Naval Research Laboratory
Washington, DC 20375-5320

NRL/MR/6110--00-8499

Real-Time Probabilistic Neural Network Performance and Optimization for Fire Detection and Nuisance Alarm Rejection: Test Series 2 Results

Susan L. Rose-Pehrsson
Sean J. Hart

Chemical Dynamics and Diagnostics Branch
Chemistry Division

Mark H. Hammond

NOVA Research, Inc.
Alexandria, Virginia

Daniel T. Gottuk
Mark T. Wright
Jennifer T. Wong

Hughes Associates, Inc.
Baltimore, Maryland

Thomas T. Street
Patricia A. Tatem
Frederick W. Williams

Navy Technology Center for Safety and Survivability
Chemistry Division

October 10, 2000

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY (*Leave Blank*)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	October 10, 2000	Memorandum 2/1/00-5/31/00

4. TITLE AND SUBTITLE

Real-Time Probabilistic Neural Network Performance and Optimization for Fire Detection and Nuisance Alarm Rejection: Test Series 2 Results

5. FUNDING NUMBERS

PE-603508N

6. AUTHOR(S)

Susan L. Rose-Pehrsson, Sean J. Hart, Mark H. Hammond,* Daniel T. Gottuk,** Mark T. Wright,** Jennifer T. Wong,** Thomas T. Street, Patricia A. Tatem, and Frederick W. Williams

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Naval Research Laboratory
Washington, DC 20375-5320

8. PERFORMING ORGANIZATION REPORT NUMBER

NRL/MR/6110--00-8499

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Office of Naval Research
800 North Quincy Street
Arlington, VA 22217-5660

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

*NOVA Research, Inc., Alexandria, VA
**Hughes Associates, Inc., Baltimore, MD

12a. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT (*Maximum 200 words*)

A second series of tests was conducted to evaluate and improve the multivariate data analysis methods and candidate sensor suites used for the Early Warning Fire Detection (EWFD) system under development. The EWFD system is to provide reliable warning of actual fire conditions in less time with fewer nuisance alarms than commercially available smoke detection systems. Tests were conducted from 25 April to 5 May 2000 onboard the ex-USS *SHADWELL*. This report documents the performance of the probabilistic neural network achieved in real-time during this test series. Further optimization of the algorithm has yielded performance gains over the real-time results. Modifications have been made that improve the real-time data acquisition and the ion sensor calibration. Background subtraction was investigated and will be used in future tests. The best performance was provided by a four sensor array consisting of ionization, photoelectric, carbon monoxide, and carbon dioxide sensors.

14. SUBJECT TERMS

Multi-sensor	Multivariate analysis	Pattern recognition
Fire detection	Smoke detector	Sensors
Sensor arrays	Probabilistic neural network	Sensor data fusion

15. NUMBER OF PAGES

44

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std 239-18
298-102

TABLE OF CONTENTS

Real-Time Probabilistic Neural Network Performance and Optimization for Fire Detection and Nuisance Alarm Rejection: Test Series 2 Results

1. Introduction

The U.S. Navy program Damage Control-Automation for Reduced Manning (DC-ARM), sponsored by the Office of Naval Research, PE0603508N, is focused on enhancing automation of ship fire and damage control systems. A key element to this objective is the improvement in situational awareness by improving current fire detection systems. As in many applications, it is desirable to increase detection sensitivity, decrease the detection time and increase the reliability of the detection system through improved nuisance alarm immunity. Improved reliability is needed such that fire detection systems can provide quick, remote and automatic fire suppression capability. The use of multi-criteria based detection technology offers the most promising means to achieve both improved sensitivity to real fires and reduced susceptibility to nuisance alarm sources.[1] A multi-year effort to develop an early warning fire detection system is currently underway. The system being developed uses the output from sensors that measure different parameters of a developing fire or from analyzing multiple aspects of a given sensor output (e.g., rate of change as well as absolute value) and a neural network for fire recognition. A second series of prototype development tests were conducted on the ex-USS SHADWELL[2] from April 25 to May 5, 2000 to evaluate candidate prototypes of the early warning fire detection system (EWFD).

Improved fire recognition and low false alarm rates were observed using data from full-scale laboratory tests.[3,4,5] Several different sensor combinations were identified for use with a probabilistic neural network (PNN). Full-scale, shipboard tests were conducted on the ex-USS SHADWELL to further develop detection algorithms and to expand the fire/nuisance source database.[6,7] Using these two data sets, two candidate suites of sensors were identified for prototype development.[7] Test Series 1 tested the real-time responses of the prototypes.[8,9] Two months later, under different environmental conditions, the optimized prototypes were tested with more fire and nuisance sources.[10] The results of Test Series 2 shipboard testing, and the subsequent optimization of the prototypes are described in this report.

The classification of fire and nuisance events and the speed of the probabilistic neural network (PNN) were used to determine the performance of the multi-criteria fire detection system in Test Series 2. The EWFD system with the PNN developed for real-time detection, demonstrated faster response times to fires compared to commercial smoke detectors while the overall classification performance was comparable to the

Manuscript approved September 12, 2000.

commercial detectors. Some problems with the real-time implementation of the algorithm using the training set that was developed following Test Series 1 were identified and have been addressed in this report. Many problems were experienced during this test series and will be discussed. Using a variety of methods for speed and classification improvements, the PNN has been extensively tested and modified accordingly. As a result of the optimization efforts, significant improvements in performance have been recognized. A detailed examination of the correlation of the ionization detectors in the training set and in the prototypes are described. This report also investigates the effects of the training set on system performance.

2. Experimental

The selection of the sensors that comprise the two prototypes that were used during Test Series 2 was completed in December 1999 and were the same as in Test Series 1. The laboratory and SHADWELL August 1999 data, which jointly comprised the PNN training set, have been described and discussed in great detail.[3,4,5,6,7] Furthermore, the down selection of sensors from a pool of 14 possible candidates has been described in detail.[7] The two sensor arrays chosen were: Prototype 1 - ionization (ION), photoelectric (Photo), carbon monoxide (CO), relative humidity (RH), and carbon dioxide (CO_2) and Prototype 2 - ION, Photo, CO, RH, and Temperature (Temp). The Simplex ionization and photoelectric detectors used in the laboratory and shipboard tests were not suitable for use in the prototypes because they could not be setup to provide analog values that could be processed in real-time. System Sensor ionization and photoelectric detectors were obtained as an available substitute. Optimization experiments were performed prior to Test Series 2 to determine the best parameters for the PNN and were described in detail in reference 9. These optimization experiments included testing background subtracted data, magnitude and slope calculation variations, and training set composition. The PNN code used during Test Series 2 had been modified from that used in Test Series 1 by removing a data buffer. The new training set described in reference 9 was used for only one test in real-time during Test Series 2 due to its poor performance. Therefore, all further tests with that training set were conducted by post processing and the real-time code used the old training set used in Test Series 1.

2.1 Real-Time PNN

The real-time deployment of the PNN required data acquisition, processing and transfer of data from LabVIEW to a Matlab script. The real-time Matlab code used during Test Series 2 is given in Appendix A. In addition, a flowchart of the code is shown in Figure 1. This flowchart shows how the PNN is incorporated into the real-time analysis of sensor data including pre-processing, pattern calculation and scaling. The vector of input sensor responses (Xcurrent), one number for each sensor in the array, comprise the set of data that is passed to the algorithm for pre-processing and PNN analysis during real-time deployment. For prototypes 1 and 2, the vector was 5 elements long, one for each sensor in the array. Since raw sensor responses had been chosen, only the ion and photo detector outputs were processed after data acquisition. The conversion from ΔMIC output to percent obscuration/ft and then from percent obscuration/ft to percent obscuration/m was performed for each ionization detector and from percent obscuration/ft output to percent obscuration/m was performed for each photoelectric detector. The resulting pattern (sensor vector) was added to the end of the 25x5 matrix, data_history, and the first row was deleted to maintain the size of the matix. In this manner new patterns were added and data_history was updated and reflects the most recent (25) patterns collected. From data_history, the pattern magnitudes and slopes were computed and then autoscaled (mean zero and unit variance) using the means and standard deviations derived from the training set. The resulting scaled pattern was then submitted to the PNN algorithm for the classification and determination of the probability of a fire event. The alarm state was triggered if the probability was greater than 0.75 for three or more consecutive predictions.

2.2 Test Series 2: Experiments and Sensor Combinations

Test Series 2 is a continuation of Test Series 1 and is described in Reference 10. The names, classifications, and descriptions of the experiments performed in both tests are given in Table 1. Tests 38-88 were collected during Test Series 2. Four prototypes were used, two were prototype 1 and two were prototype 2. One of each type was positioned in two different locations. This report describes the results from Location A. Additional sensors were included in the tests at Location A, and these were oxygen (O_2), hydrogen sulfide (H_2S), nitrogen oxide (NO), hydrocarbon (HC), residential ion with cover removed (ION Chamber), and residential ion (RION). The responses of each sensor were collected and stored in a matrix. Each of these response matrices could be used to test algorithms being developed. The response matrices were usually tested in a playback mode, where each test was treated in the same manner as if it were being collected in real-time. Each row in the matrices was a point in time from the test. Data was collected every 2-8 seconds. The columns contained the sensor responses at a given time. As shown in Table 2, the sensor combinations were assigned numbers. Column numbers 2-6 are prototype 1a, 7-11 are prototype 2a, 12-16 are prototype 1b, 17-21 are prototype 2b, and 22-27 are the extra sensors.

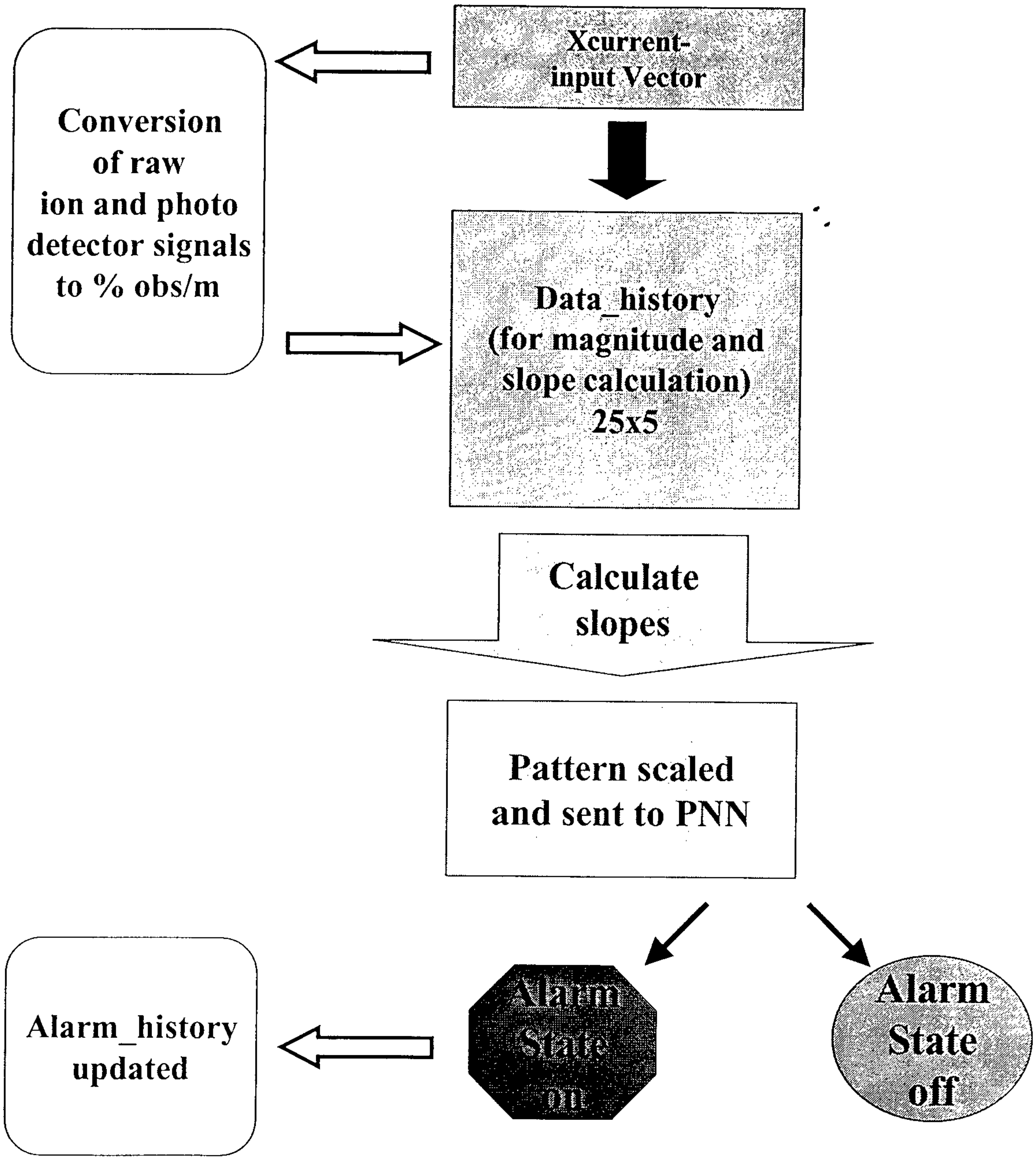

Figure 1. Flow chart for real-time PNN code: data_history and alarm_history are both inputs and outputs to code. Both variables have the most recent value added to the end of the vector or matrix and the first (oldest) value removed, thus maintaining their size.

Table 1. Test name, classification (1 = fire, 2 = nuisance) and description

DESCRIPTION	TYPE	Class	BRIEF
EWFD_001	fire, flaming	1	Heptane
EWFD_002	fire, flaming	1	Pipe insulation and fuel oil
EWFD_003	fire, flaming	1	Oily rag, newspaper, cardboard in sm. trashcan
EWFD_004	nuisance/ fire	1	Burning toast
EWFD_005	fire, smoldering	1	Smoldering trash bag
EWFD_006	nuisance	2	Cigarette smoking
EWFD_007	fire, flaming	1	Flaming trashbag, TODCO wallboard
EWFD_008	fire, flaming	1	Heptane
EWFD_009	nuisance	2	Burning popcorn
EWFD_010	fire, flaming	1	Electrical cable and pipe insulation
EWFD_011	fire, smoldering	1	Smoldering electrical cable
EWFD_012	nuisance	2	Arc welding
EWFD_013	fire, flaming	1	Flaming bedding material
EWFD_014	fire, flaming	1	Oily rag, newspaper, cardboard in sm. trashcan
EWFD_015	nuisance	2	Normal toasting
EWFD_016	fire, flaming	1	Small wood crib
EWFD_017	fire, flaming	1	Trashcan and office chair
EWFD_018	nuisance	2	Steel Cutting
EWFD_019	fire, smoldering	1	Smoldering bedding material
EWFD_020	fire, smoldering	1	Printed wire circuit board
EWFD_021	fire	1	Brief wire overheat
EWFD_022	fire, smoldering	1	Smoldering oily rag, newspaper, cardboard in sm. trashcan
EWFD_023	fire, flaming	1	Pipe insulation and fuel oil
EWFD_024	nuisance	2	Nylon rope
EWFD_025	nuisance/ fire	1	Nylon rope into sm. trashcan
EWFD_026	fire, smoldering	1	Smoldering trash bag
EWFD_027	nuisance	2	Burning popcorn
EWFD_028	nuisance	2	Steel grinding
EWFD_029	fire, smoldering	1	Smoldering bedding material
EWFD_030	nuisance/ fire	1	Burning toast
EWFD_031	fire, flaming	1	Pipe insulation and heptane
EWFD_032	nuisance	2	Cigarette smoking
EWFD_033	fire, smoldering	1	Printed wire circuit board
EWFD_034	fire	1	Brief wire overheat
EWFD_035	fire, smoldering	1	Smoldering oily rag, newspaper, cardboard in sm. Trashcan
EWFD_038	fire, flaming	1	Heptane
EWFD_039	fire, flaming	1	Pipe insulation and fuel oil
EWFD_040	fire, flaming	1	Flaming oily rag, newspaper, cardboard in sm. Trashcan
EWFD_041	nuisance	2	Pop-Tarts™ toasting (8)
EWFD_042	fire, smoldering	1	Smoldering oily rag, newspaper, cardboard in sm. Trashcan
EWFD_043	fire, flaming	1	Heptane
EWFD_044	fire, flaming	1	Heptane
EWFD_045	fire, smoldering	1	Smoldering plastic bag of mixed trash
EWFD_046	fire, flaming	1	Flaming bag of trash next to TODCO wallboard
EWFD_047	nuisance	2	Burning popcorn
EWFD_048	nuisance	2	Cutting Steel with acetylene torch

EWFD_049	nuisance	2	Cutting Steel with acetylene torch
EWFD_050	fire, flaming	1	Electrical cable and pipe insulation next to flaming laundry pile
EWFD_051	fire, smoldering	1	Long duration smoldering electrical cables
EWFD_052	nuisance	2	Welding steel plate
EWFD_053	fire, smoldering	1	Smoldering bedding
EWFD_054	fire, flaming	1	Flaming bedding
EWFD_055	fire, smoldering	1	Printed wire board (PWB) fire
EWFD_056	fire, smoldering	1	PWB fire, with fire curtain covering alcove entrance in CSO
EWFD_057	fire, smoldering	1	PWB fire, bad first PWB, new one installed 3.5 mins after first lost current. Powered up 10 minutes after first board was powered up
EWFD_058	fire, smoldering	1	PWB fire
EWFD_059	fire	1	Brief wire overheat
EWFD_060	fire	1	BSI 6266 wire test
EWFD_061	fire	1	BSI 6266 wire test
EWFD_062	nuisance	2	Cooking shortening in wok
EWFD_063	nuisance	2	Aerosol deodorants and hairspray
EWFD_064	nuisance	2	Sweeping up a dropped bag of flour
EWFD_065	nuisance	2	Pop-Tarts™ toasting (8)
EWFD_066	nuisance	2	Normal Toasting (8 slices at a time, 16 total – lost power near end)
EWFD_067	nuisance	2	Normal Toasting (8 slices at a time, 16 total)
EWFD_068	nuisance	2	Cigarette smoking (15 total)
EWFD_069	nuisance	2	Steel grinding nuisance
EWFD_070	fire, flaming	1	Flaming oily rag, newspaper, cardboard in sm. Trashcan
EWFD_071	fire, smoldering	1	Smoldering electrical cable (LSTPNW-1½ , MIL C-24643/52-01UN)
EWFD_072	nuisance	2	Cooking Oil (used 100% vegetable oil, cast iron skillet and two-burner portable propane stove)
EWFD_073	fire	1	Brief (30 sec) wire overheat
EWFD_074	fire, smoldering	1	Smoldering electrical cable (LSTPNW-1½ , MIL C-24643/52-01UN)
EWFD_075	nuisance	2	Steam generation (propane stove, cast iron skillet)
EWFD_076	nuisance	2	Steam generation (skillet preheated with torch – red hot)
EWFD_077	fire, smoldering	1	Smoldering electrical cable (LSTPNW-1½ , MIL C-24643/52-01UN)
EWFD_080	nuisance	2	Cooking oil.
EWFD_081	nuisance	2	Steam Generation (preheated steel pan w/ torch)
EWFD_082	nuisance	2	Steam generation (continuation of EWFD_081)
EWFD_083	fire, smoldering	1	Smoldering Oily rag, newspaper, cardboard in sm. Trashcan
EWFD_084	fire, smoldering	1	Smoldering bedding.
EWFD_085	fire, smoldering	1	Long duration smoldering electrical cables (wrong cable)
EWFD_086	fire, smoldering	1	Long duration smoldering electrical cables (wrong cable)
EWFD_087	nuisance	2	Cigarette smoking
EWFD_088	fire, smoldering	1	Long duration smoldering electrical cables

Table 2. Sensor number and identity. Column numbers 2-6 are prototype 1a, 7-11 are prototype 2a, 12-16 are prototype 1b, 17-21 are prototype 2b, and 22-27 are the extra sensors

Sensor	Column #
Elapsed time	1
ION#1(MIC)	2
Photo#1(%/ft)	3
CO(ppm)	4
RH(%)	5
CO2(ppm)	6
ION#4(MIC)	7
Photo#4(%/ft)	8
CO(ppm)	9
RH(%)	10
Temp(°C)	11
ION#2(MIC)	12
Photo#2(%/ft)	13
CO(ppm)	14
RH(%)	15
CO2(ppm)	16
ION#3(MIC)	17
Photo#3(%/ft)	18
CO(ppm)	19
RH(%)	20
Temp(°C)	21
O2(%)	22
H2S(ppm)	23
NO(ppm)	24
HC(ppm)	25
ION Chamber (V)	26
RION(V)	27

3. PNN Real-Time Results

The comparison of the real-time prototype performance with the COTS (commercial off the shelf) smoke detectors is given in Table 3. The results of the real-time deployment of the PNN onboard the SHADWELL in Test Series 2 are better than the COTS ion, but not as good as the COTS photo. The overall correct classification of the two prototypes is similar. The fire detection rate for both prototypes 1 and 2 was greater than the COTS ion sensors and similar to the COTS photo. Prototype 1 had better real-time performance than the COTS for fire detection, 79% of fires correctly classified. Prototype 2 correctly classified 72% of the fire scenarios. The nuisance performance for prototypes 1 was poorer than the COTS with 40% correct classification versus 50% for the COTS ion sensor and 80% for the COTS photo sensor. Prototype 2 performed better than 1 for nuisances, correctly classifying 11 of 20 tests. The prototypes were also faster to alarm for fires than the COTS. In comparison to the COTS ion, the prototype 2 was slower to alarm than the COTS for 8 nuisance sources, and faster to alarm for only 3 nuisance sources. The increased speed of the prototypes increased their false alarm rate compared to the COTS photo. The prototype response time was considered similar where the alarm is within ± 30 seconds of the COTS response time.

Table 3. Results of PNN classification during the Test Series 2

	Sensors	Total % Correct	Fires % Correct	Nuisances % Correct	# Fires Correct (29)	# Nuisances Correct (20)
Prototype 1:	2 3 4 5 6	63.3	79.3	40.0	23	8
Prototype 2:	7 8 9 10 11	65.3	72.4	55.0	21	11
COTS	Ion	49.0	48.3	50.0	14	10
	Photo	77.6	75.9	80.0	22	16
	Ion+Photo	75.5	82.8	45.0	24	9

	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
Prototype 1:	14	11	4	20	5	4	4	11	5	0	10	10	12	9	8	0	9	11
Prototype 2:	11	12	6	13	7	9	8	10	2	2	13	5	6	10	13	1	13	6

There were several problem areas during the real-time deployment of the PNN aboard the ex-USS SHADWELL. These include 1) a computational bottleneck that worsened as time increased, causing a decrease in the sampling frequency, 2) high baseline probability, 3) noisy probabilities, and 4) a calibration mismatch between the new Systems Sensor ionization detector (currently used in the prototypes) and the former Simplex ion detector (used during the collection of training data).

The first problem is characterized by the data acquisition system collecting data at a rate of 1 data point every 2 seconds, but after ≈ 2000 data points, the system requires 6 seconds between collection of data points. This delta time can represent a significant impediment to early fire warning and detection. The computational slowdown has been isolated and appears to be rooted in the data acquisition software's routines to call Matlab scripts. The instructions required for PNN analysis are contained in the Matlab scripts. The use of third party linear algebra function libraries (OptiVec for C++, Martin Sander Software Development) which removed the inefficient and problematic Matlab libraries has proved successful. This approach has solved the computational slowdown and has been tested over extended periods. The computational time required to process inputs and produce a probability output for a given prototype has been reduced by a factor of 50 compared with LabVIEW calling a Matlab script. This method will be used in Test Series 3.

Apparently, the high temperature and relative humidities experienced during Test Series 2 resulted in high baseline probabilities when the 173-pattern training set was used and noisy probabilities when the 325-pattern training set was used. The PNN optimization section will describe the methods used to reduce these effects.

The most complex problem encountered was the mismatch of the System Sensor ionization data with that of the Simplex ion detectors. Originally it was thought that swapping one manufacturers' sensor for another brand would be possible, if both responses were converted to a standard such as percent obscuration per meter (%obs/m) as measured in UL standard 268 smoke box sensitivity tests. This turned out not to be the case, and an empirical correlation was required. Based on UL 268 smoke box tests a general empirical correlation was established between the ΔMIC reading of the ion detector and the corresponding %obs/ft measurements in the smoke box. This first attempt at a correlation produced ion detector outputs that were inconsistent with those obtained from the Simplex detectors for similar tests. Magnitudes and the temporal profiles were significantly different. Testing of the Simplex detectors side-by-side with the System Sensor detectors in a UL 268 smoke box was conducted. From these tests, an empirically derived linear correlation was determined and is given in equation 1:

$$y(x) = 0.0465x - 0.6572 \qquad (1)$$

Where y(x) is the % obs/ft and x is the System Sensor ionization detector ΔMIC reading. Plots showing the raw System Sensor data for several fires and the converted data (per Eqn. 1) are given in Figure 2. Using the linear correlation, rather than the fourth order polynomial used previously, results in a change in the scale of the plot. However, the shape remains identical in the conversion process with only a change in sensor magnitude as the result. The scaling changes places the System Sensor ion measurements in the same range as the Simplex ion detectors used in the training set.

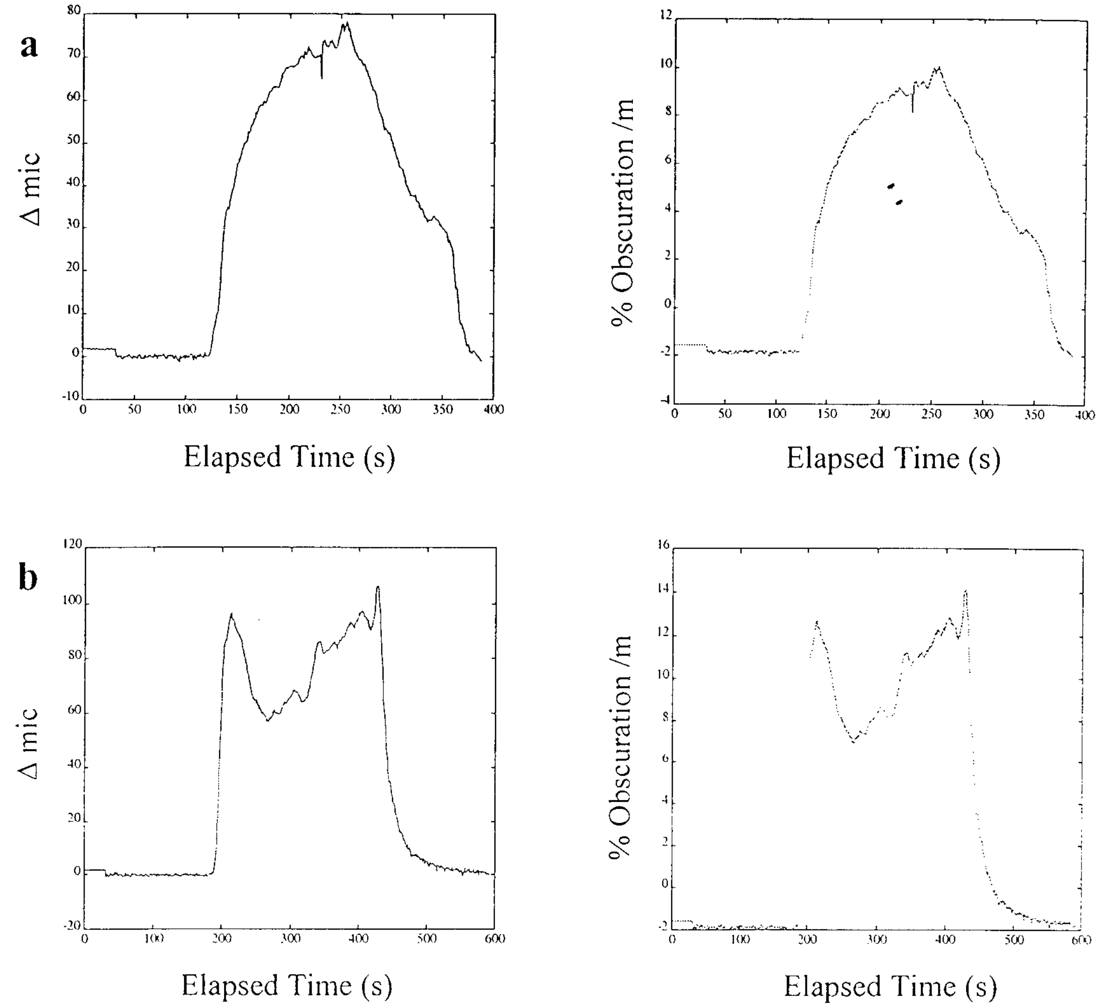

Figure 2. System Sensor ion detector output before and after conversion to % obs/m for two representative fire sources: a) flaming heptane, b) oily rag in trashcan fire.

4. PNN Optimization

The optimizations that began with the Test Series 1 data were continued with the addition of the Test Series 2 data. The first optimization was a modification to the training set to deal with the high baseline probability. Next the incompatibilities with the training and prediction data for the ion sensor were considered. Last a preliminary investigation into background subtraction was started. All experiments, unless stated otherwise, used the following parameters: the slope calculated over a 25-point region, no background subtraction, and the initial fourth order polynomial ion detector conversion from ΔMIC to %obs/ft. Both the ion and photo detector values were used in the PNN with units of %obs/m.

4.1 Training Set Optimization

Examination of the training sets used on the SHADWELL revealed some small errors in the data classifications. These problems were corrected and the data collected during Test Series 2 was reprocessed as shown in Table 4. The 325-pattern training set consisted of all the fire/nuisance sources and backgrounds from both the laboratory and August 1999 SHADWELL tests. The 173-pattern training set resulted from the removal of the alcohol and propane tests, 1 bad smoldering fire test, and a large number of backgrounds. The overall classification of the April data was not affected by these changes; however, the probability plots shown in Figures 3-9 are very different. The 325-pattern training set resulted in noisy output values, while the 173-pattern training set had very high baseline probabilities. A new training set was generated as a compromise that consisted of 200 patterns, the optimized set of 173 patterns along with 27 backgrounds from the August SHADWELL tests. The classification results are similar for all three training sets. The results of the experiments (Table 4) show the PNN classification results are almost identical with only the loss of one misclassified fire for prototype 2. The effects of the various training sets can be seen by comparing the probability plots. The plots from prototype 2 for all 49 experiments performed during Test Series 2 generated at the 11 % obs/m alarm time, for all three training set can be seen in Figures 3-9 a,b,c respectively. When comparing the modified 200-pattern training set to the 325-pattern set, the noise is reduced as shown in tests 38-51. The 200-pattern training set, compared to the 173-pattern training set, has lower baseline probabilities as shown in tests 48-88. Therefore, the 200-pattern training set produced the same classification results as the 173-training set, while the patterns generated had lower baseline probabilities similar to the 325-training set and noise levels similar to the 173-training set.

4.2 Ion Calibration

Using the new ion calibration, equation (1), Test Series 1 and 2 data were rerun with the modified 200-pattern training set as shown in Table 5 and Figure 10. The overall predictions for the prototypes (Table 5) changed only slightly with a loss of two fires for prototype 1, but a gain of one nuisance classified correctly for prototype 2. We expected a greater improvement, however, the falsely elevated results from the previous calibration allowed faster responses to fires.

The probability plots for eight of the experiments performed during the Test Series 2 generated at the 11% alarm time, comparing the old ion calibration to the new ion correlation can be seen in Figure 10 a and b respectively. The lower value of the ion sensor can be seen in the lower probabilities in tests 15, 41, and 9. Also the increased probability seen during venting in tests 9, 11, 64 also disappear with the corrected ion detector correlation. In addition, the problem caused by the incompatibility between the training set and prediction data where the PNN cannot calculate a probability (the gaps seen in tests 40, 46, and 50) disappear. The new correlation provides better agreement with the training set and will be used in future tests.

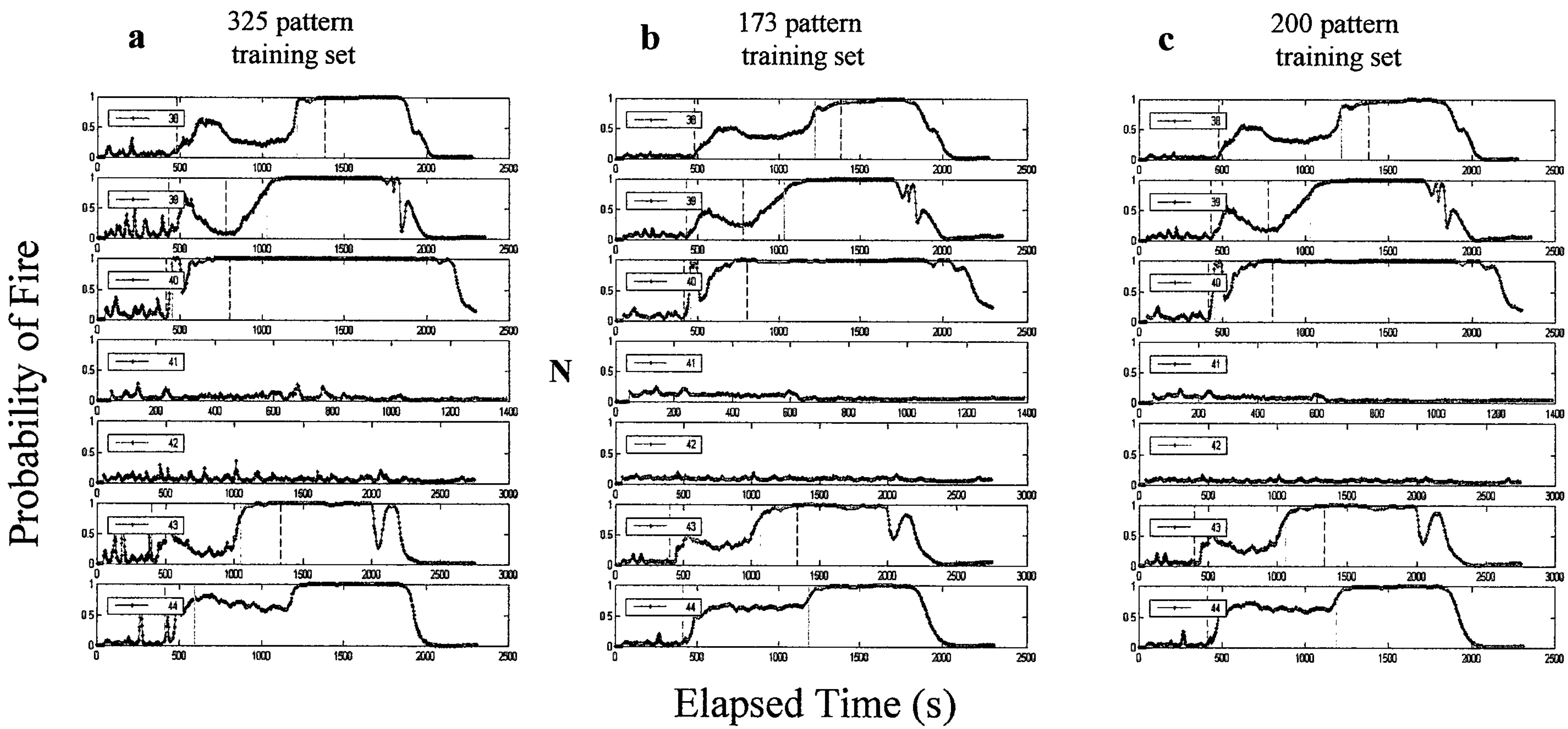

Figure 3. Probability versus elapsed time for Test Series 2, Prototype 2, experiments 38-44 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

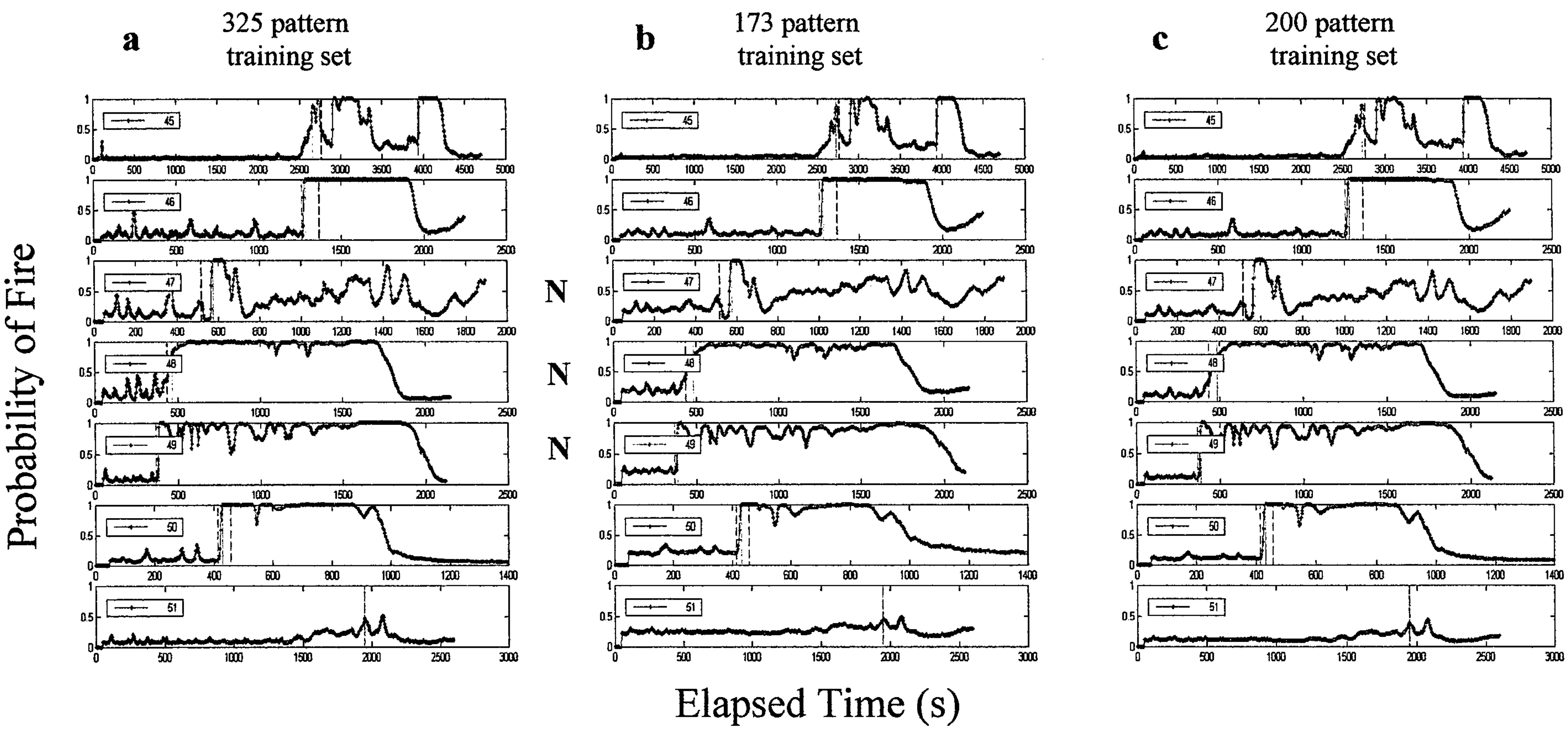

Figure 4. Probability versus elapsed time for Test Series 2, Prototype 2 experiments 45-51 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

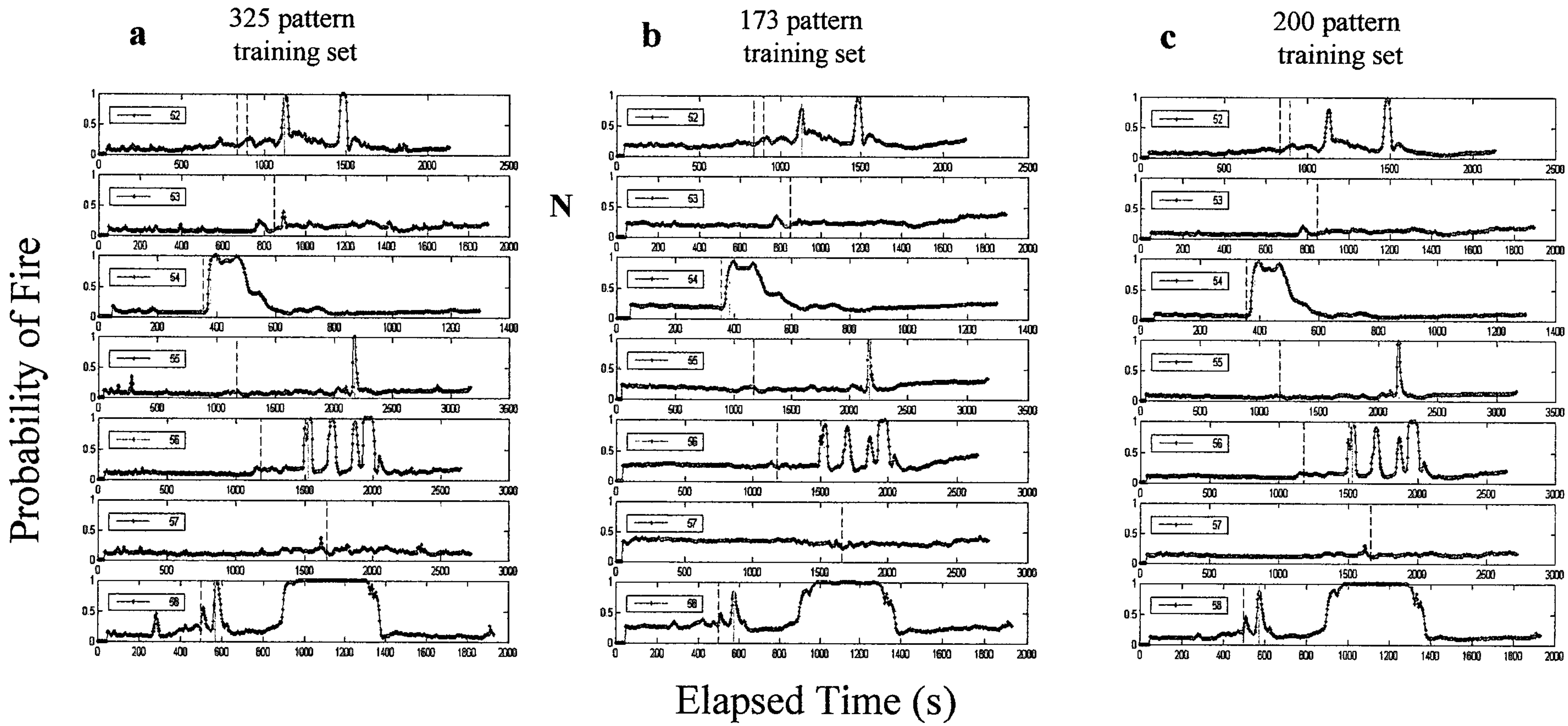

Figure 5. Probability versus elapsed time for Test Series 2, Prototype 2 experiments 52-58 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

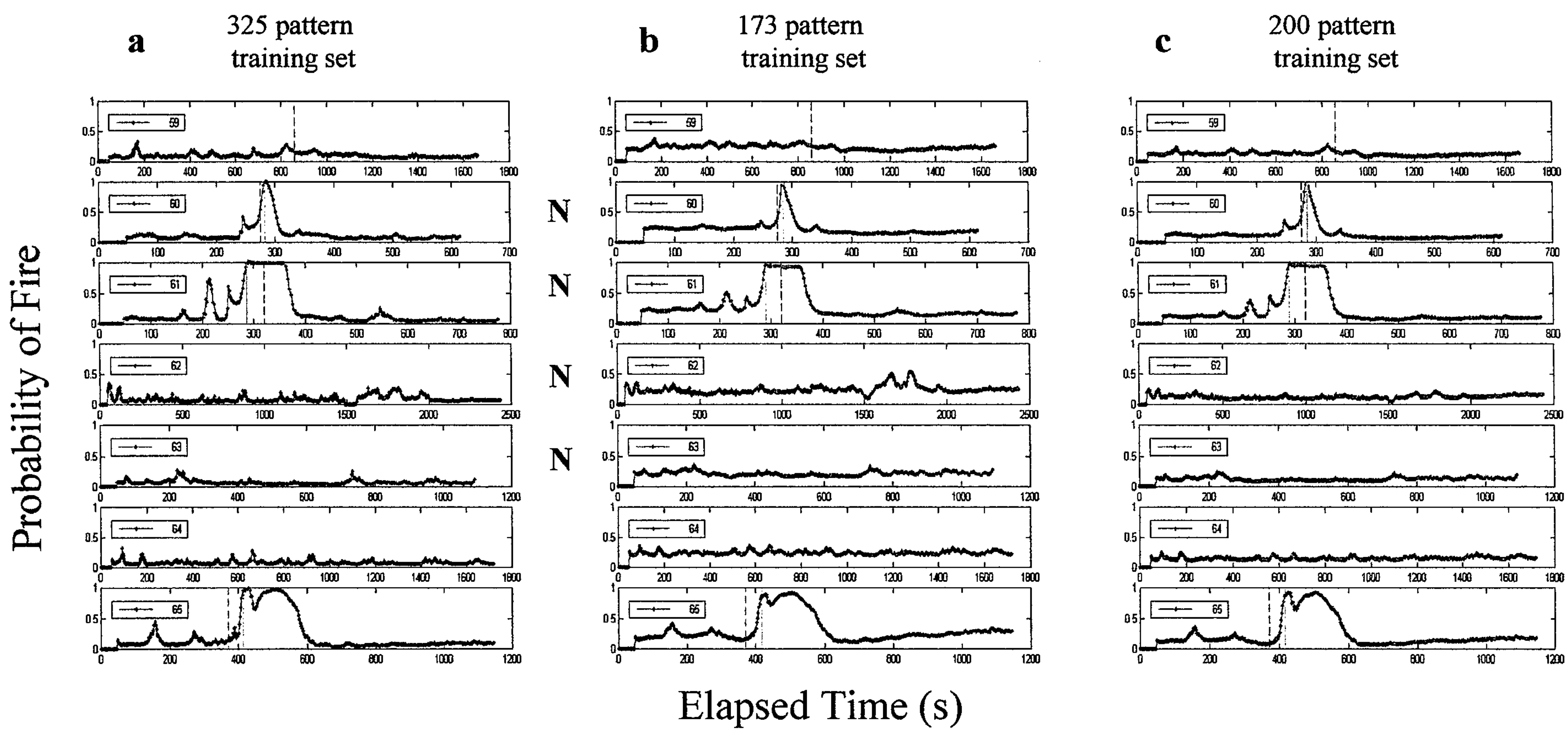

Figure 6. Probability versus elapsed time for Test Series 2, Prototype 2 experiments 59-65 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

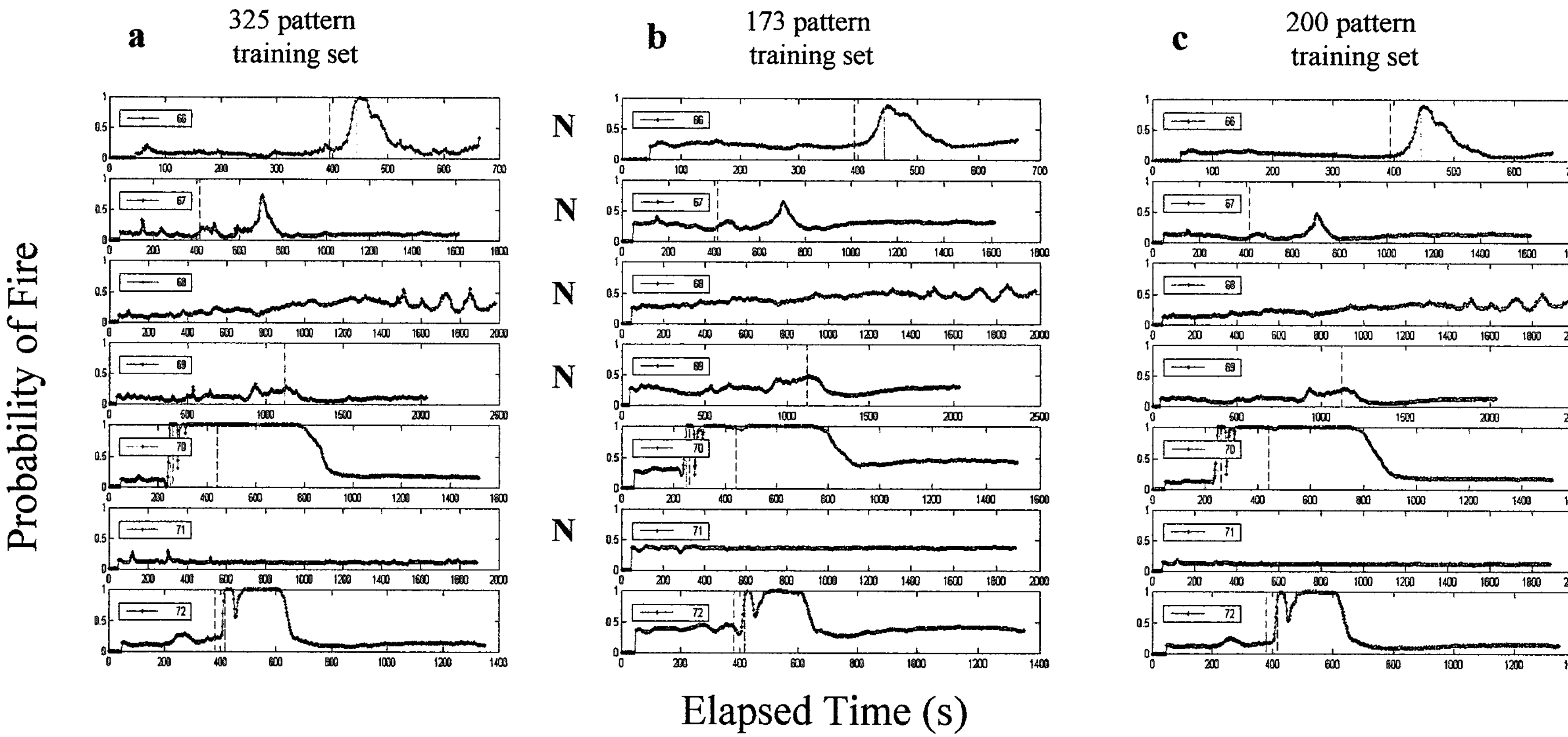

Figure 7. Probability versus elapsed time for Test Series 2, Prototype 2 experiments 66-72 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

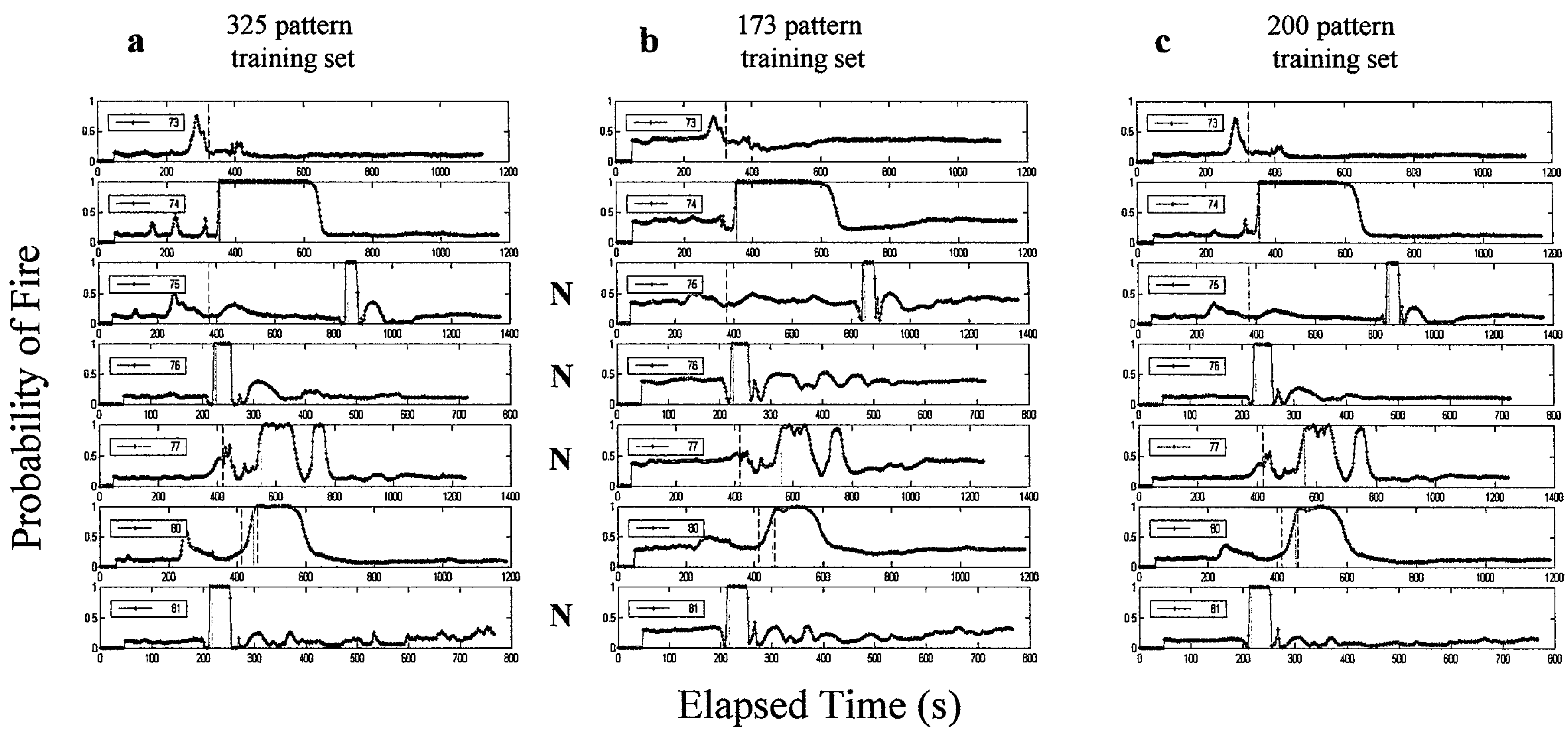

Figure 8. Probability versus elapsed time for Test Series 2, Prototype 2 experiments 73-77, 80, 81 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

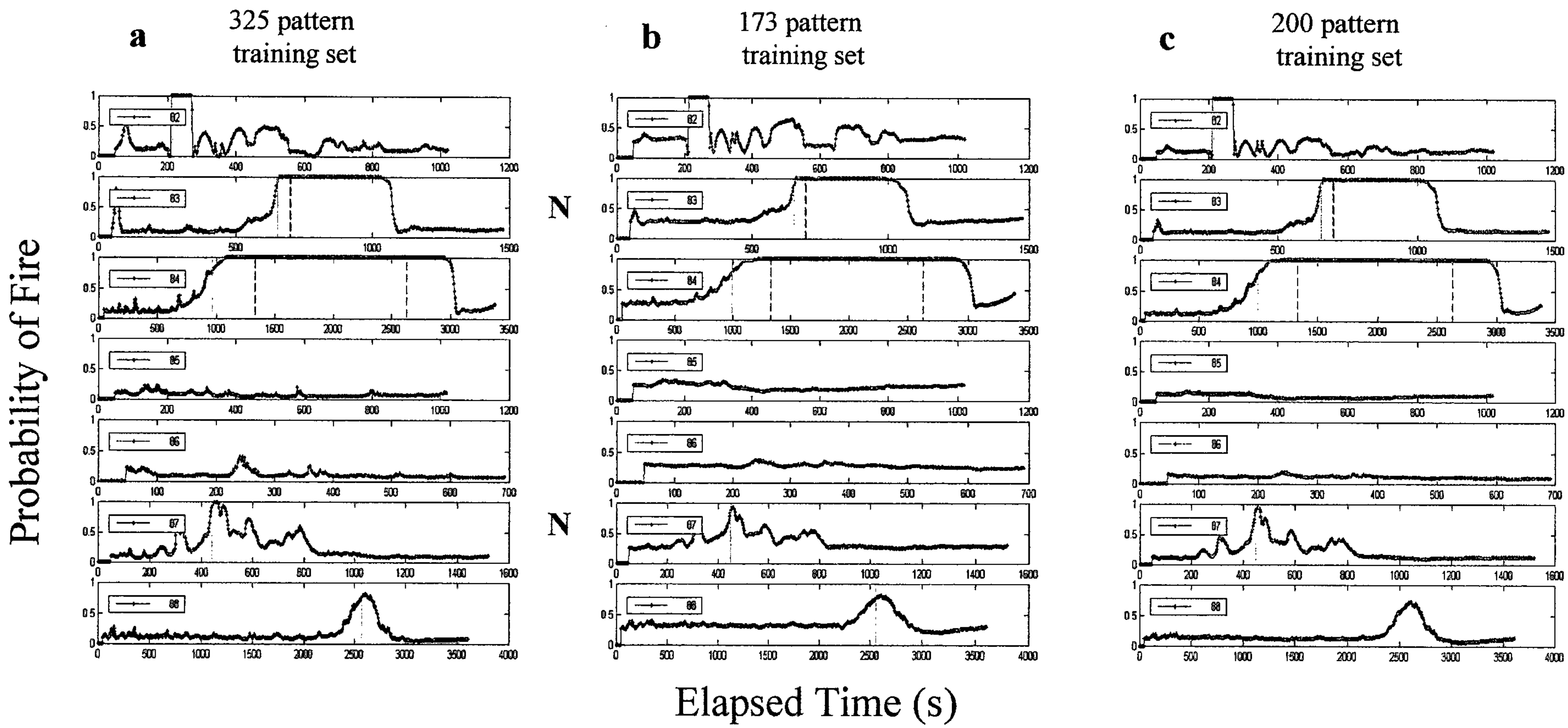

Figure 9. Probability versus elapsed time for Test Series 2, Prototype 2 experiments 82-88 (refer to Table 1 for test descriptions) generated at the 11 % alarm time, comparing a) the 325-pattern training set, b) the 173-pattern training set, and c) modified 200-pattern training set. Nuisance experiments are denoted with an "N". Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

Table 4. PNN classification comparison of training sets for prototype 1 and 2 using Test Series 2 Data

DataSet	Prototype	Total % Correct	Fires % Correct	Nuisance % Correct	Total # Correct	Fires # Correct	Nuisance # Correct	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
Test Series 2	1A	59.2	79.3	30.0	29	23	6	15	10	4	20	5	4	2	9	9	0	8	12	13	8	8	0	7	13
325 Training Set	2A	55.1	69.0	35.0	27	20	7	10	13	6	12	7	10	8	7	5	2	9	9	5	10	14	1	9	10
Test Series 2	1A	61.2	79.3	35.0	30	23	7	14	9	6	18	6	5	4	9	7	1	8	11	10	8	11	0	8	12
200 Training Set	2A	53.1	65.5	35.0	26	19	7	9	14	6	11	8	10	9	6	5	2	9	9	4	11	14	1	9	10
Test Series 2	1A	61.2	79.3	35.0	30	23	7	14	8	7	18	6	5	4	9	7	1	9	10	10	7	12	0	9	11
173 Training Set	2A	55.1	69.0	35.0	27	20	7	10	13	6	11	8	10	9	6	5	2	9	9	4	11	14	1	9	10
COTS	Ion	49.0	48.3	50.0	24	14	10																		
	Photo	77.6	75.9	80.0	38	22	16																		
	Ion+Photo	75.5	82.8	45.0	37	24	13																		

Table 5. PNN classification comparison of old and new ion correlation for prototype 1 and 2 using Test Series 1 and 2 Data

Test Series 1 and 2 Data	Prototype	Total % Correct	Fires % Correct	Nuisance % Correct	Total # Correct	Fires # Correct	Nuisance # Correct	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
200 Training Set	1A	69.0	83.6	41.4	58	46	12	22	24	9	33	12	10	6	15	8	4	11	14	15	21	19	1	13	15
old ion correlation	2A	61.9	74.5	37.9	52	41	11	16	30	9	24	16	15	12	9	8	3	13	13	9	25	21	1	14	14
200 Training Set	1A	66.7	80.0	41.4	56	44	12	20	23	12	29	15	11	9	10	10	3	12	14	13	20	22	2	12	15
new ion correlation	2A	63.1	74.5	41.4	53	41	12	17	29	9	25	15	15	12	9	8	3	14	12	10	24	21	1	15	13
COTS	Ion	56.0	58.2	51.7	47	32	15																		
	Photo	77.4	78.2	75.9	65	43	22																		
	Ion+Photo	71.4	87.3	41.4	60	48	12																		

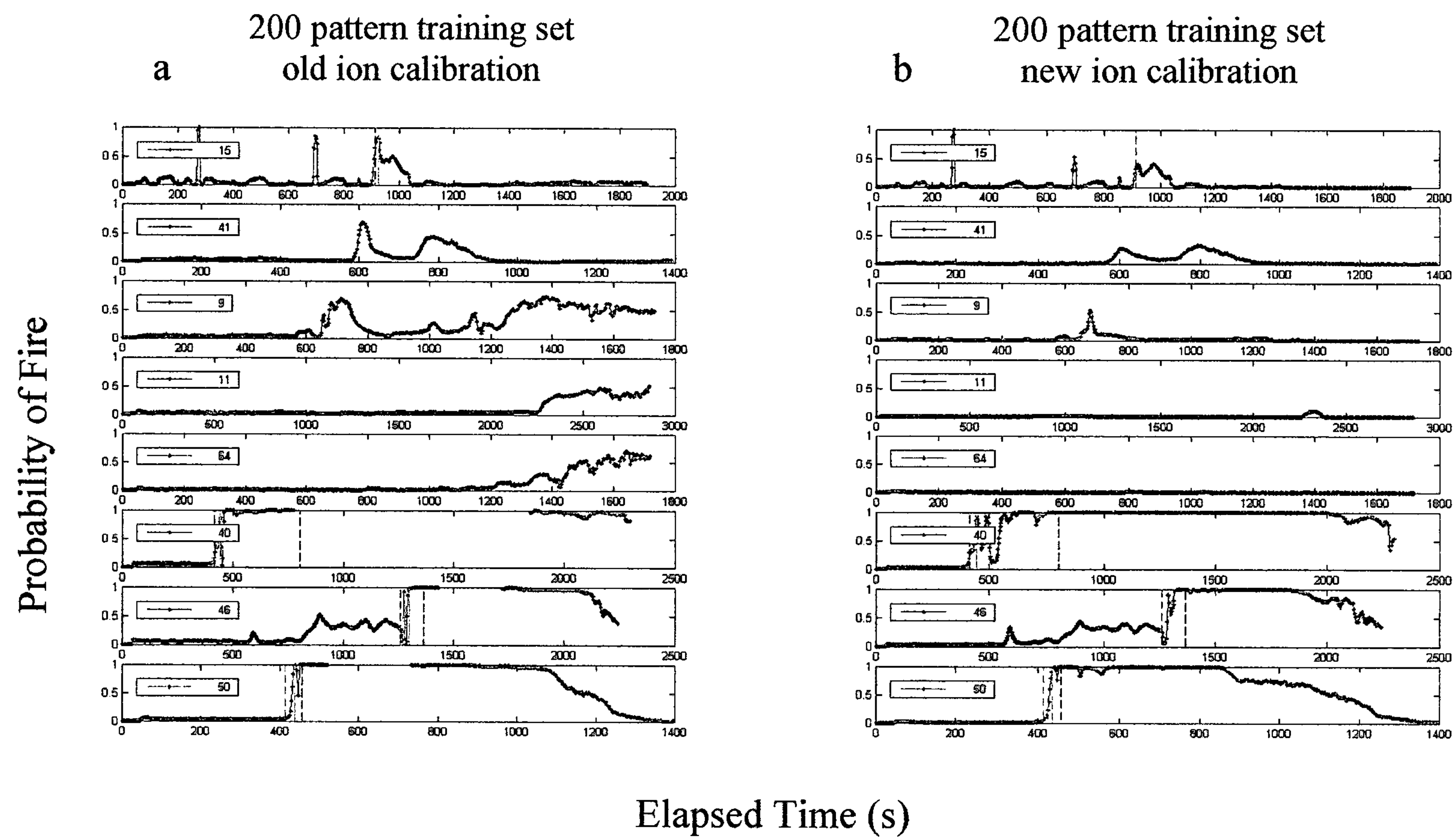

Figure 10. Probability versus elapsed time for Test Series 2 experiments 15, 41, 9, 11, 64, 40, 46, 50 (refer to Table 1 for test descriptions) generated at the 11 % alarm time with the modified 200-pattern training set, comparing a) the old ion correlation and b) the new ion correlation. Solid green line = PNN alarm time, dashed red line = COTS Ion alarm time, and dashed black line = COTS Photo alarm time.

4.3 Sensor Optimization

The PNN was modified and optimized for increased nuisance detection relative to its real-time performance during Test Series 1 and 2. The optimization was done in several ways beginning with the correction of the real-time code described in the previous section. The real-time code used for optimization was identical to the modified code (used in the Test Series 2) with the exception of provisions (if statements) for proper preprocessing of various sensor values. This was done in order to allow testing of alternative sensor combinations. Similar to the algorithm for real-time analysis, the slope was calculated over a 25-point region (number of rows in data_history), no background subtraction was performed, and the System Sensor ion detector had a correlation conversion from ΔMIC to % obs/ft, then to % obs/m, and the photo detector had a conversion from % obs/ft to % obs/m.

Using the modified 200 training set, 540 experiments were run to determine the best combination of sensors. The experiments varied 54 sensor combinations (see Table 6), along with training sets generated using the 11%, 1.63%, 0.82%, 11% + 1.63% and 11% + 0.82% COTS photoelectric alarm times. The third condition tested was the data averaging size for the magnitude, both 10 and 25-point averages were used along with a 25-point slope average. The original method involved a 10-point magnitude averaging, but recent tests used a 25-point average. The data used in the training set used 4 second intervals and the more recent data collection varied from 2-8 second intervals, over the course of a test. The PNN code was modified to allow for the selection of the magnitude/slope averaging in the prediction set.

Table 6. Sensor combinations used in optimization of Test Series 1 and 2 Data Set (see key given in Table 2)

2 3 4	7 8 9	26 3 4 5 6
2 3 5	7 8 10	26 8 9 10 11
2 3 6	7 8 11	27 3 4 5 6
2 4 5	7 9 10	27 8 9 10 11
2 4 6	7 9 11	26 4
2 5 6	7 10 11	26 6
3 4 5	8 9 10	26 4 6
3 4 6	8 9 11	27 4
3 5 6	8 10 11	27 6
4 5 6	9 10 11	27 4 6
2 3 4 5	7 8 9 10	2 4 6 24 25
2 3 4 6	7 8 9 11	2 3 4 23
2 3 5 6	7 8 10 11	2 3 4 23 25
2 4 5 6	7 9 10 11	2 4 6 23 25
3 4 5 6	8 9 10 11	2 4 6 22 23 25
2 3 6 11	7 8 11 6	4 22 23 25
2 3 4 6 11	7 8 9 11 6	2 3 4 5 6 11
2 3 4 5 6	7 8 9 10 11	7 8 9 10 11 6

4.3.1 Classification Performance

A representative set of classification results using various sensor combinations and training sets, is given in Tables 7 and 8. The data in Table 7 lists the top combinations when sorting by the best overall classification and then by nuisance classification. The data in Table 8 lists the top combinations when sorting by the best nuisance classification and then by overall classification. The results for prototype 1 and 2 are included at the bottom of each list for comparison.

The classification results using subsets of prototype 1 and 2 have shown marked improvement over the 5-sensor prototype. The highest performing sensor combinations had a better overall performance than either prototype, 73-77% vs. 63-68% respectively. When judging the results by nuisance classification, the original prototypes were beaten by 14-27%, approaching the best results from the COTS (see Table 5). The mis-classified fires for the best set, prototypes 1 and 2 and the COTS Photo are given in Table 9.

4.3.2 Speed Performance

In addition to the classification performance, the speed of PNN classification relative to COTS detectors was gauged using several criteria. The additional criteria used measured time to alarm for the sensor arrays compared to the COTS ion and photo detectors. The preferred performance observed an increase in the number of fires faster and the number of nuisances slower than the COTS ion or photo detectors. Slower alarm times for fires or faster alarm times for nuisance sources was not a desirable response. The number of fires similar to ion and the number of nuisances similar to photo are determined by counting those experiments where the prototype response is within ± 30 seconds of the COTS response time. The number of fires similar to COTS and the number of nuisances similar to COTS are additional measures with which to measure PNN performance. These figures of merit are given in Tables 7 and 8.

The new sensor combinations in general had better speed for classifying a fire compared to the original prototypes. The subsets show faster detection times for fires while not increasing the false alarm rate. The best subsets improved detection relative to COTS detectors by up to 10 fires compared to the original prototypes. When comparing those combinations with the best nuisance classification, the subsets show great improvement with little loss of fire classification. An improvement over the COTS detectors was also observed for nuisance sources with 2-8 events slower to alarm than COTS. The subsets are slower to alarm than the COTS ion, but the COTS photo consistently performed better than the prototypes or subsets.

Table 7. Representative PNN classification results of optimization of sensor combinations, training set alarm times and magnitude size averaging (sorted by %total/%nuisance)

magnitude size average	Training set alarm time	Sensors	Total % Correct	Fires % Correct	Nuisance %Correct	Total # Correct	Fires # Correct	Nuisance # Correct	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
10	11%	2 3 6 11	77.4	90.9	51.7	65	50	15	27	21	7	34	10	11	6	16	7	3	15	11	19	19	17	1	16	12
25	11%	7 8 11	76.2	85.5	58.6	64	47	17	21	23	11	25	18	12	12	14	3	2	20	7	9	24	22	1	20	8
25	11%	2 3 6 11	76.2	89.1	51.7	64	49	15	26	22	7	33	10	12	7	16	6	3	16	10	18	19	18	1	17	11
10	11%	7 8 11	75.0	87.3	51.7	63	48	15	22	23	10	28	16	11	10	14	5	2	18	9	11	24	20	0	19	10
25	11%	7 8 11 6	73.8	81.8	58.6	62	45	17	21	24	10	23	21	11	12	14	3	2	20	7	8	27	20	1	20	8
10	1.63%	7 8 9 11 6	73.8	94.5	34.5	62	52	10	34	21	0	45	8	2	4	9	16	1	10	18	30	23	2	0	10	19
25	11%	26 4 6	72.6	83.6	51.7	61	46	15	27	27	1	36	11	8	7	10	12	2	15	12	22	24	9	1	14	13
25	11%	26 4 6	72.6	83.6	51.7	61	46	15	27	25	3	34	13	8	7	10	12	2	15	12	21	23	11	1	15	13
10	11%	26 3 4 5 6	72.6	83.6	51.7	61	46	15	26	21	8	34	12	9	5	12	12	2	15	12	20	18	17	0	14	13
10	11%	2 3 6	72.6	85.5	48.3	61	47	14	24	22	9	33	11	11	6	16	7	3	15	11	18	18	19	1	16	12
25	11%	2 3 4 5 6	66.7	80.0	41.4	56	44	12	20	23	12	29	15	11	9	10	10	3	12	14	13	20	22	2	12	15
25	11%	7 8 9 10 11	63.1	74.5	41.4	53	41	12	17	29	9	25	15	15	12	9	8	3	14	12	10	24	21	1	15	13

Table 8. Representative PNN classification results of optimization of sensor combinations, training set alarm times and magnitude size averaging (sorted by %nuisance /%total)

magnitude size average	Training set alarm time	Sensors	Total % Correct	Fires % Correct	Nuisance %Correct	Total # Correct	Fires # Correct	Nuisance # Correct	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
10	11%	27 6	65.5	63.6	69.0	55	35	20	13	32	10	22	14	19	10	17	2	6	15	8	9	22	24	4	6	23
10	11%	7 9 11	66.7	69.1	62.1	56	38	18	14	36	5	26	15	14	9	13	7	3	17	9	10	27	18	1	18	10
25	11%	7 8 11	76.2	85.5	58.6	64	47	17	21	23	11	25	18	12	12	14	3	2	20	7	9	24	22	1	20	8
25	11%	7 8 11 6	73.8	81.8	58.6	62	45	17	21	24	10	23	21	11	12	14	3	2	20	7	8	27	20	1	20	8
25	11%	7 8 9 11 6	70.2	76.4	58.6	59	42	17	19	29	7	28	14	13	9	12	8	3	16	10	13	25	17	1	17	11
25	11%	7 9 11	65.5	69.1	58.6	55	38	17	14	35	6	25	15	15	9	13	7	3	16	10	10	25	20	1	17	11
25	11%	27 6	64.3	67.3	58.6	54	37	17	14	32	9	22	14	19	10	15	4	6	13	10	9	22	24	4	15	10
25	11%	7 10 11	59.5	60.0	58.6	50	33	17	5	37	13	19	14	22	12	14	3	4	16	9	3	22	30	1	19	9
10	11%	7 8 9 11 6	71.4	80.0	55.2	60	44	16	21	27	7	29	14	12	9	12	8	3	16	10	14	25	16	1	17	11
10	11%	7 8 9 11	71.4	80.0	55.2	60	44	16	20	28	7	28	15	12	9	12	8	3	16	10	12	27	16	1	17	11
25	11%	2 3 4 5 6	66.7	80.0	41.4	56	44	12	20	23	12	29	15	11	9	10	10	3	12	14	13	20	22	2	12	15
25	11%	7 8 9 10 11	63.1	74.5	41.4	53	41	12	17	29	9	25	15	15	12	9	8	3	14	12	10	24	21	1	15	13

Table 9. Misclassified Fire/Nuisance Sources

EWFD Test #	Description	EWFD Test #	Description
25/25 11%	Prototype 1	25/25 11%	Prototype 2
011, 071, 085, 086, 088	Smoldering Electrical Cable	011, 051, 071, 085, 086, 088	Smoldering Electrical Cable
060, 061	Wire Test	021, 059, 073	Wire Test
020, 033, 057, 058	PWB	020, 033, 057	PWB
		042	Smoldering Oily Rag in trashcan
012, 052	Arc Welding	053	Smoldering Bedding
027, 047	Burning Popcorn		
018, 048, 049	Steel Cutting	012, 052	Arc Welding
006, 087	Cigarette Smoking	009,027, 047	Burning Popcorn
063	Aerosol deodorants/hairspray	018, 048, 049	Steel Cutting
065	Poptarts	006, 087	Cigarette Smoking
069	Steel Grinding	065	Poptarts
072	cooking oil	072, 080	cooking oil
075, 076, 081, 082	Steam	075, 076, 081, 082	Steam

EWFD Test #	Description	EWFD Test #	Description
25/25 11%	7 8 11		COTS Photo
071, 085, 086	Smoldering Electrical Cable	011, 071, 085, 086, 088	Smoldering Electrical Cable
034, 059	Wire Test	034	Wire Test
057	PWB	001, 044	Heptane
042	Smoldering Oily Rag in trashcan	042	Smoldering Oily Rag in trashcan
053	Smoldering Bedding	013, 054	Flaming Bedding
		025	nylon rope into sm trash can
012, 052	Arc Welding		
009, 027, 047	Burning Popcorn	027, 047	Burning Popcorn
018, 048, 049	Steel Cutting	012, 052	Arc Welding
065	Poptarts	032	Cigarette Smoking
072, 080	cooking oil	072, 080	Cooking oil
066	toasting		

4.4 Background Subtraction

Background subtraction was tested by removing all backgrounds from the 200-pattern training set leaving only 140 patterns. These patterns were background subtracted using the first 30 seconds of each test to determine the baseline reading. The prediction set was also background subtracted again using the first 30 seconds to determine the baseline, with the exception of the ion and photo detector which were background subtracted when the data was collected. Using the background subtracted 140-pattern training set, 288 experiments were run using 48 sensor combinations and 3 training set alarm conditions (11, 1.63, and 0.82%). Both the 10 and 25-point data averaging size was used for the magnitude, along with a 25-point slope average. The PNN code was modified from the above sensor optimization to allow for the background subtraction of the sensor values, again with the exception of the ion and photo detectors, in the prediction set. The best results along with the results for prototypes 1 and 2 are listed in Tables 10 and 11, sorted by total percent correct and nuisance percent correct, respectively.

For both prototypes, background subtraction experiments were performed with the same parameters, 11% training set alarm times / 25/25 magnitude/slope data averaging, as the non-background subtracted for comparison. The overall correct classification of the data sets did not change significantly, however, prototype 1 showed a 7% improvement in nuisance classification and misclassified 8% more of the fires. Prototype 2 on the other hand showed 17% increase in nuisance detection with no difference in fire classification. The results are better than the COTS ion and worse than the COTS photo.

The classification performance of the subsets of the original prototypes showed a 5% improvement over the background subtracted results of the original 5 sensor prototypes. The improvement was mostly in the number of fires classified correctly. The speed of the classification relative to the COTS detectors also improved with 5-10 fires identified faster than the original prototypes. As seen in Table 11, good nuisance source rejection results in reduced speed and fewer fires correct. The best overall performance observed in Table 10 is from ION, Photo, and CO_2 (sensors: 7 8 6) using 11% obs/m for the alarm time and a 25 point magnitude average. The best nuisance source rejection was also observed for ION, Photo, and CO_2, using the same 11% obs/m for the alarm time and a 25 point magnitude average. The best classification performance while maintaining a fast detection speed relative to the COTS detectors was observed with ION, Photo, CO, and CO_2 (sensors: 7 8 9 6) using the 1.63% obs/m for the alarm time and a 10 point magnitude average. The types of fires misclassified by this sensor array are given in Table 12.

These preliminary investigations into background subtraction look promising and would solve many problems associated with different environmental conditions. When background subtraction is used, it is no longer necessary to include a large number of backgrounds in the training set. The need to represent extreme conditions should be reduced.

Table 10. Representative PNN classification results of optimization of sensor combinations, training set alarm times and magnitude size averaging using background subtraction (sorted by %total/%nuisance)

magnitude size average	Training set alarm time	Sensors	Total % Correct	Fires % Correct	Nuisance %Correct	Total # Correct	Fires # Correct	Nuisance # Correct	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
25	11%	7 8 6	76.2	74.5	79.3	64	41	23	13	29	13	17	21	17	13	14	2	4	23	2	2	27	26	1	25	3
25	11%	7 8 11	75.0	74.5	75.9	63	41	22	12	29	14	16	19	20	12	15	2	5	20	4	2	25	28	2	22	5
25	11%	7 8 11 6	75.0	74.5	75.9	63	41	22	12	29	14	18	18	19	12	15	2	5	20	4	2	25	28	2	22	5
10	11%	7 8 6	75.0	78.2	69.0	63	43	20	15	27	13	20	20	15	12	13	4	3	22	4	4	27	24	1	23	5
10	1.63%	7 8 9 6	75.0	81.8	62.1	63	45	18	23	27	5	36	12	7	8	11	10	3	16	10	18	25	12	2	16	11
10	1.63%	7 8 9	75.0	87.3	51.7	63	48	15	26	24	5	37	12	6	8	10	11	1	17	11	19	25	11	0	17	12
25	1.63%	7 8 9	75.0	87.3	51.7	63	48	15	25	26	4	35	13	7	8	13	8	1	17	11	17	28	10	0	17	12
10	1.63%	7 8 9 11	73.8	81.8	58.6	62	45	17	23	27	5	35	13	7	8	11	10	3	15	11	17	26	12	2	15	12
10	11%	2 4 6	72.6	74.5	69.0	61	41	20	18	30	7	29	12	14	10	13	6	4	18	7	14	23	18	3	18	8
25	11%	7 8 9	72.6	74.5	69.0	61	41	20	15	31	9	22	18	15	12	13	4	4	19	6	7	27	21	2	20	7
25	11%	2 3 4 5 6	64.3	72.7	48.3	54	40	14	20	25	10	24	19	12	10	8	11	3	13	13	13	22	20	2	13	14
25	11%	7 8 9 10 11	69.0	74.5	58.6	58	41	17	17	30	8	22	16	17	12	10	7	4	16	9	7	28	20	2	17	10

Table 11. Representative PNN classification results of optimization of sensor combinations, training set alarm times and magnitude size averaging using background subtraction (sorted by %nuisance/%total)

magnitude size average	Training set alarm time	Sensors	Total % Correct	Fires % Correct	Nuisance %Correct	Total # Correct	Fires # Correct	Nuisance # Correct	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
25	11%	7 8 6	76.2	74.5	79.3	64	41	23	13	29	13	17	21	17	13	14	2	4	23	2	2	27	26	1	25	3
10	11%	27 6	66.7	60.0	79.3	56	33	23	9	33	13	20	15	20	11	16	2	6	17	6	6	22	27	4	19	6
25	11%	7 8 11	75.0	74.5	75.9	63	41	22	12	29	14	16	19	20	12	15	2	5	20	4	2	25	28	2	22	5
25	11%	7 8 11 6	75.0	74.5	75.9	63	41	22	12	29	14	18	18	19	12	15	2	5	20	4	2	25	28	2	22	5
25	11%	27 6	67.9	63.6	75.9	57	35	22	11	31	13	20	14	21	11	15	3	6	16	7	7	21	27	4	18	7
10	0.82%	27 6	63.1	56.4	75.9	53	31	22	6	37	12	19	16	20	9	17	3	6	16	7	4	24	27	3	19	7
25	11%	7 9 6	65.5	61.8	72.4	55	34	21	9	38	8	22	15	18	12	13	4	5	18	6	6	26	23	3	19	7
25	0.82%	27 6	63.1	58.2	72.4	53	32	21	7	37	11	18	16	21	8	18	3	6	15	8	4	24	27	3	18	8
10	11%	7 8 6	75.0	78.2	69.0	63	43	20	15	27	13	20	20	15	12	13	4	3	22	4	4	27	24	1	23	5
10	11%	2 4 6	72.6	74.5	69.0	61	41	20	18	30	7	29	12	14	10	13	6	4	18	7	14	23	18	3	18	8
25	11%	2 3 4 5 6	64.3	72.7	48.3	54	40	14	20	25	10	24	19	12	10	8	11	3	13	13	13	22	20	2	13	14
25	11%	7 8 9 10 11	69.0	74.5	58.6	58	41	17	17	30	8	22	16	17	12	10	7	4	16	9	7	28	20	2	17	10

Table 12. Misclassified Fire/Nuisance Sources using Background Subtraction

EWFD Test #	Description	EWFD Test #	Description
25/25 11%	7 8 6	10/25 1.63%	7 8 9 6
011, 051, 071 085, 086, 088	Smoldering Electrical Cable	011, 071, 085, 086	Smoldering Electrical Cable
020, 057	PWB	020, 033, 057	PWB
042	Smoldering Oily Rag in trashcan	042	Smoldering Oily Rag in trashcan
053	Smoldering Bedding	029	Smoldering Bedding
021, 034, 059 073	Brief Wire overheat	059	Brief Wire overheat
012	Arc Welding		
		009, 027, 047	Burning Popcorn
009, 047	Burning Popcorn	006, 087	Cigarette Smoking
049	Steel Cutting	018, 048, 049	Steel Cutting
072, 080	Cooking oil	075	Steam generation w/ propanre burner
		072, 080	Cooking oil

5. PNNCV Training of Both Test Series 1 and 2

Test Series 1 and 2 were also tested using cross validation (PNNCV) as described in earlier reports.[3,4,5,7] All of the tests for both test series were reviewed and a training set and a prediction set were generated. In some cases, the responses for tests were weak and not consistent across several replications. The tests that had questionable responses were not included in the training set. Table 13 lists all 54 tests included in the training set. The prediction set shown in Table 14 includes the replicates from the test series (17 tests) and as well as the weak responses (13 tests) that were discarded from the training set. All the experiments in italics were not included in the training set due to weak responses.

Table 13. Summary of Scenarios in training Set.

EWFD Tests	Fire Scenario Description
001,008,038,043	Heptane Pool Fire
002,039	Pipe Insulation Exposed to Fuel Oil Fire
003,040	Flaming Oily Rag and Paper in Small Trash Can
022, 083	Smoldering Oily Rag and Paper in Small Trash Can
005,045	Smoldering Plastic Bag of Mixed Trash
007,046	Plastic Trash Bag Fire next to TODCO Wallboard
010,050	Electrical Cables and Pipe Insulation exposed to Laundry Pile Fire
088	Smoldering Electrical Cables (LSDSGU-14)
019, 084	Smoldering Bedding Material
013,054	Flaming Bedding Material
056, 058	Printed Wire Board Fire
021,073	Brief Overheat of a Wire
060,061	BSI 6266 Wire Overheat
074,077	Smoldering Electrical Cables (LSTPNW-1½ , MIL C-24643/52-01UN)
016	Wood Crib
017	Trashcan/office Chair
031	F02a: Pipe Insulation Exposed to Heptane Fire
004,030	Burning Toast
EWFD Tests	**Nuisance Scenario Description**
041,065	Toasting Pop Tarts™
012,052	Welding Steel
018,048	Cutting Steel with acetylene torch
009,047	Burning popcorn
006,068	Cigarette smoke
015,066	Normal Toasting
028,069	Grinding Steel
063	Aerosol Deodorants
064	Sweeping up a dropped bag of flour
076	Steam generation.
062,072	Cooking oil
024	Nylon Rope

Table 14. Summary of Scenarios in Prediction Set.

EWFD Tests	Fire Scenario Description
044	Heptane Pool Fire
023	Pipe Insulation Exposed to Fuel Oil Fire
014,070	Flaming Oily Rag and Paper in Small Trash Can
035, *042*	Smoldering Oily Rag and Paper in Small Trash Can
026	Smoldering Plastic Bag of Mixed Trash
	Plastic Trash Bag Fire next to TODCO Wallboard
	Electrical Cables and Pipe Insulation exposed to Laundry Pile Fire
011,051,085,086	Smoldering Electrical Cables (LSDSGU-14)
029, *053*	Smoldering Bedding Material
	Flaming Bedding Material
020,033,055, 057	Printed Wire Board Fire
034, *059*	Brief Overheat of a Wire
	BSI 6266 Wire Overheat
071	Smoldering Electrical Cables (LSTPNW-1½ , MIL C-24643/52-01UN)
	Wood Crib
	Trashcan/office Chair
	F02a: Pipe Insulation Exposed to Heptane Fire
	Burning Toast
025	Nylon Rope into trashcan
EWFD Tests	**Nuisance Scenario Description**
	Toasting Pop Tarts™
	Welding Steel
049	Cutting Steel with acetylene torch
027	Burning popcorn
032, 087	Cigarette smoke
067	Normal Toasting
	Grinding Steel
	Aerosol Deodorants
	Sweeping up a dropped bag of flour
081,082, *075*	Steam generation.
080	Cooking oil
	Nylon Rope

The training set was generated similar to the previous training sets with only slight changes being required. The raw sensor data was used for all sensors except the photo, which was converted to % obs/m. The ion detector was left as ΔMIC since an accurate conversion was not available at the time. The patterns were generated at the alarm times from the COTS detectors used in the field tests. The time used was from the first alarming detector, ion or photo, or 300 sec after ignition if neither detector alarmed. The patterns in the training set used a 10-point magnitude and 25-point slope averaging. The studies were conducted with and without backgrounds in the training and prediction sets. Background patterns were also generated for each experiment at the time just before ignition. For the training set with backgrounds, there is one background for each member of the training set; resulting in 108 patterns. Using PNNCV, Prototype 1 misclassified 18 fire/nuisance sources with and without backgrounds in the training set. The results are shown in Table 15. Prototype 2 misclassified 19 when no backgrounds were present, and only misclassified 13 using backgrounds as shown in Tables 16 and 17.

Table 15. Summary of Prototype 1 Misclassified Events Using PNNCV

EWFD Tests	Fire Scenario Description
003,040	Flaming Oily Rag and Paper in Small Trash Can
022	Smoldering Oily Rag and Paper in Small Trash Can
046	Plastic Trash Bag Fire next to TODCO Wallboard
010,050	Electrical Cables and Pipe Insulation exposed to Laundry Pile Fire
088	Smoldering Electrical Cables (LSDSGU-14)
019	Smoldering Bedding Material
054	Flaming Bedding Material
058	Printed Wire Board Fire
021, 073	Brief Overheat of a Wire
060,061	BSI 6266 Wire Overheat
004	Burning Toast
EWFD Tests	**Nuisance Scenario Description**
041	Toasting Pop Tarts™
018	Cutting Steel with acetylene torch
072	Cooking oil

Table 16. Summary of Prototype 2 Misclassified Events Using PNNCV with no Backgrounds.

EWFD Tests	Fire Scenario Description
001,008,038,043	Heptane Pool Fire
039	Pipe Insulation Exposed to Fuel Oil Fire
003,040	Flaming Oily Rag and Paper in Small Trash Can
022	Smoldering Oily Rag and Paper in Small Trash Can
005,045	Smoldering Plastic Bag of Mixed Trash
046	Plastic Trash Bag Fire next to TODCO Wallboard
050	Electrical Cables and Pipe Insulation exposed to Laundry Pile Fire
088	Smoldering Electrical Cables (LSDSGU-14)
019	Smoldering Bedding Material
058	Printed Wire Board Fire
021,073	Brief Overheat of a Wire
EWFD Tests	**Nuisance Scenario Description**
018	Cutting Steel with acetylene torch
028	Grinding Steel

Table 17. Summary of Prototype 2 Misclassified Events Using PNNCV with Backgrounds

EWFD Tests	Fire Scenario Description
022	Smoldering Oily Rag and Paper in Small Trash Can
010,050	Electrical Cables and Pipe Insulation exposed to Laundry Pile Fire
088	Smoldering Electrical Cables (LSDSGU-14)
084	Smoldering Bedding Material
054	Flaming Bedding Material
056,058	Printed Wire Board Fire
021,073	Brief Overheat of a Wire
077	Smoldering Electrical Cables (LSTPNW-1½ , MIL C-24643/52-01UN)
EWFD Tests	**Nuisance Scenario Description**
012	Welding Steel
	Background

Varselpr, a feature selection routine, was used to determine the best set of sensors to correctly classify the training set. Several different sets of sensors were available for selection, (a) all, (b) all except prototype 1, (c) all except prototype 2, (d) prototype 1, and (e) prototype 2. Using the subsets of sensors determined by this method, the best PNNCV results were achieved with the hydrogen sulfide and hydrocarbon sensor in the set. However, subsets of prototypes 1 and 2 were also very strong as shown in Table 18. The results for the slope of CO (rCO), Photo, and the slope of ION (rION) are given in Table 19.

Using the 54 and 108 training sets, the prediction set was investigated with different combinations of sensors using the same methods as in Section 4, PNN optimization (playback mode). The results are shown in Table 20. The results in this Table are for the prediction set, a combination of the 17 replicates and the 13 discarded tests. The COTS and the prototype sensors generally perform poorly on the discarded tests, therefore all the results are low. The overall classification results are better than the COTS ion and similar to the COTS photo. The 108 training set was usually much faster than the COTS for predicting fires. More Nuisance sources are correctly classified with no backgrounds in the training set.

Table 21 divides the prediction set into two parts, so that the results for the weak tests (discarded tests) are easier to see. This table also consolidates the prediction set results with the training set results to give an overall classification to Test Series 1 and 2 that can be compared to Table 7, 8 10, and 11. The overall correct results are better than the COTS ion (56%), but weaker than the COTS photo (77%). Using Test Series 1 and 2 for the training data, the largest correct classifications of nuisance sources was achieved, but this PNN does not detect several of the fires. Prototype 1, using training set 54, did the best predicting the replicates and gave the best nuisance source recognition. Prototype 2 was best when backgrounds are present and was able to detect several of the discarded fires. The sensor subset ION, photo, and CO (sensors: 7 8 9) was also very strong. However, this method does not provide a significant improvement over the methods described in Section 4.

Table 18. Feature Selection Results

Sensor Sets with No Backgrounds	**Sensors (r means slope of sensor)**	# missed
A	H2S HC rO2 CO(4) CO(9)	9
B	H2S HC rO2 CO	10
C	H2S HC rO2 CO	9
D	CO rCO	17
E	rCO rION Photo	16
Sensor Sets with Backgrounds		
A	rCO CO rRION-C Photo rRION ION(2)	11
B	rCO rRION-C Photo HC rION H2S rH2S rION CO	11
C	CO rRION-C rHC rCO2 rRION NO	12
D	CO rCO rPhoto photo rCO2 CO2	17
E	rCO Photo rION	12

Table 19. Summary of rCO Photo rION Misclassified Events Using PNNCV

EWFD Tests	Fire Scenario Description
002	Pipe Insulation Exposed to Fuel Oil Fire
040	Flaming Oily Rag and Paper in Small Trash Can
022	Smoldering Oily Rag and Paper in Small Trash Can
046	Plastic Trash Bag Fire next to TODCO Wallboard
088	Smoldering Electrical Cables (LSDSGU-14)
084	Smoldering Bedding Material
054	Flaming Bedding Material
073	Brief Overheat of a Wire
077	Smoldering Electrical Cables (LSTPNW-1½ , MIL C-24643/52-01UN)
EWFD Tests	**Nuisance Scenario Description**
052	Welding Steel
047	Burning popcorn
006	Cigarette smoke

Table 20. PNN classification comparison of training sets for Several Sensor Combinations using Test Series 1 and 2 Data

DataSet	Prototype	Total % Correct	Fires % Correct	Nuisance % Correct	Total # Correct	Fires # Correct	Nuisance # Correct
54	1A	66.7	52.4	100.0	20	11	9
108	1A	60.0	66.7	44.4	18	14	4
54	2A	46.7	42.9	55.6	14	9	5
108	2A	60.0	71.4	33.3	18	15	3
54	2 3 4	63.3	57.1	77.8	19	12	7
108	2 3 4	66.7	81.0	33.3	20	17	3
54	7 8 9	56.7	47.6	77.8	17	10	7
108	7 8 9	63.3	66.7	55.6	19	14	5
108	4 8 27	70.0	76.2	55.6	21	16	5
108	4 8 23 25 27	56.7	66.7	33.3	17	14	3
108	4 6 24 25 27	60.0	71.4	33.3	18	15	3
COTS	Ion	43.3	38.1	55.6	13	8	5
	Photo	63.3	61.9	66.7	19	13	6
	Ion+Photo		71.4	33.3			

DataSet	Prototype	fires faster than ion	fires similar to ion	fires slower than ion	fires faster than photo	fires similar to photo	fires slower than photo	nuisances slower than ion	nuisances similar to ion	nuisances faster than ion	nuisances slower than photo	nuisances similar to photo	nuisances faster than photo	total fires faster	total fires similar	total fires other	total nuisances slower	total nuisances similar	total nuisances other
54	1A	4	14	3	7	8	6	4	5	0	3	6	0	2	11	8	1	8	0
108	1A	7	12	2	11	6	4	1	4	4	2	2	5	6	9	6	0	4	5
54	2A	4	15	2	5	8	8	4	2	3	2	3	4	2	10	9	1	4	4
108	2A	8	13	0	9	7	5	3	3	3	2	3	4	4	12	5	1	3	5
54	2 3 4	6	13	2	7	9	5	3	5	1	3	4	2	3	11	7	1	6	2
108	2 3 4	10	10	1	13	5	3	2	4	3	2	3	4	8	9	4	0	3	6
54	7 8 9	3	16	2	6	8	7	3	6	0	2	6	1	1	12	8	0	8	1
108	7 8 9	7	14	0	9	7	5	2	5	2	1	4	4	4	12	5	0	5	4
108	4 8 27	9	11	1	9	7	5	3	4	2	1	5	3	4	11	6	0	6	3
108	4 8 23 25 27	6	14	1	9	9	3	3	2	4	1	4	4	4	13	4	0	4	5
108	4 6 24 25 27	8	12	1	12	7	2	1	3	5	1	3	5	7	11	3	0	3	6

Table 21. Results Using Test Series 1 and 2 For Training and Prediction

Training Set	Sensors	Prediction Set				Overall Correct for Test Series 1 and 2 #Correct*		
		Replicate Tests # Correct		Discarded Tests #Correct				
		Fires (9)	Nuis. (8)	Fires (12)	Nuis. (1)	Fires (55)	Nuis (29)	%
54	1A	9	8	2	1	30	26	66.7
108	1A	9	4	5	0	33	21	60.7
54	2A	7	5	2	0	26	23	58.3
108	2A	9	3	6	0	38	22	71.4
54	2 3 4	8	6	4	1	32	22	64.3
108	2 3 4	9	3	8	0	37	18	65.5
54	7 8 9	8	6	2	1	35	24	70.2
108	7 8 9	9	4	5	1	37	21	69.0
108	4 8 27	9	4	7	1			
108	4 8 23 25 27	9	2	5	1			
108	4 6 24 25 27	9	2	6	1			

*Results combine the prediction results with the PNNCV results for the training set

6. Conclusions

This test series demonstrated an early warning fire detection system consisting of a sensor array and a PNN operated in real-time on the ex-USS SHADWELL. The EWFD provides very good results with faster fire detection than COTS ion and photo detectors. Significant improvements have been demonstrated by optimizing the training set and the ion sensor calibration. For Test Series 1 and 2, a subset of sensors rather than the full set used in prototypes 1 and 2 gave the best results. In addition, background subtraction improved the overall classification as well as the detection speed.

Based on the results described in this report, the ION, Photo, CO, and CO_2 (sensors: 7 8 9 6) sensors are recommended for real-time analysis during Test Series 3 using 10-point magnitude and 25-point slope determinations, background subtraction and trained at 1.63% obs/m photoelectric detector alarm times. Several other sensor combinations will also be evaluated after each test. If it is determined that any of the alternative methods are better than the real-time analysis methods, the real-time analysis method will be changed. The best method will be tested before Test Series 3 is complete.

The following combinations will be tested during Test Series 3:

Real-time			
ION, Photo, CO, CO_2	10/25	background subtraction	1.63% Alarm times
Playback Mode(off line)			
ION, Photo, Temp	25/25	background subtraction	11% Alarm times
ION, Photo, Temp	25/25	no background subtraction	11% Alarm times
ION, Photo, CO	25/25	no background subtraction	Test Series 1 and 2
Prototype 1	25/25	no background subtraction	All data
Prototype 2	25/25	no background subtraction	All data
ION, CO, CO_2	10/25	background subtraction	11% Alarm times

The probability cut off for alarm will also be investigated during Test Series 3. To date, a probability cut off of 0.75 has been used. It may be possible to improve nuisance source rejection and maintain fast fire detection if this level is increased to 0.85-0.90%. Tests will be conducted to determine if it is more appropriate to issue a warning at 0.75 and alarm at 0.85.

7. References

1. Gottuk, D. T. and Williams, F. W. "Multi-Criteria Fire Detection: A Review of the State-of-the-Art," NRL Ltr Rpt Ser 6180/0472, September 10, 1998.

2. Carhart, H. W.; Toomey, T. A.; and Williams, F. W. " The ex-USS SHADWELL Full-Scale Fire Research and Test Ship", NRL Memorandum Report 6074, October 1987, Reissue, September, 1992.

3. Gottuk, D. T.; Hill S. A.; Schemel, C. F.; Strehlen, B. D.; Shaffer, R. E.; Rose-Pehrsson, S. L.; Tatem, P. A.; and Williams, F. W. "Identification of Fire Signatures for Shipboard Multi-criteria Fire Detection Systems", NRL Memorandum Report, NRL/MR/6180-99-8386, June 18, 1999.

4. Shaffer, R. E.; Rose-Pehrsson, S. L.; Barry, C.; Gottuk, D. T.; and Williams, F. W. "Development of an Early Warning Multi-Criteria Fire Detection System: Analysis of Transient Fire Signatures Using a Probabilistic Neural Network", NRL Memorandum Report, NRL/MR/6110-00-8429, February 16, 2000.

5. Rose-Pehrsson, S. L.; Shaffer, R. E.; Hart, S. J.; Williams, F. W.; Gottuk, D. T.; Hill, S. A.; and Strehlen, B. D. "Multi-Criteria Fire Detection Systems using a Probabilistic Neural Network", Sensors and Actuators, B, in press.

6. Wong, J. T.; Gottuk, D. T.; Shaffer, R. E.; Rose-Pehrsson, S. L.; Hart, S. J.; Tatem, P. A.; and Williams, F. W. "Results of Multi-Criteria Fire Detection System Tests", NRL Memorandum Report, NRL/MR/6180-00-8452, May 22, 2000.

7. Rose-Pehrsson, S. L.; Hart, S. J.; Shaffer, R. E.; Wong, J. T.; Gottuk, J. T.; Tatem, P. A.; and Williams, F. W. "Analysis of Multi-Criteria Fire Detection Systems Results for Test Series 1," NRL Letter Report, NLR Ltr Rpt Ser 6110/116, 16 May 2000.

8. Wright, M. T.; Gottuk, D. T.; Wong, J. T.; Rose-Pehrsson, S. L.; Hart, S. J.; Tatem, P. A.; and Williams, F. W. "Prototype Early Warning Fire Detection System: Test Series 1 Results," NRL Letter Report, NLR Ltr Rpt Ser 618/0163A:FWW, 27 April, 2000.

9. Hart, S. J.; Hammond, M. H.; Rose-Pehrsson, S. L.; Shaffer, R. E.; Wong, J. T.; Gottuk, D. T.; Wright, M. T.; Street, T. T.; Tatem, P. A.; and Williams, F. W. "Real-Time Probabilistic Neural Network Performance and Optimization for Fire Detection and Nuisance Alarm Rejection: Test Series 1 Results," NRL Memorandum Report, NLR/MR/6110-00-XXXX, August 2000. (in press)

10. Wright, M. T.; Gottuk, D. T.; Wong, J. T.; Rose-Pehrsson, S. L.; Hart, S. J.; Hammond, M. H.; Tatem, P. A.; Street, T. T.; and Williams, F. W. "Prototype Early Warning Fire Detection System: Test Series 2 Results," NRL Letter Report, NLR Ltr Rpt Ser 618/0242A:FWW, 15 June, 2000.

Appendix A

Real-time PNN Matlab code

```
function [w,p,pattern,alarm_state,data_history,alarm_history] =
rtpnncode_lab4(Xcurrent,bckgrd,data_history,alarm_history,train,tinfo,s
igma,alarmprob)
% RTpnncode_lab - Code written to be incorporated into Labview for use
during real-time fire testing on the ex-USS Shadwell
%
% Version 0.1 - 1/11/00 - Sean J.  Hart
% Version 0.2 - 1/20/00 - SJH - Modified averaging, added alarm
probability and fire criterion for alarms
% Version 0.3 - 1/28/00 - SJH - Removed redundant variable data_average
from input and output lists
% Version 0.4 - 1/31/00 - SJH - Modified code to use preprocess type 3
(engineering units and no background subtraction with selection code 8
(mag/slope calc)
% Version 0.5 - 1/31/00 - SJH - Removed redundant variables buffer size
and average size as they are no longer needed
% Version 1.0 - 4/13/00 - SJH - Removed buffer_data as averaging was
slowing us down and allowing averaged zeros to be included in data
history
% Outputs-
% w:                  class winner determined by PNN
% p:                  PNN probability
% pattern:            processed sensor values used by the PNN
% alarm_state:        current alarm condition
% data_history:       a buffer of data points from which to calculate
baselines and slopes
% data_average:       the averaged raw data points from buffer_data
% buffer_data:        a buffer of raw data points from which to calculate
an average raw input
% alarm_history:      a record of alarm conditions
%
% Inputs-
% Xcurrent:           sensor input values
% bckgrd:             backgr supplied by HAI
% data_history:       record of
% alarm_history:      record of alarm states
% train:              Training set patterns
% tinfo:              Training set info
% sigma:              Training kernel width
% alarmprob:          Probability at which to alarm
%
%
```

```
[junk,numsensors] = size(Xcurrent);

% *************************** Some constants
*****************************************************

slopeflag = 1;
slopelength = 25;
maglength = 25;
x = (1:slopelength)';

if maglength > slopelength
   startcalc = maglength;
else
   startcalc = slopelength;
end


% *************************** Background subtraction and conversion
calculations **************

 converted_data = Xcurrent;

 [y] = polyval([0.0000034 -0.0004140 0.0171968 -0.2070225
0.0004794],converted_data(1)); % convert delta mic to %obs/ft
 converted_data(1) = (1-((1-(y/100)).^(3.28)))*100; % convert to
%/meter
 converted_data(2) = (1-((1-(converted_data(2)/100)).^3.28))*100; %
convert %/ft to %/meter

% *************************** Data History - average data for baseline
/ slope calc *********************

data_history = [data_history;converted_data]; %add row to end of matrix
- Size of data_history limits the number of points that can be used for
the slope calc
data_history = delsamps(data_history,1); %remove oldest row in matrix

%*************************** MAG / slope calc
*****************************************************

for k = 1:numsensors      % each sensor (column)
   testpointsmag = data_history(:,k);
   pattern(:,k) = mean(testpointsmag);
   if slopeflag == 1
      testpointsslope = data_history(:,k);
      temp2 = polyfit(x,testpointsslope,1);
      pattern(:,k+numsensors) = temp2(1);
   end
end

%Select combination of MAG and Slopes to match training set
%pattern = pattern([1 2 3 4 5 6 7 8]);
```

```
% **************************** Call PNN and trigger alarm state
*************************************

   rowstoaverage = find(mean(data_history,2)== 0); % makes sure that
zeros are not included in the average at start of data collection

   if (isempty(rowstoaverage) == 1)

      %[atrain,mx] = mncn(train); %Mean center training set - can
remove this set and pass it in each time if speed is required
      %[apattern] = scale(pattern,mx); % Scale prediction pattern
according to training set scaling

      [atrain,mx,stdx] = auto(train); %Autoscale training set - can
remove this set and pass it in each time if speed is required
      [apattern] = scale(pattern,mx,stdx); % Scale prediction pattern
according to training set scaling
      [w,p] = pnnpred(atrain,tinfo,apattern,sigma,2); % Evaluate
pattern using PNN

   else

      w = 0;
      p = zeros(1,2);

   end

% **************************** Probability alarm
decision*********************************************************

if (p(1) > alarmprob) % If PNN probability is greater than cutoff then
set alarm_history
   alarm = 1; % alarm on
   alarm_history = [alarm_history;alarm];
else
   alarm = 0; % alarm on
   alarm_history = [alarm_history;alarm];
end

alarm_history = delsamps(alarm_history,1); %remove oldest row in matrix


% **************************** Fire criterion alarm
decision*********************************************************

alarmzeros = find(alarm_history == 0); % Find out if the alarm has been
set in any of the last n alarms (size of alarm_history define the check
window)
if (isempty(alarmzeros) == 1) % Set the alarm state on if all elements
of alarm_history have been non-zero (i.e.  Fire present)
   alarm_state = 1; %Alarm state on - signals a fire
else
   alarm_state = 0; %Alarm state off - signals no fire
end
```