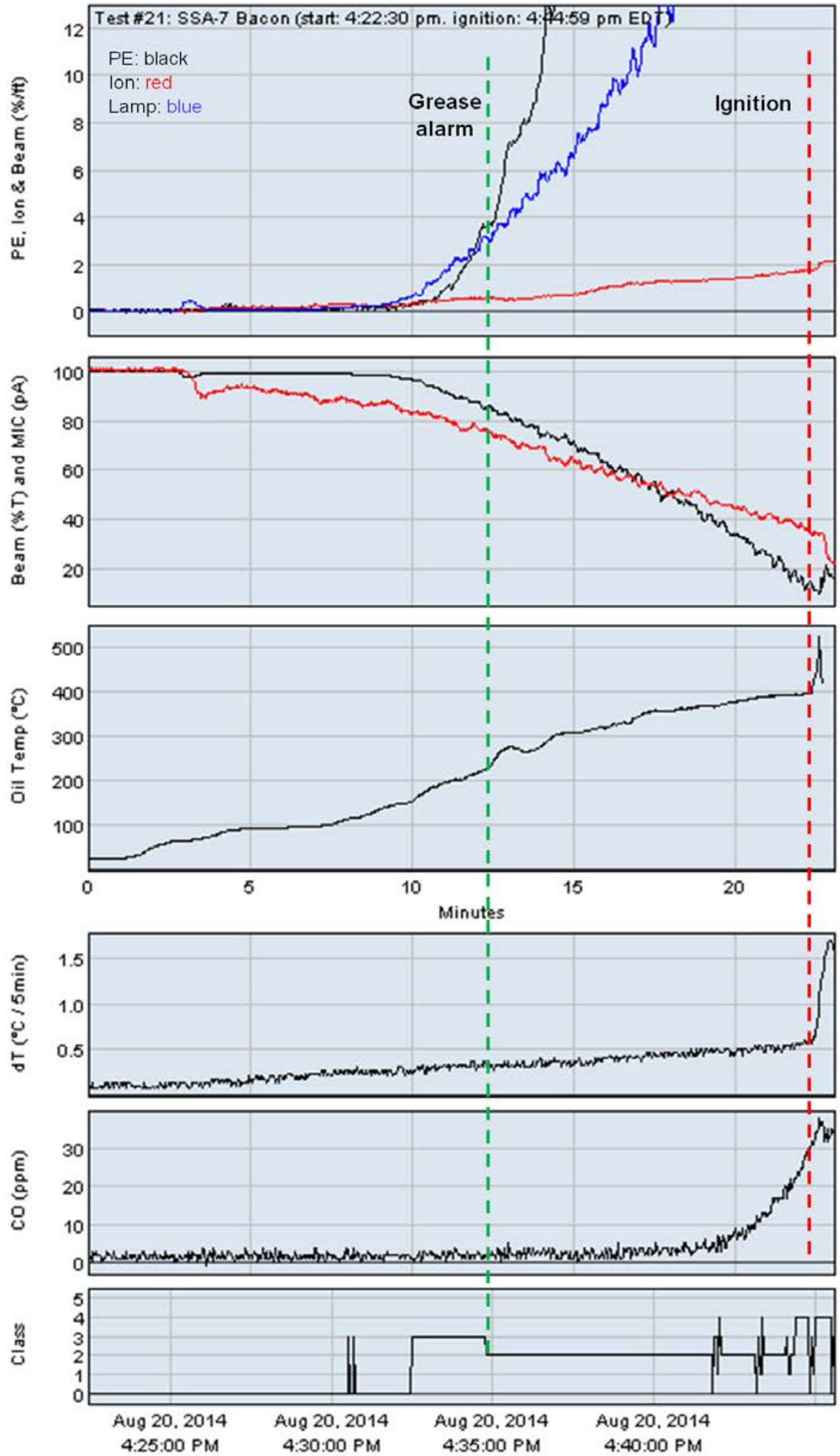
Test 19: Oil (large skillet)



Test 20: Toast (until heavily charred)



Test 21: Bacon



Acronyms

AC	alternating current
CPSC	Consumer Product Safety Commission
LD	linear discriminant
LDA	linear discriminant analysis
MIC	Measuring Ionization Chamber
NFPA	National Fire Protection Association
NIST	National Institute of Standards and Technology
ORNL	Oak Ridge National Laboratory
PC	principal component
PCA	principal components analysis
ppm	parts per million
SAS	Statistical Analysis System
SPSS	Statistical Package for the Social Sciences
UL	Underwriters Laboratories
USFA	U.S. Fire Administration