DISCRIMINATING FIRE DETECTION WITH MULTIPLE SENSORS AND NEURAL NETWORKS

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Introduction

A primary objective of residential smoke detection is to increase the time available for evacuation [1]. In a recent experimental study, only 200 to 300 seconds of available egress time was provided by a smoke detector located in the room of origin with a smoldering fire. In some cases the smoke detector in an adjacent room actuated after untenable conditions had developed in the room of origin [2].

The time to detection is a function of the sensitivity of the detector. However, a highly sensitive detector may provide a high frequency of unnecessary alarms because contemporary smoke detectors cannot discriminate between fire and non-fire sources of smoke and odors. Data from U.S. fire incidents during the 1980's indicates that 95% of all alarms from smoke detectors were unnecessary [3]. One solution proposed by Thuillard for minimizing unnecessary alarms without sacrificing prompt activation involves using intelligence along with combinations of current sensor technology [4]. Grosshandler outlined advances in sensor technology along with intelligence that could be implemented to improve detection time while limiting the frequency of unnecessary alarms [5].

An interdisciplinary team from the Departments of Fire Protection Engineering and Chemical Engineering at the University of Maryland has conducted research to determine the characteristics of an advanced fire detector which is sensitive and can discriminate between airborne products from fire and non-fire sources. The fire protection engineering team concentrated on selecting the fire and non-fire sources and characterizing the signatures from each source. The chemical engineering team applied analytical methods such as neural networks and multivariate statistical methods to investigate the signature and sensor response patterns and provide the discrimination capability between the flaming fire, non-flaming fire and non-fire sources. This effort has been conducted in three phases.

Small-Scale Experimental Program

Small-scale tests are conducted to characterize the signatures from fire and non-fire sources and confirm the observations by Okayama [6,7]. Modifications to Okayama's study are incorporated to provide a greater range of measurements for describing the signature.

The small-scale experimental apparatus is a simplified tunnel with the airborne products of the sources introduced into a hood located at the inlet. Relatively elementary measurements are collected to provide a rudimentary view of the signatures. Measurements include temperature at the inlet and outlet of the apparatus. At the center of the apparatus, light obscuration, gas species concentrations (CO, CO_2 and O_2) and presence of any oxidizable gas are measured. The presence of oxidizable gases is measured by a Taguchi metal oxide sensor. Sources of the smoke or odor are placed under a hood at the inlet end of the apparatus. A variety of fuels and non-fire (nuisance) sources are selected to be representative of a residential environment. Airborne products are generated from a wide range of conditions: samples with flaming and pyrolyzing combustion, heated samples and aerosols.

An elementary expert system formulated from a manual review of the data successfully classifies 28 of 31 sources in the small-scale tests. The rules of the expert system are:

- Flaming fires are indicated by a CO_2 concentration greater than 1500 ppm.
- Pyrolyzing solids provide signatures with a peak CO concentration of at least 28 ppm and the Taguchi detector response is less than 6V.
- All other signatures are acquired from nuisance sources.

An ellipsoidal neural network provides an improved classification rate of the small-scale data. Data from two-thirds of the tests is used for training and the remainder for testing [8,9]. All sources except one smoldering source is accurately classified, where the improperly classified source is identified as a flaming source, *i.e.* is still detected as a "fire". The level of success attained from the small-scale experimental program confirms the feasibility of the concept presented by Okayama.

Large-Scale Experimental Program

Effort in the subsequent phases continued by conducting large-scale experiments and expanding the number of sources to determine whether the trends identified in the small-scale experimental effort are also applicable in full-scale. The large-scale experiments are similar to the small-scale experiments where signatures from a wide variety of fire and nuisance sources are monitored, with the sensor response patterns explored. In the second phase, either fire or non-fire sources are introduced alone. In contrast, in the third phase multiple sources including both fire and non-fire sources are provided simultaneously.

The large-scale experiments are conducted in a 3.6 x 3.6 m room with a height of 2.4 m [10-12]. The room is unconditioned, with the temperature and humidity dictated by atmospheric conditions. Measurements include temperature, mass loss of the fire source, CO, CO_2 and O_2 concentrations, light obscuration and the voltage output from two metal oxide sensors (Taguchi models 822 and 880). In addition, two commercial smoke detectors (one photoelectric and one ionization) are located on the ceiling, at the center of the room. A diagram of the room, including the relative locations of the sensors, is provided as Figure 1.

The Taguchi 822 and 880 metal oxide sensors are sensitive to the presence of a wide range of oxidizable gases and environmental odors respectively. Mass loss measurements are used to estimate the yield fractions of the signatures from the fire sources. Yields of the non-fire sources are estimated based on the quantity of material introduced. Because the tests are conducted in an unconditioned space, data is collected for at least two minutes prior to introducing any source in order to document variations in ambient conditions and be able to note the change in conditions posed by a fire or non-fire source.

Single Source Experiments

The variety of sources used in the second phase to generate conditions within the room are summarized in Table 1 [10,11]. The sources are intended to be representative of fire and nuisance sources in residential environments. The 87 tests included 34 flaming sources, 16 smoldering sources and 37 nuisance sources, with several sources repeated in numerous tests. The method of generating the airborne signatures varied for each of the source categories. A detailed description of the methods and measurements is provided by Hagen [10].

Table 1 Test Sources

Heated Fuels			Environmental Sources
Liquid	Solid	Gas	
heptane, 1-propanol, methanol, toluene, vegetable oil[1]	paper, cotton, polystyrene, pine, cardboard, cheesecloth, toast[2]	propane	propane, aerosols (disinfectant, furniture polish, cooking spray, hair spray), nail polish remover, ammonia-based window cleaner, bleach, water mist, boiling water, toast, cigarette smoke, coffee
[1] Boiling only [2] Pyrolyzing only			

Data from the sensors is reviewed for the purpose of identifying patterns associated with the categories of sources. General trends are noted from a manual review of the maximum values recorded for each sensor leading to the development of another elementary expert system similar to that developed for the data from the small-scale tests. This expert system gave insight into the patterns present in the experiments.

A multivariate statistical analysis is applied to the maximum values recorded for each sensor during each test to identify the nature of the source. The type of statistical analysis, a principal component analysis (PCA) makes use of the experimental maxima, arranged in a data matrix, **X** [11-15]. Each row of **X** consists of one set of readings for all m sensors of the x_i variables under consideration. The number of rows in **X** equals the number of experiments. PCA determines the linear combinations of the maxima that are capable of explaining most of the variations in the measurements. The linear combination are called scores, t_i, and the number of t_i's used is typically much smaller than the number of sensors. These scores are used to reconstruct the raw sensor measurements. The squared difference between the raw sensor values and the reconstructed values is called the squared prediction error (SPE). The SPE is used to detect abnormal situations [14]. Both the scores and the SPE reflect all of the sensor measurements because both the scores and the SPE involve data compression as well as synthesis.

Measurements from the following six sensors are applied to develop the PCA model: CO, CO_2, two Taguchi sensors (T880 and T822), temperature and light obscuration. The data for each sensor is scaled to zero mean and unit variance. The data collected from each sensor prior to the introduction of the source is used to establish normal, background conditions for that test. Three PCA components are selected for the analysis, based on a desire to obtain the greatest accuracy with the least number of components. and explain approximately 76% of the variability in the ambient data (collected for two minutes prior to the introduction of any source). Consequently, three components are used to classify the sources.

The SPE is used to flag abnormal situations, with its confidence limit set at 99.5%. Three successive values outside of the established limit identified conditions resulting from the introduction of a source to be abnormal. The SPE is successful in identifying all 87 tests as differing from normal conditions. The scores (t_i) are used to distinguish the type of source, using the following rules:

- if $t_3 > 5$, then the source is a flaming fire
- if $-8 < t_2 < 0$, then the source is a smoldering fire
- otherwise the source is a nuisance source.

The results of applying the above rules are summarized in Table 2. All of the flaming sources are properly classified, with smoldering sources classified properly in 88% of the tests. Commercial detectors responded to 97% of the flaming fires (one was missed) and 25% of the non-flaming fires. Nuisance and ambient sources were classified properly in 73% of the tests by the prototype detector. 27% of the nuisance source cases are misclassified as smoldering sources and hence represent false alarms.

In addition to the improved classification rate, the time for detection of the signatures from fire sources is significantly less with the measurements included and the PCA-based intelligence (the "prototype detector") than that for the commercial detectors. The time required for detection of flaming fires is reduced by an average of 45 s (representing a decrease of 57%), with the detection time for the prototype detector being 6 to 244 s less than that for the first responding commercial detector. The decrease in detection time was greater for the non-flaming fires, having an average reduction of 245 s and a range of 182 to 332 s.

Table 2 Classification of Test Sources

	Classification			Summary	
	Flaming	Smoldering	Nuisance/ Ambient	Total	% Correct
Flaming Fire	34			34	100
Smoldering Fire		14	2	16	88
Nuisance/ Ambient		10	27	37	73
Total				87	86

Discrimination between smoldering and nuisance sources is relatively good, especially considering the ambiguity that can be present relative to the two types of sources, *e.g.*, when is "burning toast" a fire hazard or merely an inconvenience (being inedible)? Despite the challenges in distinguishing between the two sources for a person with five senses, recently effort has been expended to improve the distinction for a detector through the use of rates of rise of the concentration of CO_2.

Preliminary analysis of the long-term average (on the order of 300 s) of the rate of rise of the CO_2 gas concentration is able to distinguish between smoldering and nuisance sources. Only 2 of the nuisance sources had prolonged rates of rise of CO_2 in excess of 0.10 ppm/s. In contrast, all except three of the smoldering sources had prolonged rates of rise of CO_2 in excess of 0.10 ppm/s. Examples of the CO_2 history and rate of rise for two nuisance sources and two smoldering sources are presented in Figures 2-5 and summarized in Table 3. Of these four noted tests, the commercial detectors actuated only in the test with the smoldering cotton cloth (missing the smoldering bread and properly not responding to the nuisance sources). The PCA approach properly classified both of the smoldering sources, but misclassified both of the nuisance sources as smoldering.

Table 4 Maximum Rate of Rise of CO_2 Concentration

Description of Source	Type	Maximum rate of CO_2 (ppm/s)
Cotton Cloth	Smoldering	0.15
Bread on Hotplate	Smoldering	0.08
Cigarette Smoke	Nuisance	0.03
Bread in Toaster	Nuisance	0.02

Multiple Source Experiments

The sources used in the third phase to generate signatures from combinations of sources used in the second phase are summarized in Table 4 [12]. The methods of introduction for the fire and non-fire sources is similar to that used in the second phase, with a detailed description of each method provided by Hopkins [12]. In general, the combinations are produced by recording ambient conditions for two minutes, followed by the introduction of the nuisance source for 90 s throughout the room. Except for the boiling water source which is continued along with the fire source, the nuisance source is discontinued and the fire source initiated.

Table 4 Combinations of Fire and Non-Fire Sources

	Non-fire Sources				
Fire Sources	None	Aerosol Disinfectant	Window Cleaner	Aerosol Hairspray	Boiling Water
None	-	x	x	x	x
Heptane	x	x	x	x	x
Paper	x	x	x	x	x
Cloth	x	x	x	x	x
Hamburger	x	x	x	x	x

The history of the CO/CO_2 ratio for each of the tests with heptane is presented as Figure 6. The curves for the combination sources have been shifted such that zero time is associated with ignition of the heptane, following the 90 s introduction of the nuisance source. As indicated in the figure, the difference in the ratio for the case with the flaming heptane alone and the cases with the flaming heptane and the additional sources is relatively modest. The greatest value of the ratio is obtained for the aerosol spray, which contained an assortment of hydrocarbons. The average CO/CO_2 ratio for the entire duration of the test for the other fire sources with the nuisance sources is presented in Table 5.

Table 5 Average CO/CO_2 Ratio for Fire and Nuisance Source Combinations

	Nuisance Source				
Fire Source	None	Disinfectant	Window Cleaner	Hairspray	Boiling Water
Heptane	0.01	0.02	0.01	0.02	0.01
Flaming Paper	0.11	0.09	0.08	0.14	0.06
Pyrolyzing Cotton	0.37	0.24	0.49	0.29	0.23

As indicated in Table 5, an elementary expert system can be proposed based only on the CO/CO_2 ratio to distinguish between flaming fire and non-flaming fire sources, given the limited data available. Support for this system is based on the observation that each of the fire sources appears to have a characteristic CO/CO_2 ratio, as is confirmed in the literature for a wider range of fuels and burning modes [16]. The range of the CO/CO_2 ratio for all of the combinations involving heptane and the flaming paper fires is 0.01 to 0.14, while the ratio for the pyrolyzing cotton is significantly greater at 0.23 to 0.49.

However, the CO/CO_2 ratio for the variety of combinations involving hamburger ranged from 0.20 to 0.30. Consequently, an expert system based only on the CO/CO_2 ratio will yield unnecessary alarms for the combination sources with hamburger. As a result, discrimination of the non-flaming and nuisance sources requires the use of additional sensors. The average and maximum values of the signals received from the metal oxide sensors are not easily categorized for the variety of multiple sources. After the period of introduction of the nuisance source, the two metal oxide sensors responded differently to the combined signature. The response of one sensor approached that of the heptane alone, while the other appeared to reach an average value of response for heptane alone and the nuisance source alone. These differences are attributable to the inherent characteristics of each sensor. However, the difficulty with these different sensors is that a method of discrimination suggested in the second phase using only threshold values is not appropriate. Consequently, a method of discrimination is being investigated which considers transient data (rather than just maximum values) to overcome the tendency of the maximum value algorithm to be easily tricked by the non-fire sources.

Summary

As a result of the experimental effort, an early fire detector consisting of an array of six sensors appears feasible, with discrimination provided by a neural network or multivariate statistical analysis of the sensor responses. The PCA approach for a prototype detector provides an improvement by responding more quickly and being less prone to false alarms as compared to currently available commercial detectors. The preliminary analysis of the CO_2 rates appears promising to further improving the discrimination ability. Additional research is necessary to characterize the signatures from scenarios involving additional combination sources which can mask fire signatures or cause unnecessary alarms. The merits of a more comprehensive characterization of the signatures of fire and non-fire sources through the use of additional sensors should be investigated.

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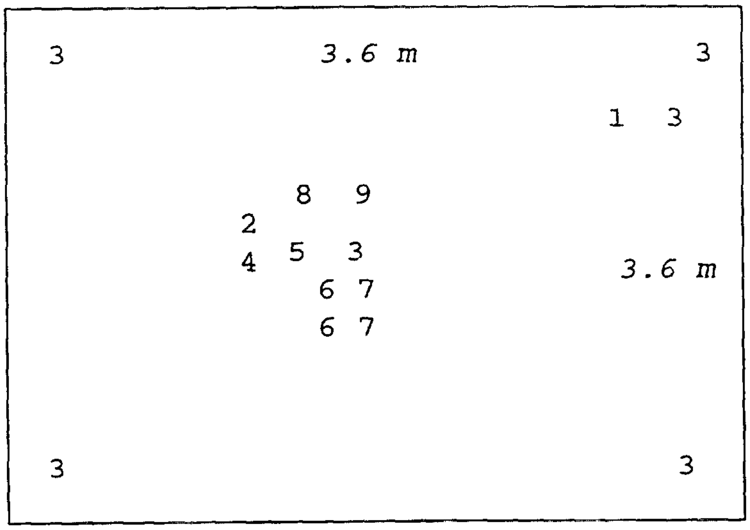
Figure 1 Diagram of Test Room



1. Load cell and fire source
2. Photocell
3. Thermocouple tree
4. Helium-neon laser
5. 4.75 mm copper sampling tube
6. Ionization smoke detector
7. Photoelectric smoke detector
8. Taguchi 822
9. Taguchi 880

Figure 2 Cloth, 100% Cotton (Smoldering)

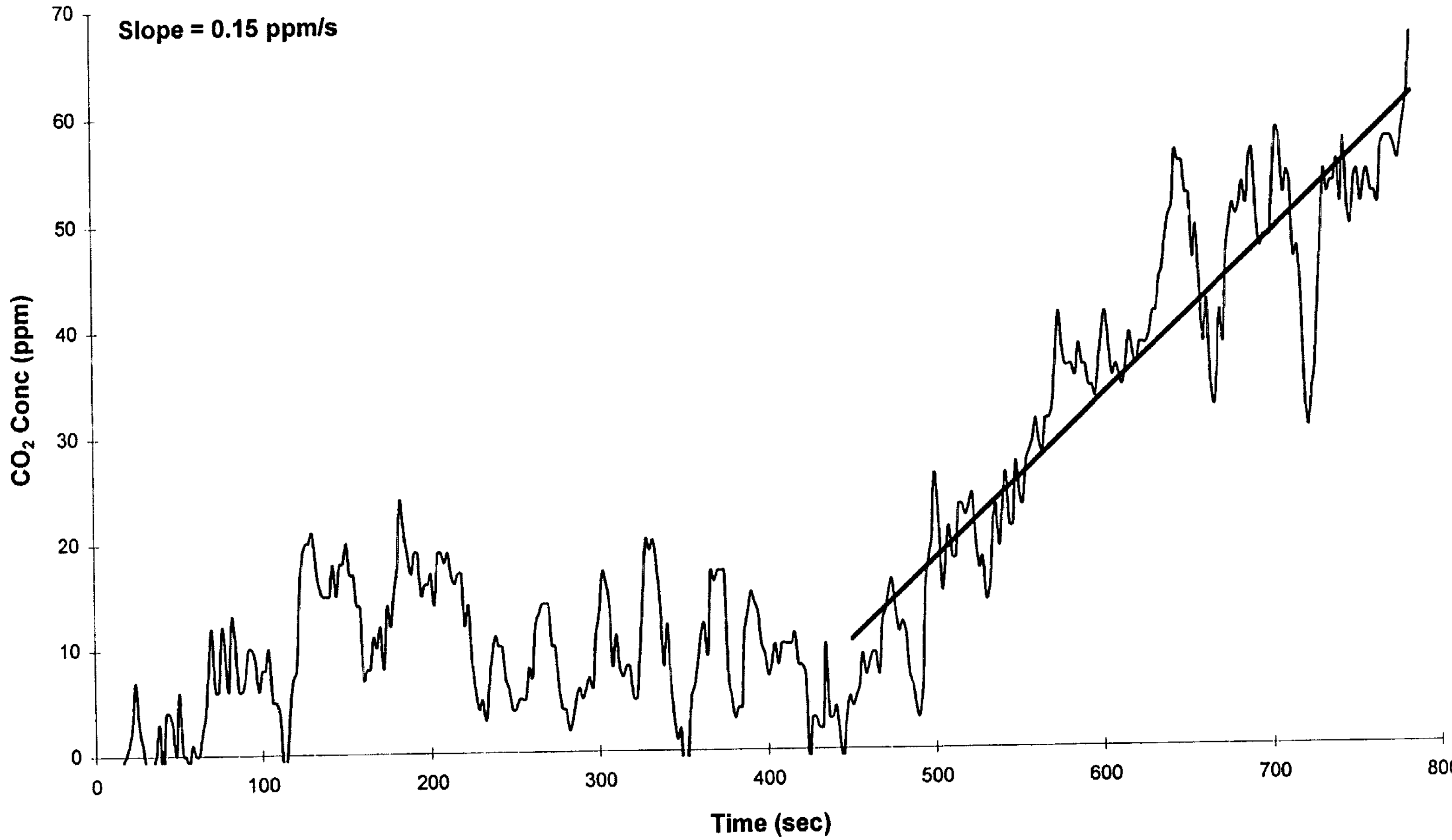


Figure 3 Bread (Smoldering)

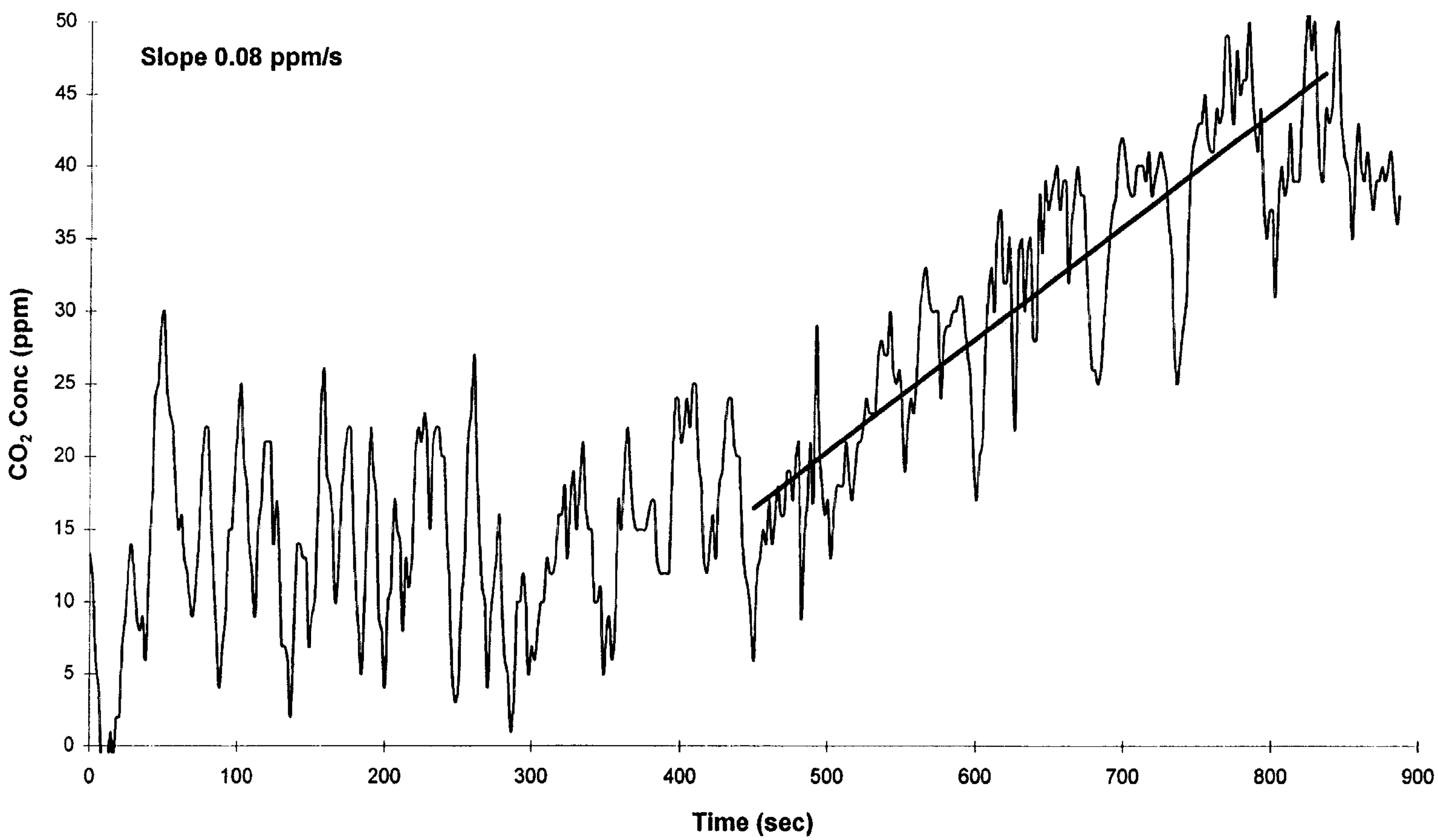


Figure 4 Bread in Toaster (Nuisance)

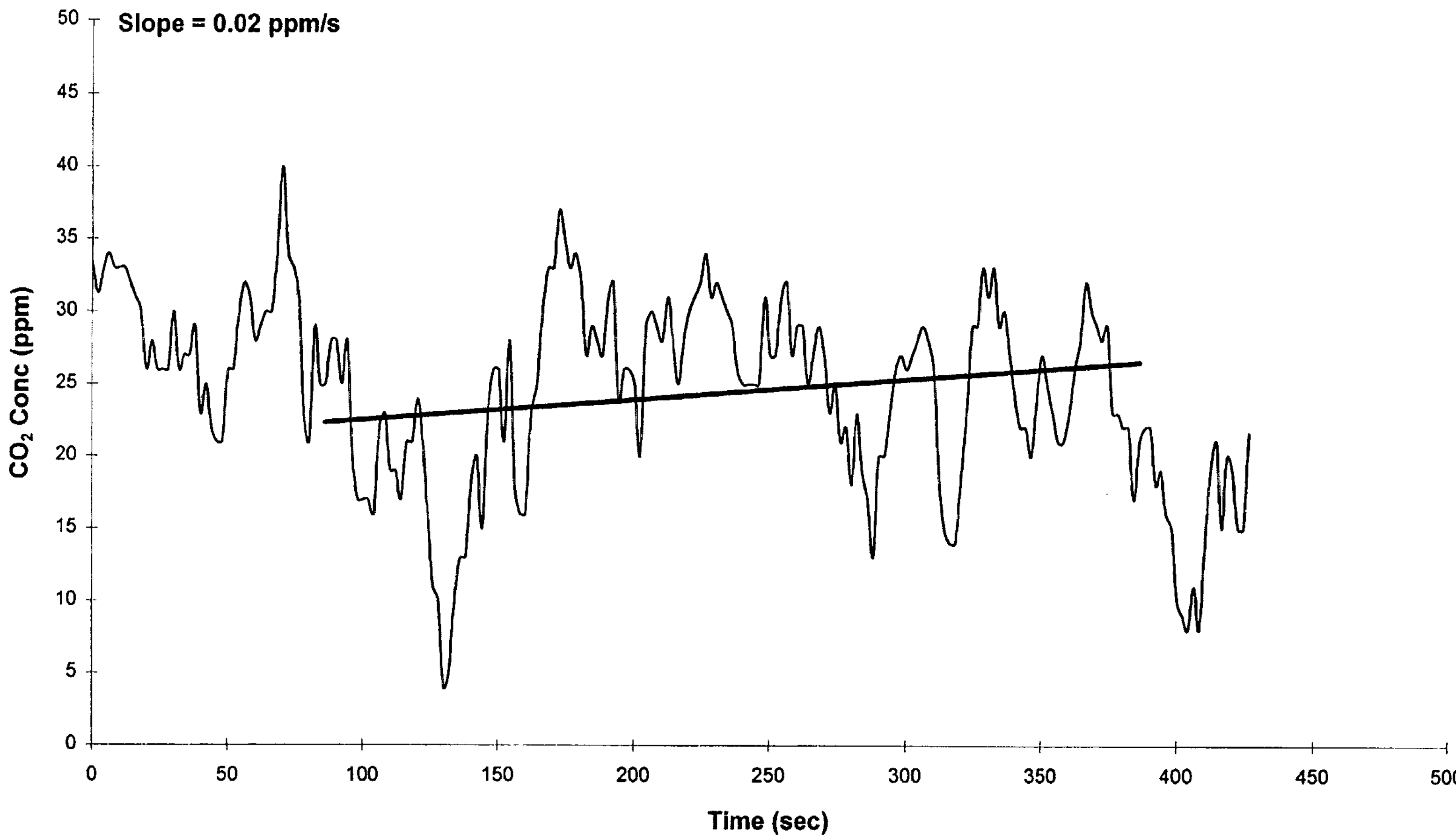


Figure 5 Cigarette Smoke (Nuisance)

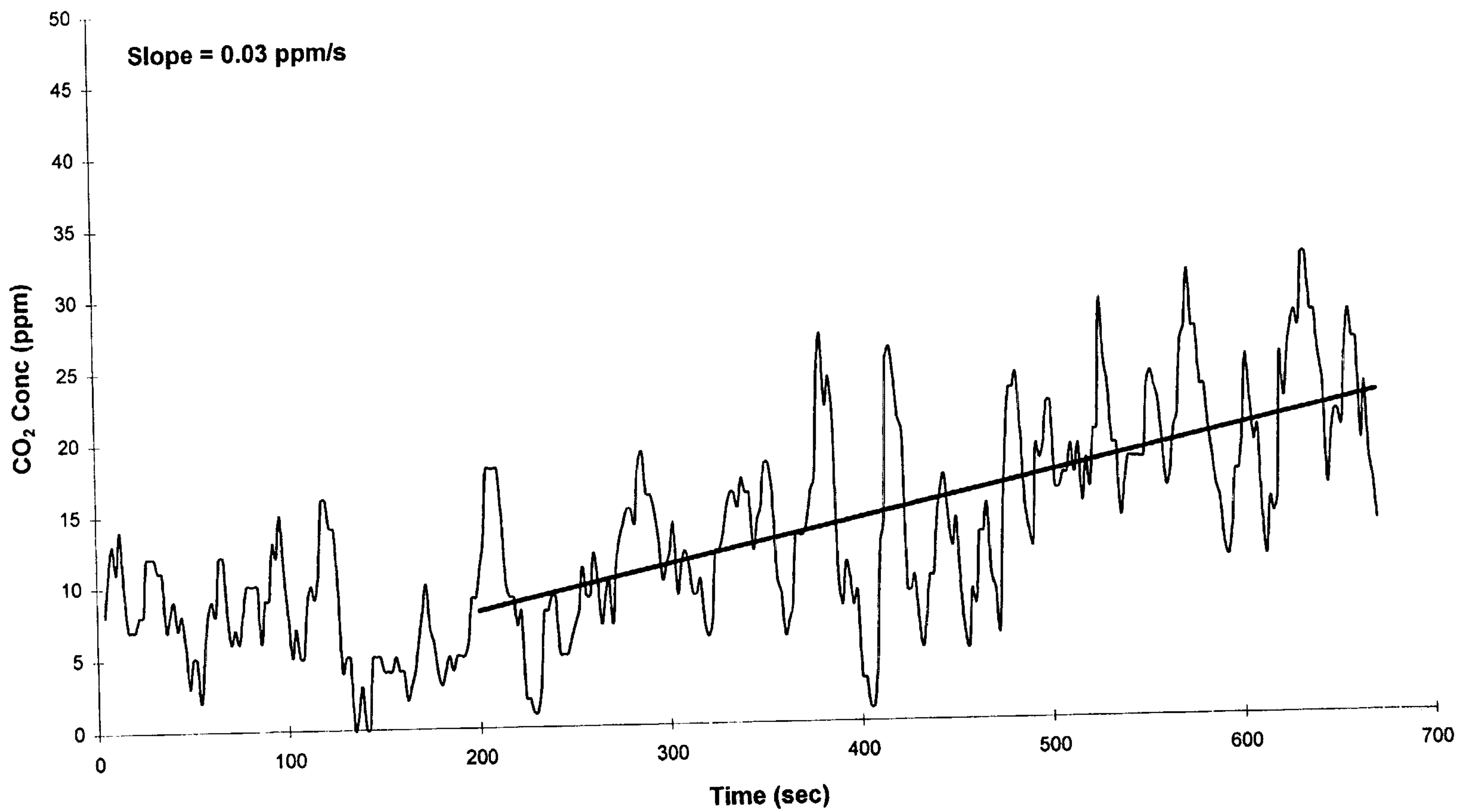


Figure 6 CO/CO_2 Ratio for Heptane with Nuisance Sources