

THESIS

BASELINE EVALUATION OF INDOOR AIR QUALITY FROM NICARAGUAN
HOUSEHOLDS USING TRADITIONAL COOK STOVES

Submitted by

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WE HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER OUR SUPERVISION BY HEATHER BAZEMORE ENTITLED BASELINE EVALUATION OF INDOOR AIR QUALITY FROM NICARAGUAN HOUSEHOLDS USING TRADITIONAL COOK STOVES BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE.

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ABSTRACT OF THESIS

BASELINE EVALUATION OF INDOOR AIR QUALITY FROM NICARAGUAN HOUSEHOLDS USING TRADITIONAL COOK STOVES

Indoor cook stoves are still used as a primary energy source across the world in many developing countries. Inefficient stoves cause incomplete combustion of biomass fuel, resulting in an unhealthy increase of indoor air pollutants, including carbon monoxide (CO) and particle matter (PM). Use of these stoves is a global problem that must be addressed to help reduce indoor air pollutant exposures and combustion emissions. Most studies assessing traditional cook stoves are limited; the extended length and thorough exposure assessment of this study make it unique, providing better data for evaluation.

This part of the study will assess the baseline exposure data from a longitudinal study of 123 Nicaraguan households collected over the summer of 2008. Fine particulate matter (PM_{2.5}) was assessed continuously via 48-hour indoor monitoring using the UCB Particle Monitor. Indoor and personal carbon monoxide levels were assessed continuously via 48-hour indoor and personal monitoring using the lightweight, portable, data-logging Drager Pac 7000. PM_{2.5} and carbon monoxide indoor sampling devices were collocated inside the kitchen at a height representative of breathing zones. The

personal carbon monoxide device was worn by the participant during the day and placed by her bedside overnight. Regression exposure models were developed using variables from the kitchen that can predict ventilation, including amount of eave space, kitchen volume, number of windows, number of doors, number of walls, and primary type of wall material. Cooking practices and activities were also considered in the models including exposure to environmental tobacco smoke, hours spent cooking per day, hours fire burns per day, and hours spent in the room with the fire burning per day. At the end of the summer baseline collection, improved cook stoves were installed in each participating household.

High concentrations of indoor air pollution were recorded in households using traditional cook stoves. For indoor carbon monoxide, mean concentrations were 146 ppm (1-hour max), 67 ppm (8-hour max), and 26 ppm (48-hour). For personal CO, mean concentrations were 32 ppm (1-hour max), 8 ppm (8-hour max), and 2 ppm (48-hour). For indoor PM_{2.5}, mean concentrations were 11,272 $\mu\text{g}/\text{m}^3$ (1-hour max), 3655 $\mu\text{g}/\text{m}^3$ (8-hour max), and 1364 $\mu\text{g}/\text{m}^3$ (48-hour). In exposure assessment models, kitchen volume and exposure to environmental tobacco smoke were found to explain the most variation in indoor carbon monoxide levels. For personal carbon monoxide, number of doors and hours spent cooking per day influenced levels most. Amount of eave space and environmental tobacco smoke explained the most variation in indoor PM_{2.5} levels. Peaks in pollutant exposure were also evaluated in assessment models. However, all model results should be interpreted with caution. R-square values were very low for

these models, meaning that the variables we collected data on did not explain much variation in pollutant concentrations. The data collected on exposure parameters did not explain much variation in indoor air quality. Further research is needed as to which housing factors and/or cooking practices affect pollutant levels most.

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CHAPTER 1: INTRODUCTION

Approximately three billion people around the world rely on burning biomass fuel for their energy needs. According to the World Health Organization (WHO), the use of cleaner fuels among the underprivileged is slowing and reliance on biomass fuels has started increasing over the past 25 years (Bruce et al. 2002). Causing an estimated 1.6 million annual deaths worldwide and representing 2.6 percent of the global burden of disease, indoor air pollution is only surpassed by water, sanitation, and hygiene (collectively) as an environmental health risk factor (Naeher et al. 2007). Biomass fuel is defined as plant or animal material that is burned for energy and includes wood, dung, crop residues, and charcoal (Fullerton et al. 2008). Biomass is typically burned in open fire pits or poorly functioning stoves in homes of developing countries, which results in high levels of indoor air pollution from the incomplete combustion process. Ninety-five percent of solid fuel used in these households consists of wood and agricultural residues; combustion emissions of these fuels have been shown to cause significant health effects (Naeher et al. 2007).

Indoor smoke from traditional burning of biomass fuels is likely the greatest source of indoor air pollution across the world (Smith et al. 2004). Indoor fuel-use conditions seen in underdeveloped countries tend to maximize exposures from emissions due to inefficient stove use in unvented areas or use of stoves without chimneys or hoods

(Naeher et al. 2007). Emissions accumulate without proper ventilation, leading to very high exposures. There have been many studies suggesting that exposure levels in the kitchens of these homes can be over 20 times the US EPA's ambient air standards (Bruce et al. 2002). Women are affected the most by these exposures since they do most of the cooking, while children are also greatly affected since they stay near their mothers during these activities. Due to these high pollutant exposures, these individuals are at an increased risk of developing serious health effects including acute respiratory infections (ARI) and chronic obstructive pulmonary disease (COPD) (Smith et al. 2000a).

Some studies have examined the effect of household factors (amount of eave space, kitchen volume, number of windows, wall/roof material, etc.) on air pollution concentrations from cook stoves (Riojas-Rodriguez et al. 2001, Bruce 2004, Begum 2008, and Clark et al. 2010); however, more information is needed to provide sufficient evidence for factors that influence exposure concentrations the most. Along with housing characteristics, behavioral factors (e.g., time spent cooking) should also be considered to determine their contribution to personal exposure (Ezzati and Kammen 2002). Similar information needs to be collected by researchers on household conditions relating to exposure such as factors relating to ventilation to create exposure models to predict indoor pollutant concentrations (Smith 2002). Once these factors are known, they can be used in conjunction with other interventions as cost-effective ways to lower exposures to indoor air pollution. Our study attempts to fill some of the aforementioned gaps in indoor air pollution literature. By collecting real-time exposure data, housing information, and behavioral data, we can compare and add knowledge to existing research by providing more insight into which factors influence pollutant exposure the most.

Our study collected exposure information for particulate matter and carbon monoxide, along with housing characteristics and cooking practices of female participants, in El Fortin, a semi-rural community outside of Granada, Nicaragua. These data were used to construct exposure models to help determine which factors influenced concentration of these pollutants in the kitchen most.

CHAPTER 2: LITERATURE REVIEW

Background

The general population usually associates indoor air pollution with industrialized, developed countries; however, the WHO Air Monitoring Information System has shown that the worst air pollution exists in the developing world. Most indoor air quality research has been conducted in buildings of developed countries while the largest exposures to well-known pollutants occur in the rural and urban households of underdeveloped nations (Bruce et al. 2002). Through the research that has been conducted in developing countries, it is well established that these households have very high levels of indoor air pollution from use of biomass fuel used for cooking and heating. Unfortunately, exposure and adverse health outcomes affect women and children disproportionately since they are the individuals who spend the most time in the kitchen (Smith et al. 2006). These adverse health effects from biomass fuel use are often worsened by poor ventilation in the home and use of stoves without chimneys or hoods which help exhaust pollutants from the room (Fullerton et al. 2008). In 2000, it was estimated that exposure to smoke from indoor use of solid fuels attributed to over 1.6 million deaths and greater than 38.5 million disability-adjusted life years (DALYs), making indoor solid fuel use responsible for almost three percent of the global burden of disease (Smith et al. 2004).

Health Effects

Acute Respiratory Infections

Current quantitative research shows that acute lower respiratory infections (ALRIs) and chronic obstructive pulmonary disease (COPD) are the major causes of disease burden and mortality from exposure to indoor air pollution (IAP) from use of solid fuels (Ezzati and Kammen 2002). Acute lower respiratory infections are the number one contributor to mortality for children under the age of five across the globe and cause an estimated two million deaths every year for this age category (Bruce et al. 2002).

Smith reports that collective evidence from 13 studies conducted in underdeveloped countries yields an odds ratio of 2-3 for acute respiratory infections. This means that children who live in households where solid fuels are used have 2-3 times greater risk of acute respiratory infections than children who are not exposed, even after adjusting for potential confounders (Smith et al. 2000a). Another study conducted in Kenya by Ezzati and Kammen found that risk of acute respiratory infections and acute lower respiratory infections increase with increasing PM₁₀ exposures (2001).

Chronic Obstructive Pulmonary Disease

A meta-analysis of eight studies conducted in underdeveloped countries provides an adjusted odds-ratio of 2-4 of chronic obstructive pulmonary disease (COPD) for women who have chronic exposure to biomass fuel emissions (Bruce et al. 2000). This combined odds-ratio paints a clear picture of the increased risk these women face of having some form of COPD. Similarly, two studies of Mexican women found that exposure to biomass smoke is associated with an increased risk of chronic obstructive

pulmonary disease that shows clinical characteristics similar to those of tobacco smokers including lower quality of life and increased mortality (Ramirez-Venegas et al. 2006, Regalado et al. 2006).

Lung Cancer

There is limited evidence associating the use of biomass fuel to lung cancer. It is well established, however, that exposure to coal stoves is a risk factor for developing lung cancer (Smith et al. 2002). That being said, there have been studies of non-smoking women exposed to biomass smoke in Mexico and India that suggest long-term exposures from cooking may facilitate the development of adenocarcinoma in the lung (Behera and Balamugesh 2005, Hernandez-Garduno et al. 2004). Much more research is needed before a possible association between wood smoke and lung cancer can be confirmed or rejected.

Cataracts

There have been several studies linking cataracts to biomass fuel exposure. A study conducted through the Indian national survey found an increased risk in blindness for women using biomass for fuel (Mishra et al. 1999a). In addition, two case-control studies in India found similar results, with a 1.6 and 2.4 adjusted odds ratio for blindness caused by cataracts from use of biomass fuel (Mohan et al. 1989 and Zodpey and Ughade 1999). For further confirmation of these epidemiological studies, there have also been animal studies reporting the development of cataracts from wood smoke condensate exposure. Wood smoke condensate was shown to cause lens damage by possible toxin

absorption and accumulation, which can lead to oxidation and cataract formation (Rao et al. 1995).

Tuberculosis

Several studies have reported an increased risk of tuberculosis associated with exposure to solid fuel use, especially for wood. Mishra and colleagues found an increased risk of tuberculosis (adjusted OR = 2.74; 95% confidence interval of 1.86-4.05) for women using solid-fuel in their Indian national survey based on self-reporting (1999b). Another study conducted in India also found an increased risk (2.5), though they did not adjust for potential confounders (Gupta et al. 1997). However, Perez-Padilla and colleagues' study in Mexico City found an increased risk of tuberculosis (adjusted OR = 2.4; 95% confidence interval of 1.04-5.6) for individuals using wood for fuel after adjusting for potential confounders and confirming cases clinically (2001). This increase in tuberculosis could be explained by a reduction in respiratory immune response from exposure to wood smoke, which has been observed in animal studies (Thomas and Zelikoff 1999).

Cardiovascular Effects

Long-term prospective cohort studies have shown a significant association between ambient fine particulate matter exposure and an increased risk of death overall and specifically from cardiovascular disease (Brook et al. 2004, Dockery et al. 1993, and Pope III et al. 1995). A recent study of Guatemalan women saw an increase in diastolic blood pressure for those exposed to biomass emissions (McCracken et al. 2007), while

similar results have been observed in ambient pollution (Brook et al. 2004). This blood pressure increase could greatly impact the cardiovascular health of those exposed to these emissions.

Birth Outcomes

Some studies have shown that exposure to biomass fuel emissions can lead to adverse birth outcomes. These studies have shown associations with low birthweight, perinatal mortality, intrauterine growth retardation, and perinatal mortality with exposure to air pollution (Dejmek et al. 1999, Mavalankar et al. 1991, Wang et al. 1997). Boy and colleagues' study reported that children of mothers who use open wood-burning fires weighed 67 grams lighter on average compared to children born to mothers who used cleaner-burning fuels (Boy et al. 2002).

Mechanisms of Disease

Particulate Matter and Wood Smoke

Several biological mechanisms have been studied on how exposure to biomass fuels can cause the aforementioned health effects. Acute exposure to particulate matter from biomass smoke can cause bronchial irritation and increased inflammation and reactivity of the airways. Exposure to aerosolized particulates also reduces mucociliary clearance and macrophage response to pathogens. These mechanisms can lead to symptoms such as wheezing and asthma irritation, as well as respiratory infections, chronic bronchitis, and chronic obstructive pulmonary disease (Bruce et al. 2002).

These mechanisms have been evaluated toxicologically through use of animal studies and biological assays. An early toxicological study exposed rabbits to relatively low levels of wood smoke and monitored effects on macrophage function following exposure. The authors found there was reduced phagocytosis and intracellular killing of the gram-negative bacteria *Pseudomonas aeruginosa*, suggesting that inhalation of wood smoke can lead to an increased susceptibility of the lung to infectious disease (Fick et al. 1984). A more recent study that performed repeated short-term exposures (1 hour/day over 4 days) of nose inhalation of wood smoke in rats found inhibited lung clearance of *Staphylococcus aureus* at particulate concentrations of 750 $\mu\text{g}/\text{m}^3$ and carbon monoxide less than 2 ppm, further confirming that exposure to wood smoke interferes with normal immune functions (Zelikoff et al. 2000).

Inhalation studies using chronic, lower level exposures are very limited. Lal and colleagues studied hematological and histological responses of rats exposed to repeated smoke from wood combustion (1993). Although there was a lack of information on wood smoke concentration and type of wood, the researchers found pathologies similar to those reported in acute wood smoke exposures. These observations included desquamation of cellular epithelium, pulmonary edema, and infiltration of polymorphonuclear neutrophils in surrounding bronchioles and vasculature. The results also suggested that pulmonary lesions induced by wood smoke progress with repeated exposures (Lal et al. 1993).

Wood Combustion and Smoke Composition

Wood is made up by weight of 50-70 percent cellulose and 30 percent lignin and also contains small amounts of inorganic salts and low molecular weight organic compounds (Simoneit et al. 1999). During the combustion process pyrolysis occurs, breaking polymers apart, producing an array of smaller particles. Since biomass combustion is inefficient, partially oxidized organic compounds are generated, most of which are associated with adverse health effects (Naehler et al. 2007). At the source of emission, wood smoke includes a mixture of solid, liquid, and gaseous substances that alter with time, sunlight, humidity, temperature, and other pollutants and surfaces (Naehler et al. 2007). Emission factors for organic chemicals found in wood smoke are also dependent on wood moisture content and burn efficiency (Khalil and Rasmussen 2003, Guillen and Ibargoitia 1999).

When wood is not efficiently burned to carbon dioxide, many combustion products are created. These products contain mostly carbon monoxide, but also nitrogen dioxide, benzene, butadiene, formaldehyde, quinones, polycyclic aromatic hydrocarbons, and free radicals along with many others that can cause adverse health effects. Combustion smoke is also a health hazard due to small, aerosolized particulates, which can contain many chemicals. Most of these compounds are irritants and known or suspected carcinogens, while others are asphyxiants or cause oxidative stress and inflammation (Smith et al. 2006, Naehler et al. 2007). Though there are many components to wood smoke, our study focuses on exposures to particulate matter and carbon monoxide.

Particulate Matter

Health impacts of combustion emissions are thought to be best determined by exposure to fine particulate matter (PM_{2.5}). Although the size of wood smoke particles are normally within the range that is thought to cause the most health damage, the chemical composition of these particulates differs from fossil fuel combustion particles, which most health effect studies have concentrated on (Naeher et al. 2007). Characteristics of particulate matter from wood-burning emissions greatly vary and are highly dependent on the character of the wood and burning conditions (such as stove efficiency) (Naeher et al. 2007).

Fresh wood smoke contains a considerable amount of ultra-fine particles (less than 100 nanometers), which rapidly condense as they cool. Particles of this size effectively avoid the body's mucociliary defenses and are deposited in the airways where they can wield toxic effects (Naeher et al. 2007). Studies have shown that wood smoke particulates are usually smaller than 1 µm, with the majority falling between 0.15 and 0.4 µm (Kleeman et al. 1999, Hays et al. 2002). Approximately 5-20 percent of the mass of wood smoke particulate is elemental carbon. Rogge and colleagues conducted a detailed analysis of aerosolized wood smoke and found almost 200 different organic compounds, mostly derived from wood polymers and resins (Rogge et al. 1998).

Aerosolized particulate matter from incomplete combustion easily comes in contact with the airways and can cause damage at many levels, depending on the size and composition of the particle (Driscoll et al. 1997). Small, fine particles with a diameter less than 2.5 microns (PM_{2.5}) are anticipated to have the greatest health impact due to their ability to penetrate into the lower airways of the lung (Boyce et al. 2006).

Carbon Monoxide

Carbon monoxide is an odorless, colorless, and tasteless gas that is produced when organic materials do not undergo complete combustion (Meredith and Vale 1988). It is classified as a chemical asphyxiant due to its binding to hemoglobin (creating carboxyhemoglobin), which prevents blood oxygenation. Without proper oxygenation, the body's tissues cannot function normally (Costa 2008). Normal levels of carboxyhemoglobin (COHb) in the blood are around 0.5% for non-smokers. Blood COHb levels are a function of carbon monoxide concentration in the air, exposure time, and breathing-rate of the individual (Costa 2008, Meredith and Vale 1988). Also, intake of carbon monoxide is "ventilation-limited" meaning that almost all carbon monoxide that is inhaled will be absorbed and readily bound to hemoglobin (Costa 2008).

Adverse health effects from carbon monoxide exposure are well established and can be divided into effects caused by acute CO exposure (poisoning) and chronic CO exposure (Zhang et al. 1999). Repeated exposure to lower concentrations of carbon monoxide (around 2-6% COHb) can result in symptoms including fatigue, headaches, trouble thinking, dizziness, nausea, impaired vision, chest pain, and heart palpitations (Kirkpatrick 1987, Costa 2008). No health effects from carbon monoxide exposure have been seen with COHb levels under 2%, but levels greater than 40% can easily result in fatal asphyxiation (Costa 2008). For perspective in relating carbon monoxide air concentrations to COHb levels, human volunteers breathed air containing 50 ppm carbon monoxide for two hours, resulting in 27% COHb (Gosselin et al. 1984). In addition, the National Institute of Occupational Safety and Health (NIOSH) reports that CO levels of

1200 ppm are immediately dangerous to life or health (IDLH) based on acute inhalation toxicology data (NIOSH 1996).

Exposure Assessment of Particulate Matter and Carbon Monoxide

From research evidence over the years, indoor exposures to fine particulate derived from combustion are thought to be greater than combined outdoor particulate exposures across the globe (Smith et al. 1993). It is estimated that 76% of pollution from particulate matter worldwide occurs indoors in developing countries (Smith et al. 1993). Indoor particulate concentrations from biomass combustion have been measured to be 10-50 times greater than urban communities in developed countries where most epidemiological studies for standards have been done (Smith et al. 2004). Carbon monoxide levels in homes using biomass fuel typically average from 2-50 ppm over 24 hours and 10-500 ppm while cooking (Boy et al. 2002). Also, many factors can affect these exposures including burning rate, cooking methods and behavior, moisture content of the fuel, ventilation, and season (Smith et al. 2004).

The majority of epidemiological studies use surrogates of exposure, such as type of fuel, housing and ventilation characteristics, and time spent cooking, to study the health impacts of indoor air pollution. However, these indirect techniques lack the detail needed to observe patterns of exposure and accurately assess the impact of implemented interventions (Ezzati and Kammen 2002); thus, use of direct measurement techniques are very important in determining factors affecting exposure.

There have been many studies that have assessed indoor pollutant concentrations of biomass fuel use. A study in Michoacan, Mexico found a mean PM_{2.5} personal

exposure of 0.29 mg/m^3 over 24-hours and a 1.269 mg/m^3 mean for the 48-hour kitchen concentration for women who used a traditional stove in an enclosed kitchen. Personal exposure to CO resulted in a 24-hour mean of 2.35 ppm for women who used the traditional stove, while the mean 48-hour concentration in the kitchen was 8.2 ppm (Cynthia et al. 2008). A study conducted in Guatemala found a 24-hour mean of 12.38 ppm for carbon monoxide levels in the kitchen, along with a 3.34 ppm 24-hour mean for personal CO exposure. In a subset of homes, Bruce and colleagues also reported a 24-hour mean $\text{PM}_{3.5}$ concentration of $1019 \text{ } \mu\text{g/m}^3$ ($\text{SD} = 547$) for those using open fires (Bruce et al. 2004). Another study in Guatemala reported that 24-hour averages of PM_{10} concentrations in homes using traditional wood fires ranged from $800\text{-}1000 \text{ } \mu\text{g/m}^3$ (Naeher et al. 2000). A study in Honduras found 8-hour $\text{PM}_{2.5}$ mean concentration of $1002.3 \text{ } \mu\text{g/m}^3$ and indoor 1-hour maximum carbon monoxide concentrations of 14.3 ppm in kitchens with traditional wood stoves (Clark et al. 2010). These studies all used gravimetric methods for particulate concentration, except for Cynthia and colleagues, who used the UCB monitors used in our study. These studies also used electrochemical sensor monitors for carbon monoxide, for the exception of Bruce and colleagues, who used diffusion tubes. These sampling techniques are described later in this chapter, along with their limitations of use.

Peaks in Exposure

There is some developing evidence that peak concentrations may be an important indicator of exposure. Ezzati and colleagues reported that cook stove emissions greatly vary throughout the day and include large peaks over a short time period (2000). They

also found that during these peak times participants were consistently close to the fire performing activities such as adding fuel, placing or removing a cooking pot, or stirring food. Constant exposure to these peaks suggests that the sole use of mean daily concentrations may not be the most effective measurement of exposure (Ezzati et al. 2000). Other studies have monitored fluctuations in stove emissions and also found that exposures can vary drastically over a short period of time (McCracken and Smith 1998, Ballard-Tremeer and Jawurek 1996). Due to the large variability of stove emissions over short time periods and peak concentrations that occur while individuals are cooking close to the fire, it is important to analyze which factors influence these peak values most (Ezzati and Kammen 2002).

Air Quality Sampling Techniques

Particulate Matter

The two main techniques used for particulate matter sampling are use of direct-reading, optical instruments and filter-based (or gravimetric) methods (Burge et al. 2003). Direct-reading instruments usually provide continuous data-logging which can save an investigator copious amounts of work entering exposure data and allows the opportunity to run more detailed statistical analysis (Todd 2003). Direct-reading instruments for detection of aerosols operate using one of four techniques: optical, electrical, resonance oscillation, and beta absorption (Todd 2003). Since the monitor used for our study used an optical device, we will only focus on that technique.

The most commonly used direct-reading monitors for aerosols are light-scattering devices (or aerosol photometers). These devices work by illumination of aerosols as they

pass through a chamber, then the light that is scattered by the particles is measured at a given angle. The higher the concentration of particles in the air, the more light reaches the detector (or photodiode). The amount of light is then read and correlated with a concentration that is displayed or stored. The scattering angle of a device can greatly influence measurements. Smaller scattering angles better detect larger particles, while an angle of 90 degrees best detects small particles (Todd 2003).

Light-scattering monitors are calibrated in the factory and the field. Calibration performed in the factory ensures accuracy when compared to similar instruments. Field calibration should be done with an aerosol of known size and refractive index similar to those that will be sampled. These readings can be compared with a gravimetric method conducted at the same time (Todd 2003).

Another commonly used sampling method for particulate matter is gravimetric analysis. This method consists of pulling a known volume of air through a filter whose initial, pre-sampling weight has been determined. The filter is then re-weighed after sampling to determine the mass of particulate matter captured (Johnson and Vincent 2003). The mass is then divided by the total volume of air sampled, yielding an average concentration over the sampling period. This is a drawback of gravimetric analysis when compared to direct-reading devices that provide information on variance in concentration throughout the sampling time. The filters used in this method can also become saturated in high-concentration environments, causing inaccurate and falsely lower average concentrations.

Carbon Monoxide

Carbon monoxide can be monitored through use of active or passive direct-reading monitors with electrochemical sensors. These monitors often log data continuously so trends can be evaluated over time (Burge et al. 2003). Monitors developed for use in the field are typically portable and lightweight, while also being easy to operate (Todd 2003). Monitors that work by passive sampling use diffusion or basic physical penetration of a membrane instead of active air movement through the air sampler's membrane. Active sampling monitors rely on air to be forced through a collection device by use of a pump (Dietrich 2003).

An electrochemical sensor contains a particulate filter, two electrodes attached to an electrochemical cell, an electrolyte, and a membrane. When the gas diffuses into the electrochemical cell, it dissolves in the electrolyte and reacts with the "sensing electrode." This action causes charged ions and electrons to move across the electrolyte to a "counting electrode." A change in electrochemical potential occurs between the two electrodes which is measured and amplified. This results in an electronic signal that is converted into a concentration reading that is displayed and/or stored (Todd 2003).

There are some drawbacks to using monitors with electrochemical sensors. Sometimes measurements from these sensors can be inaccurate due to interference by gases similar in size and reactivity. Also, the sensors can become contaminated by acidic or basic gases, which can neutralize the electrolytic solution and decrease sensitivity. The filter can also become saturated with particles, other aerosols, water vapor, and other gases which limit gas diffusion into the sensor causing an underestimation of exposure (Todd 2003).

Colorimetric detector tubes can also be used to monitor carbon monoxide.

Detector tubes are the most commonly used direct-reading devices because they are easy to use, require little training, and provide fast results (Todd 2003). A colorimetric indicator tube or detector tube is a sealed glass tube that contains an inert media such as silica gel, pumice, or ground glass. This inert material contains a reagent that changes color when it reacts with a specific chemical or group of chemicals. When air is forced through the tube using a pump, the length or intensity of color change is read to determine the concentration in the air (Todd 2003).

Detector tubes are best suited for determining if a chemical is present in the air. If a chemical is present, then a more precise and accurate sampling method can be used (such as real-time sampling), since detector tubes only yield an overall average for the sampling period. Use of detector tubes also provides no evidence of peaks or variability in the sample. If these tubes are the only possible sampling source, then multiple samples and readings should be taken to account for concentration variability. Detector tubes are also limited due to their sensitivity to humidity, temperature, atmospheric pressure, time, light, and presence of other interfering chemicals. The reagents in the tubes can also degrade over time, thus expiration dates should be checked before use (Todd 2003).

Personal exposure to carbon monoxide can also be detected through use of an exhaled CO monitor. These monitors have electrochemical cells that read levels of carbon monoxide exhaled by an exposed individual (Que Hee 2003). These exhaled CO readings correlate to levels of carboxyhemoglobin in the participant. This technique can be used as a biological monitoring system and may provide insight to symptoms experienced by the individual.

Exposure Regulations and Guidelines

Regulation of air pollutant exposure is largely concentrated on outdoor levels and indoor levels in industrial settings of well-developed countries. The United States Environmental Protection Agency (US EPA) does not have indoor air standards for fine particulate matter and carbon monoxide, but instead has set ambient air quality standards that must be attained nationally. These standards are revised every five years, reviewing the latest scientific research for updating. The current standard for ambient fine particulate matter concentrations is $35 \mu\text{g}/\text{m}^3$ for a 24-hour average and $15 \mu\text{g}/\text{m}^3$ for the annual mean. The carbon monoxide standard has an outdoor mean value of 9 ppm for 8 hours and 35 ppm for 24 hours (USEPA 2010).

The World Health Organization (WHO) released updated Air Quality Guidelines in 2005 based on scientific evidence of air pollutants and their health effects. These guidelines set a concentration for fine particulate matter at $25 \mu\text{g}/\text{m}^3$ for the 24-hour mean and $10 \mu\text{g}/\text{m}^3$ for the yearly mean (WHO 2005). The annual concentration was chosen based on the lowest range that produced effects on survival found by the American Cancer Society Study (ACS) (WHO 2005, Pope et al. 2002). The guideline set for carbon monoxide is 25 ppm for 1-hour exposures and 10 ppm over 8 hours. The time-weighted averages for CO were chosen so that individuals exposed to these levels would not exceed a COHb level of greater than 2.5%, even if engaging in light to moderate activity (WHO 2000).

Factors Affecting Exposure

Recent studies have shown that structural characteristics and cooking practices can predict indoor air pollutant concentrations, though there are still some questions as to

which factors are the best predictors of exposure. Researchers of a study conducted in Mexico reported use/non-use of an improved stove, the amount of firewood used, and the number of windows accounted for the most variation in particulate matter (PM₁₀) concentration (Riojas-Rodriguez et al. 2001). Begum and colleagues reported that open-style cooking areas can significantly lower particulate exposures from biomass emissions (2008). Investigators of a study in India found that fuel type, type of kitchen, and how close the participant was to the stove during cooking were associated with respirable particulate matter concentrations. Authors of this study also suggested that further assessment of factors including window and room dimensions, quantity of fuel used, and amount of ventilation should be done to provide a better understanding of which factors predict indoor air pollutant exposures accurately (Balakrishnan et al. 2002). A study conducted in Guatemala found that for predicting kitchen carbon monoxide levels, stove/fuel type was most influential, with some effect from the eave space size and kitchen volume. They found no association between kitchen CO concentration and window size, number of rooms, or whether someone smoked in the household (Bruce et al. 2004). Another study conducted by a colleague in Honduras found that the most important kitchen parameters that affected pollutant exposure were kitchen volume, number of doors in the kitchen, and total area of windows in the kitchen (Clark et al. 2010). Our study attempts to further the research in this area and provide more insight into which factors best predict exposure in households using traditional cook stoves.

CHAPTER 3: PURPOSE AND SCOPE

Purpose

The purpose of this study is to establish a baseline in pollutant concentrations for comparison to future years after improved cook stoves are installed and used by the participants. These concentrations will be utilized in creating exposure models that use housing characteristics and cooking practices to predict mean and peak pollutant exposures.

Specific Aims

1. Create a database containing particulate matter and carbon monoxide exposure data for each household
2. Create graphs for each house plotting area PM, area CO, and personal CO exposure over the 48-hour sampling period
3. Calculate 1-hour, 8-hour, and 48-hour average metrics for each pollutant
 - a. Descriptive statistics for each metric
 - b. Correlation between metrics
 - c. Correlation between pollutants
4. Determine peak criteria and creation of a database containing peak information for each household

5. Develop prediction models for 1-hour, 8-hour, and 48-hour metrics and peak exposures using housing characteristics

Scope

The investigative group collected baseline $PM_{2.5}$ (particulate matter with an aerodynamic diameter of less than or equal to 2.5 microns) area concentrations, along with area and personal carbon monoxide measurements of 128 women and their kitchens in the community of El Fortin, Nicaragua. The participants had to be female non-smokers, use traditional cook stoves, and be willing to purchase a subsidized improved cook stove at the end of the baseline data collection.

Hypothesis

Baseline exposure measurements of fine particulate matter ($PM_{2.5}$) and carbon monoxide (CO) were conducted in kitchens where traditional cook stoves were used for primary heating and cooking needs. A household survey was completed for each kitchen space to assess factors that may affect ventilation of indoor air pollution from cook stove emissions. A questionnaire was also administered to collect information on cooking practices and environmental tobacco smoke. We hypothesized that kitchen volume, size of eave space and number of walls would explain the largest amount of variance in the pollution concentration

CHAPTER 4: MATERIALS AND METHODS

Study Population

We collected baseline exposure and health measurements from 128 households in the small community of El Fortin, outside of Granada, Nicaragua. Data collection started in late May and continued through the end of July in 2008. Participants had to be female, primary cooks of the household, non-smokers, and willing to purchase a subsidized, improved cook stove at the end of baseline data collection. Women were recruited through a volunteer women's organization, Casa de la Mujer, in Nicaragua. We obtained approval for all study procedures from the Colorado State University Institutional Review Board (Appendix A) and the Nicaraguan Ministry of Health. For data analysis, five houses along with their participant exposures were dropped from the database due to various reasons that could bias our analysis (Appendix E).

Exposure Assessment

Data collection occurred over an approximate 48-hour period for each household. Indoor PM_{2.5} concentrations were monitored using the UCB Particle Monitor manufactured by the Berkeley Air Monitoring Group (www.berkeleyair.com). These monitors are small, modified smoke detectors that are lightweight, portable, and battery-operated for ease of use in the field. The UCB monitors log data continuously, as

opposed to other methods which only yield average concentrations, and are field validated (Chowdhury et al. 2007). These monitors work by using light-scattering technology; when aerosolized particulate matter enters into the chamber it scatters the light which is read by a photodiode. The reading is amplified and converted into volts, which is read as a concentration that is logged continuously every minute (Litton et al. 2004).

Indoor and personal carbon monoxide levels were monitored continuously using the Drager Pac 7000. The participant wore a Drager Pac 7000 for the entire 48-hour sampling period by use of a clip and lanyard, except for when bathing and at night when they were instructed to take it off and put it nearby. The Drager Pac 7000 is a small, portable, battery-operated passive sampler mostly used to monitor workers for exposure to dangerous gases. The Pac 7000 has a passive sensor where the pollutant gas causes an electrochemical reaction that is read as a concentration. This concentration is logged continuously every minute, yielding the maximum concentration reached during the minute interval (Drager Safety, Inc).

The area monitors for PM_{2.5} and CO were set-up approximately 40 inches from the combustion zone and around 57 inches from the floor (to represent the breathing zone of the participant). While monitors were being set-up, another team member would conduct the housing survey, gathering information about the kitchen and stove. A questionnaire was also given to the participant regarding health and cooking practices. The team would return after 48-hours to collect equipment and download data.

The UCB monitors were pre- and post-calibrated (one month prior to and two months after sampling) using the Dust Trak to compare readings across the monitors and

to another direct-reading instrument. The calibration was conducted in an aerosol chamber using incense to generate particulate matter. The size of incense particles are in the same size distribution range as those of smoke from solid fuel use (0.001 – 1 μm) (Hinds 1999). These calibration data were also used to ensure there was no greater than a 10% difference in instrument performance (drift) before the beginning and end of baseline data collection. The UCB particle monitor has a limit of detection of approximately $50\mu\text{g}/\text{m}^3$ and an upper range of detection that is greater than $10\text{ mg}/\text{m}^3$. The Drager Pac 7000s were also pre- and post-calibrated using 50 ppm carbon monoxide calibration gas (Drager), which was also used to make sure post-study calibration readings were within ten percent of the pre-calibration. The Pac 7000 has a limit of detection of 3 ppm and a range of detection from 0 to 1999 ppm.

Exposure/Housing Survey

An investigator conducted an exposure/housing survey for each household (Appendix B). This sheet contained information regarding the start and end of the sampling period and monitor information for that specific household. The set-up and survey portion was adapted from ITDG – Smoke, Health and Household Energy project survey (Practical Action, Warwickshire, UK) and the CEIHD/UC-Berkeley protocol. The investigator drew an illustration of the kitchen including the location of windows, doors, fire/stove(s), monitors, walls, eave spaces, and surrounding living spaces. Next, the investigator answered a series of questions based on kitchen and stove characteristics including the type of kitchen (enclosed, semi-open, or open), type of material used for walls (brick, mud, sheet metal, wood, cement, or other), type of material used for the roof

(sheet metal, concrete, ceramic tiles, wood, or other), the amount of eave space (none, <30 cm, or \geq 30 cm), permanent roof ventilation (none, yes - <10 cm in diameter, yes - \geq 10 cm in diameter), type of stove (three-stone fire, shielded mud or mud stove – no chimney, shielded mud or mud stove – with chimney, metal stove – no chimney, metal stove – with chimney, charcoal stove, gas stove, solar cooker, electric stove, or other), stove quality (scale from 1-4 – dirty to clean), condition of chimney (poor condition, fairly good condition, very good condition), and exposure to traffic (none, low, medium, or high).

Questionnaire

The questionnaire asked a series of questions to the participant regarding health and cooking practices. For the purpose of this study, only a few questions concerning cooking practices and exposure to environmental tobacco smoke were used in conjunction with pollutant measures to better estimate personal exposures. The following questions and their data were used from the questionnaire:

3.5 Do others smoke in the kitchen? (1=yes; 2=occasionally; 3=no)

3.6 Do others smoke in your home in places other than the kitchen (1=yes;

2=occasionally; 3=no)

5.10 How many hours do you typically spend cooking each day?

5.11 For how many hours during a typical day is the fire burning?

5.12 How much time do you spend in the room with the fire burning? (hours)

Data Analysis

Creation of databases and metrics

Information recorded on the exposure/housing survey was entered into an Excel spreadsheet for each household. A random sample of ten percent was re-entered to check data-entry quality.

Data from the UCB monitors ($PM_{2.5}$) were extracted using the UCB Monitor Manager software (Berkeley Air Monitoring Group). Graphs were observed before exporting data to Excel for visual inspection of any problems that occurred during sampling (such as battery dysfunction). The initial zeroing period and sampling times were entered into the software to compute the values recorded during the sampling period. The data were then exported as a .CSV file for use in Excel. Each individual household's data were checked to ensure all times during the sampling period had a value recorded. Unfortunately, many households lost some minute-to-minute data on account of loose battery connections, thus periods were entered for these missing values. Once each household had a working data file, all households were combined into one file to create a database including house identity, date/time, and their respective $PM_{2.5}$ concentrations ($n = 114$).

Area and personal carbon monoxide samples ($n = 123$, $n = 113$, respectively) (Drager Pac 7000) were imported to Excel from text files. The monitor information was double-checked with what was listed on the exposure/housing survey. Each household and personal file was cleaned, leaving only the house or participant identity number, date/time stamp, and their respective carbon monoxide reading. As with the $PM_{2.5}$, all data files were combined into one database, stacking houses and participants with their

time stamped readings on top of one another. Graphical representations were created containing all per-minute exposure data collected for each household.

The PM_{2.5}, area CO, and personal CO databases from Excel were then combined into one large exposure database using the SAS computer program (SAS 9.2, SAS Institute, Cary, NC) for analysis. Pollutant metrics of maximum 1-hour average (1-hour max), maximum 8-hour average (8-hour max), 24-hour mean, and 48-hour mean were created for PM_{2.5} (area) and carbon monoxide (area and personal) levels.

A database yielding the number of peaks per household was also created. Peaks in exposure have been identified as times when individuals are closest to the fire, thus possibly having an impact on health outcomes (Ezzati et al. 2000). Criteria for peaks were determined as values which were greater than two positive standard deviations away from the 48-hour mean for the household. The output yielded the number of peaks over the 48-hour sampling period for each household.

Statistical Analysis

Data were analyzed using the SAS computer program (SAS 9.2, SAS Institute, Cary, NC). Codes for data can be found in Appendix C. Frequency tables were created for variables to determine if there was enough variability for possible inclusion in further analysis and whether categories needed to be collapsed due to sparse cells. Descriptive statistics (mean, standard deviation, minimum, maximum, median, and interquartile range) were calculated for each measurement of exposure and quantitative predictors (hours spent cooking per day, hours fire burns per day, hours spent in room with fire burning, and kitchen volume). Descriptive tables for frequency and percent were created

for categorical variables including number of windows, number of doors, number of walls, amount of eave space, primary type of wall material, and exposure to environmental tobacco smoke. Spearman correlations were determined for all pollutant metrics, as well as comparing 48-hour means to Day 1 24-hour means and Day 1 metrics to Day 2 metrics.

Exposure Assessment Models

Univariate associations for each predictor were calculated to determine their individual contributions to pollutant exposures. Next, a best subsets method was used to determine the final multivariate model. Number of windows (collapsed to 0, 1, and 2 or more), number of doors (collapsed to 0, 1, and 2 or more), number of walls (1, 2, 3, or 4), kitchen volume (cubic feet), primary type of wall material (brick or cement, wood, or sheet metal), amount of eave space (none, < 30cm, or \geq 30 cm), hours fire typically burns per day, hours typically spent cooking per day, and exposure to environmental tobacco smoke (none or yes/occasionally – kitchen or home) were evaluated as predictors for all exposure models. Hours spent in the kitchen with the fire burning per day was also considered for personal carbon monoxide exposure models. All exposure measurements were log-transformed (base 10) in order to satisfy assumptions for linear regression.

To assess collinearity among predictors, Spearman correlation coefficients were calculated for quantitative variables and contingency tables with Fisher's exact tests were calculated for categorical variables. Hours spent cooking and hours spent in kitchen with fire burning were not allowed in the same model due to their high correlation with one another ($r=0.70$).

Databases for number of peaks per household were created. Peaks were defined as an hour mean that exceeded two standard deviations above the mean 48-hour value for that household. The calculation yielded an output of number of peaks per household (over the 48-hour sampling period). Two databases were created for peaks. One database counted each individual peak, regardless of whether it was preceded and/or followed by a peak. The second database counted peaks that were preceded and/or followed by a peak (a consecutive group) as only one peak. For example, if three consecutive hours were greater than two standard deviations above the mean, the first database would count those hours as three peaks, whereas the second database would count them as one. For the remainder of this paper, the first database will be referred to as the “individual peak database” and the second database will be called the “grouped peak database.” The numbers of peaks per household were then used as the dependent variable in models using housing characteristics and cooking practices to see which predictors most influenced air quality. The same method was used for computing and choosing models as described below for PM_{2.5} and carbon monoxide levels.

Univariate associations (R-square calculations) were conducted using all nine exposure metrics (indoor PM_{2.5}, indoor CO, personal CO – 1-hour max, 8-hour max, 48-hour mean for each pollutant) to determine how much variation in the exposure metric each variable explained by itself. The ten variables that were considered for inclusion in the models were listed previously. Next, multivariate models were assessed for each pollutant metric. Instead of using R-square values alone to select the best model, we used a combination of R-square and Mallow’s Cp for selection criteria. Selection criteria can be computed for each model and then used to compare the models to each other

(Kleinbaum et al. 1998). Since adding variables always increases the R^2 (even if only slightly) and the R^2 is always the largest for models with the maximum number of variables, it is best to use more than one criterion for selecting the best model. A reduced variable model may be a better choice because it only sacrifices a small amount of predictive power and greatly simplifies the model. Mallows' C_p is an estimate of prediction error, so that a lower C_p value corresponds to a smaller mean squared error (MSE). Using C_p as an additional criterion helps simplify the decision of how many variables to include in the best model (Kleinbaum et al. 1998). A best subsets method was used, yielding the top five 1-, 2-, 3-, 4-, and 5-variable models. Using these best subsets, first-order interactions, squared, and cubed terms were forced into the model to determine if they explained more variation. Models were selected based on the amount of variables that had an increased R-square and a lower Mallows' C_p . If these numbers were similar to each other, then the reduced model (having the fewest variables) was chosen.

CHAPTER 5: RESULTS

Results

Descriptive

The mean age for participants in our study was 34.7 years, with an average BMI (body mass index) of 28 kg/m^3 and height of 59.9 inches (Table 5.1) ($n=123$). BMI was calculated by dividing the participant's mass (kg) by their height-squared (m^2).

According to information collected from non-smoking participants, these women spent an average of four hours per day cooking and kept the fire burning for a mean of 6.6 hours per day (Table 5.2). The average kitchen volume was 692 cubic feet, with most kitchens having no windows (71.3%), one door (64.8%), four walls (68.9%), < 30 cm of eave space (68.9%), and the primary type of wall material consisted of sheet metal (46.7%) or wood (40.2%) (Table 5.2 and 5.3). A majority of the women reported no exposure to environmental tobacco smoke in their kitchen or home (65%) (Table 5.3).

As mentioned previously, the United States EPA and WHO have set standards and guidelines outlining exposure to fine particulate and carbon monoxide (USEPA 2010, WHO 2005). Though the EPA standards are for outdoor concentrations, we will still use them for comparison since these standards are based on pollutant levels and their health effects. Many of the indoor pollutant concentrations from our study greatly exceeded these guidelines, while others yielded lower values. WHO has a 24-hour mean guideline for $\text{PM}_{2.5}$ of $25 \mu\text{g/m}^3$, while the EPA's standard is $35 \mu\text{g/m}^3$ over a 24-hour period

(USEPA 2010, WHO 2005). Our study found 24-hour mean concentrations of PM_{2.5} of approximately 1350µg/m³ (Table 5.4), making them 38.5 times the EPA standard and 54 times the WHO guideline.

The EPA has an outdoor 24-hour standard of 35 ppm for carbon monoxide and an 8-hour standard of 9 ppm (USEPA 2010). WHO has indoor guidelines for carbon monoxide of 10 ppm over 8 hours and 25 ppm for 1-hour exposures (WHO 2005). Our study found an indoor mean concentration of 26 ppm for 24 hours (Table 5.4), 67 ppm for 8-hour maximum (Table 5.5), and 146 ppm for 1-hour maximum (Table 5.5). Our 24-hour concentration was below the EPA standard, but the 8-hour maximum exceeded both the EPA standards and WHO guidelines by 7 fold. In addition, the 1-hour maximum was almost 6 times the WHO guideline.

For personal exposure to carbon monoxide, levels were much lower across the board. This is most likely due to the fact that participants did not stay in the kitchen for the entire 48-hour sampling period where the indoor monitors remained for data collection. Our 8-hour and 24-hour exposures were substantially lower than the EPA standards and WHO guidelines (USEPA 2010, WHO 2005). The 1-hour maximum exceeded the WHO guideline of 25 ppm, yielding a value of 32 ppm (Table 5.5); however, this value is still a great deal lower than the indoor area carbon monoxide concentrations we found.

The mean number of individual peaks per household were 2.77 (indoor carbon monoxide), 2.39 (personal carbon monoxide), and 2.37 (indoor PM_{2.5}), with standard deviations of 1.07, 0.96, and 1.25, respectively (Table 5.6). The number of peaks ranged from 0-6 for indoor carbon monoxide and 0-5 for personal carbon monoxide and PM_{2.5}

(Table 5.6). The median was 3.0 individual peaks per household for indoor carbon monoxide and 2.0 individual peaks per household for personal carbon monoxide and PM_{2.5} over the 48-hour sampling period (Table 5.6). The mean number of grouped peaks per household were 2.07 (indoor carbon monoxide), 2.03 (personal carbon monoxide), and 1.98 (indoor PM_{2.5}) with standard deviations of 0.96, 0.85, and 1.06, respectively (Table 5.7). The number of peaks ranged from 0-5 and had a median value of 2.0 for all pollutants (Table 5.7). Based on the preceding information, neither individual peaks per household nor grouped peaks per household showed much variation.

Correlations

All metrics (1-hour maximum, 8-hour maximum, 48-hour mean) within each pollutant were highly correlated with each other (all correlations were at least 0.88), meaning that if the 1-hour concentrations for a pollutant were high, then the 8-hour and 48-hour mean was also likely to be high, and vice versa (Table 5.8). Indoor carbon monoxide and particulate matter were most highly correlated across the air quality measures, with Spearman correlation coefficients of 0.75, 0.72, and 0.60 for 48-hour, 8-hour, and 1-hour readings, respectively (Table 5.8). Personal carbon monoxide had a slightly higher correlation with indoor particulate matter than with indoor carbon monoxide across all metrics, though these were not as strongly correlated as the area samples (Table 5.9). The correlations between area and personal pollutants can be observed in the following graph of exposure data collected for House 67 (Figure 5.1). Exposure graphs for each household can be found in Appendix D.

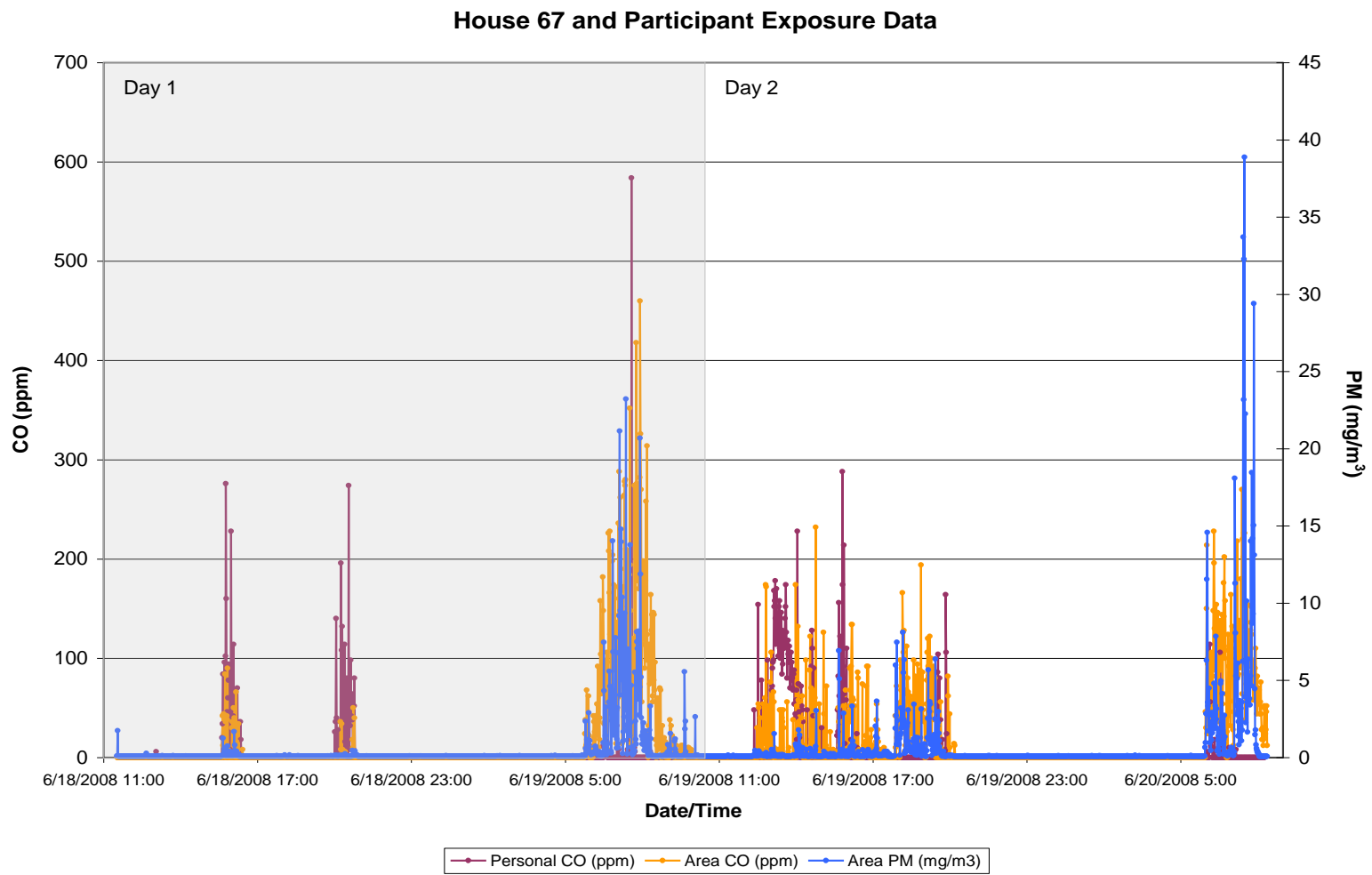


Figure 5.1. Exposure data for House 67 in graphical form.

Spearman correlation coefficients show that pollutant concentrations for 48-hour averages and 24-hour averages were highly correlated with one another (all coefficients were at least 0.89) (Table 5.10). Also, the Day 1 and Day 2 24-hour means, as well as the 8-hour maximum for indoor pollutant measures were highly correlated ($r = 0.71, 0.78$ for $PM_{2.5}$ and $r = 0.86, 0.86$ for CO, respectively) (Table 5.11). In addition, the 24-hour means for Day 1 and Day 2 for each pollutant were almost identical (Table 5.4). Personal carbon monoxide metrics were not as highly correlated with one another between Day 1 and Day 2 (Table 5.11). This is probably due to a greater amount of variation in day-to-day activities and constant movement from one microenvironment to another.

Exposure Prediction Models

Univariate Analyses

Since the 48-hour and 24-hour means were so highly correlated (Table 5.10), only the 48-hour means were used (along with 1-hour and 8-hour maximum) for this analysis. Univariate calculations provided very small R-square values meaning individual variables did not explain much variation in pollutant concentrations. For indoor carbon monoxide, kitchen volume (log-transformed) explained the most variation in the 1-hour max with an R-square of 0.0838, while environmental tobacco smoke exposure explained the most variation in 8-hour max and 48-hour mean with R-squares of 0.0588 and 0.0622, respectively (Table 5.12).

For personal carbon monoxide, primary type of wall material explained the most variation in each metric with R-square values of 0.0562, 0.0517, and 0.0561 for 1-hour max, 8-hour max, and 48-hour means, respectively (Table 5.13). It should be mentioned

that primary type of wall material includes three categories (it was divided into dummy variables), thus the R-square values may be higher due to the inclusion of one extra variable, especially with our low overall R-square values. Number of doors had similar R-squared values for personal carbon monoxide for 8-hour max (0.0447) and 48-hour mean (0.0531) levels (Table 5.13).

For particulate matter, kitchen volume ($R^2 = 0.0356$) and environmental tobacco smoke exposure ($R^2 = 0.0325$) explained the most variation in 1-hour maximum concentrations, while exposure to environmental tobacco smoke ($R^2 = 0.0432$) explained the most variation in 8-hour max levels (Table 5.14). Exposure to environmental tobacco smoke ($R^2 = 0.0294$) and amount of eave space ($R^2 = 0.0239$) explained the most variation in 48-hour mean $PM_{2.5}$ levels (Table 5.14).

Univariate assessments were also calculated for peak data. For individual number of peaks over 48-hours for indoor carbon monoxide, primary type of wall material explained the most variation ($R^2 = 0.0817$), while number of doors was second-best with an R-square of 0.0308 (Table 5.15). For individual number of peaks for personal carbon monoxide, hours spent cooking per day explained the most variation ($R^2 = 0.0342$), while hours spent in the room with the fire burning explained a similar amount of variation ($R^2 = 0.0300$) (Table 5.15). For $PM_{2.5}$, hours spent cooking per day explained the most variation in individual peaks over 48-hours with an R-square of 0.0427 (Table 5.15).

For number of grouped peaks over 48-hours, amount of eave space explained the most variation for indoor carbon monoxide having an R-square of 0.0629 (Table 5.16). For number of grouped peaks for personal carbon monoxide, hours spent cooking per day explained the most variation with an R-square of 0.0372 (Table 5.16). For indoor $PM_{2.5}$,

amount of eave space ($R^2 = 0.0349$) and hours spent cooking per day ($R^2 = 0.0318$) explained the most variation in grouped number of peaks over 48-hours (Table 5.16).

Multivariate Analyses

Multivariate assessments also yielded low R-square values. For 1-hour max indoor carbon monoxide levels, kitchen volume (log-transformed) and environmental tobacco smoke exposure explained 12.45% of the variation and had the lowest Cp value of -3.43 (Table 5.17). The addition of hours fire burns per day, number of doors, and number of walls only increased the R-square by 0.0108 with a Cp value of 1.2961, thus not explaining much more variation than the simpler, two-variable model (Table 5.17). Also, including interaction terms only increased the R-square by 0.0160 (Table 5.18), also not explaining much more variation, so the reduced model (kitchen volume and environmental tobacco smoke) was chosen. For 8-hour max indoor carbon monoxide levels, environmental tobacco smoke exposure and kitchen volume (log-transformed) explained 8.44% of the variation yielding the lowest Cp value of -1.6429 (Table 5.19). The addition of number of doors, number of walls, and hours spent cooking per day only increased the R-square by 0.0208, not explaining much more variation (Table 5.19). Similarly, the addition of interaction terms only increased the R-square by 0.0355 (Table 5.20), thus the most parsimonious model chosen was the one including only environmental tobacco smoke and kitchen volume. For 48-hour mean indoor carbon monoxide levels, environmental tobacco smoke exposure and kitchen volume (log-transformed) explained 7.91% of the variation yielding the lowest Cp value of -1.5858 (Table 5.21). The addition of number of walls, number of doors, and hours spent cooking

per day only increased the R-square by 0.0207 (Table 5.21), while the inclusion of interaction terms only increased the R-square by 0.0351 (Table 5.22). Thus, the most parsimonious model for 48-hour mean indoor carbon monoxide levels included only environmental tobacco smoke exposure and kitchen volume.

For 1-hour max personal carbon monoxide exposure, number of doors, hours spent cooking per day, and primary type of wall material explained 8.67% of the variation and had a Cp value of -0.5939 (Table 5.23). Number of doors and hours spent cooking per day together yielded an R-square of 0.0490, while primary wall type alone had an R-square of 0.0562 (Table 5.23). By combining these variables into one model, the R-square increased by 0.0377 and 0.0305, respectively, while still maintaining a low Cp value (-0.5939) (Table 5.23). By adding number of walls and amount of eave space, the R-square only increased by 0.0091. With the inclusion of interaction terms, the R-square value only increased by 0.0206 (Table 5.24). The most parsimonious model was chosen to include number of doors, hours spent cooking per day, and primary wall type. For 8-hour max personal carbon monoxide levels, number of doors and hours spent cooking per day explained 9.17% of the variation (Table 5.25). The addition of primary type of wall material, number of walls, and amount of eave space only increased the R-square by 0.0259 (Table 5.25). When interaction terms were included, the R-square increased slightly by 0.0274 (Table 5.26), thus the reduced model including only number of doors and hours spent cooking per day was thought to best explain variation. For 48-hour personal carbon monoxide levels, number of doors and hours spent cooking per day explained 10.39% of the variation (Table 5.27). With the addition of primary type of wall material, number of walls, and amount of eave space, the R-square only increased by

0.0231 (Table 5.27). No interaction, squared, or cubed terms were found to produce a greater R-square value, thus the model including number of doors and hours spent cooking per day was chosen as most parsimonious.

For 1-hour max $PM_{2.5}$ levels, kitchen volume (log-transformed), environmental tobacco smoke exposure, and amount of eave space explained 8.86% of the variation yielding the lowest Cp value of -0.5248 (Table 5.28). With the addition of number of doors and hours fire burns per day, the R-square only increased by 0.0121 (Table 5.28). When squared and cubed kitchen volume terms were added to the model (along with environmental tobacco smoke exposure), the R-square increased to 0.1394 (Table 5.29). For 8-hour max $PM_{2.5}$ levels, environmental tobacco smoke exposure, amount of eave space, and number of doors explained 11.02% of the variation, while also having the lowest Cp value of -1.589 (Table 5.30). After including number of walls and number of windows, the R-square only increased by 0.0094 (Table 5.30). With the addition of interaction terms, the R-square increased by 0.0319 (Table 5.31). The most parsimonious model was considered to be the reduced model containing only environmental tobacco smoke exposure, amount of eave space, and number of doors. For 48-hour mean $PM_{2.5}$ levels, amount of eave space, number of doors, and environmental tobacco smoke exposure explained 8.59% of the variation and had the lowest Cp value of -1.2943 (Table 5.32). After including number of walls and hours spent cooking per day, the R-square only increased by 0.0126 (Table 5.32). With the inclusion of interaction terms, the R-square increased by 0.0332 (Table 5.33). Due to these low increases in R-square, the reduced model including amount of eave space, number of doors, and environmental tobacco smoke exposure was chosen as the most parsimonious for this metric.

For individual number of indoor carbon monoxide peaks per household (over 48-hours), primary type of wall material explained the most variation, having an R-square of 0.0817 and the lowest Cp value of -1.1188 (Table 5.34). With the addition of amount of eave space, hours fire burns per day, hours spent cooking per day, and number of windows, the R-square only increased by 0.0352 (Table 5.34). After adding interaction terms, the R-square was 0.1188, resulting in an increase of 0.0371 (Table 5.35). The reduced model containing only primary type of wall material was chosen as most parsimonious due to its low Cp value and the low increases in R-square from adding more terms. For number of individual personal carbon monoxide peaks per household, hours spent cooking per day explained 3.42% of variation, while having the lowest Cp value of -2.6551 (Table 5.36). After being included with environmental tobacco smoke (ETS) exposure in the best two-variable model (based on highest R-square), both hours spent cooking per day and ETS were dropped making the best 3-variable model contain amount of eave space, hours spent in room with fire burning, and number of windows (Table 5.36). This three-variable model had an R-square of 0.0549 (Table 5.36). The addition of a squared term (number of windows - squared) increased the R-square to 0.0934 (Table 5.37). For number of individual area PM_{2.5} peaks, hours spent cooking per day explained 4.27% of variation, having the lowest Cp value of -1.2431 (Table 5.38). With the addition of number of doors, primary type of wall material, and amount of eave space the R-square only increased by 0.0303 (Table 5.38). However, with the addition of the squared term to hours spent cooking per day, the R-square almost doubled, yielding a value of 0.0800 (Table 5.39).

For number of grouped peaks per household, amount of eave space and hours fire burns per day explained 9.81% of variation in area carbon monoxide (Table 5.40). After adding primary type of wall material and number of doors, the R-square increased by 0.0333 (Table 5.40). With the addition the squared amount of eave space variable to amount of eave space and hours fire burns per day, the R-square jumped to 0.1382 (Table 5.41). For number of grouped personal carbon monoxide peaks, hours spent cooking per day explained 3.72% of variation in number of peaks per household (Table 5.42). The addition of number of doors, number of walls, and primary type of wall material only increased the R-square by 0.0266 (Table 5.42), while including interaction terms raised the R-square by 0.0355 (Table 5.43). For number of grouped peaks in area PM2.5, amount of eave space and hours spent cooking per day explained 6.85% of variation (Table 5.44). By adding primary type of wall material and kitchen volume (log-transformed), the R-square had a slight increase of 0.0263 (Table 5.44). The addition of interaction terms only increased the R-square by 0.0312 (Table 5.45).

Table 5.1. Baseline population characteristics among non-smoking primary cooks in households using traditional stove in Nicaragua.

<i>Population characteristics</i>	<i>Mean</i>	<i>SD</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>	<i>IQR</i>
Age, years (n=123)	34.7	15.8	31	11	80	20
Body Mass Index, kg/m ² (n=123)	28.0	6.6	27.5	14	54.9	8.7
Height, inches (n=122)	59.9	2.4	59.8	52.8	65.8	3.3
Education, years (n=122)	4.2	4.2	3	0	23	6
Average meals cooked per week (n=123)	19.2	3.6	21	7	24	0

SD, standard deviation; IQR, interquartile range

Table 5.2. Descriptive statistics for quantitative variables.

<i>Variable</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>	<i>IQR</i>
Hours typically spent cooking per day	123	4.19	1.86	4	0.67	9	3
Hours fire burns during a typical day	122	6.64	3.57	6	0.50	16	5
Hours spent in room with fire burning	121	4.21	2.17	4	0.50	12	3
Volume – cubic feet (log-transformed)	121	2.72	0.31	2.72	1.86	3.54	0.38
Volume – cubic feet	121	692.14	598.17	522.16	73.26	3466.11	483.98

SD, standard deviation; IQR, interquartile range

Table 5.3. Frequency tables for categorical variables.

<i>Variable</i>	<i>Category</i>	<i>Frequency</i>	<i>Percent</i>
Number of windows (n=122)	Zero	87	71.3
	1	21	17.2
	2 or more	14	11.5
Number of doors (n=122)	Zero	23	18.9
	1	79	64.8
	2 or more	20	16.4
Number of walls (n=122)	1	17	13.9
	2	0	0
	3	21	17.2
	4	84	68.9
Amount of eave space (n=122)	None	12	9.8
	< 30 cm	84	68.9
	≥ 30 cm	26	21.3
Primary type of wall material (n=123)	Sheet metal	57	46.7
	Wood	49	40.2
	Brick or cement	16	13.1
Exposure to environmental tobacco smoke (n=122)	No	79	64.8
	Yes	43	35.2

Table 5.4. Descriptive statistics for comparison of Day 1 and Day 2 among individual pollutants.

<i>Pollutant</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>	<i>IQR</i>
Day 1 24-hour mean Indoor PM _{2.5} (µg/m ³)	114	1373	1376	947	128	8465	1079
Day 2 24-hour mean Indoor PM _{2.5} (µg/m ³)	114	1343	1441	877	90	8611	1264
Day 1 24-hour mean Indoor CO (ppm)	123	26.53	25.33	18.45	0.08	137.24	28.09
Day 2 24-hour mean Indoor CO (ppm)	123	26.43	27.69	17.75	0.11	173.87	27.72
Day 1 24-hour mean Personal CO (ppm)	113	2.46	2.66	1.51	0	13.48	2.68
Day 2 24-hour mean Personal CO (ppm)	113	2.38	3.28	1.26	0	18.86	2.04

SD, standard deviation; IQR, interquartile range; CO, carbon monoxide; PM_{2.5}, particulate matter less than 2.5 micrometers in diameter

*All t-tests among days were non-significant

Table 5.5. Air quality measures among traditional stove users during the baseline assessment of an intervention study in a rural community of Nicaragua.

<i>Pollutant</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>	<i>IQR</i>
48-hour mean Indoor PM _{2.5} (µg/m ³)	114	1364	1275	923	154	6901	1212
1-hour max Indoor PM _{2.5} (µg/m ³)	114	11272	10341	8638	641	50728	8980
8-hour max Indoor PM _{2.5} (µg/m ³)	114	3655	3597	2445	347	20232	3163
48-hour mean Indoor CO (ppm)	123	26.44	24.57	17.81	0.40	123.82	24.25
1-hour max Indoor CO (ppm)	123	146.30	120.09	104.97	6.20	693.20	127.83
8-hour max Indoor CO (ppm)	123	67.26	62.80	43.40	1.28	350.25	63.34
48-hour mean Personal CO (ppm)	113	2.43	2.54	1.56	0.07	14.08	2.41
1-hour max Personal CO (ppm)	113	32.17	38.70	20.03	1.37	238.60	30.43
8-hour max Personal CO (ppm)	113	7.56	8.08	5.37	0.25	47.47	7.54

SD, standard deviation; CO, carbon monoxide; PM_{2.5}, particulate matter less than 2.5 micrometers in diameter; IQR, interquartile range

Table 5.6. Descriptive statistics for individual peak values per household.

<i>Number of peaks per household over 48-hours</i>	<i>Mean</i>	<i>SD</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>	<i>IQR</i>
Indoor carbon monoxide (n=123)	2.77	1.07	3	0	6	1
Personal carbon monoxide (n=117)	2.39	0.96	2	0	5	1
Indoor PM2.5 (n=123)	2.37	1.25	2	0	5	1

SD, standard deviation; IQR, interquartile range

Table 5.7. Descriptive statistics for grouped peak values per household.

<i>Number of peaks per household over 48-hours</i>	<i>Mean</i>	<i>SD</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>	<i>IQR</i>
Indoor carbon monoxide (n=123)	2.07	0.96	2	0	5	2
Personal carbon monoxide (n=117)	2.03	0.85	2	0	5	2
Indoor PM2.5 (n=123)	1.98	1.06	2	0	5	2

SD, standard deviation; IQR, interquartile range

Table 5.8. Spearman correlation coefficients (p-values) comparing pollutant metrics collected during the baseline assessment.

<i>Pollutant</i>	<i>48-hour mean Indoor PM_{2.5}</i>	<i>1-hour max PM_{2.5}</i>	<i>8-hour max PM_{2.5}</i>	<i>48-hour mean Indoor CO</i>	<i>1-hour max Indoor CO</i>	<i>8-hour max Indoor CO</i>	<i>48-hour mean Personal CO</i>	<i>1-hour max Personal CO</i>
48-hour mean Indoor PM _{2.5} (µg/m ³)	1.00 --							
1-hour max Indoor PM _{2.5} (µg/m ³)	0.88 (<0.0001)	1.00 --						
8-hour max Indoor PM _{2.5} (µg/m ³)	0.97 (<0.0001)	0.92 (<0.0001)	1.00 --					
48-hour mean Indoor CO (ppm)	0.75 (<0.0001)	0.58 (<0.0001)	0.70 (<0.0001)	1.00 --				
1-hour max Indoor CO (ppm)	0.63 (<0.0001)	0.60 (<0.0001)	0.63 (<0.0001)	0.88 (<0.0001)	1.00 --			
8-hour max Indoor CO (ppm)	0.73 (<0.0001)	0.59 (<0.0001)	0.72 (<0.0001)	0.96 (<0.0001)	0.91 (<0.0001)	1.00 --		
48-hour mean Personal CO (ppm)	0.44 (<0.0001)	0.33 (0.0007)	0.38 (<0.0001)	0.36 (<0.0001)	0.27 (0.0036)	0.32 (0.0006)	1.00 --	
1-hour max Personal CO (ppm)	0.32 (0.0010)	0.26 (0.0083)	0.28 (0.0041)	0.25 (0.0089)	0.21 (0.0274)	0.21 (0.0254)	0.90 (<0.0001)	1.00 --
8-hour max Personal CO (ppm)	0.40 (<0.0001)	0.32 (0.0008)	0.36 (0.0001)	0.32 (0.0007)	0.26 (0.0062)	0.30 (0.0015)	0.97 (<0.0001)	0.94 (<0.0001)

CO, carbon monoxide; PM_{2.5}, particulate matter less than 2.5 micrometers in diameter

Table 5.9. Spearman correlation coefficients (p-values) comparing pollutant metrics.

<i>Spearman Correlation Coefficients, Comparing pollutants:</i>	
48-hour mean Indoor PM _{2.5} & Indoor CO:	0.75 (<0.0001)
48-hour mean Indoor PM _{2.5} & Personal CO:	0.44 (<0.0001)
48-hour mean Indoor CO & Personal CO:	0.36 (<0.0001)
1-hour max Indoor PM _{2.5} & Indoor CO:	0.60 (<0.0001)
1-hour max Indoor PM _{2.5} & Personal CO:	0.26 (0.0083)
1-hour max Indoor CO & Personal CO:	0.21 (0.0240)
8-hour max Indoor PM _{2.5} & Indoor CO:	0.72 (<0.0001)
8-hour max Indoor PM _{2.5} & Personal CO:	0.36 (0.0001)
8-hour max Indoor CO & Personal CO:	0.30 (0.0015)

CO, carbon monoxide; PM_{2.5}, particulate matter less than 2.5 micrometers in diameter

Table 5.10. Spearman correlation coefficients (p-values) comparing 48-hour and 24-hour mean concentrations of each pollutant.

<i>Spearman Correlation Coefficients (p-value):</i>	
Indoor PM _{2.5} mean 48-hour & Day 1 24-hour	0.92 (<0.0001)
Indoor CO mean 48-hour & Day 1 24-hour	0.96 (<0.0001)
Personal CO mean 48-hour & Day 1 24-hour	0.89 (<0.0001)

CO, carbon monoxide; PM_{2.5}, particulate matter less than 2.5 micrometers in diameter

Table 5.11. Spearman correlation coefficients (p-values) comparing Day 1 and Day 2 among pollutants.

<i>Spearman Correlation Coefficients, Comparing days:</i>	
24-hour mean Indoor PM _{2.5} Day 1 & Day 2:	0.71 (<0.0001)
1-hour max Indoor PM _{2.5} Day 1 & Day 2:	0.55 (<0.0001)
8-hour max Indoor PM _{2.5} Day 1 & Day 2:	0.78 (<0.0001)
24-hour mean Indoor CO Day 1 & Day 2:	0.86 (<0.0001)
1-hour max Indoor CO Day 1 & Day 2:	0.84 (<0.0001)
8-hour max Indoor CO Day 1 & Day 2:	0.86 (<0.0001)
24-hour mean Personal CO Day 1 & Day 2:	0.59 (<0.0001)
1-hour max Personal CO Day 1 & Day 2:	0.51 (<0.0001)
8-hour max Personal CO Day 1 & Day 2:	0.70 (<0.0001)

CO, carbon monoxide; PM_{2.5}, particulate matter less than 2.5 micrometers in diameter

Table 5.12. Univariate (R-squared) values of log-transformed indoor carbon monoxide explained by kitchen characteristics and cooking practices.

<i>Predictive Variables</i>	<i>Indoor CO 1-hour max</i>	<i>Indoor CO 8-hour max</i>	<i>Indoor CO 48-hour mean</i>
Amount of eave space (none, < 30cm, or ≥ 30 cm)	0.0002	0.0012	0.0007
ETS (none or yes/occasionally – kitchen or home)	0.0524	0.0588	0.0622
Hours spent cooking per day	0.0001	0.0114	0.0085
Hours fire burns per day	0.0101	0.0007	0.0002
Kitchen volume (log-transformed), cubic feet	0.0838	0.0326	0.0257
Number of windows (0, 1, and 2 or more)	0.0028	0.0006	0.0018
Number of doors (0, 1, and 2 or more)	0.0230	0.0211	0.0174
Number of walls (1, 2, 3, or 4)	0.0007	0.0009	0.0020
Primary wall material (brick or cement, wood, or sheet metal)	0.0156	0.0162	0.0177

CO, carbon monoxide; ETS, environmental tobacco smoke

Table 5.13. Univariate (R-squared) values of log-transformed personal carbon monoxide explained by kitchen characteristics and cooking practices

<i>Predictive Variables</i>	<i>Personal CO 1-hour max</i>	<i>Personal CO 8-hour max</i>	<i>Personal CO 48-hour</i>
Amount of eave space (none, < 30cm, or ≥ 30 cm)	0.0063	0.0064	0.0054
ETS (none or yes/occasionally – kitchen or home)	0.0017	0.0021	0.0003
Hours spent cooking per day	0.0163	0.0334	0.0356
Hours fire burns per day	0.0026	0.0055	0.0061
Hours spent in room with fire	0.0125	0.0101	0.0129
Kitchen volume (log-transformed), cubic feet	0.0049	0.0072	0.0131
Number of windows (0, 1, and 2 or more)	0.0005	0.0018	0.0024
Number of doors (0, 1, and 2 or more)	0.0256	0.0447	0.0531
Number of walls (1, 2, 3, or 4)	0.0004	0.0002	0.0003
Primary wall material (brick or cement, wood, or sheet metal)	0.0562	0.0517	0.0561

CO, carbon monoxide; ETS, environmental tobacco smoke

Table 5.14. Univariate (R-squared) values of log-transformed particulate matter explained by kitchen characteristics and cooking practices

<i>Predictive Variables</i>	<i>Indoor PM_{2.5} 1-hour max</i>	<i>Indoor PM_{2.5} 8-hour max</i>	<i>Indoor PM_{2.5} 48-hour</i>
Amount of eave space (none, < 30cm, or ≥ 30 cm)	0.0232	0.0293	0.0239
ETS (none or yes/occasionally – kitchen or home)	0.0325	0.0432	0.0294
Hours spent cooking per day	0.0001	0.0090	0.0164
Hours fire burns per day	0.0070	0.0003	0.0001
Kitchen volume (log-transformed), cubic feet	0.0356	0.0088	0.0074
Number of windows (0, 1, and 2 or more)	0.0037	0.0015	0.0001
Number of doors (0, 1, and 2 or more)	0.0122	0.0236	0.0225
Number of walls (1, 2, 3, or 4)	0.0009	0.0036	0.0053
Primary wall material (brick or cement, wood, or sheet metal)	0.0045	0.0062	0.0049

PM_{2.5}, particulate matter less than 2.5 micrometers in diameter; ETS, environmental tobacco smoke

Table 5.15. Univariate (R-squared) values of individual peaks per household (over 48-hours) explained by kitchen characteristics and cooking practices

<i>Predictive Variables</i>	<i>Indoor CO</i>	<i>Personal CO</i>	<i>Indoor PM_{2.5}</i>
Amount of eave space (none, < 30cm, or ≥ 30 cm)	0.0156	0.0092	0.0069
ETS (none or yes/occasionally – kitchen or home)	0.0004	0.0195	0.0008
Hours spent cooking per day	0.0023	0.0342	0.0427
Hours fire burns per day	0.0120	0.0005	0.0062
Hours spent in room with fire	--	0.0300	--
Volume (log-transformed), cubic feet	0.0127	0.0003	0.0046
Number of windows (0, 1, and 2 or more)	0.0156	0.0136	0.0006
Number of doors (0, 1, and 2 or more)	0.0308	0.0116	0.0176
Number of walls (1, 2, 3, or 4)	0.0012	0.0022	0.0028
Primary wall material (brick or cement, wood, or sheet metal)	0.0817	0.0006	0.0104

Table 5.16. Univariate (R-squared) values of grouped peaks per household (over 48-hours) explained by kitchen characteristics and cooking practices

<i>Predictive Variables</i>	<i>Indoor CO</i>	<i>Personal CO</i>	<i>Indoor PM_{2.5}</i>
Amount of eave space (none, < 30cm, or ≥ 30 cm)	0.0629	0.0001	0.0349
ETS (none or yes/occasionally – kitchen or home)	0.0014	0.0050	0.0003
Hours spent cooking per day	0.0019	0.0372	0.0318
Hours fire burns per day	0.0383	0.0073	0.0035
Hours spent in room with fire	--	0.0252	--
Volume (log-transformed), cubic feet	0.0033	0.0004	0.0010
Number of windows (0, 1, and 2 or more)	0.0100	0.0051	0.0001
Number of doors (0, 1, and 2 or more)	0.0182	0.0242	0.0033
Number of walls (1, 2, 3, or 4)	0.0102	0.0002	0.0052
Primary wall material (brick or cement, wood, or sheet metal)	0.0351	0.0074	0.0147

Table 5.17. R-square and Mallor’s Cp (Cp) values used for selecting the model that best explains variation in 1-hour maximum area carbon monoxide (log-transformed) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0838	-0.522	Kitchen volume (log-transformed); cubic feet
2	0.1245	-3.4319	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home
3	0.1299	-2.083	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Hours fire burns per day
4	0.1321	1.4125	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Hours fire burns per day Number of doors; 0, 1, and 2 or more
5	0.1353	1.2691	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Hours fire burns per day Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4

Table 5.18. R-square values used for selecting the model with interaction terms that best explains variation in 1-hour maximum area carbon monoxide (log-transformed) levels.

Model Number	R-square	Variables in Model
1	0.1405	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Interaction: Kitchen volume and ETS
2	0.1386	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Hours fire burns per day Interaction: Environmental tobacco smoke and Hours fire burns per day
3	0.1403	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Hours fire burns per day Number of doors; 0, 1, and 2 or more Interaction: Environmental tobacco smoke and Hours fire burns per day

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.13.

Table 5.19. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in 8-hour maximum area carbon monoxide (log-transformed) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0588	-0.6935	Environmental tobacco smoke; none or yes/occasionally – kitchen or home
2	0.0840	-1.6429	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet
3	0.0908	-0.4419	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of doors; 0, 1, and 2 or more
4	0.1016	0.2894	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4
5	0.1052	1.8709	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Hours spent cooking per day

Table 5.20. R-square values used for selecting the model with interaction terms that best explains variation in 8-hour maximum area carbon monoxide (log-transformed) levels.

Model Number	R-square	Variables in Model
1	0.0944	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Interaction: Environmental tobacco smoke and kitchen volume
2	0.1076	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of doors; 0, 1, and 2 or more Interaction: Environmental tobacco smoke and number of doors
3	0.1199	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Interaction: Kitchen volume and Number of walls

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.15.

Table 5.21. R-square and Mallows' Cp (Cp) values used for selecting the model that best explains variation in 48-hour mean area carbon monoxide (log-transformed) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0622	-1.3296	Environmental tobacco smoke; none or yes/occasionally – kitchen or home
2	0.0791	-1.5858	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet
3	0.0868	-0.4852	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of walls; 1, 2, 3, or 4
4	0.0980	0.2165	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of walls; 1, 2, 3, or 4 Number of doors; 0, 1, and 2 or more
5	0.0998	2.0049	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of walls; 1, 2, 3, or 4 Number of doors; 0, 1, and 2 or more Hours spent cooking per day

Table 5.22. R-square values used for selecting the model with interaction terms that best explains variation in 48-hour mean area carbon monoxide (log-transformed) levels.

Model Number	R-square	Variables in Model
1	0.0985	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of walls; 1, 2, 3, or 4 Interaction: Kitchen volume and number of walls
2	0.1142	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Kitchen volume (log-transformed); cubic feet Number of walls; 1, 2, 3, or 4 Number of doors; 0, 1, and 2 or more Interaction: ETS and Number of doors

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.17.

Table 5.23. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in 1-hour maximum personal carbon monoxide (log-transformed) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0256	-0.2688	Number of doors; 0, 1, and 2 or more
2	0.0490	-0.6913	Number of doors; 0, 1, and 2 or more Hours spent cooking per day
	0.0562	-1.4374	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
3	0.0867	-0.5939	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
4	0.0905	1.0179	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of walls; 1, 2, 3, or 4
5	0.0958	2.4743	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of walls; 1, 2, 3, or 4 Amount of eave space; none, < 30cm, or > 30 cm

Table 5.24. R-square values used for selecting the model with interaction terms that best explains variation in 1-hour maximum personal carbon monoxide (log-transformed) levels.

Model Number	R-square	Variables in Model
1	0.1073	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Interaction: Number of doors and hours spent cooking per day

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.19.

Table 5.25. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in 8-hour maximum personal carbon monoxide (log-transformed) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0447	0.5551	Number of doors; 0, 1, and 2 or more
2	0.0917	-2.4390	Number of doors; 0, 1, and 2 or more Hours spent cooking per day
3	0.1129	-0.6890	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
4	0.1175	0.8178	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of walls; 1, 2, 3, or 4
5	0.1176	3.1734	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of walls; 1, 2, 3, or 4 Amount of eave space; none, < 30cm, or > 30 cm

Table 5.26. R-square values used for selecting the model with interaction terms that best explains variation in 8-hour maximum personal carbon monoxide (log-transformed) levels.

Model Number	R-square	Variables in Model
1	0.1191	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Interaction: Number of doors and hours spent cooking per day

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.21.

Table 5.27. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in 48-hour mean personal carbon monoxide (log-transformed) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0531	0.2800	Number of doors; 0, 1, and 2 or more
2	0.1039	-3.1583	Number of doors; 0, 1, and 2 or more Hours spent cooking per day
3	0.1201	-0.8921	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
4	0.1255	0.5333	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of walls; 1, 2, 3, or 4
5	0.127	2.3782	Number of doors; 0, 1, and 2 or more Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of walls; 1, 2, 3, or 4 Amount of eave space; none, < 30cm, or > 30 cm

Table 5.28. R-square and Mallor’s Cp (Cp) values used for selecting the model that best explains variation in log-transformed 1-hour maximum area fine particulate (PM_{2.5}) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0356	1.2029	Kitchen volume (log-transformed); cubic feet
2	0.0648	0.0467	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home
3	0.0886	-0.5248	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm
4	0.0951	0.7723	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more
5	0.1007	2.1759	Kitchen volume (log-transformed); cubic feet Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Hours fire burns per day

Table 5.29. R-square values used for selecting the model with squared, cubed, and interaction terms that best explains variation in log-transformed 1-hour maximum area fine particulate (PM_{2.5}) levels.

Model Number	R-square	Variables in Model
1	0.0838	Kitchen volume (log-transformed); cubic feet Kitchen volume - squared
2	0.1147	Kitchen volume (log-transformed); cubic feet Kitchen volume - squared Kitchen volume - cubed
3	0.1308	Kitchen volume (log-transformed); cubic feet Kitchen volume - squared Kitchen volume - cubed Environmental tobacco smoke; none or yes/occasionally – kitchen or home
4	0.1394	Kitchen volume (log-transformed); cubic feet Kitchen volume - squared Kitchen volume - cubed Environmental tobacco smoke; none or yes/occasionally – kitchen or home Interaction: Kitchen volume and Environmental tobacco smoke

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.24.

Table 5.30. R-square and Mallor’s Cp (Cp) values used for selecting the model that best explains variation in log-transformed 8-hour maximum area fine particulate (PM_{2.5}) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0432	1.7468	Environmental tobacco smoke; none or yes/occasionally – kitchen or home
2	0.0768	0.0709	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm
3	0.1102	-1.589	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more
4	0.1171	-0.343	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4
5	0.1196	1.38	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Number of windows; 0, 1, and 2 or more

Table 5.31. R-square values used for selecting the model with squared, cubed, and interaction terms that best explains variation in log-transformed 8-hour maximum area fine particulate (PM_{2.5}) levels.

Model Number	R-square	Variables in Model
1	0.1327	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Interaction: Amount of eave space and Number of doors
2	0.1421	Environmental tobacco smoke; none or yes/occasionally – kitchen or home Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Interaction: Amount of eave space and Number of walls

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.26.

Table 5.32. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in log-transformed 48-hour mean area fine particulate (PM_{2.5}) levels.

Model Number	R-square	Cp	Variables in Model
1	0.0294	0.7418	Environmental tobacco smoke; none or yes/occasionally – kitchen or home
2	0.0584	-0.3566	Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more
3	0.0859	-1.2943	Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Environmental tobacco smoke; none or yes/occasionally – kitchen or home
4	0.0958	-0.3524	Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Environmental tobacco smoke; none or yes/occasionally – kitchen or home Number of walls; 1, 2, 3, or 4
5	0.0985	1.3621	Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Environmental tobacco smoke; none or yes/occasionally – kitchen or home Number of walls; 1, 2, 3, or 4 Hours spent cooking per day

Table 5.33. R-square values used for selecting the model with squared, cubed, and interaction terms that best explains variation in log-transformed 48-hour mean area fine particulate (PM_{2.5}) levels.

Model Number	R-square	Variables in Model
1	0.1047	Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Environmental tobacco smoke; none or yes/occasionally – kitchen or home Interaction: Amount of eave space and Number of doors
2	0.1191	Amount of eave space; none, < 30cm, or > 30 cm Number of doors; 0, 1, and 2 or more Environmental tobacco smoke; none or yes/occasionally – kitchen or home Number of walls; 1, 2, 3, or 4 Interaction: Amount of eave space and Number of walls

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.28.

Table 5.34. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in number of individual peaks per household for area carbon monoxide over 48-hours.

Model Number	R-square	Cp	Variables in Model
1	0.0817	-1.1188	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
2	0.0959	-0.2787	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm
3	0.1047	0.6786	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day
4	0.1102	2.0279	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Hours spent cooking per day
5	0.1169	3.2396	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Hours spent cooking per day Number of windows; 0, 1, and 2 or more

Table 5.35. R-squared values used for selecting the model including interaction terms that best explains variation in number of individual peaks per household for area carbon monoxide over 48-hours.

Model Number	R-square	Variables in Model
1	0.1118	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Interaction: Amount of eave space and hours fire burns per day
2	0.1188	Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Hours spent cooking per day Interaction: Amount of eave space and hours fire burns per day

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.32.

Table 5.36. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in number of individual peaks per household for personal carbon monoxide over 48-hours.

Model Number	R-square	Cp	Variables in Model
1	0.0342	-2.6551	Hours spent cooking per day
2	0.0443	-1.7111	Hours spent cooking per day Environmental tobacco smoke; none or yes/occasionally – kitchen or home
3	0.0549	-0.8297	Amount of eave space; none, < 30cm, or > 30 cm Hours spent in the room with fire burning Number of windows; 0, 1, and 2 or more
4	0.0686	-0.2624	Amount of eave space; none, < 30cm, or > 30 cm Hours spent in the room with fire burning Number of windows; 0, 1, and 2 or more Number of doors; 0, 1, and 2 or more
5	0.0770	0.8553	Amount of eave space; none, < 30cm, or > 30 cm Hours spent in the room with fire burning Number of windows; 0, 1, and 2 or more Number of doors; 0, 1, and 2 or more Environmental tobacco smoke; none or yes/occasionally – kitchen or home

Table 5.37. R-square values used for selecting the model including squared, cubed, and interaction terms that best explains variation in number of individual peaks per household for personal carbon monoxide over 48-hours.

Model Number	R-square	Variables in Model
1	0.0533	Hours spent cooking Hours spent cooking - squared
2	0.0641	Hours spent cooking Hours spent cooking - squared Environmental tobacco smoke
3	0.0934	Amount of eave space; none, < 30cm, or > 30 cm Hours spent in the room with fire burning Number of windows; 0, 1, and 2 or more Number of windows – squared
4	0.1053	Amount of eave space; none, < 30cm, or > 30 cm Hours spent in the room with fire burning Number of windows; 0, 1, and 2 or more Number of windows – squared Number of doors; 0, 1, and 2 or more

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.34.

Table 5.38. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in number of individual peaks per household for area PM_{2.5} over 48-hours.

Model Number	R-square	Cp	Variables in Model
1	0.0427	-1.2431	Hours spent cooking per day
2	0.0532	-0.4409	Hours spent cooking per day Number of doors; 0, 1, and 2 or more
3	0.0584	0.9520	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Environmental tobacco smoke
4	0.0672	1.9434	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
5	0.0730	3.2877	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Amount of eave space; none, < 30cm, or > 30 cm

Table 5.39. R-square values used for selecting the model including squared, cubed, and interaction terms that best explains variation in number of individual peaks per household for area PM_{2.5} over 48-hours.

Model Number	R-square	Variables in Model
1	0.0800	Hours spent cooking per day Hours spent cooking per day - squared
2	0.0917	Hours spent cooking per day Hours spent cooking per day - squared Hours spent cooking per day - cubed
3	0.0951	Hours spent cooking per day Hours spent cooking per day - squared Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
4	0.1014	Hours spent cooking per day Hours spent cooking per day - squared Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of doors; 0, 1, and 2 or more

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.36.

Table 5.40. R-square and Mallor’s Cp (Cp) values used for selecting the model that best explains variation in number of grouped peaks per household for area carbon monoxide over 48-hours.

Model Number	R-square	Cp	Variables in Model
1	0.0629	2.6228	Amount of eave space; none, < 30cm, or > 30 cm
2	0.0981	0.3590	Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day
3	0.1107	0.8284	Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Number of windows; 0, 1, and 2 or more
4	0.1249	1.1102	Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
5	0.1314	2.3194	Amount of eave space; none, < 30cm, or > 30 cm Hours fire burns per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Number of windows; 0, 1, and 2 or more

Table 5.41. R-square values used for selecting the model including squared, cubed, and interaction terms that best explains variation in number of grouped peaks per household for area carbon monoxide over 48-hours.

Model Number	R-square	Variables in Model
1	0.0999	Amount of eave space; none, < 30cm, or > 30 cm Amount of eave space - squared
2	0.1382	Amount of eave space; none, < 30cm, or > 30 cm Amount of eave space - squared Hours fire burns per day
3	0.1458	Amount of eave space; none, < 30cm, or > 30 cm Amount of eave space - squared Hours fire burns per day Number of windows; 0, 1, and 2 or more
4	0.1669	Amount of eave space; none, < 30cm, or > 30 cm Amount of eave space - squared Hours fire burns per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.38.

Table 5.42. R-square and Mallow’s Cp (Cp) values used for selecting the model that best explains variation in number of grouped peaks per household for personal carbon monoxide over 48-hours.

Model Number	R-square	Cp	Variables in Model
1	0.0372	-4.1301	Hours spent cooking per day
2	0.0537	-3.8445	Hours spent cooking per day Number of doors; 0, 1, and 2 or more
3	0.0592	-2.4138	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4
4	0.0615	-0.6479	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Number of windows; 0, 1, and 2 or more
5	0.0638	1.1103	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)

Table 5.43. R-square values used for selecting the model including squared, cubed, and interaction terms that best explains variation in number of grouped peaks per household for personal carbon monoxide over 48-hours.

Model Number	R-square	Variables in Model
1	0.0616	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Interaction: Hours spent cooking per day and Number of doors
2	0.0635	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Number of windows; 0, 1, and 2 or more Interaction: Hours spent cooking per day and Number of doors
3	0.0727	Hours spent cooking per day Number of doors; 0, 1, and 2 or more Number of walls; 1, 2, 3, or 4 Number of windows; 0, 1, and 2 or more Interaction: Number of walls and Number of windows

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.40.

Table 5.44. R-square and Mallow's Cp (Cp) values used for selecting the model that best explains variation in number of grouped peaks per household for area PM_{2.5} over 48-hours.

Model Number	R-square	Cp	Variables in Model
1	0.0349	0.3627	Amount of eave space; none, < 30cm, or > 30 cm
2	0.0685	-1.5139	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day
3	0.0711	0.1873	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day Kitchen volume (log-transformed); cubic feet
4	0.0882	0.2162	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables)
5	0.0948	1.4477	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Kitchen volume (log-transformed); cubic feet

Table 5.45. R-square values used for selecting the model including squared, cubed, and interaction terms that best explains variation in number of grouped peaks per household for area PM_{2.5} over 48-hours.

Model Number	R-square	Variables in Model
1	0.0847	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day Interaction: Amount of eave space and Hours spent cooking per day
2	0.0947	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day Kitchen volume (log-transformed); cubic feet Interaction: Amount of eave space and Kitchen volume
3	0.0997	Amount of eave space; none, < 30cm, or > 30 cm Hours spent cooking per day Primary type of wall material (brick or cement, wood, or sheet metal – entered as dummy variables) Interaction: Amount of eave space and Hours spent cooking per day

*Cp would be based on a model set that included interaction terms, thus it cannot be compared to other models in Table 5.42.

CHAPTER 6: DISCUSSION AND CONCLUSIONS

Discussion

In this study, extremely high levels of indoor air pollution were recorded in kitchens using traditional cook stoves. These increased levels are similar to those found in other studies conducted in underdeveloped countries (Albalak et al, 2001, Bruce et al. 2004, Clark et al. 2010, Naeher et al. 2000). The lower personal exposures seen in our study also correspond with other studies (Bruce et al. 2004, Cynthia et al. 2008, Naeher et al. 2000). Due to these high concentrations that continue to be found in the developing world, interventions are the key to reducing these indoor air pollutant exposures that have such a great impact on global health.

Correlations between pollutants were also similar to other studies (Bruce et al 2004, Naeher et al. 2000). Bruce and colleagues found a Pearson correlation of 0.73 ($p < 0.001$) between 24-hour carbon monoxide and $PM_{3.5}$ and a lesser Spearman association between CO in the kitchen and personal CO of 0.54 (2004). Naeher and colleagues reported Spearman correlation coefficients of 0.50 – 0.70 for open fires between 24-hour area carbon monoxide and $PM_{2.5}$ readings (2000). Though we calculated 48-hour concentrations, our Spearman correlation for indoor carbon monoxide and $PM_{2.5}$ was 0.75 (Table 5.7). For 48-hour concentrations of indoor and personal carbon monoxide, our Spearman correlation coefficient was also smaller, yielding 0.36 (Table 5.7).

Indoor carbon monoxide and particulate matter (PM_{2.5}) were most highly correlated with each other across all metrics (Table 5.8). This corresponds well with our study since both of these monitors were right next to each other for the entire 48-hour sampling period, unlike the personal carbon monoxide monitors which traveled with the participant. That being mentioned, personal carbon monoxide metrics were not as highly correlated with area carbon monoxide or particulate matter, most likely due to the variation in activities of the participants.

Correlations between 48-hour means and Day 1 24-hour means were very high (all coefficients were at least 0.89) and Day 1 and Day 2 24-hour means were also highly correlated (Tables 5.10, 5.11). It should also be noted that 24-hour means for Day 1 and Day 2 were almost identical to one another (Table 5.4). From the above mentioned correlations and means, it could be suggested that a 24-hour sample would have been sufficient for data collection and could be useful for future studies in order to save time and resources. However, variations in temperature, wind, and other seasonal effects should be considered if only sampling for one 24-hour period, as these factors can affect pollutant concentrations as well as the monitors used to measure them.

By observing the minute-by-minute plots of household and participant pollutant levels, trends in concentrations can be seen across the households (Appendix D). Area concentrations and personal exposures tend to increase and decay at the same times throughout the day, presumably while cooking or stoking the fire. However, personal exposures did have some spikes in concentration when the area levels were lower, providing an explanation for why correlations between area and personal concentrations were reduced (compared to correlations among area samples). These outlying peaks

most likely occurred while the participant was not in their kitchen, meaning there are other sources of carbon monoxide exposure. These other sources could include socializing with smokers or being in another person's home while they are cooking with a non-efficient stove. Presence of other pollutant sources plays an important role in overall personal exposure, relaying how important it is to monitor personal exposures.

These plots of pollutant levels can also give us information about peaks in exposure (Appendix D). From these graphs, it can be seen that peaks vary in size, shape, and duration. Some households have many sharp, short duration peaks, while other houses have fewer peaks that are lower and more prolonged. This variety in peak characteristics provides insight as to how peak criteria should be selected. Instead of using a more simplistic approach to detecting peaks (as done in this study), more complex criteria integrating size, shape, duration, and area under the curve could better identify peaks. An example showing how these types of criteria are used can be seen in a paper published in conjunction with the US Environmental Protection Agency (Croghan and Williams, 2006).

For univariate analyses, kitchen volume explained the most variation in 1-hour maximum concentrations of area carbon monoxide. Since this metric only covers a 1-hour time span, kitchen volume could greatly influence the pollutant concentration by allowing more space for pollutants to disperse in larger kitchens, thus resulting in a lower exposure. For 8-hour max and 48-hour mean area carbon monoxide levels, environmental tobacco smoke exposure explained the most variation. Variables explaining particulate matter (PM_{2.5}) were identical to those of area carbon monoxide metrics. If future studies want to focus more specifically on housing factors that

influence indoor air quality, it could be suggested that households used for research be smoke-free since environmental tobacco smoke was a top predictor of pollutant levels in our study. For personal carbon monoxide levels, surprisingly primary type of wall material explained the most variation by itself for all metrics. Primary type of wall material is most likely a surrogate for another explanation of variation or may also be due to low R-square values.

Descriptive statistics were very similar for individual and grouped peaks per household. This should be noted and suggests that decisions made about how to organize this type of data may not affect analyses as much as expected. However, that being mentioned, not all variables were the same when explaining variation in number of pollutant peaks per household over 48-hours. For example, with indoor carbon monoxide, primary type of wall material explained the most variation for individual peaks, while amount of eave space explained the most variation for grouped peaks. This disparity could quite possibly be due to the low R-square values and the inability of our variables to explain much variation in the data. The R-square values were all so small that it may have been more chance as to which individual variable explained the most variation.

For multivariate assessments, kitchen volume (log-transformed) and exposure to environmental tobacco smoke best explained variation for all area carbon monoxide metrics. Volume of the kitchen could greatly influence pollutant exposures, as mentioned previously, by larger kitchens allowing for pollutants to disperse over a larger area. Environmental tobacco smoke could also influence carbon monoxide pollutant levels

since it is given off in cigarette smoke. Depending on the proximity of the smoker to the monitors, this could have a great impact on pollutant levels.

For personal carbon monoxide metrics, number of doors and hours spent cooking per day best explained variation in levels. Since number of doors did not explain much variation in area concentrations, it is likely that this variable is also a product of low R-square values in our analysis. The number of doors may also have influenced whether the participant stayed in the kitchen as long, meaning they had an easy way to step outside while cooking, possibly reducing their exposure. Hours the participant spent cooking per day directly relates to how long they are exposed to smoke produced from using cooking fuel. It is important to note that this variable better explained variation in personal exposure, but not in area pollutant levels. This makes sense since this variable is based on the activity of the participant relating to when they had potential to be exposed (by being in the kitchen while cooking).

For area $PM_{2.5}$, amount of eave space and environmental tobacco smoke exposure were found to influence all metrics, while kitchen volume helped explain 1-hour max levels, and number of doors helped explain 8-hour max and 48-hour mean levels. It should also be noted that kitchen volume squared and cubed terms helped explain more variation than the best untransformed 3-variable model. As mentioned previously, kitchen volume can greatly influence pollutant levels. Amount of eave space can also influence shorter time periods of exposure, allowing pollutants to escape outdoors when first introduced into the room; however, as seen for 8-hour max and 48-hour means, amount of eave space did not influence exposure as much probably due to the overall accumulation of pollutants in the room. Environmental tobacco smoke can also have a

great impact on $PM_{2.5}$ concentrations since this pollutant is also given off in cigarette smoke. Once again, proximity of the smoker to the monitor could alter these levels immensely. The number of doors in the kitchen was also found to influence $PM_{2.5}$ 8-hour max and 48-hour mean levels. This larger opening (compared to eave space) allows for pollutants to disperse outside over longer periods of time.

For number of individual peaks per household, primary type of wall material explained the most variation in area carbon monoxide levels. The number of grouped peaks per household for area carbon monoxide was influenced most by amount of eave space and hours the fire burns per day. This differs from the 1-hour max area CO, where kitchen volume and environmental tobacco smoke explained the most variation. These discrepancies are likely due to lack of variation in number of peaks per household, along with the low R-square values.

For number of individual and grouped peaks per household, hours spent cooking per day explained the most variation for personal carbon monoxide. This corresponds with the variables explaining the most variation in 1-hour max personal carbon monoxide levels. However, these R-square values were extremely low, even for our analyses. After three or more variables were added to the peak models for personal CO, all models contained different sets of variables that best explained variation. Once again, this is probably due to not obtaining the correct information on variables that better explain personal exposure, resulting in low R-square values.

For number of individual and grouped area $PM_{2.5}$ peaks per household, hours spent cooking helped explain variation. Amount of eave space also influenced grouped peaks for area particulate. For 1-hour max, 8-hour max, and 48-hour mean $PM_{2.5}$ levels,

ave space was included in all best three-variable models, however, hours spent cooking per day was not included in any of the best metric models. Again, lack of variation in data along with low R-square values could be causing these discrepancies.

There are many other factors that could have contributed to our low R-square values. For this baseline study, only households using traditional cook stoves were recruited, providing a smaller amount of variation in concentrations when compared to studies that included a wider variety of traditional and more efficient stoves. Also, monitor readings could have been affected by ambient conditions such as temperature, humidity, and wind which were not accounted for in data collection. Information was not collected on the type of fuel and mass burned during the sampling period, which may also have helped explained more variation in pollutant levels. It is well-known that increased moisture content, as well as an increased amount of fuel, can lead to higher indoor air pollution. Information on the distance from the stove to the monitor was recorded for this study, however, it was not included in analysis. This information could provide to be very useful since it has been reported that pollutant levels can vary spatially in kitchens where biomass-burning cook stoves are used (Ezzati et al. 2000). Location of openings in the kitchen relating to placement of the stove could also have a great impact on pollutant concentrations. If the stove is located in front of a window and there is another opening on the opposing wall, wind and air can more easily pass through the space, helping ventilate stove emissions. This information could have also helped explain more variation in indoor air pollution.

Compared to other studies conducted on indoor air quality in developing countries, some of our findings agreed with other research, while others did not. A

fellow colleague conducted similar research in Honduras and found that kitchen volume, number of doors in the kitchen, and total area of windows influenced area carbon monoxide levels, while total area of kitchen windows explained the most variation in $PM_{2.5}$ (Clark 2010). It was also reported by Riojas-Rodriguez and colleagues that number of windows affected particulate (PM_{10}) exposure (2001). We did see some effect from kitchen volume and number of doors in carbon monoxide exposure; however, we did not find the windows affected either carbon monoxide or $PM_{2.5}$ levels. It should be mentioned that in this study, only number of windows in the kitchen was recorded, not total area of kitchen windows, which may have been a better measure of ventilation. Bruce and colleagues reported some effect from eave space and kitchen volume in carbon monoxide levels (2004). We also saw an effect from kitchen volume in CO levels, but did not see an effect from eave space (yet it did have some effect on $PM_{2.5}$ in our study). Bruce and colleagues also reported no association between window size and whether someone smoked in the household (2004). We also saw no effect of windows on pollutant levels in our study; however, we did find that environmental tobacco smoke played a role in explaining variation in both area carbon monoxide and particulate ($PM_{2.5}$) levels.

Overall Summary of Exposure Model Findings

For indoor carbon monoxide, kitchen volume and exposure to environmental tobacco smoke were found to explain the most variation in concentrations. These factors differed for personal carbon monoxide exposure, having number of doors and hours spent cooking per day explain the most variation. For indoor $PM_{2.5}$, amount of eave space and

exposure to environmental tobacco smoke helped explain the most variation, though kitchen volume also contributed to 1-hour max variation and number of doors contributed to 8-hour max and 48-hour mean concentrations. For individual peaks per household, primary type of wall material helped explain variation in indoor carbon monoxide levels, while hours spent cooking per day helped predict personal carbon monoxide exposure and indoor PM_{2.5} concentrations. Number of grouped peaks per household differed, having amount of eave space and hours the fire burned per day explain variation in indoor carbon monoxide, hours spent cooking per day explain variation in personal carbon monoxide, and hours spent cooking per day and amount of eave space explain variation in indoor PM_{2.5} levels.

Limitations

Our study, like all others, has its limitations. Our greatest limitation is due to our low R-square values, providing that caution be taken when interpreting the results of our exposure models. Also relating to the low R-square values, we did have enough variation in the types of stoves used in our study, as well as little variation in our peak data which compounded this problem. Studies have shown that exposure to stove emissions can vary greatly by season due to characteristics of fuel, ventilation changes, type of meals prepared, and differences in activities (Ezzati and Kammen 2002). This information was not collected in our study and may have provided more insight into variation of pollutant concentrations.

Ezzati and Kammen report that the relationship between carbon monoxide and particulate matter exposures are extremely dependent on the cooking conditions and

combination of fuel and stove, making local calibration of equipment necessary (2002). Since our monitors were not calibrated at the study site, exposure measurements could have been affected by factors such as humidity, temperature, and atmospheric pressure. Though calibration in the field environment is difficult, it does result in the best practice for providing the most accurate measurements of pollutant concentrations.

For personal exposure measurement, factors influencing exposure may have been limited due to the reliance on recall of participants. Issues can arise such as perception of time (may differ between cultures) or whether the participant recalls time accurately. Use of ultrasound personal locators can help to accurately assess when and how long participants are in the kitchen without being overly intrusive (Allen-Piccolo et al. 2009). Use of these locators can also help assess whether individuals are in the kitchen during times of peak exposure, providing further knowledge as to how much these peaks have an effect on health outcomes.

Strengths

While several studies have measured total suspended particulate (TSP) or PM₁₀ (particulate matter less than 10 micrometers in diameter), our study assessed PM_{2.5} (particulate matter less than 2.5 micrometers in diameter) which deposits lower in the airways and better relates to health effects from exposure (Balakrishnan et al. 2002). Also, use of indirect exposure indicators overlook the complex nature of indoor smoke exposure and can lead to incorrect exposure estimates and little reflection into the quantitative relationship between pollutant exposure and health outcomes (Ezzati and Kammen 2002). By using direct measures of exposure in our study, we help to avoid

these inaccurate estimates. It has also been reported that area kitchen concentrations cannot be used to accurately estimate personal exposures. Cynthia, et al found that for PM_{2.5} and CO, personal exposures were only equivalent to 17 percent of the kitchen concentrations during the same sample (2008). By having our participants wear personal monitors, our exposures should be more accurately estimated. Also, by monitoring personal exposure, other sources of pollutants can be identified that contribute to overall exposure.

Although it has been suggested that a 24-hour sample may be sufficient, it has been reported that measuring samples in successive 24-hour periods can show significant reduction in variability (60% reduction in the coefficient of variation) after a 48-hour period (Cynthia et al. 2008). Also, direct exposure measurements provide the ability to see day-to-day changes, daily activity patterns, and seasonal variations (Ezzati and Kammen 2002). Using both of these methods enabled our study to capture a better estimate of daily pollutant concentrations, even though we did not see very much variation in 24-hour versus 48-hour data.

Conclusions and Recommendations

As mentioned previously, the low R-square values for our exposure models indicate that the variables we collected data for do not explain much variation in pollutant concentrations. It is very likely that the questions asked of participants (relating to exposure) and the housing data collected did not include other variables or details about these variables that would help explain a greater amount of variation in these pollutant levels. For future research, it may be helpful to collect more data on variables affecting

ventilation such as stove location relative to openings (windows, doors, etc), area measurements of openings (using them individually or combined), and/or quantitative ventilation assessments (if applicable) of the kitchen. Using area measures of openings versus simply the number of openings could provide more predictive power for this variable because it gives more detail into how much of the wall space is allowing for ventilation. Minute-by-minute data could be used to determine the room exchange and pollutant decay rate of each kitchen, giving a more quantitative assessment of ventilation. Information on ambient conditions could also be collected, such as wind, humidity, and temperature, since these factors can affect monitor readings and pollutant concentrations. Distance from the stove to the monitor should also be considered due to spatial variation in kitchen concentrations as discussed earlier. Time-activity logs or personal locators may also be useful for explaining variation in personal exposure by providing more information as to when and how long the participant is in the kitchen, as well as identifying other sources of pollutants. Also, inclusion of a greater variety in types of stoves in future studies could help better identify variables affecting indoor air pollution. By having a wider variety of stoves and pollutant concentrations, factors affecting exposure can be more easily identified, helping increase R-square values.

Since we found that environmental tobacco smoke had an effect on pollutant levels, it could be recommended that when recruiting participants for future studies, that non-smoking households be used. This would allow for more focus to be placed on housing characteristics and cooking practices that affect indoor air quality, thus providing better information on how these variables can be changed in order to reduce exposures.

Much more research on peaks in exposure is needed in order to better quantify criteria that best describe what a “peak in exposure” truly is. It has been shown that individuals are usually closest to the stove during these peak concentrations, thus it is important to look into how these peaks affect personal exposure (Ezzati and Kammen 2000). Since our R-square values were so low, along with the small amount of variation among household number of peaks, it is hard to determine where to begin improvement for future research. Various criteria should be examined on how to best determine peak values, whether relating to a certain increase above mean concentrations (as in this study) or possibly how these peaks correlate to specific health outcomes. As mentioned previously, peaks vary by size, shape, and duration, thus criteria may need to be more complex in order to capture these characteristics.

It is obvious from the pollutant levels seen in our study, along with many others conducted in developing countries, that research and resources should continue to go toward interventions in these areas in order to reduce indoor air pollution exposures. These exposures have a great impact on global health and affect the lives of millions of people worldwide. Much more research is needed in order to make these interventions effective, whether it involves providing improved cook stoves or changing housing characteristics to create a better quality of life for those populations who continue to use biomass as their main source of heating and cooking.

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APPENDIX A

IRB Approval



Research Integrity & Compliance Review Office
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321 General Services Building - Campus Delivery 2011
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NOTICE OF APPROVAL FOR HUMAN RESEARCH

DATE: April 21, 2009
Peel, Jennifer , Envir. & Radio. Health - Env.

TO: Swiss, Evelyn , RICRO, Nickoloff, Jac , Envir. & Radio. Health - Env., Reynolds, Stephen, Envir. & Radio. Health - Env.

FROM: CSU IRB 1, Janell Barker

PROTOCOL TITLE: Improved Cookstove Intervention to Assess Changes in Wood-smoke Exposures and Health Status among Nicaraguan Families

FUNDING SOURCE: CVMBSCC; CSU NIOSH Mountains & Plains ERC; CSU Clean Energy Supercluster & CVMBSCRC

PROTOCOL NUMBER: 09-848H

APPROVAL PERIOD: Approval Date: April 17, 2009 Expiration Date: April 16, 2010

The CSU Institutional Review Board (IRB) for the protection of human subjects has reviewed the protocol entitled: Improved Cookstove Intervention to Assess Changes in Wood-smoke Exposures and Health Status among Nicaraguan Families. The project has been approved for the procedures and subjects described in the protocol. This protocol must be reviewed for renewal on a yearly basis for as long as the research remains active. Should the protocol not be renewed before expiration, all activities must cease until the protocol has been re-reviewed.

If approval did not accompany a proposal when it was submitted to a sponsor, it is the PI's responsibility to provide the sponsor with the approval notice.

This approval is issued under Colorado State University's Federal Wide Assurance 00000647 with the Office for Human Research Protections (OHRP). If you have any questions regarding your obligations under CSU's Assurance, please do not hesitate to contact us.

Please direct any questions about the IRB's actions on this project to:

Janell Barker, Senior IRB Coordinator - (970) 491-1655 Janell.Barker@Research.Colostate.edu
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Janell Barker

Janell Barker

Includes: Approval is for the remaining 100 secondary women and 13 children. Because of the nature of this research, it will not be necessary to obtain a signed consent form. However, all subjects must be consented verbally. Verbal assent from the participants who are minors must be obtained. Consent from the parents must be obtained for the children who are under the age of 18. The requirement of documentation of a consent form is waived under § 117(c)(2).

Approval Period:	April 17, 2009 through April 16, 2010
Review Type:	Biomedical - RENEWAL
IRB Number:	00000202
Funding:	CVMBSCC; CSU NIOSH Mountains & Plains ERC; CSU Clean Energy Supercluster & CVMBSCRC

Protocol

APPENDIX B

Exposure/Housing Survey

EXPOSURE / HOUSING SURVEY

(Adapted ITDG & CEIHD/UC-Berkeley protocol)

Set-up Date: _____ **Home ID:** _____
Take-down Date: _____ **Participant IDs:** _____
Investigator Initials: _____

AIR SAMPLING:

UCB Monitor: Monitor ID#: _____

1st Calibration Session: _____ (hh:mm); _____
(mm/dd/yy)
(zeroing the monitor; time and date)

Time place in the home: _____ (hh:mm); _____
(mm/dd/yy)
(Monitoring session start time and date)

Time removed from the home: _____ (hh:mm); _____
(mm/dd/yy)
(Monitoring session end time and date)

2nd Calibration Session Start time: _____ (hh:mm); _____
(mm/dd/yy)
(zeroing the monitor; time and date)

2nd Calibration Session End time: _____ (hh:mm); _____
(mm/dd/yy)
(time and date)

File Name: _____
(Add Home ID to beginning of given file name)

Downloaded?

No	0
Yes	1

Graph OK?

No	0
Yes	1

CO Pac 7000:

Personal: Monitor ID#: _____

Start Time: _____ (hh:mm); _____ (mm/dd/yy)

End Time: _____ (hh:mm); _____ (mm/dd/yy)

File Name: _____
(Add **participant ID** to beginning of given file name)

Indoor: Monitor ID#: _____

Start Time: _____ (hh:mm); _____ (mm/dd/yy)

End Time: _____ (hh:mm); _____ (mm/dd/yy)

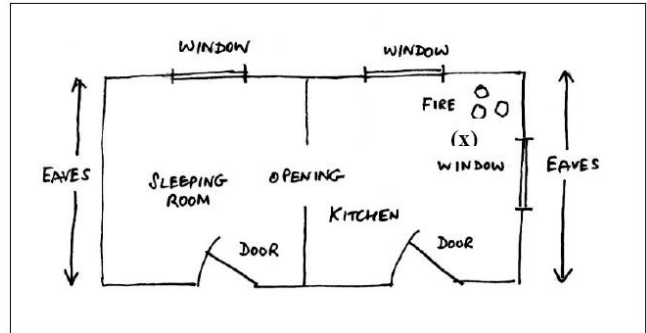
File Name: _____
(Add **home ID** to beginning of given file name)

NOTES (Describe any disturbances to the monitors):

HOUSING SURVEY:

Sketch of House – simple outline plan (see example), indicating:

- Rooms, identifying kitchen
- Position of the fire/stove
- Position of door(s) and opening(s)
- Position of window(s)
- Position of eaves spaces
- Interior walls
- Position of monitors (X)



Referring to the manual:

Please circle the correct shape code to describe the **kitchen**.

A B C D

Measure the dimensions (inches; according to the shape of the kitchen):

a.)		in
b.)		in
c.)		in
d.)		in

ADDITIONAL NOTES:

1. How many walls does the kitchen have? _____ Walls

1.1 Is the kitchen enclosed, semi-open, or open?

Enclosed	0
Semi-open	1
Open	2

2. What type of walls does the kitchen have?

Brick	1
Mud	2
Sheet metal	3
Wood	4
Cement	5
Other (specify)	6

3. Is there a secondary type of materials used for the kitchen walls? If yes, what type?

NA	0
Brick	1
Mud	2
Sheet metal	3
Wood	4
Cement	5
Other (specify)	6

4. What type of roof does the kitchen have?

NA (no roof)	0
Sheet metal	1
Concrete (solid)	2
Ceramic tiles	3
Wood	3
Other (specify)	4

5. Are there open eaves between the walls and roof of the kitchen?

No	0
Yes, < 30 cm	1
Yes, ≥ 30 cm	2

6. Is there permanent ventilation in the **roof** of the kitchen?

NA (no roof)	0
None	1
Yes, < 10 cm in diameter	2
Yes, ≥ 10 cm in diameter	3

7. By how much is the kitchen influenced by nearby traffic pollution?

None	0
Low	1
Medium	2
High	3

8. Describe the primary stove in the house?

3-stone fire	1
Shielded mud or mud stove (no chimney)	2
Shielded mud or mud stove (with chimney)	3
Metal stove (no chimney)	4
Metal stove (chimney)	5
Charcoal stove	6
Gas stove	7
Solar cooker	8
Electric stove	9
Other (specify)	10

9. Describe the overall quality of the stove. Circle the number that best represents the condition or quality of the stove in terms of pollutants released into the kitchen.

1 2 3 4
 Dirty → → Clean

- 9.1 Was the stove in use when this assessment was made?

No	0
Yes	1

10. If there is a chimney (primary stove), describe the condition of the chimney.

Poor condition	1
Fairly good condition	2
Very good condition	3

11. Is there a second stove in the house? If yes, specify.

No	0
3-stone fire	1
Shielded mud or mud stove (no chimney)	2
Shielded mud or mud stove (with chimney)	3
Metal stove (no chimney)	4
Metal stove (chimney)	5
Charcoal stove	6
Gas stove	7
Solar cooker	8
Electric stove	9
Other (specify)	10

APPENDIX C

Definitions of Data Coding

Definitions of Data Coding

Data Name	Explanation	Code Input
CHIMCOND	Condition of the chimney	. = no answer; 0=no chimney or N/A; 1=poor condition; 2=fairly good condition; 3=very good condition
DATE1	Set-up Date	MM/DD/YYYY
EAVES	Presence of eave spaces; default to highest # checked	0=no eaves, 1=eaves <30 cm, 2=eaves >or= 30 cm
ETS	Any exposure to environmental tobacco smoke	0=if answered 3 to both etskit and etshome, 1=answered 1 or 2 to etskit or etshome
ETSHOME	Do others smoke in your home in places other than the kitchen	1=yes; 2=occasionally; 3=no
ETSKIT	Do others smoke in the kitchen?	1=yes; 2=occasionally; 3=no
GPSACC	GPS Accuracy value (ft)	
GPSELEV	GPS Elevation value (ft)	
GPSN	GPS North value	
GPSW	GPS West value	
HOUSEID	House ID	
HRSCOOK	How many hours do you typically spend cooking each day?	
HRSFIRE	For how many hours during a typical day is the fire burning?	
INUSE	Was the stove in use while assessing?	0=no, 1=yes
KITCHEN	Kitchen characterization	enclosed, semi-enclosed, open
LOG_VOLUME	Volume of the kitchen (log-transformed)	
NOBS	Number of observations	
NODOOR	Number of kitchen doors (from sketch)	0, 1, 2, 3, 4
NOWALLS	Number of kitchen walls	0, 1, 2, 3, 4
NOWIN	Number of kitchen windows (from sketch)	0, 1, 2, 3, 4, 5
PERMVENT	Presence of permanent ventilation in the roof	0=no roof, 1=none, 2= <10 cm in diameter, 3= >or= 10 cm in diameter

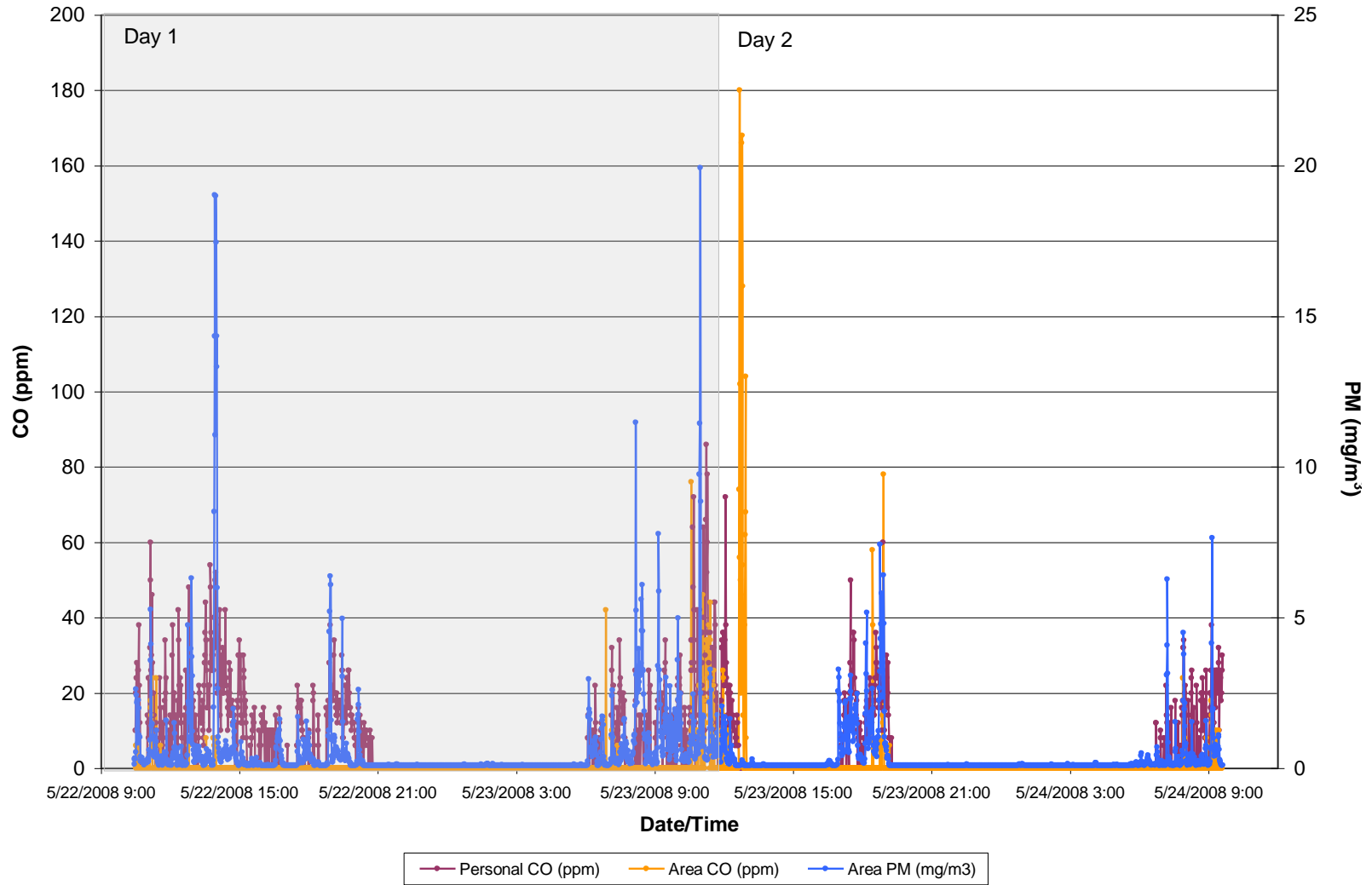
Definitions of Data Coding - Continued

Data Name	Explanation	Code Input
SHAPE	Shape of the Kitchen	A=1, B=2, C=3, D=4
SHAPEA	Dimension a of the Kitchen (in)	
SHAPEB	Dimension b of the Kitchen (in)	
SHAPEC	Dimension c of the Kitchen (in)	
SHAPED	Dimension d of the Kitchen (in)	
STOVE1	Primary stove type	1=3-stone fire, 2=shielded mud or mud stove (no chimney), 3=shielded mud or mud stove (with chimney), 4=metal stove (no chimney), 5=metal stove (with chimney), 6=charcoal stove, 7=gas stove, 8=solar cooker, 9=electric stove, 10=other
STOVE2	Secondary stove type	0=no, 1-10 same as primary stove
STOVQUAL	Overall quality of the primary stove	1--4 (clean to dirty) scale
TIMEBURN	How much time do you spend in the room with the fire burning? (hours)	
TRAFFIC	Is kitchen influenced by nearby traffic pollution?	0=none, 1=low, 2=medium, 3=high
TYPROOF	Type of roof	1=sheet metal, 3=ceramic tiles or wood, 4=other
TYPWALL1	Type of walls (primary)	0=N/A, 1=brick, 2=mud, 3=sheet metal, 4=wood, 5=cement, 6=other, 7=cardboard, 15=brick or cement
TYPWALL2	Type of walls (secondary)	1=brick, 2=mud, 3=sheet metal, 4=wood, 5=cement, 6=other, 7=cinder block, 8=plastic, 9=fiberglass, 10-cardboard
XDIST	Distance from monitor to stove - inches	
XHEIGHT	Height of monitor - inches	

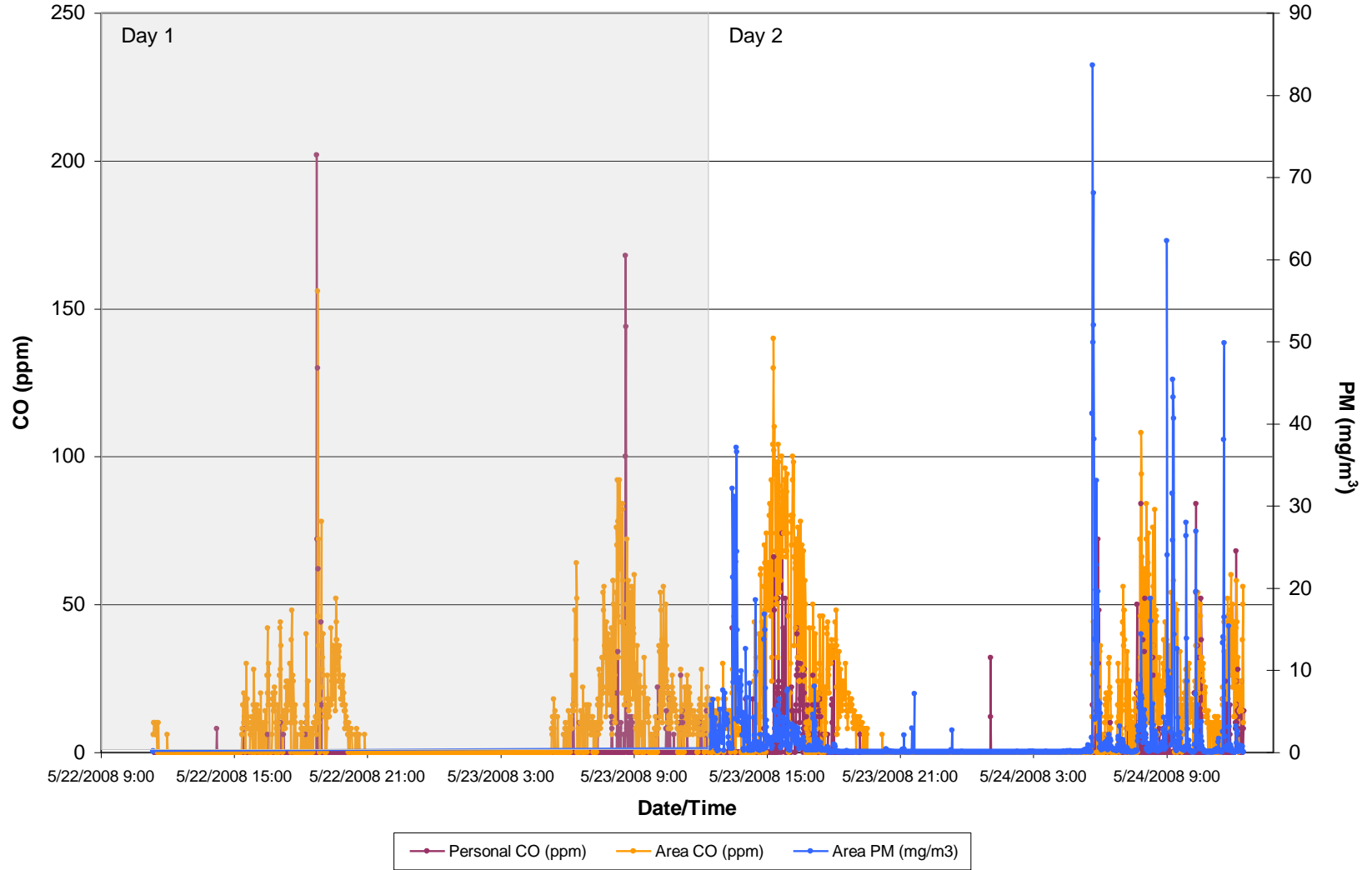
APPENDIX D

Household graphs of minute-by-minute exposure data

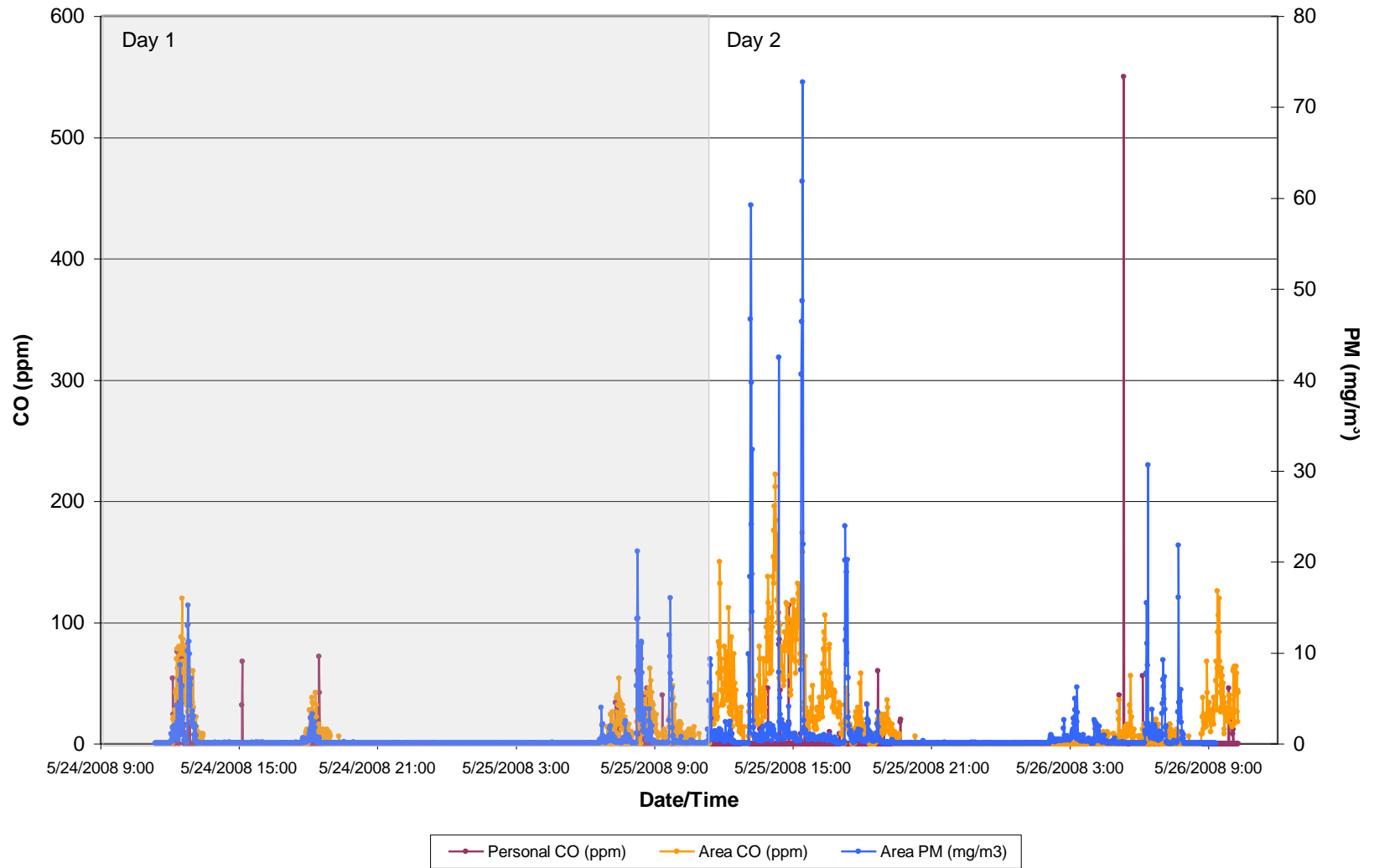
House 1 and Participant Exposure Data



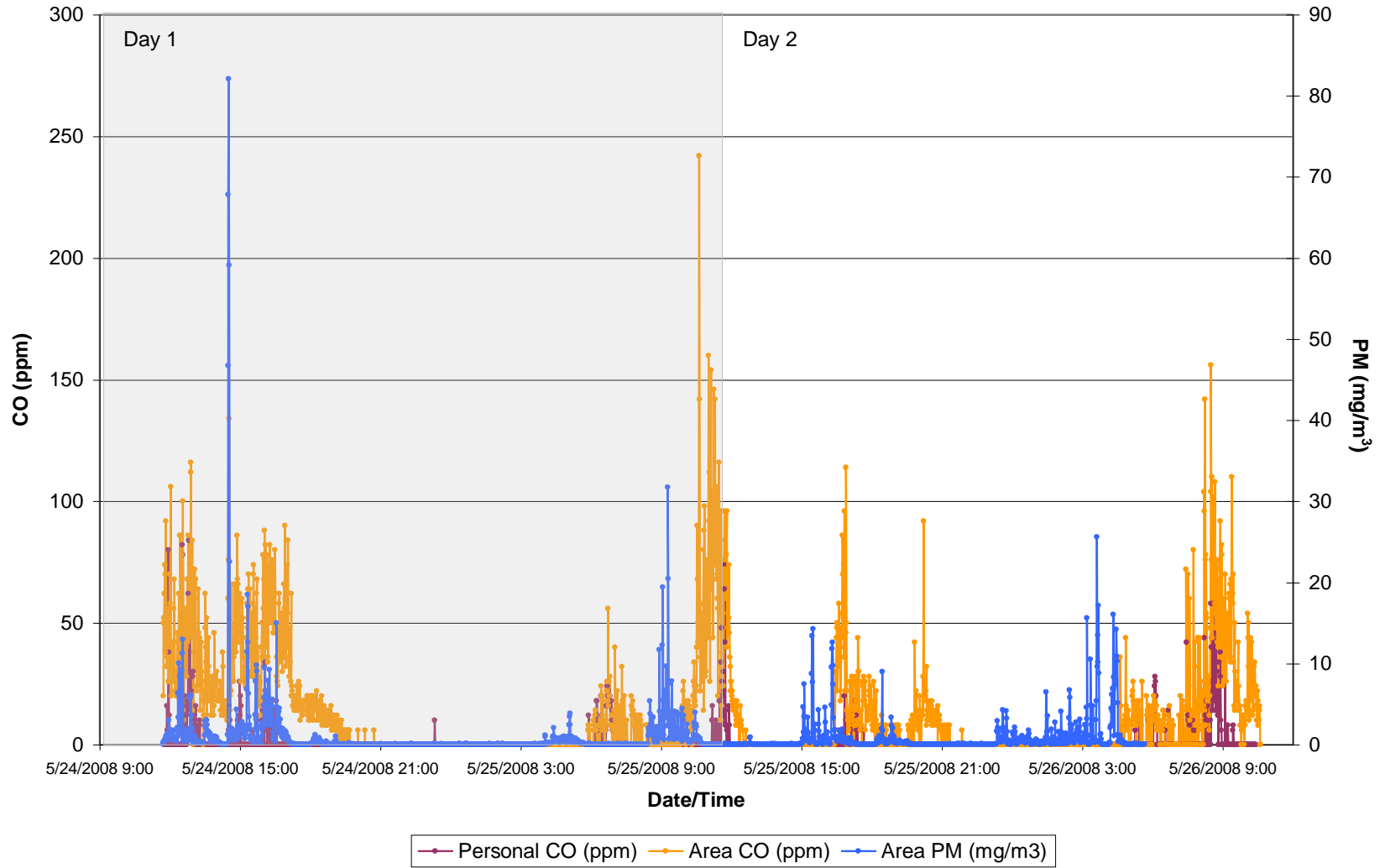
House 2 and Participant Exposure Data



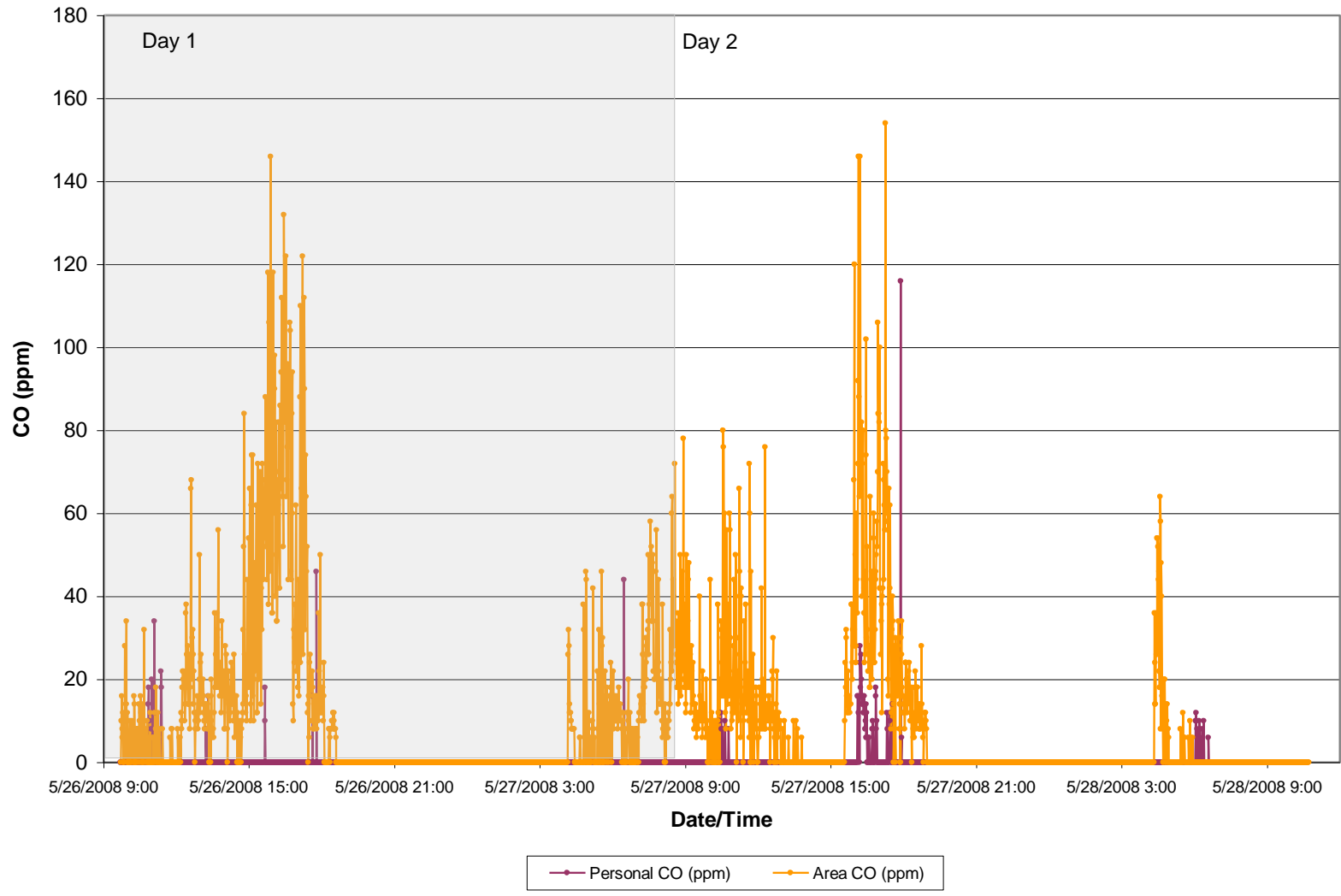
House 3 and Participant Exposure Data



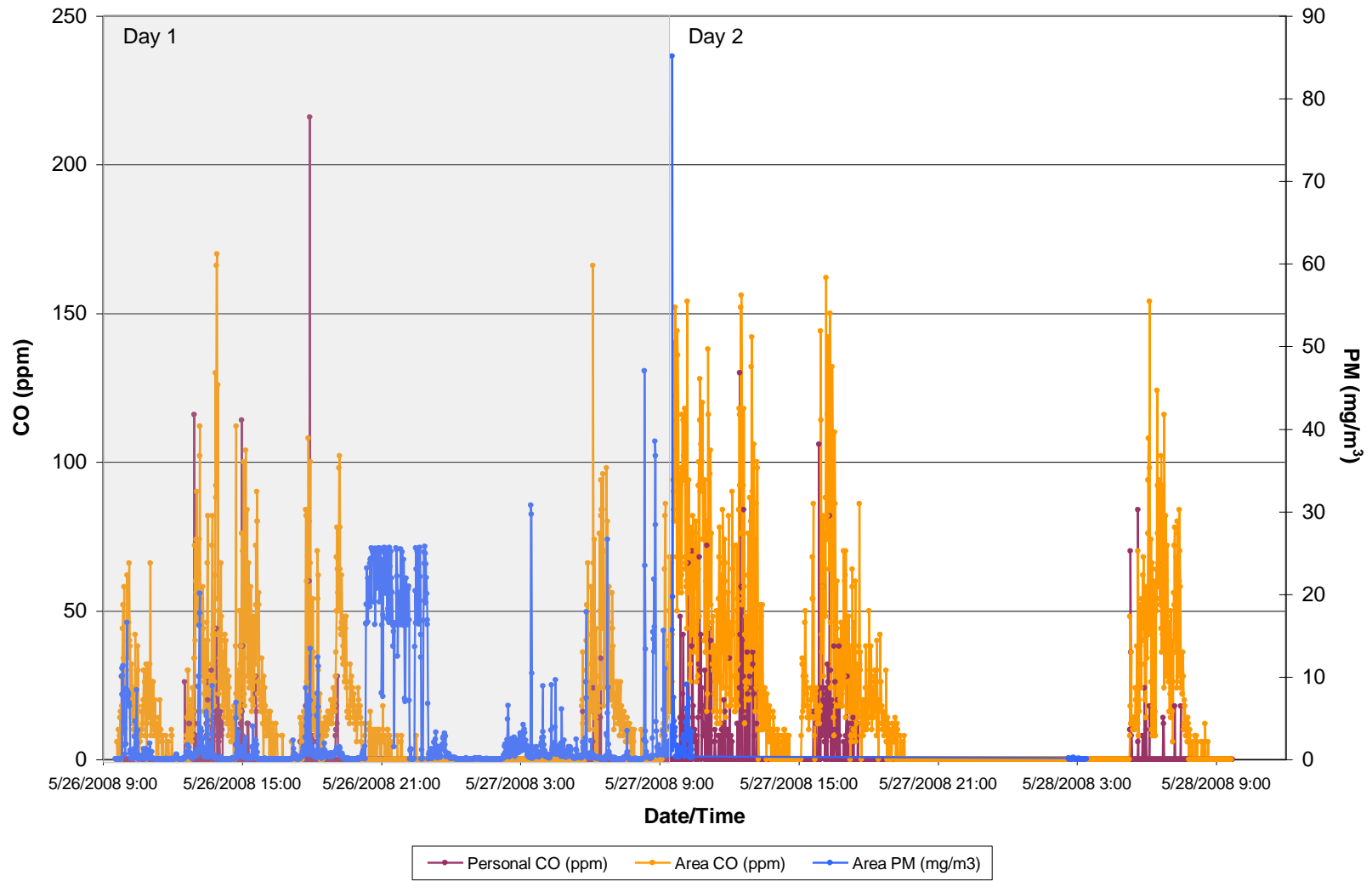
House 4 and Participant Data



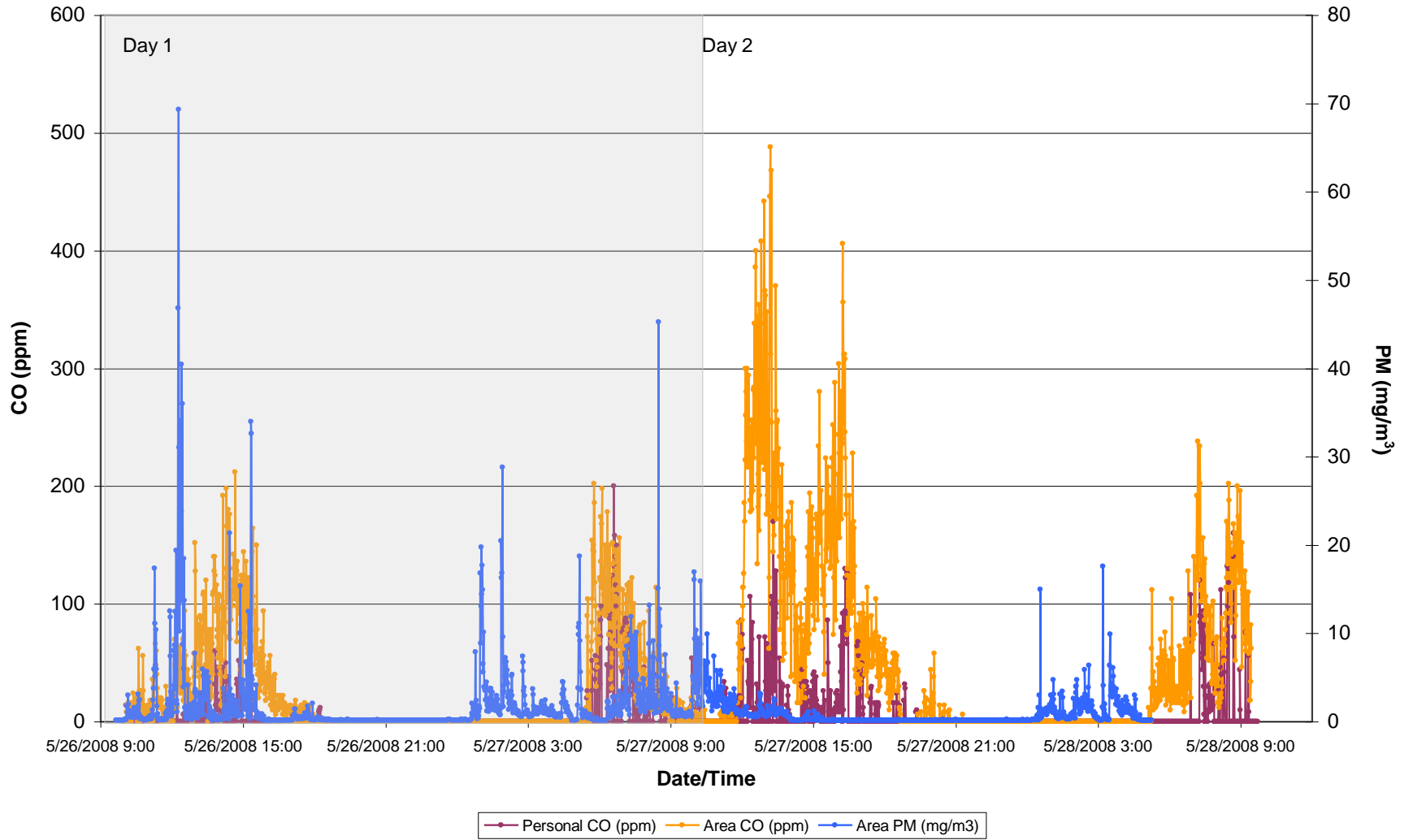
House 5 and Participant Exposure Data



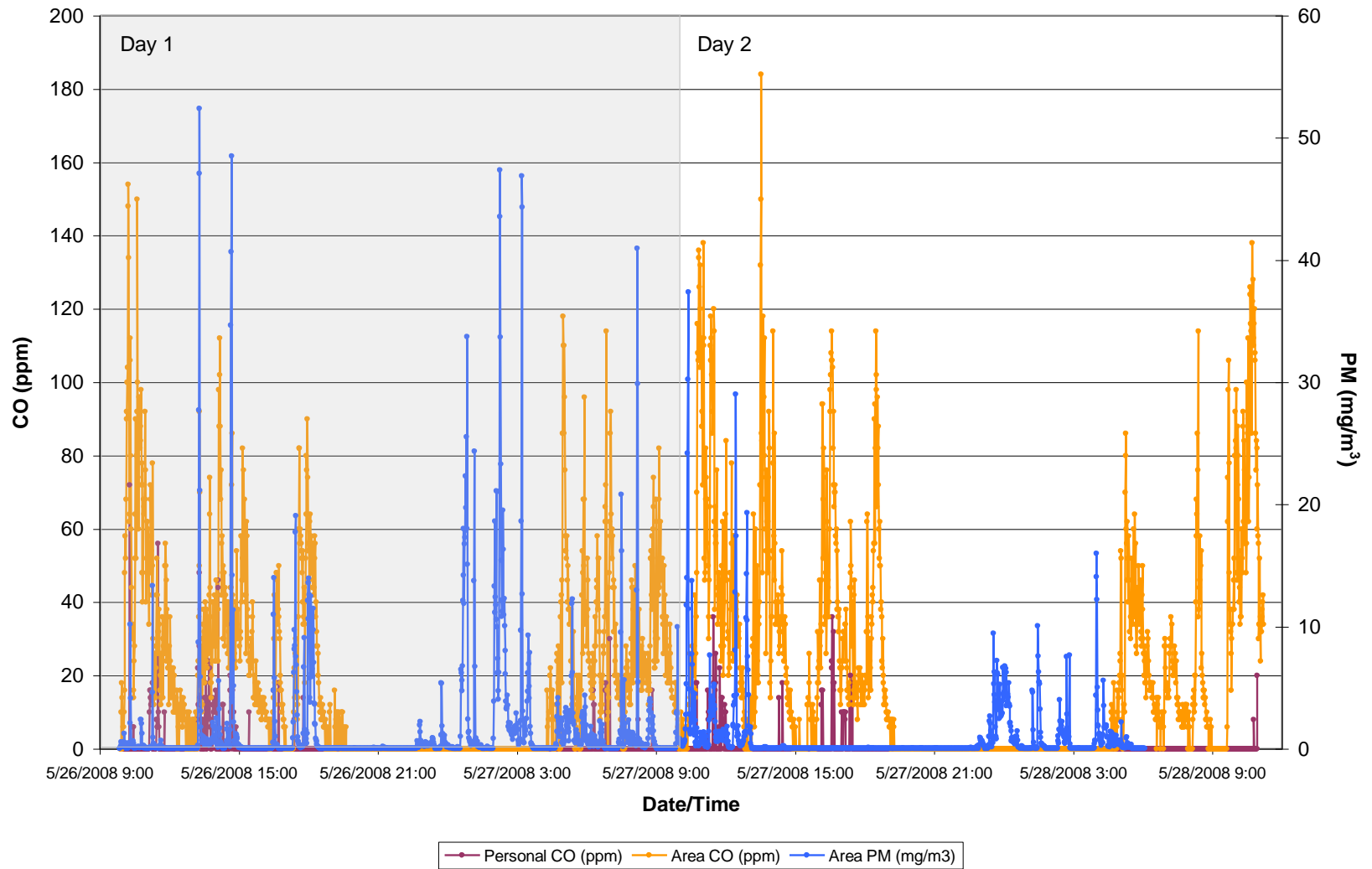
House 6 and Participant Exposure Data



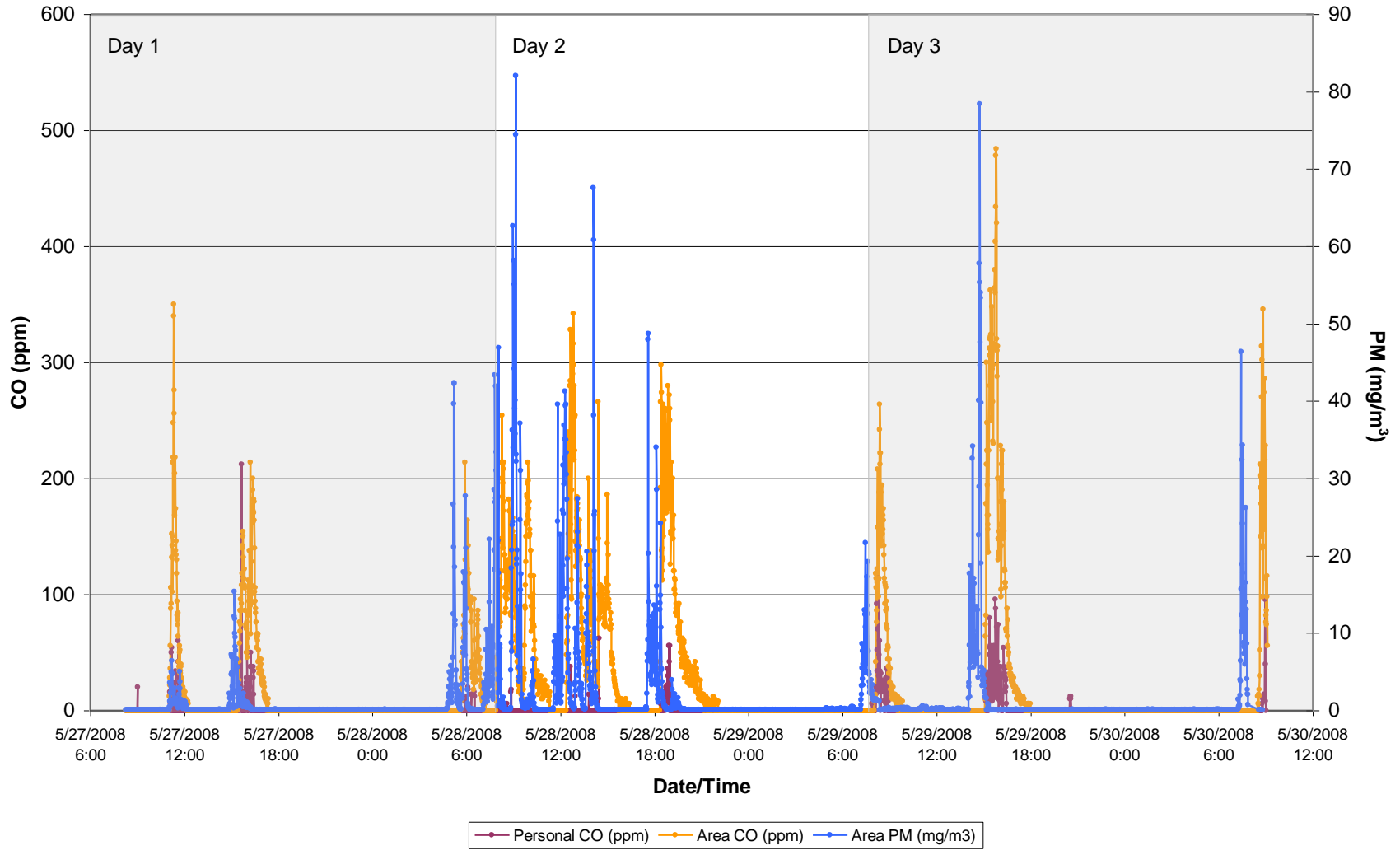
House 7 and Participant Exposure Data



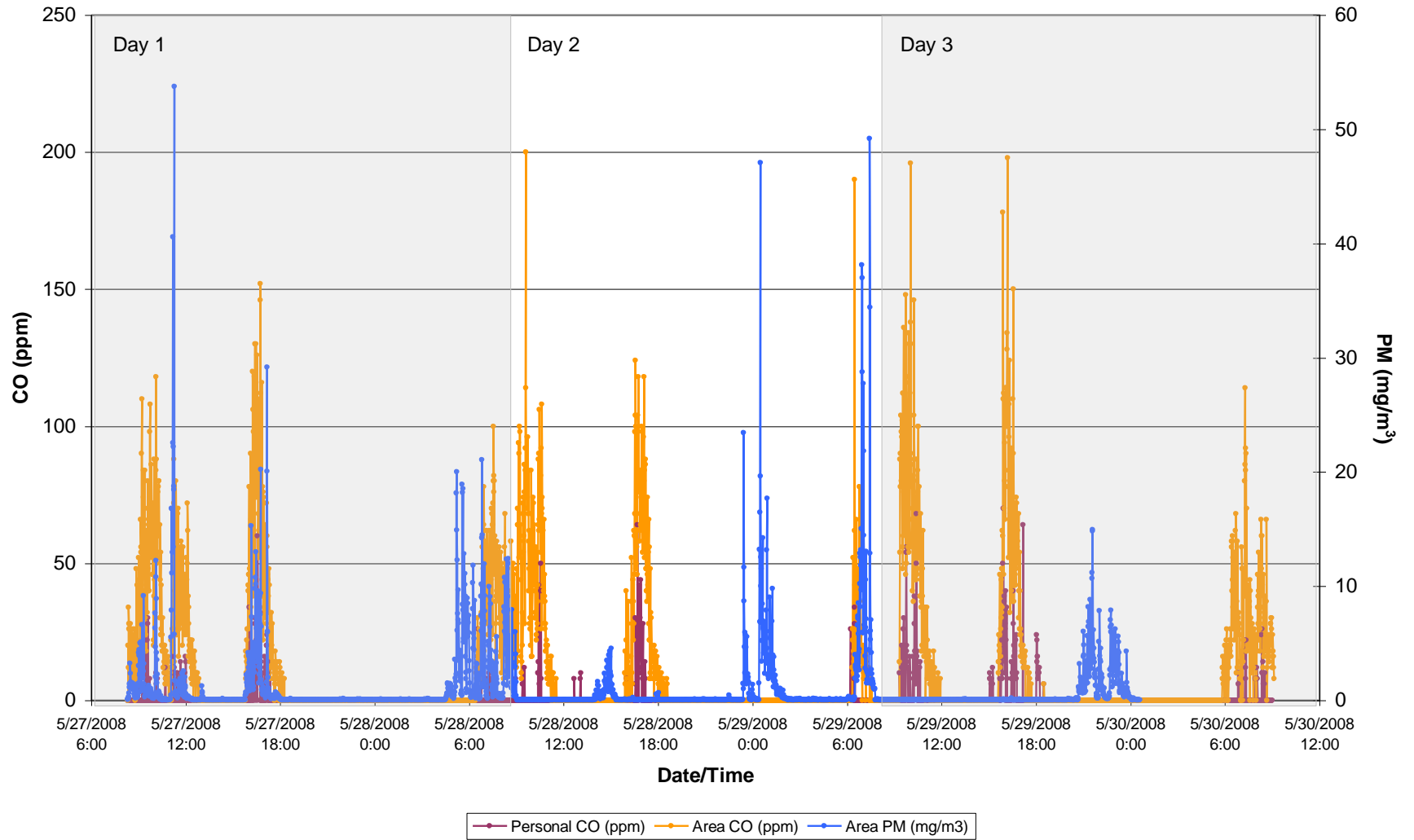
House 8 and Participant Exposure Data



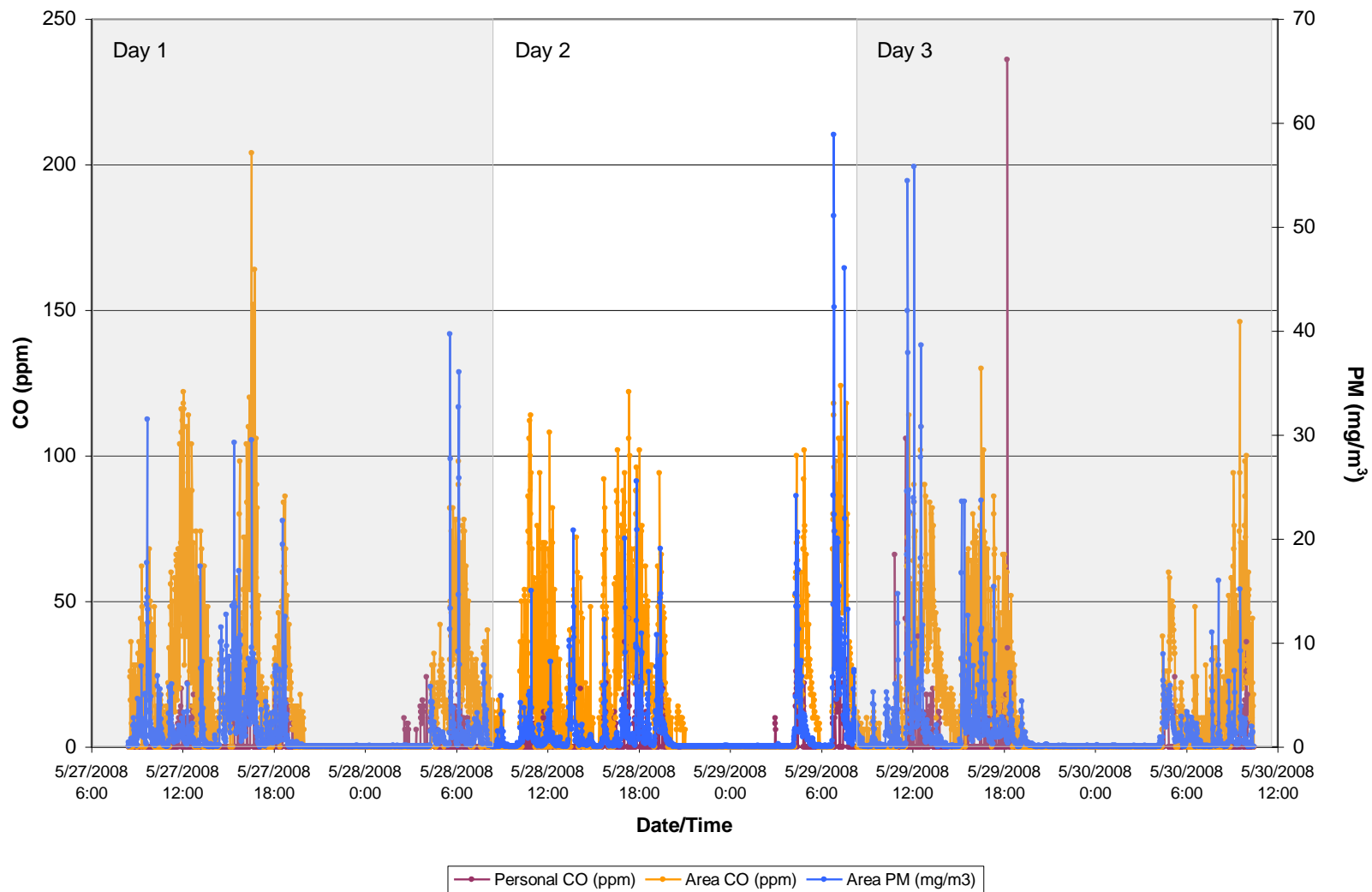
House 9 and Participant Exposure Data



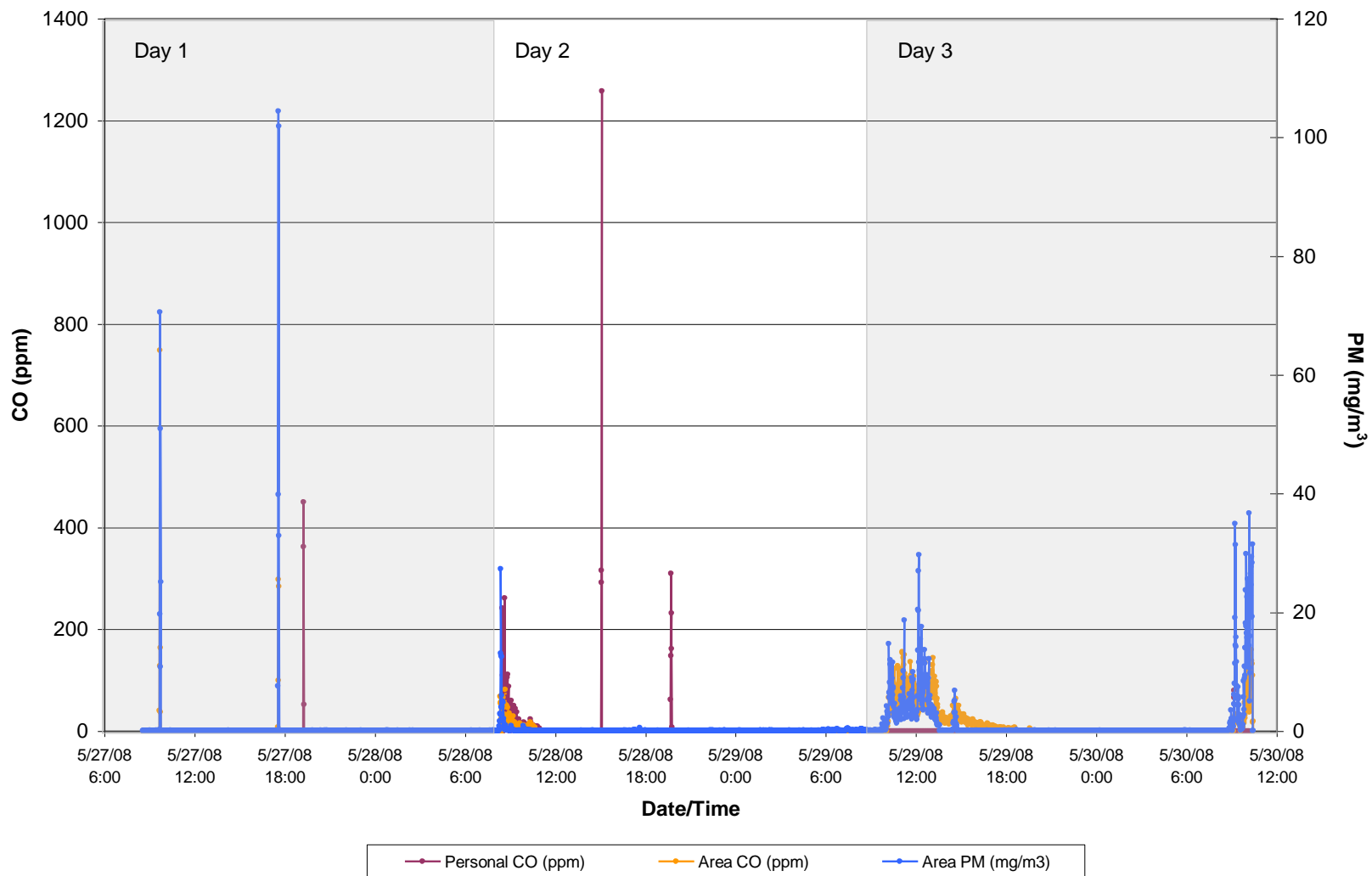
House 10 and Participant Exposure Data



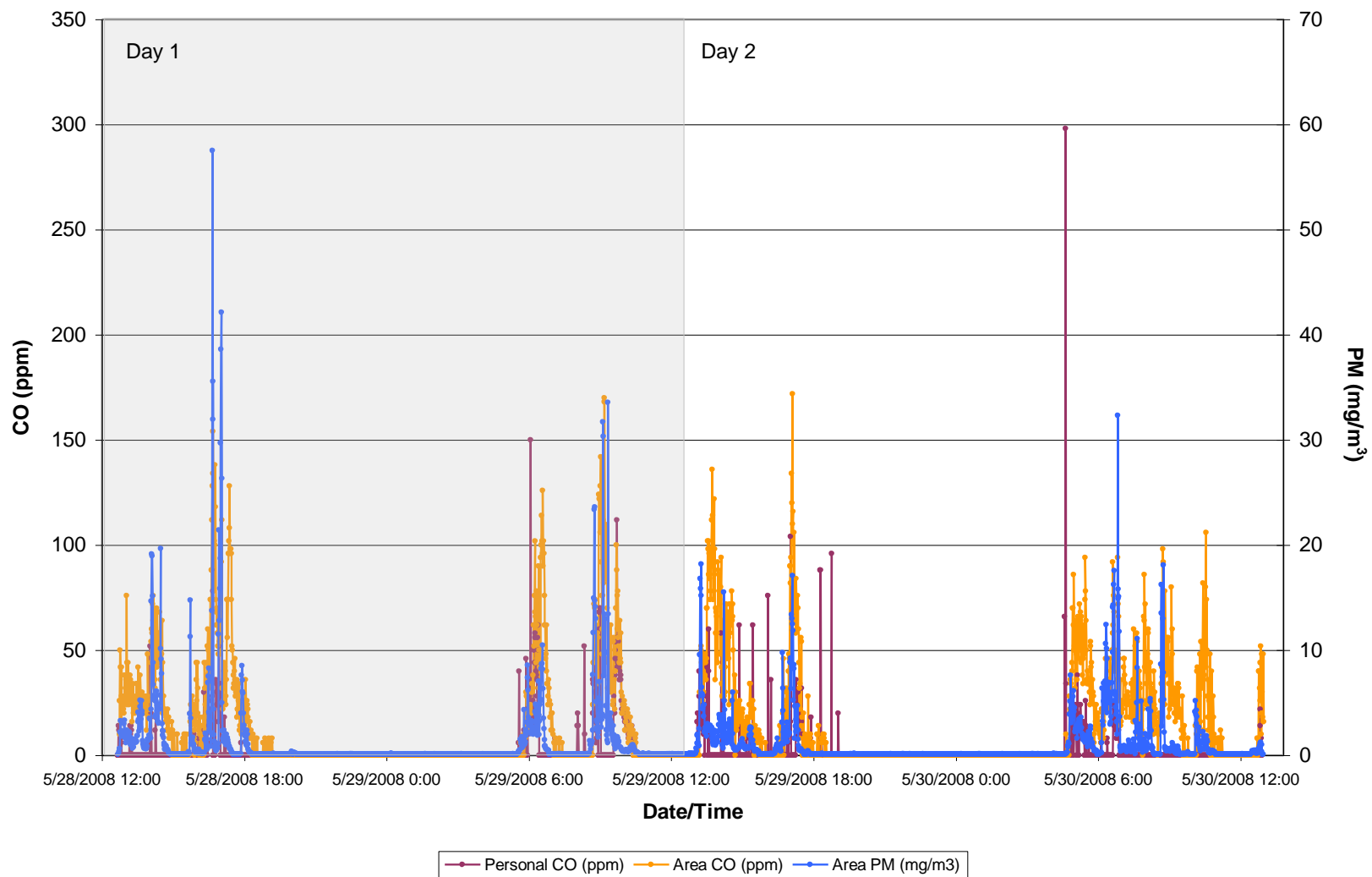
House 11 and Participant Exposure Data



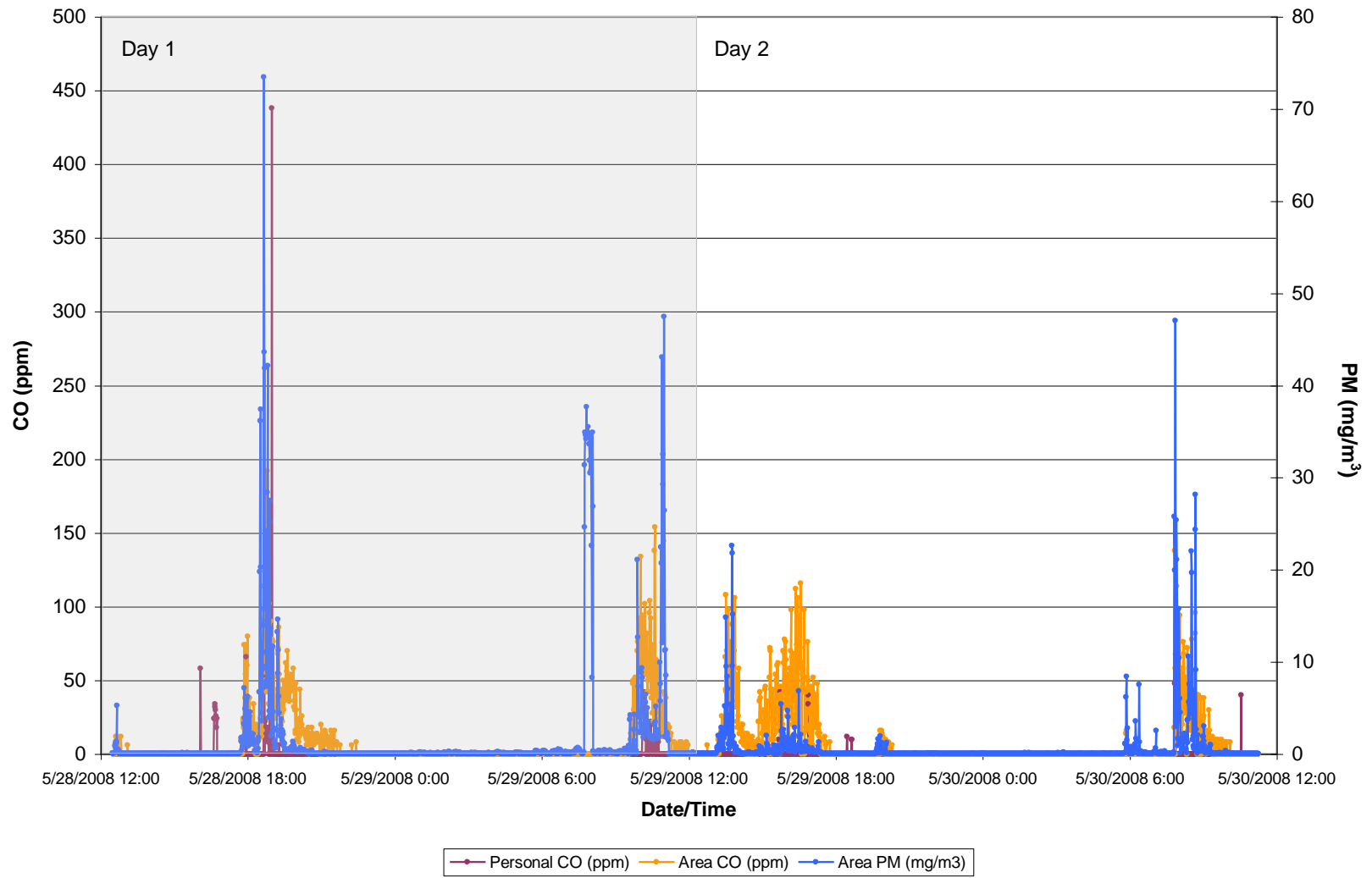
House 12 and Participant Exposure Data



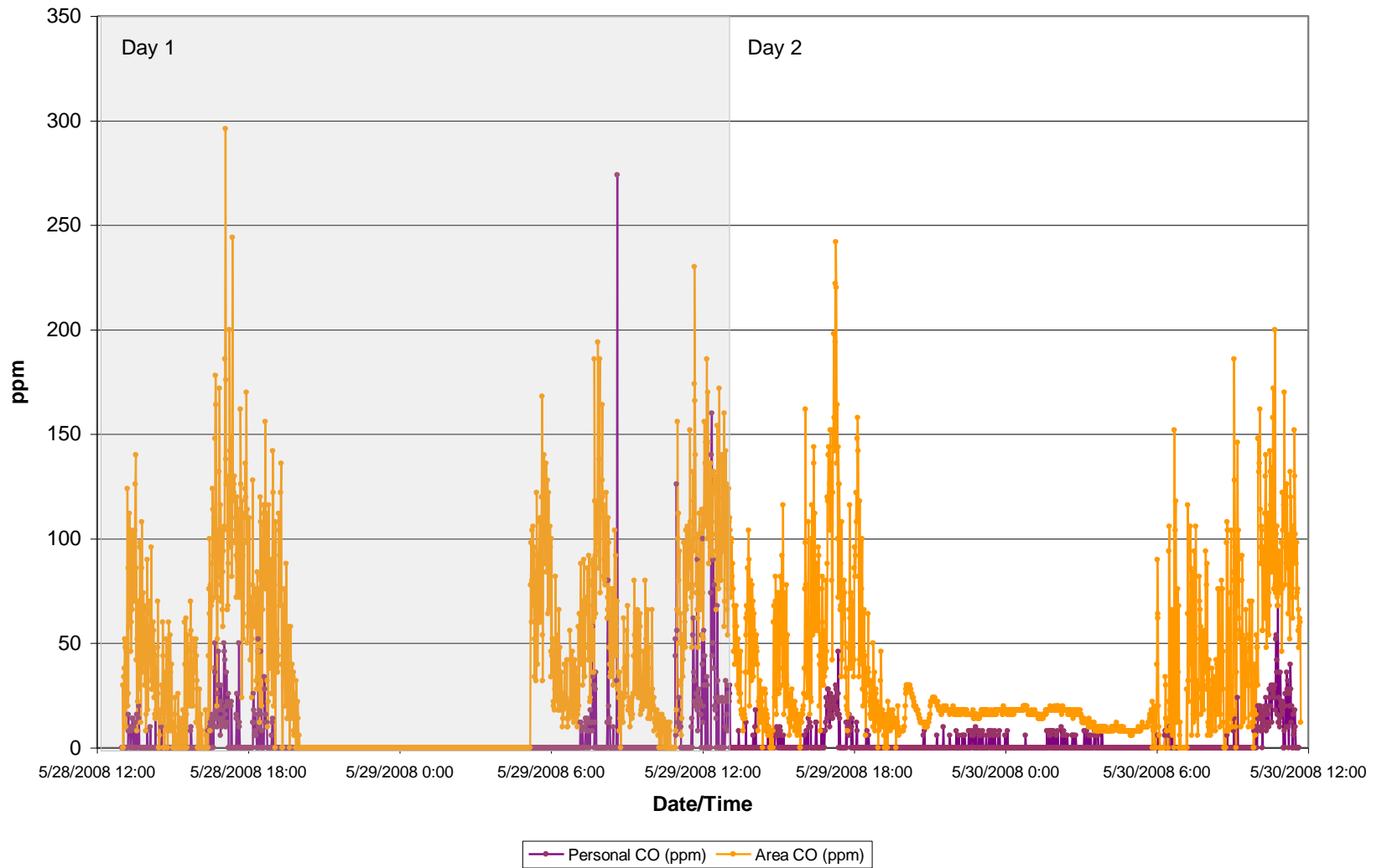
House 13 and Participant Exposure Data



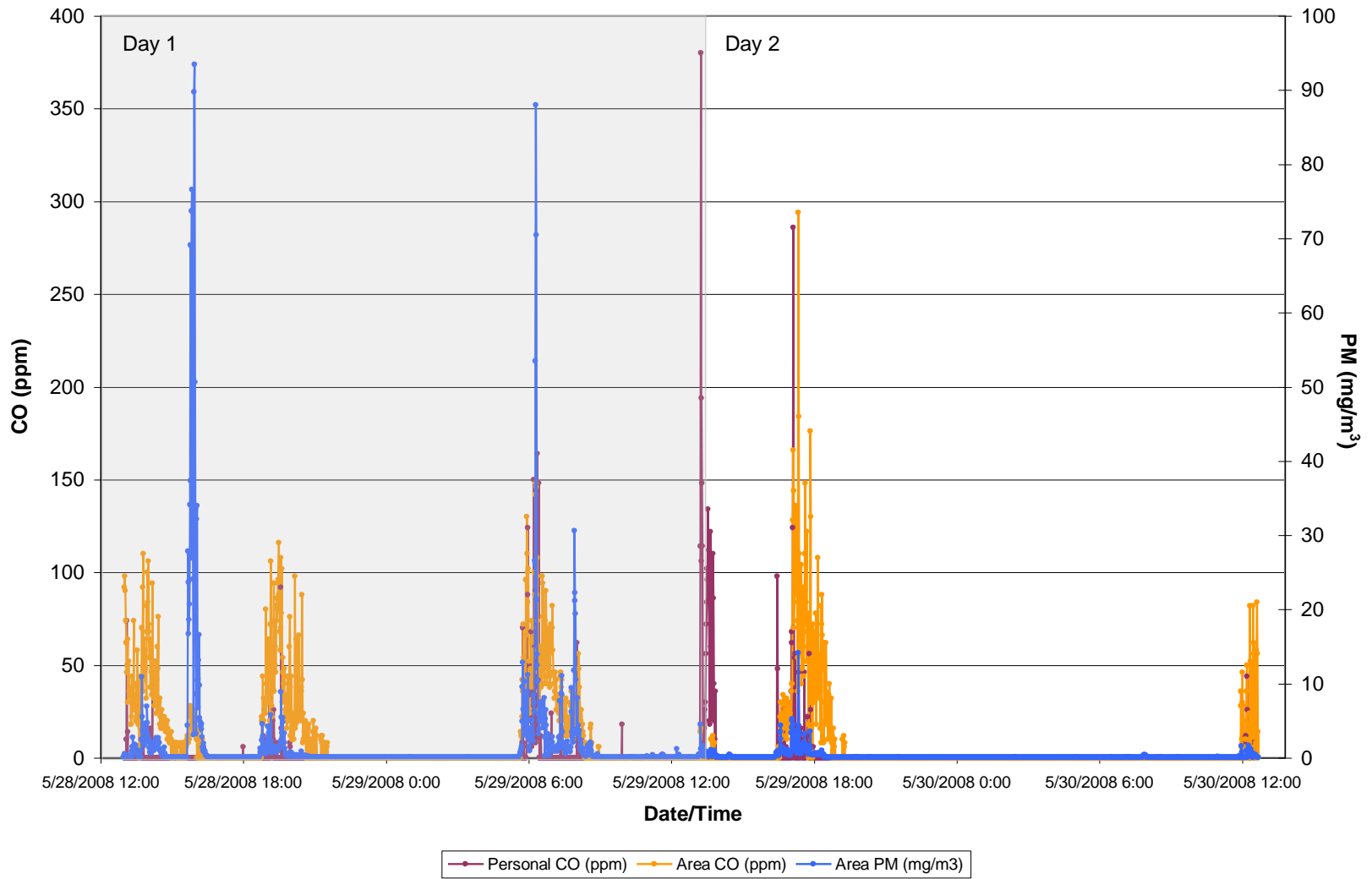
House 14 and Participant Exposure Data



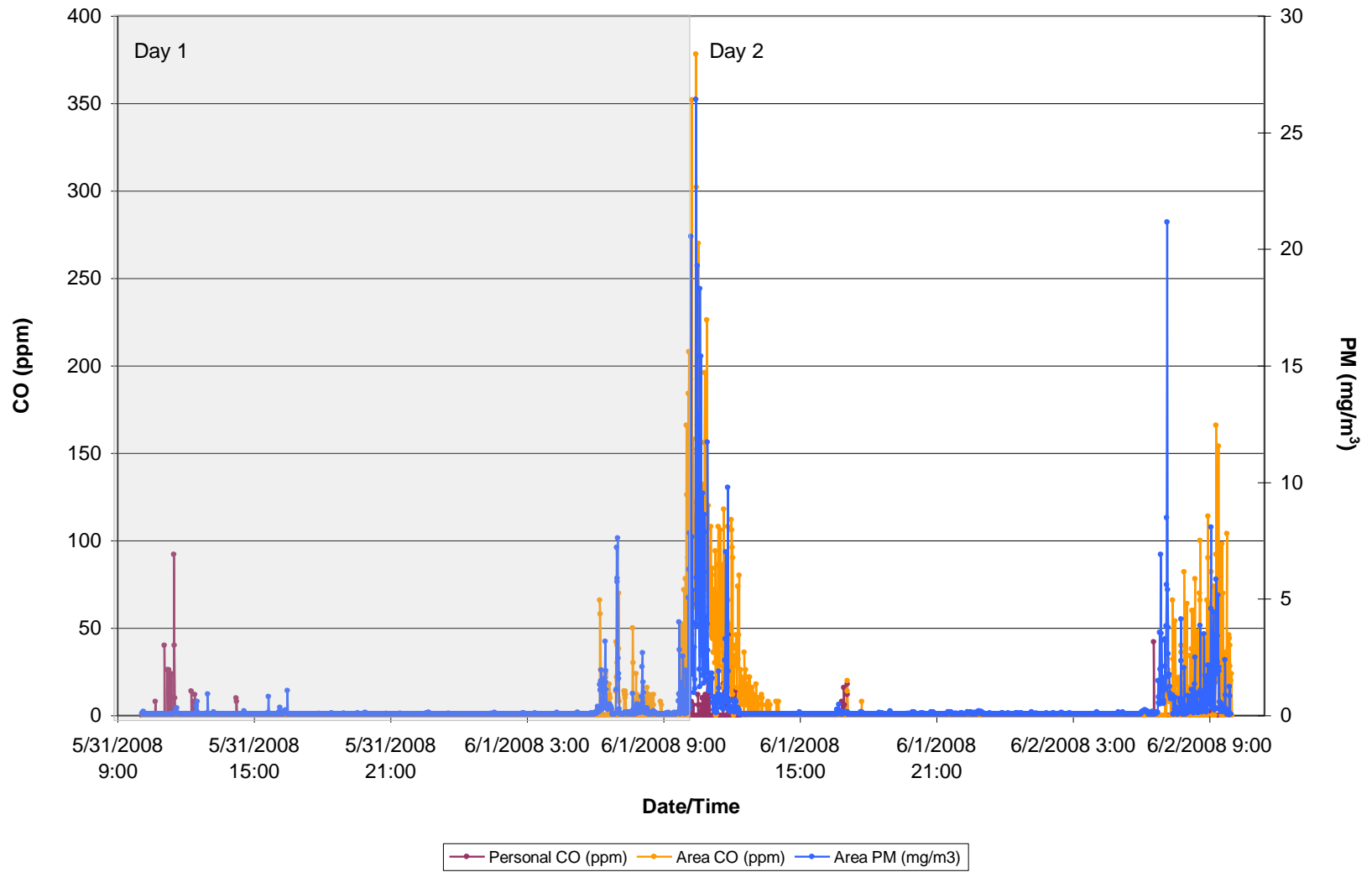
House 15 and Participant Exposure Data (PM Data N/A)



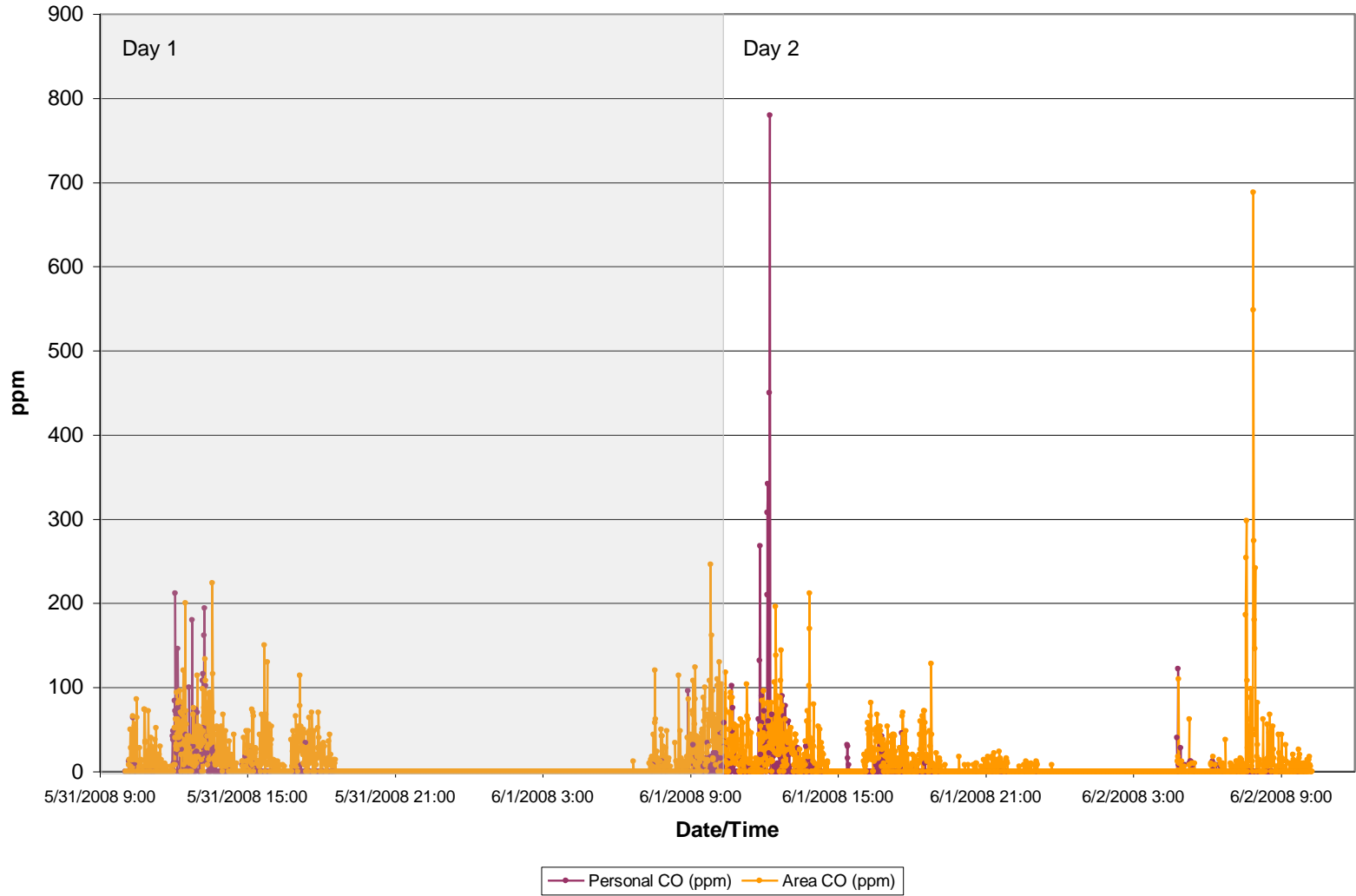
House 16 and Participant Exposure Data



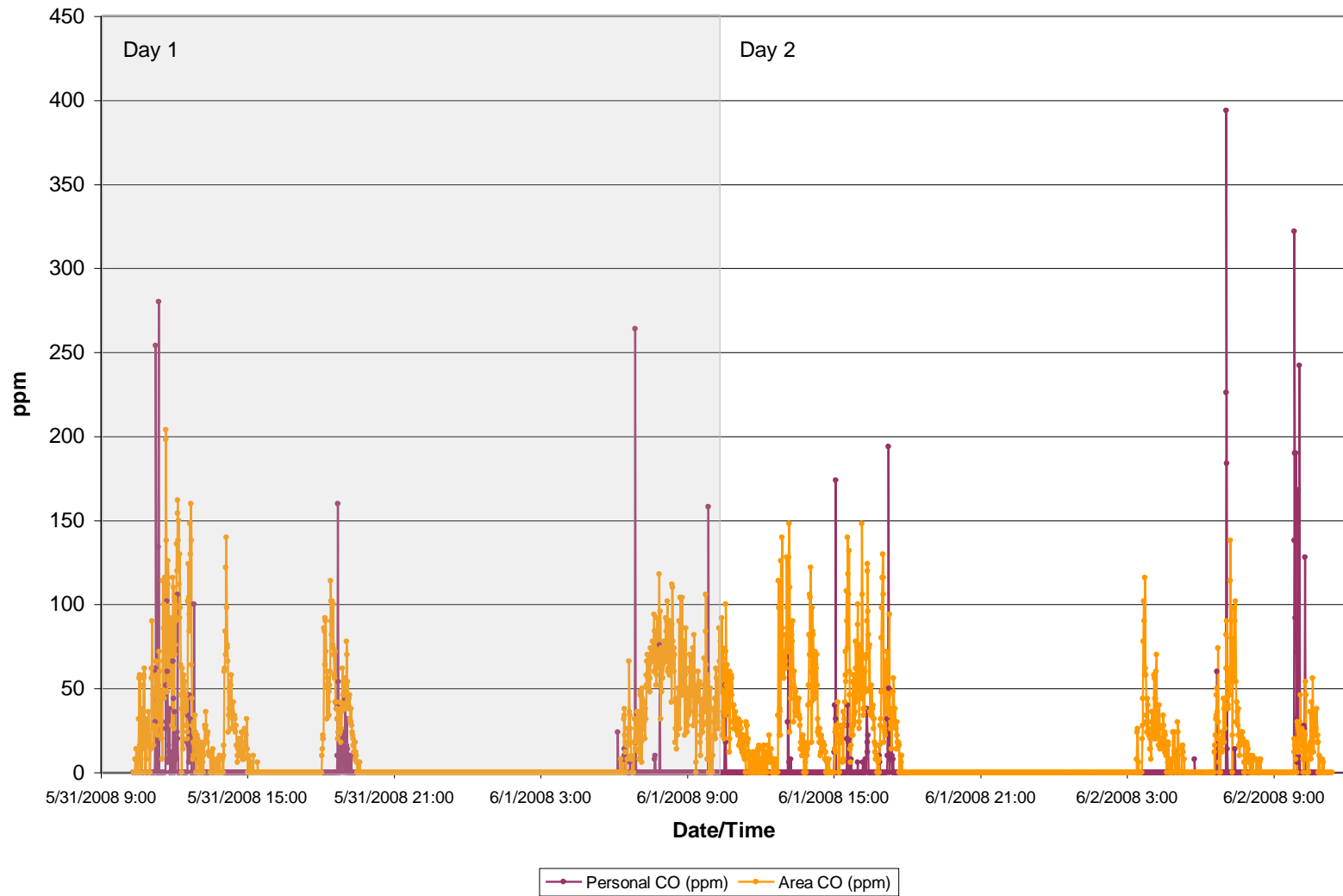
House 17 and Participant Exposure Data



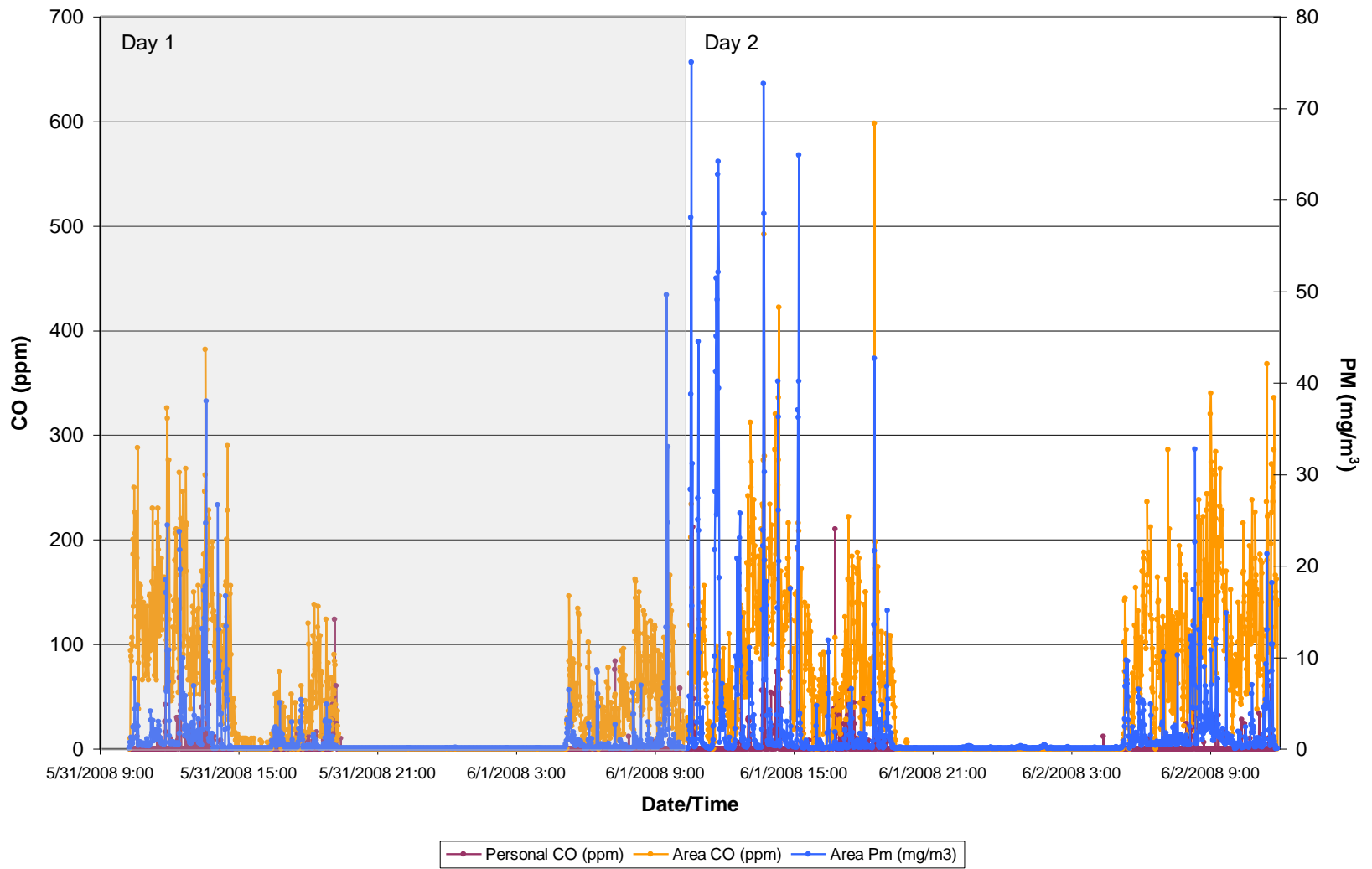
House 18 and Participant Exposure Data (PM Data N/A)



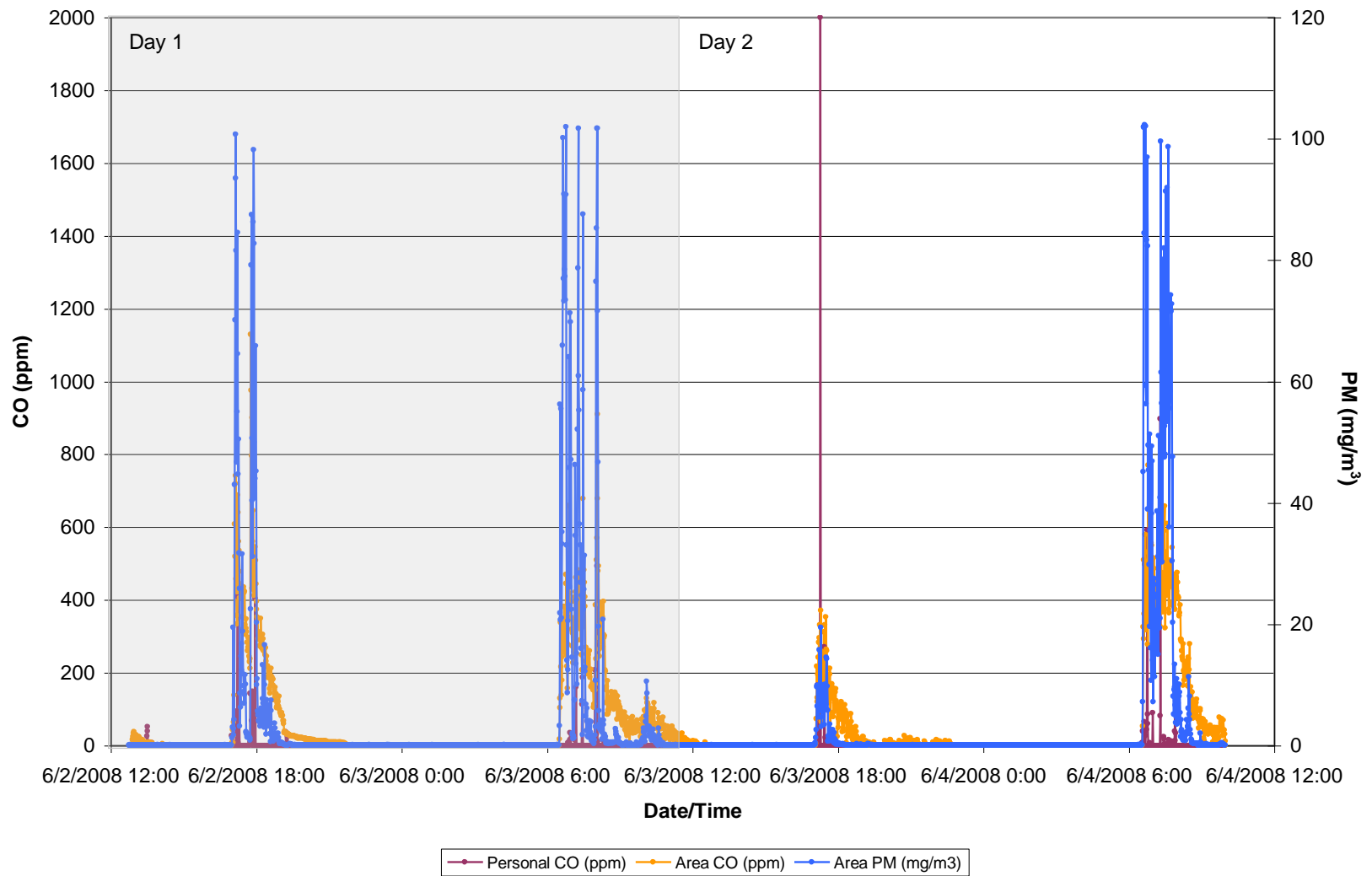
House 19 and Participant Exposure Data (PM Data N/A)



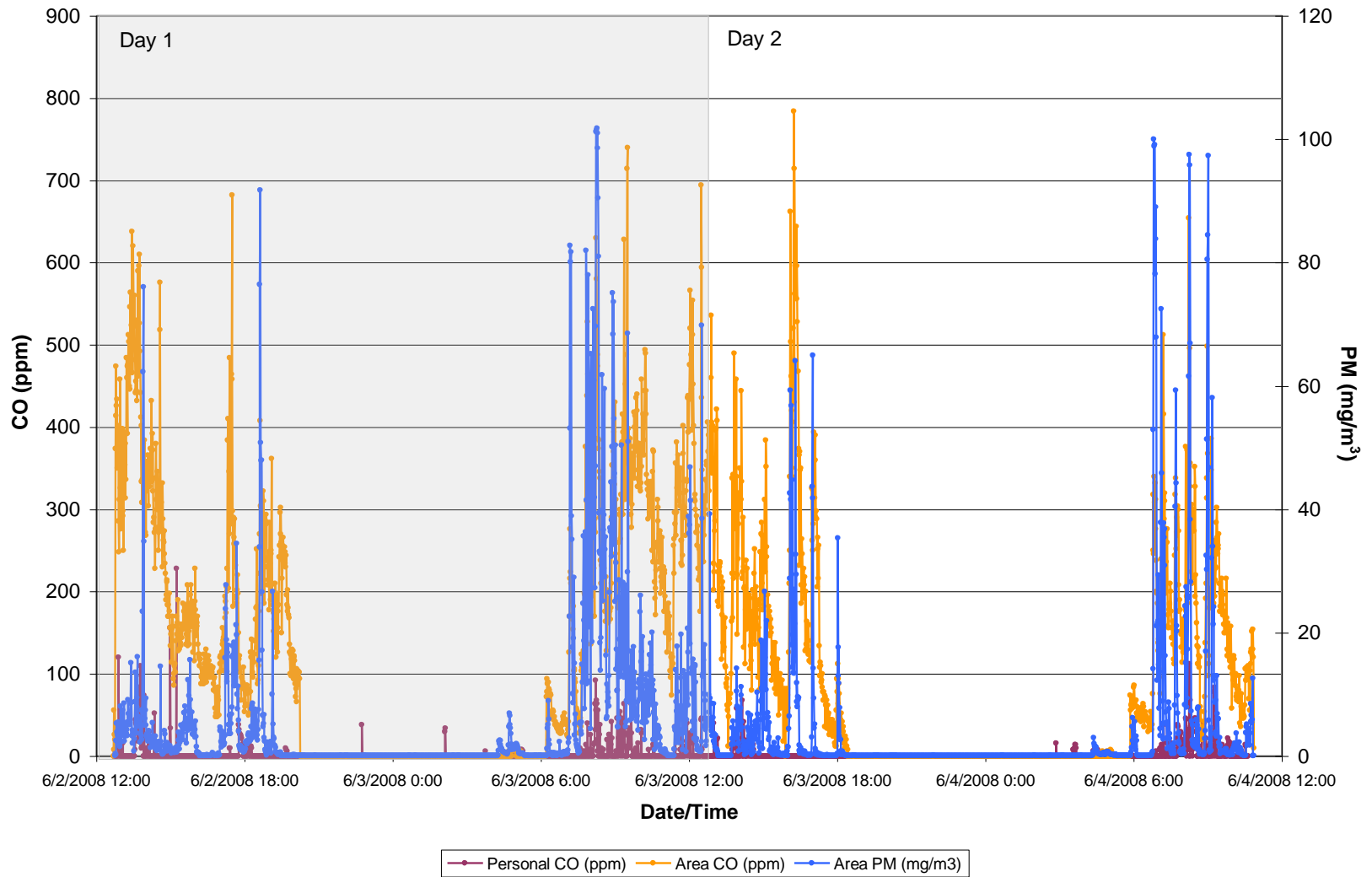
House 20 and Participant Exposure Data



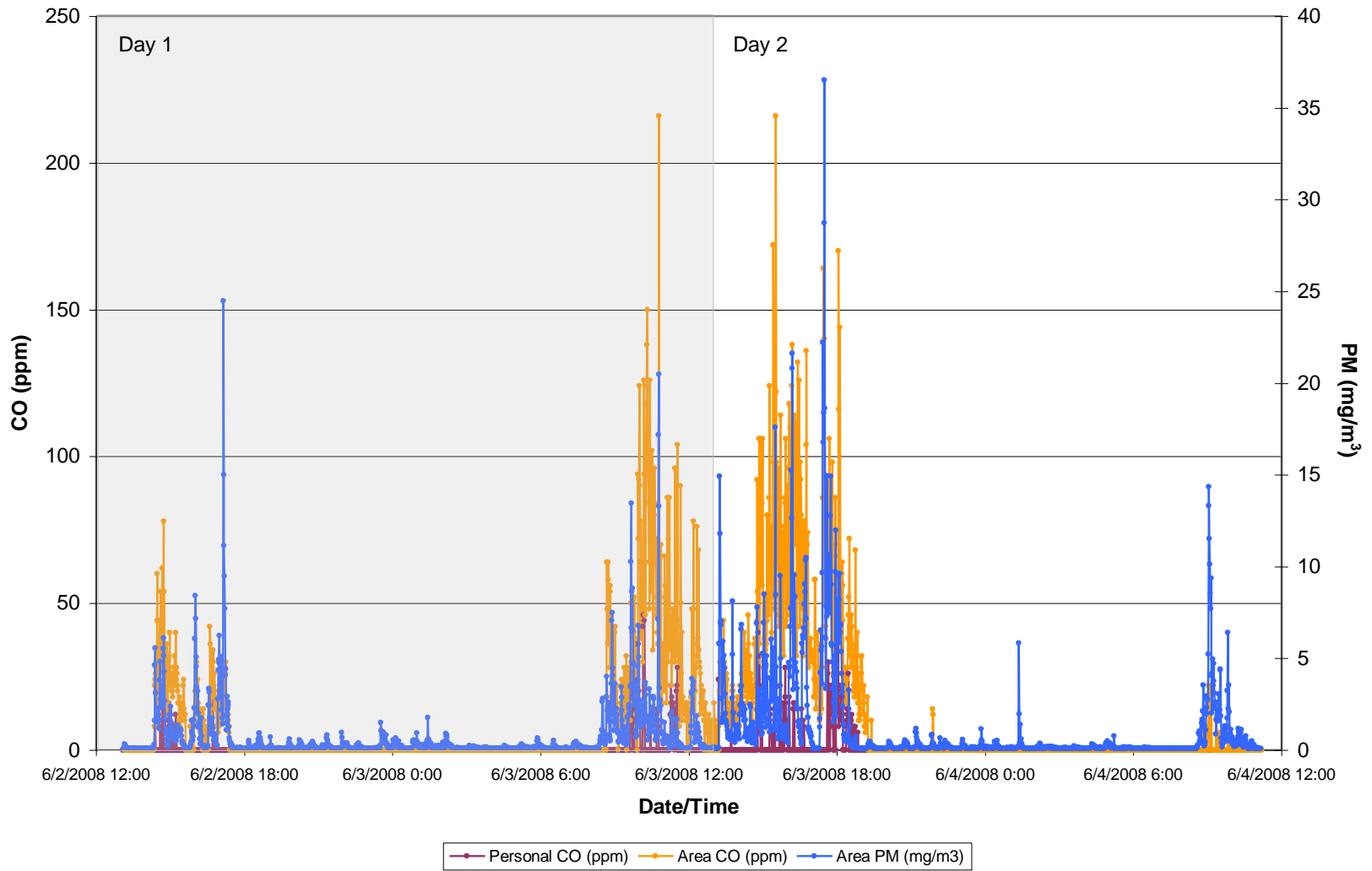
House 21 and Participant Exposure Data



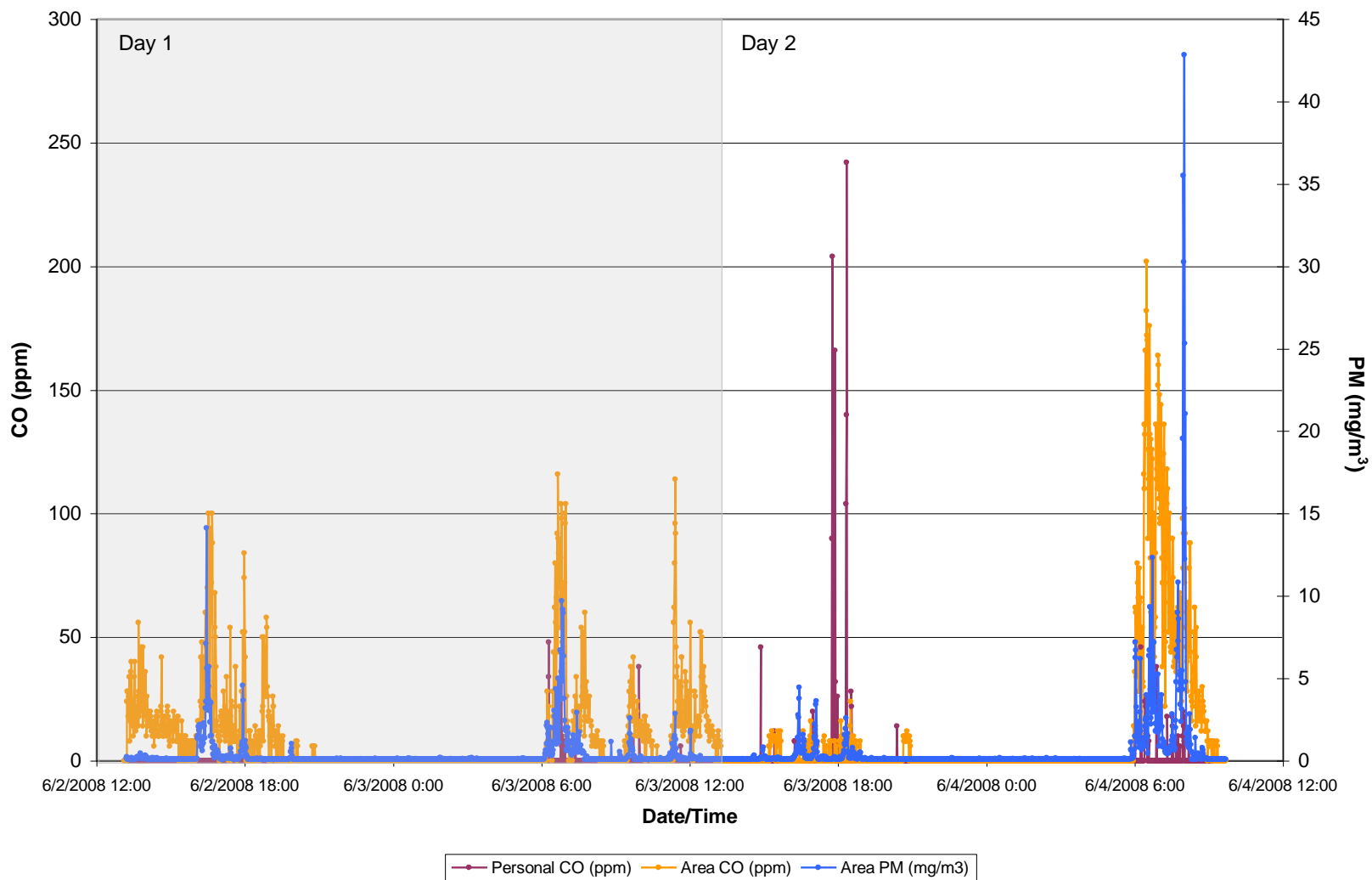
House 22 and Participant Exposure Data



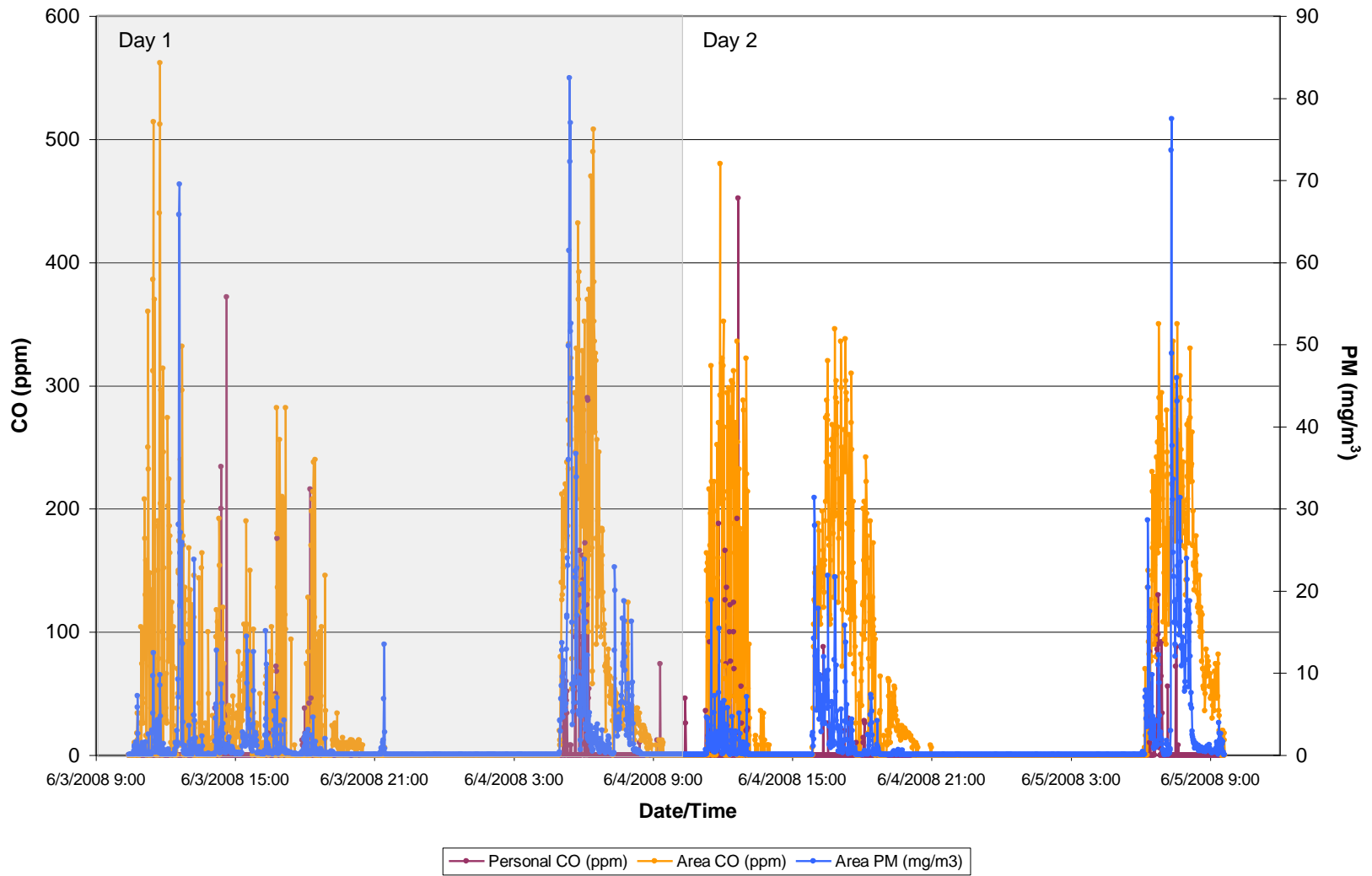
House 23 and Participant Exposure Data



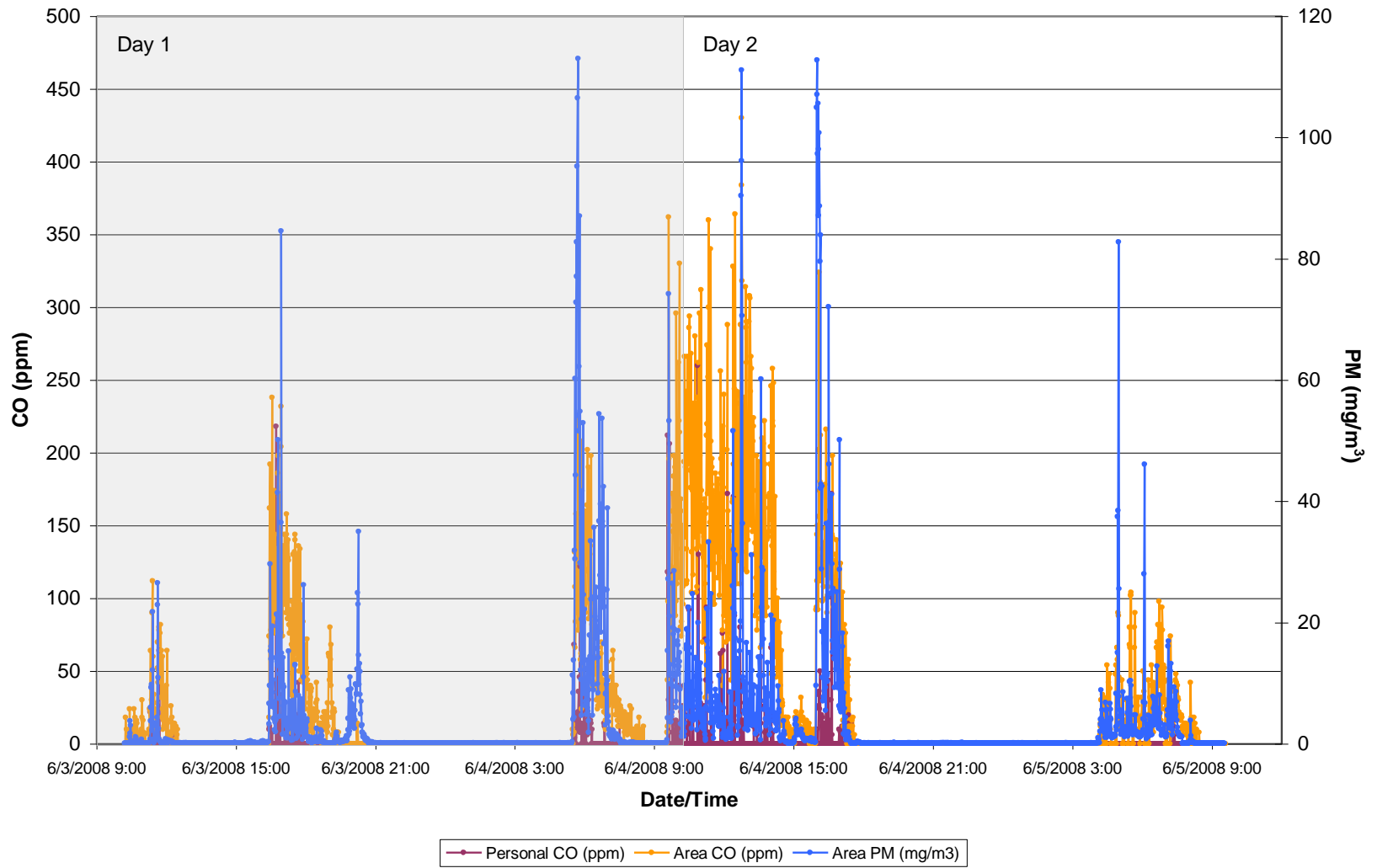
House 24 and Participant Exposure Data



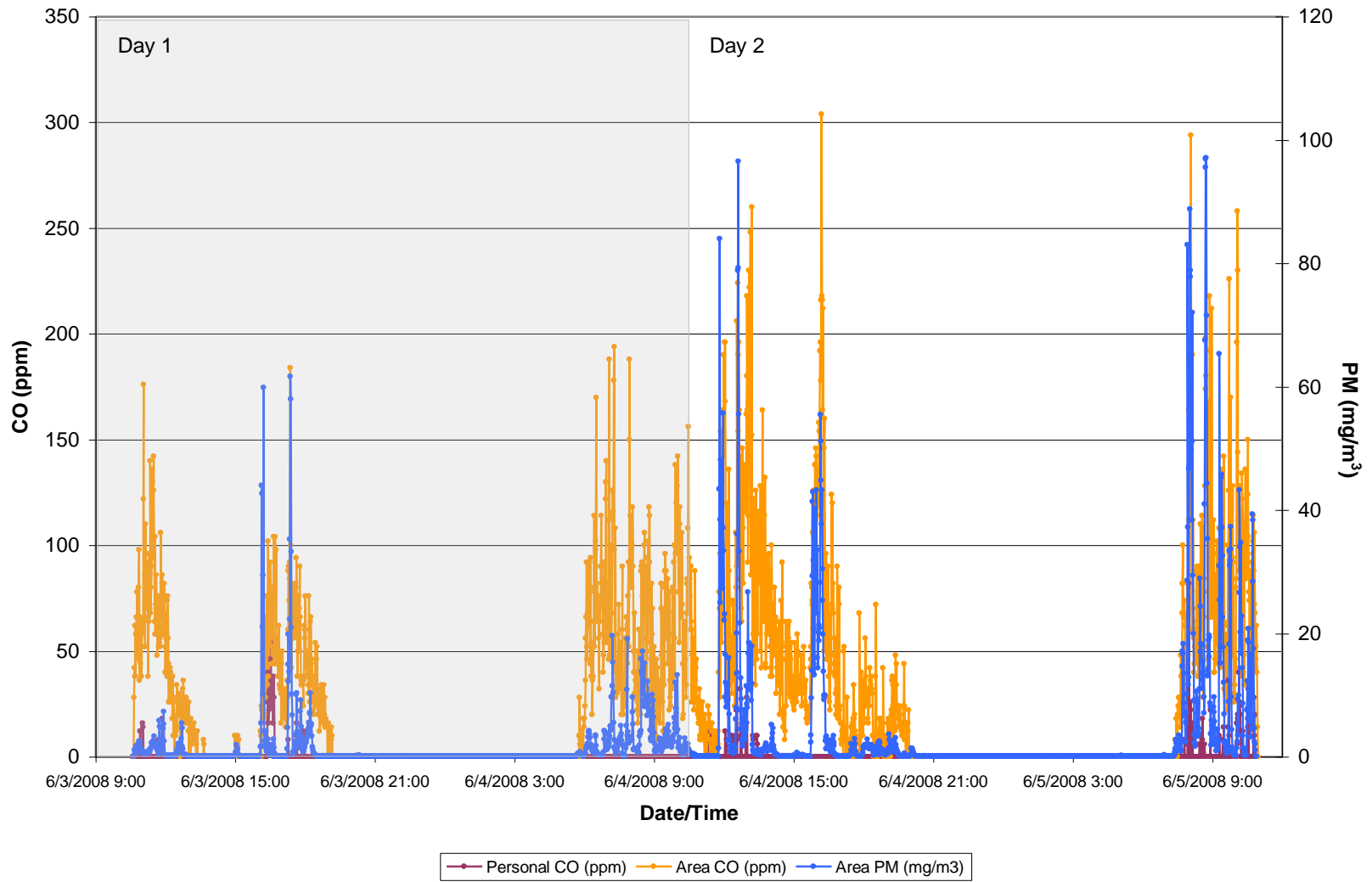
House 25 and Participant Exposure Data



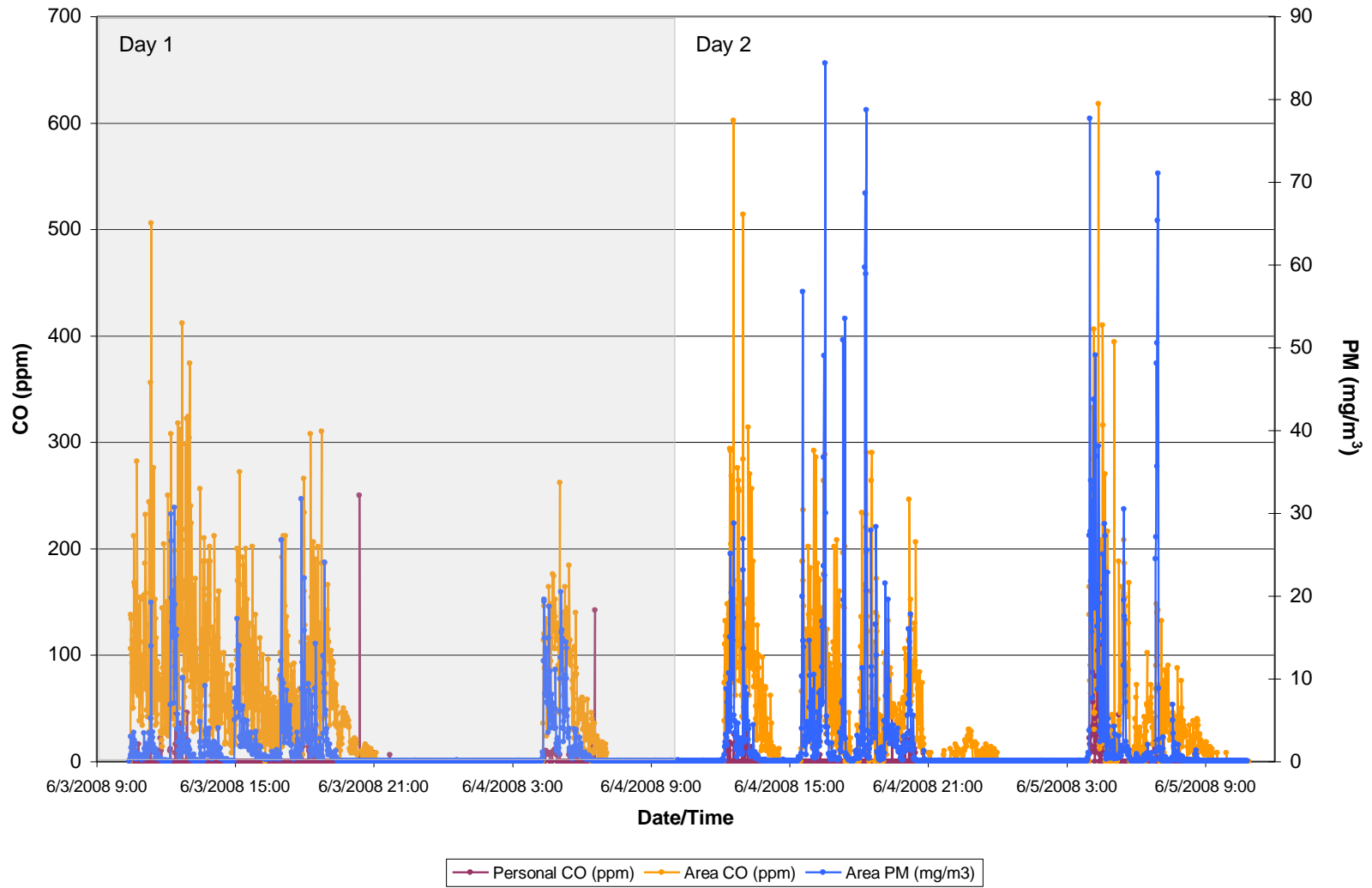
House 26 and Participant Exposure Data



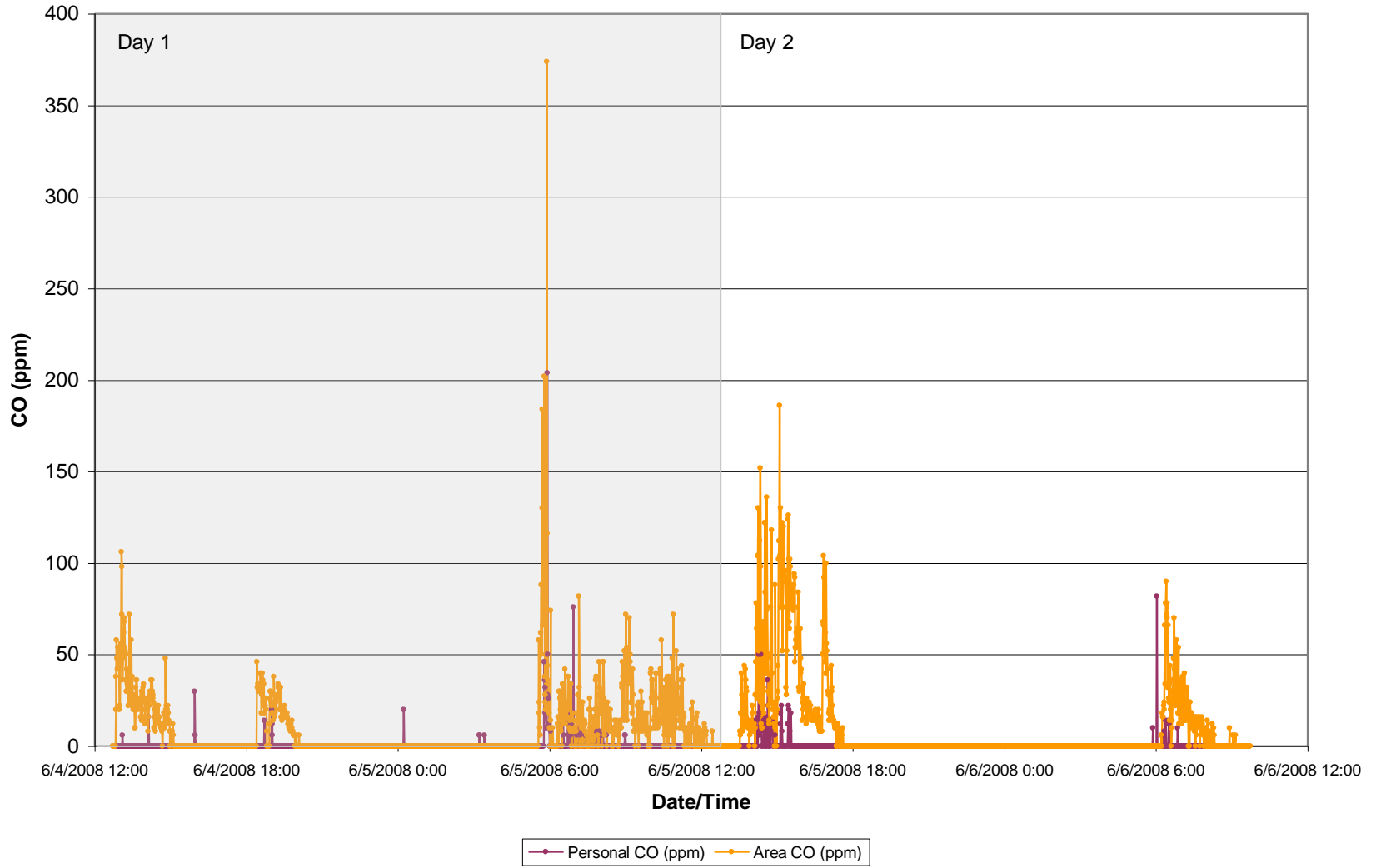
House 27 and Participant Exposure Data



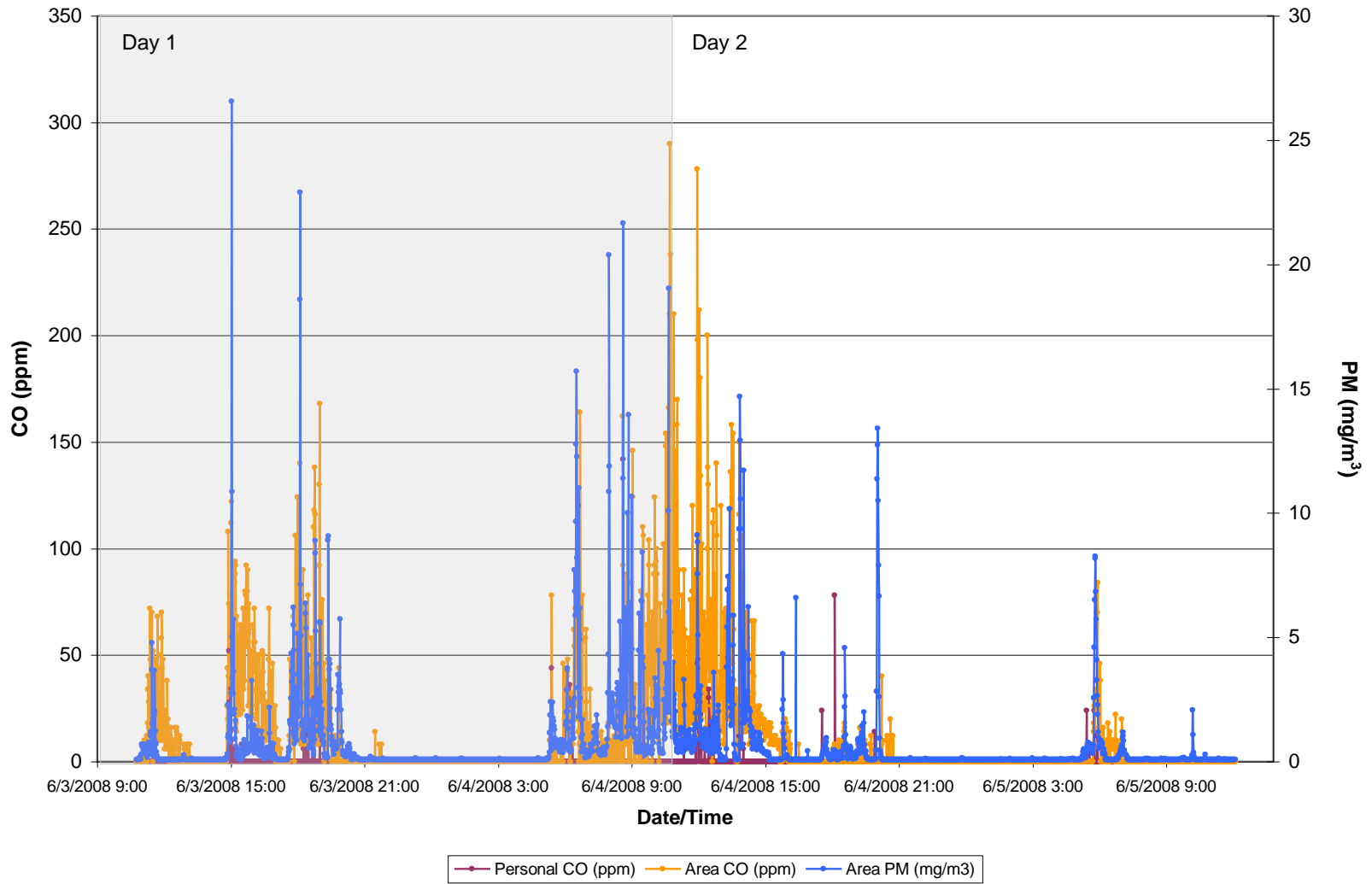
House 28 and Participant Exposure Data



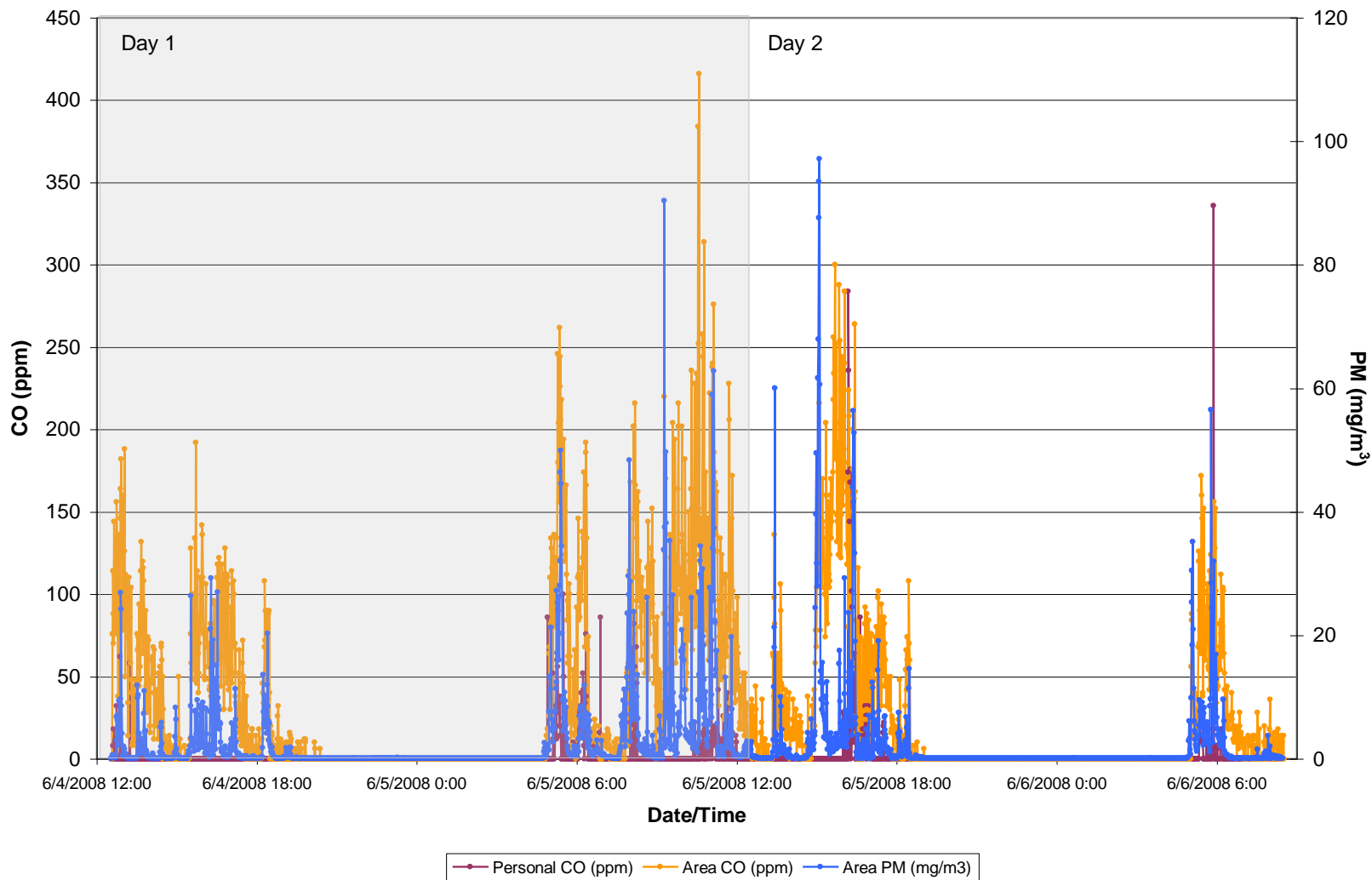
House 29 and Participant Exposure Data (PM Data N/A)



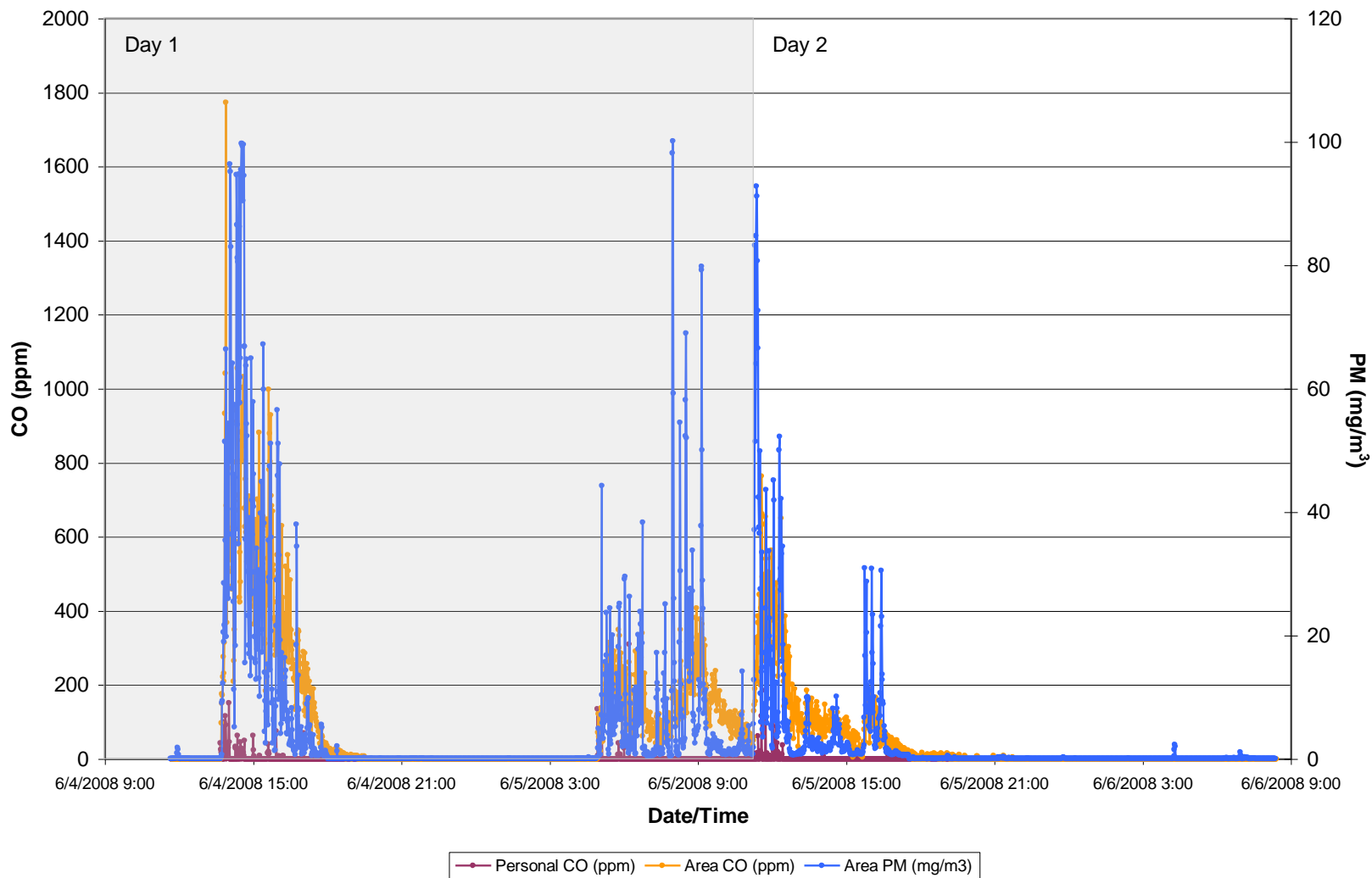
House 30 and Participant Exposure Data



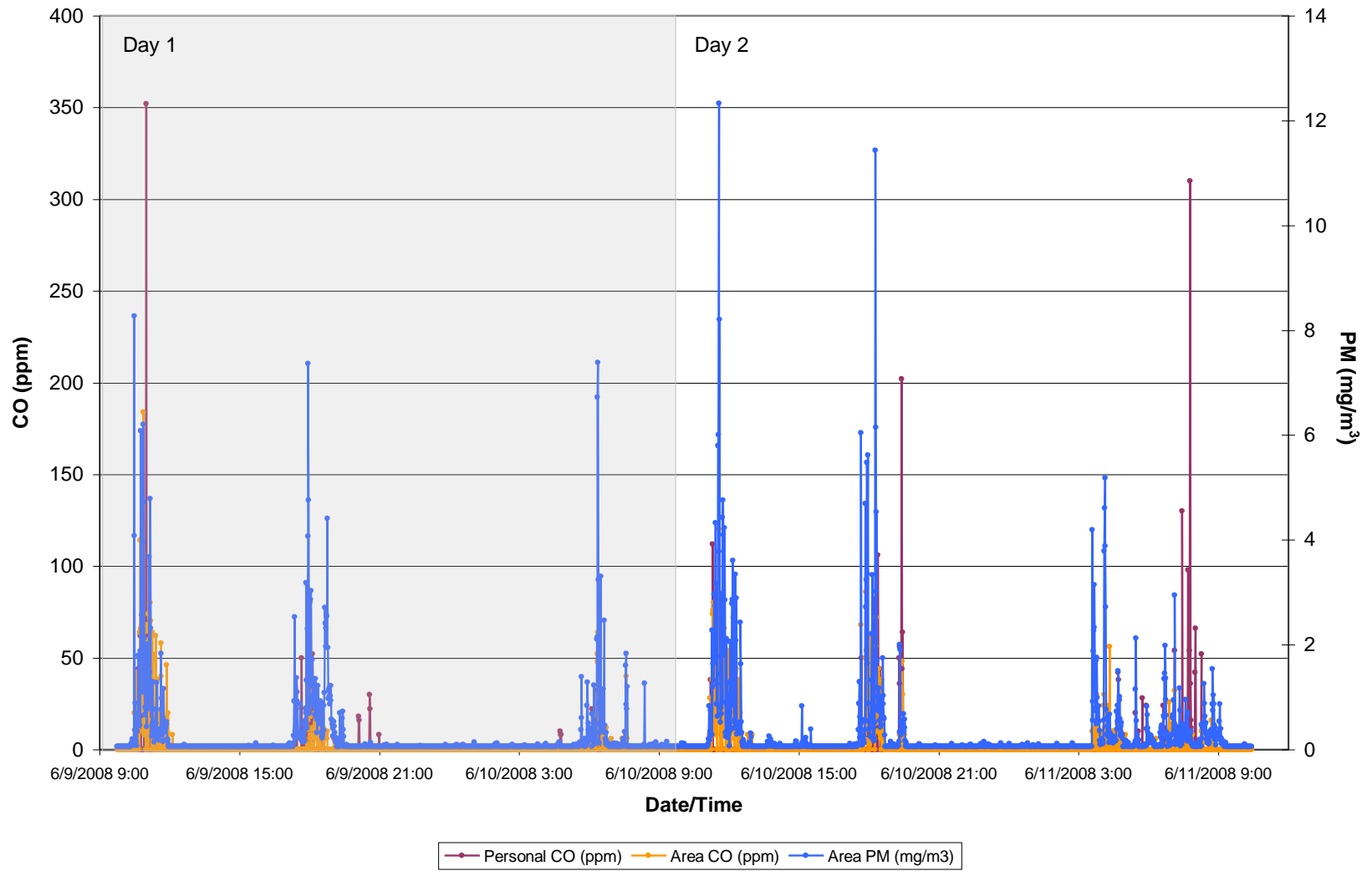
House 31 and Participant Exposure Data



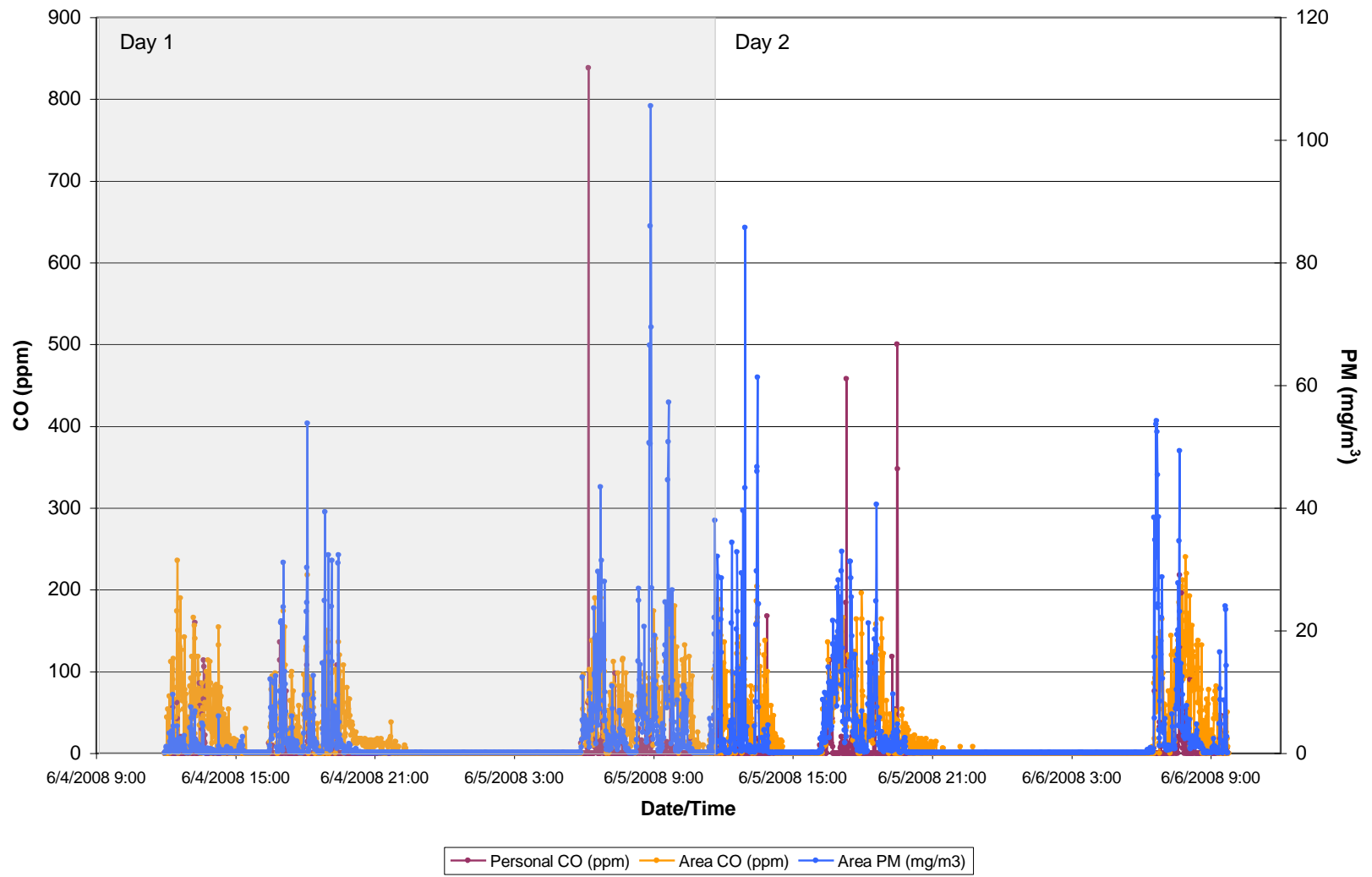
House 32 and Participant Exposure Data



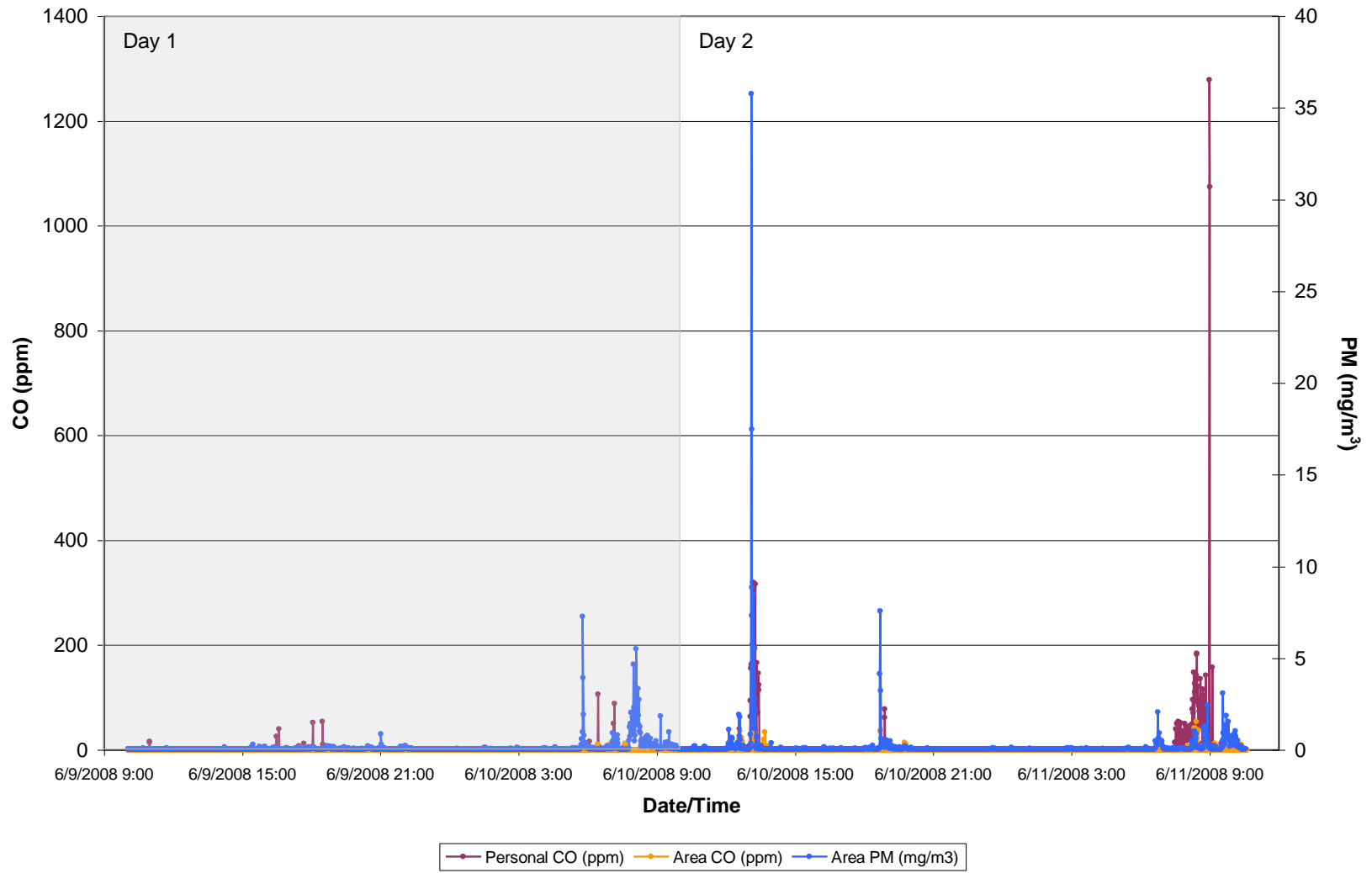
House 33 and Participant Exposure Data



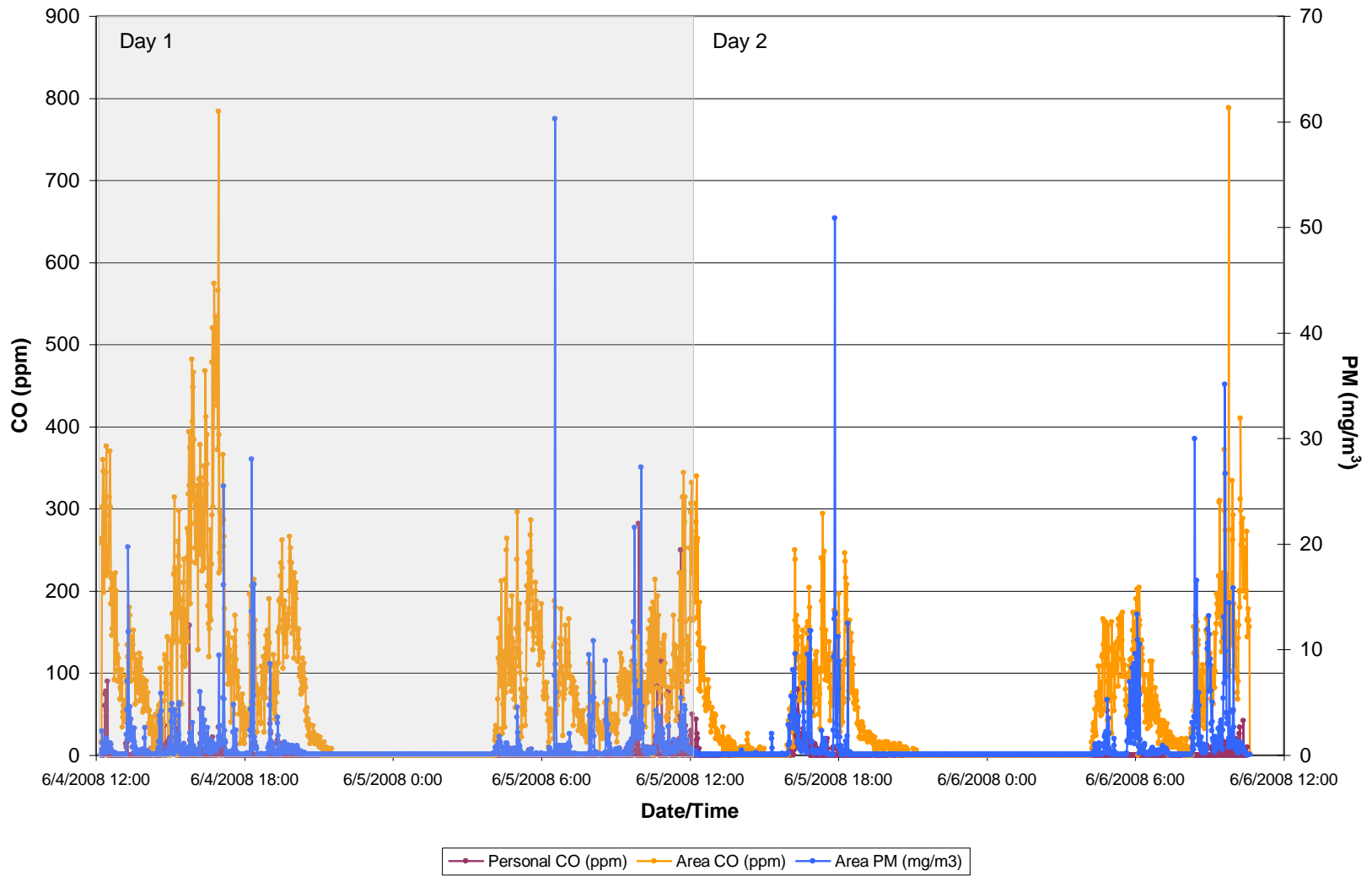
House 34 and Participant Exposure Data



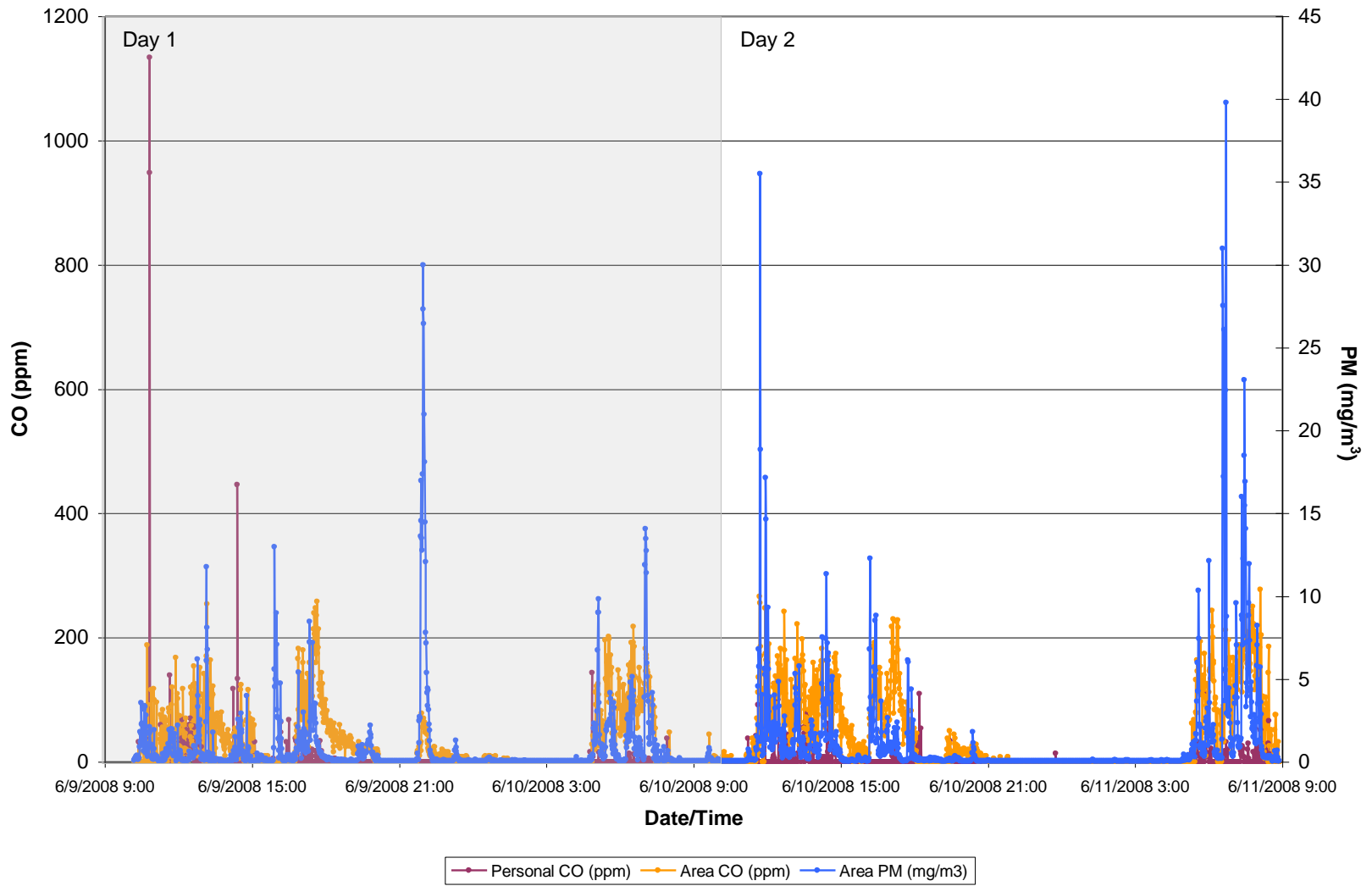
House 35 and Participant Exposure Data



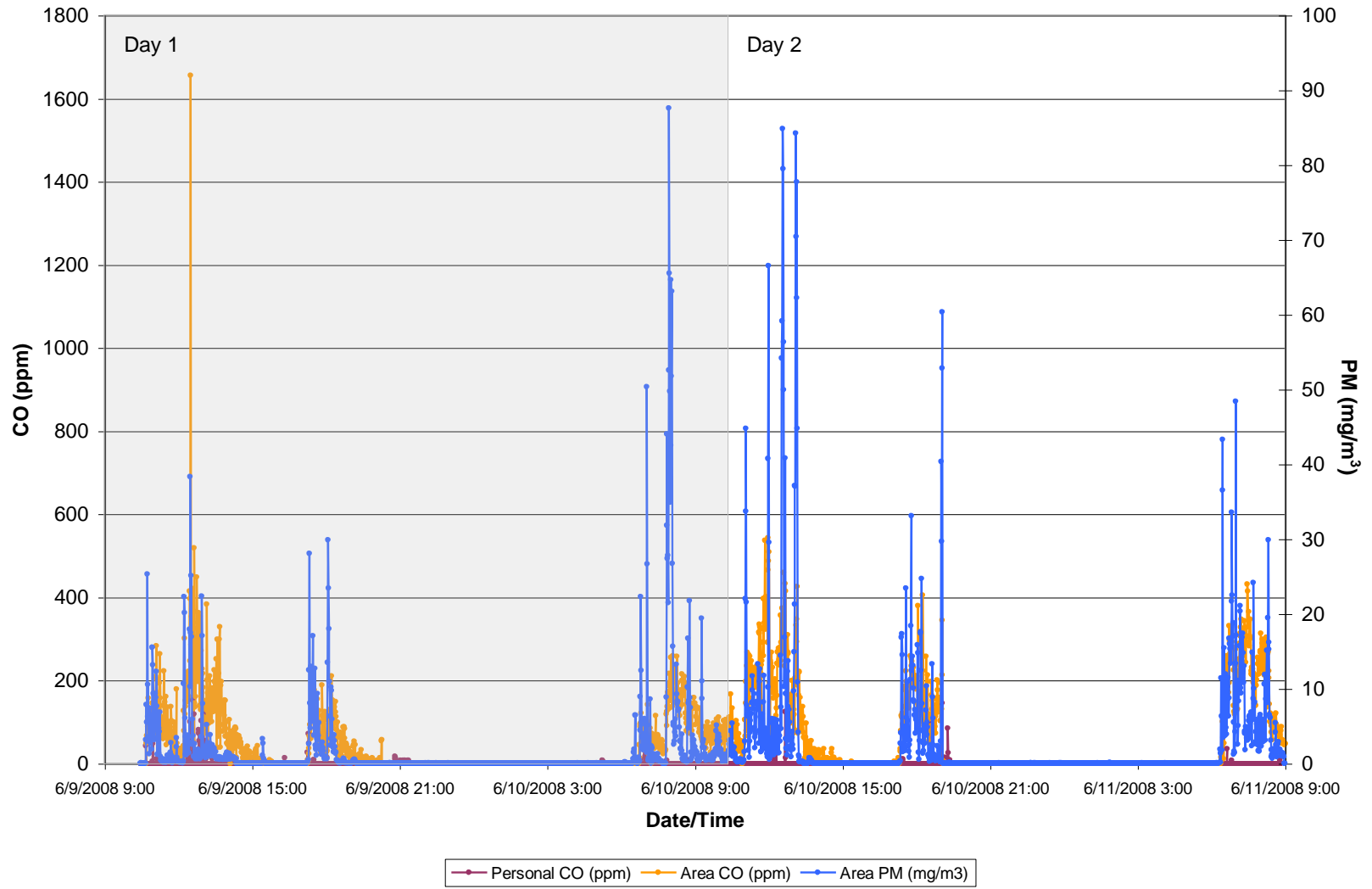
House 36 and Participant Exposure Data



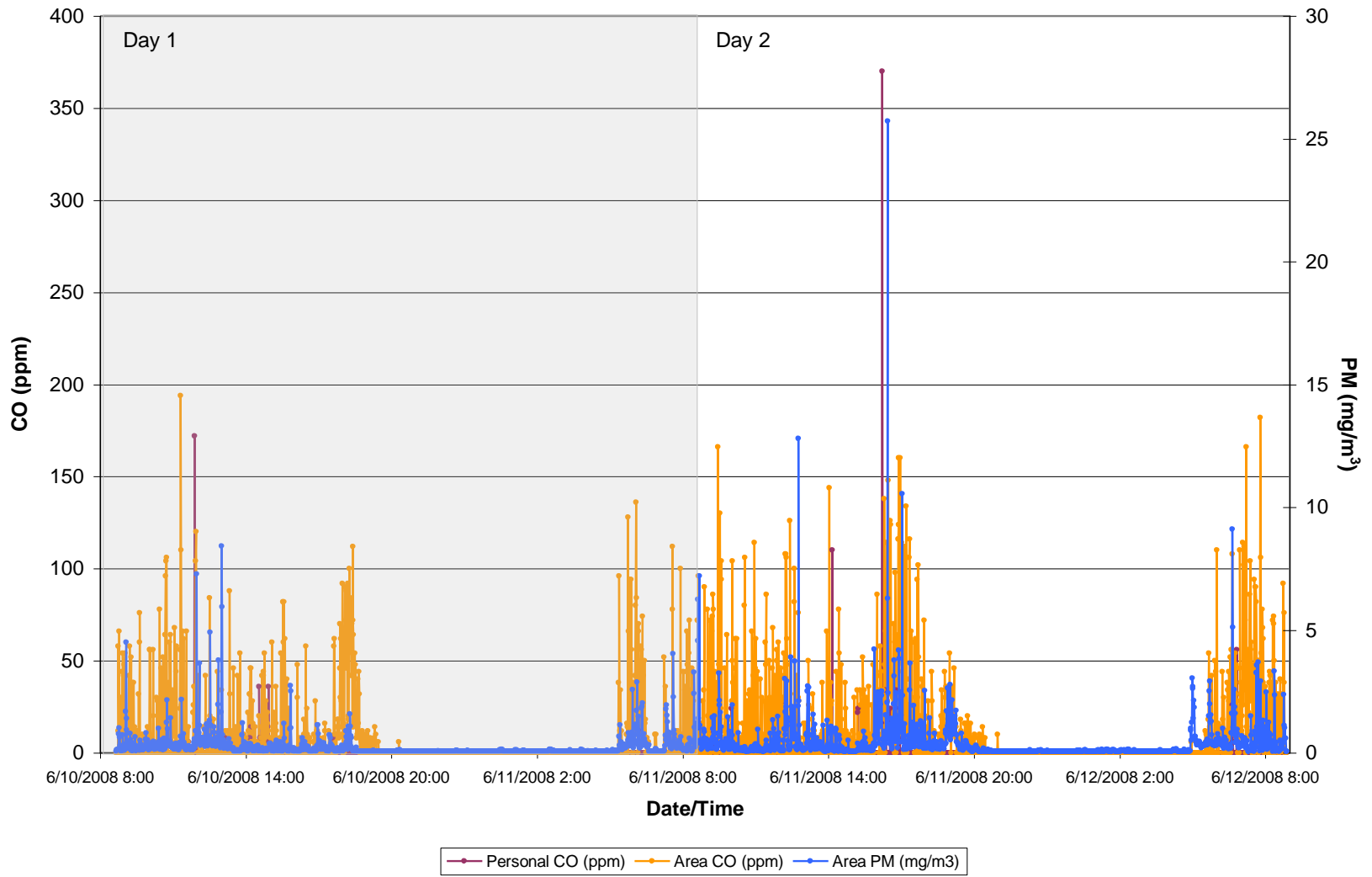
House 37 and Participant Exposure Data



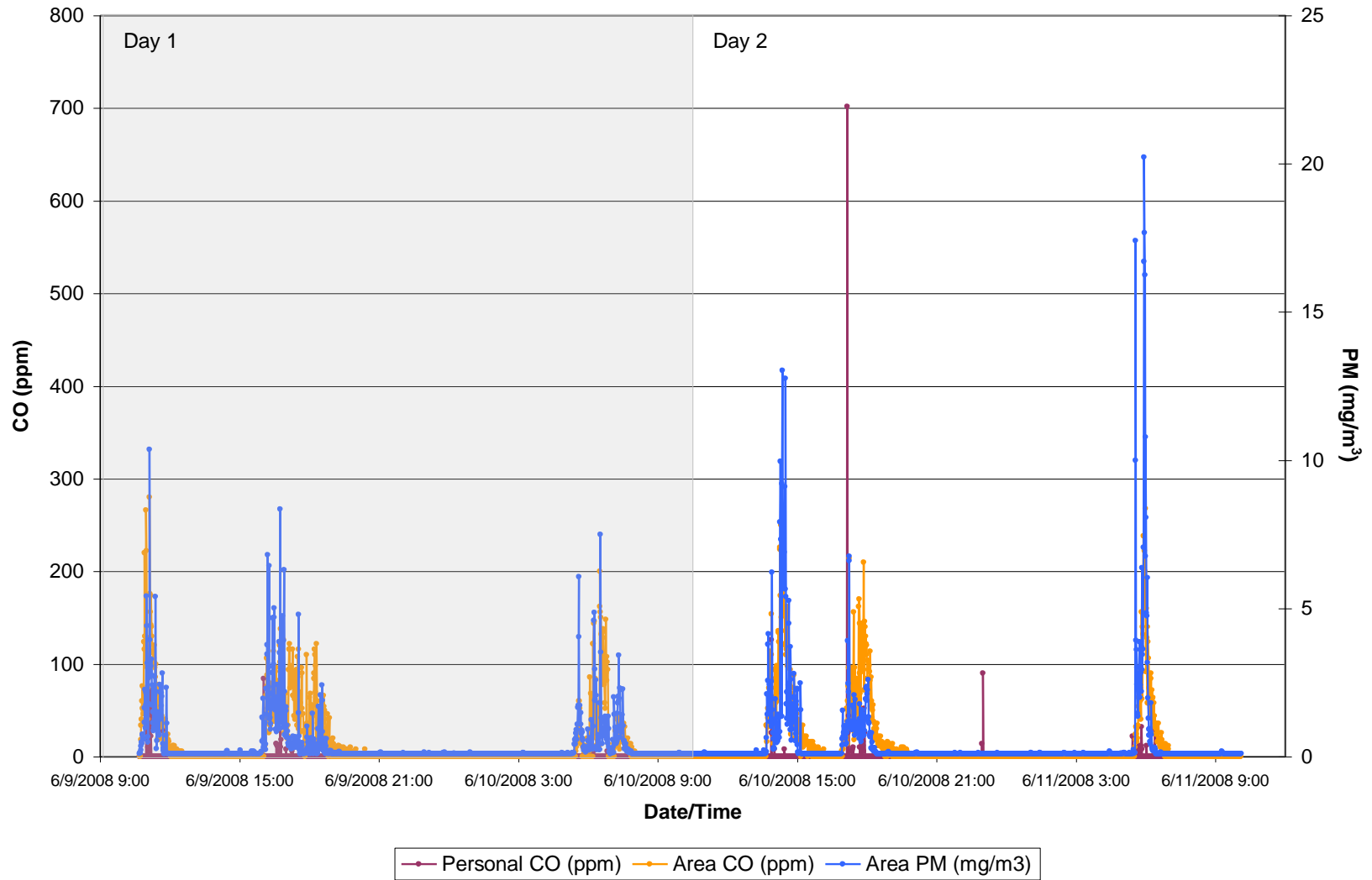
House 38 and Participant Exposure Data



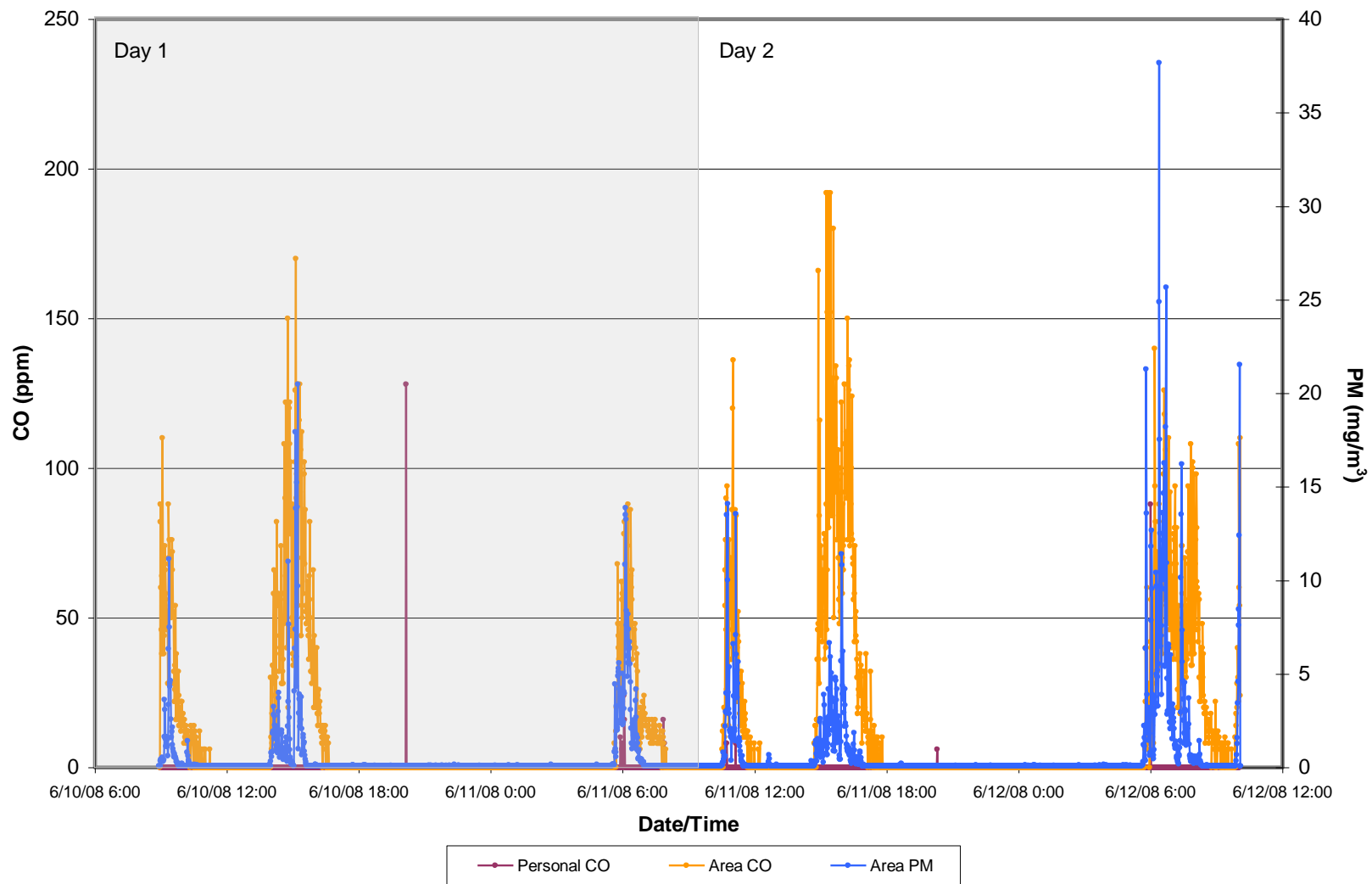
House 39 and Participant Exposure Data



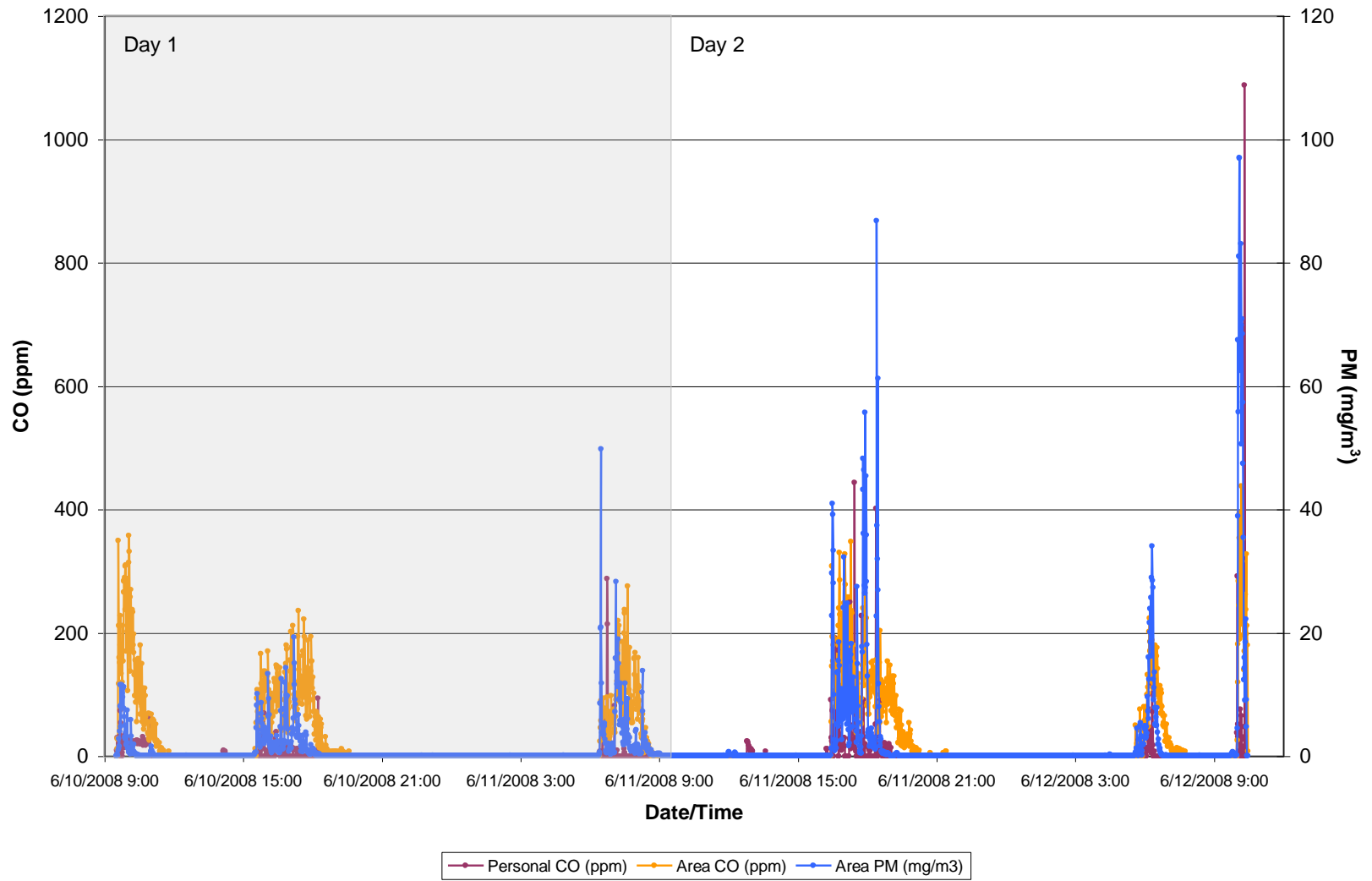
House 40 and Participant Exposure Data



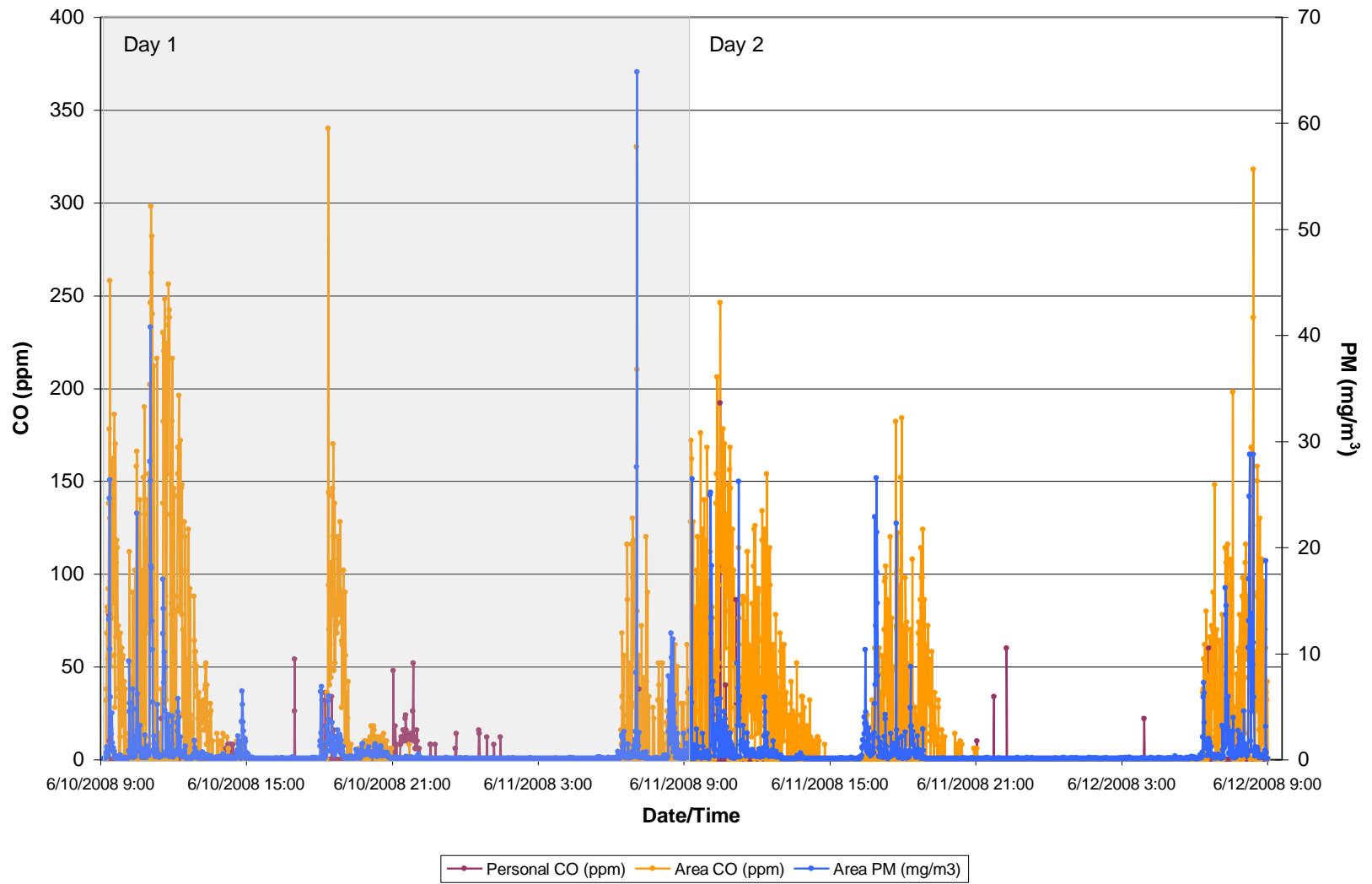
House 41 and Participant Exposure Data



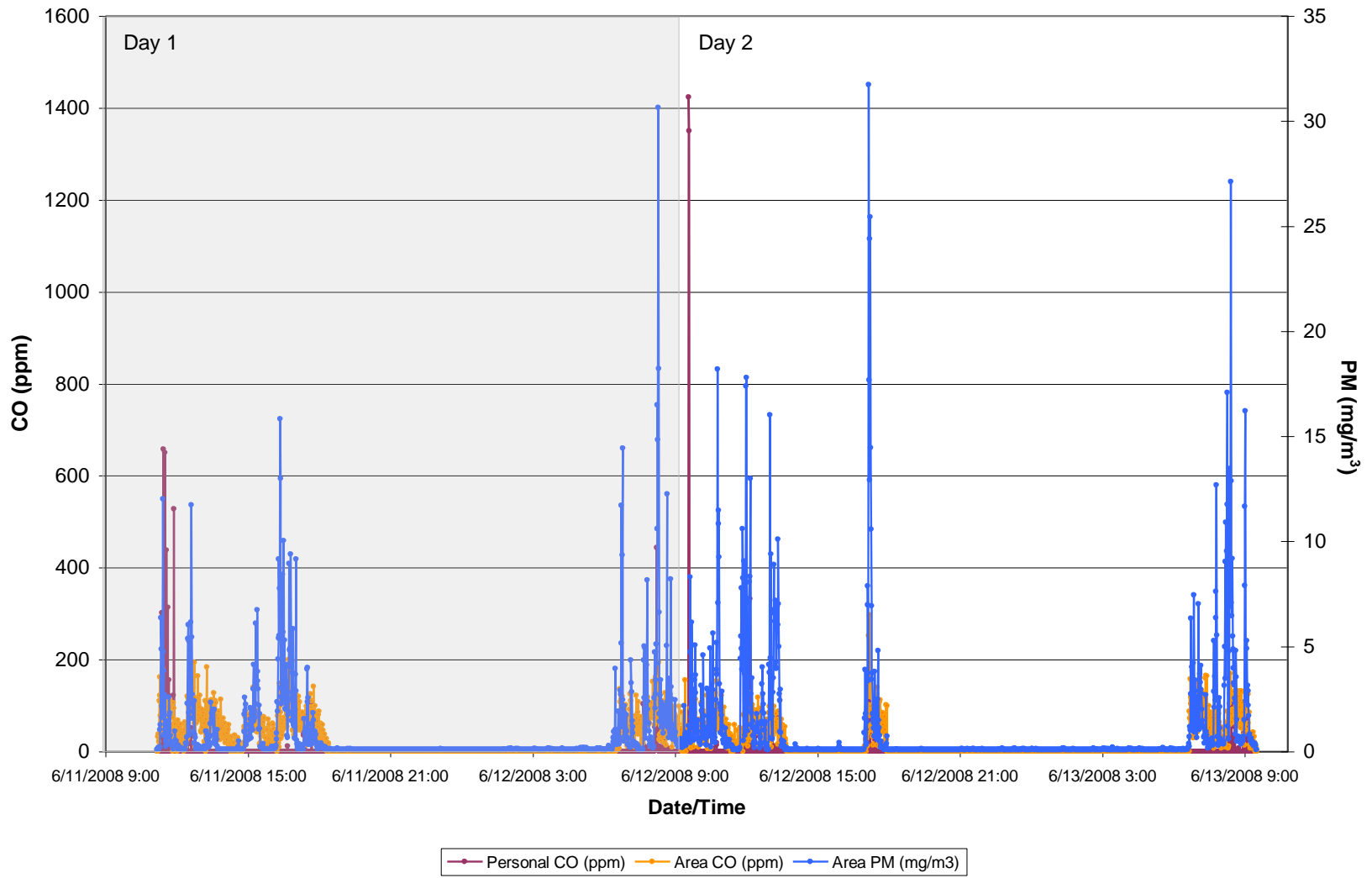
House 42 and Participant Exposure Data



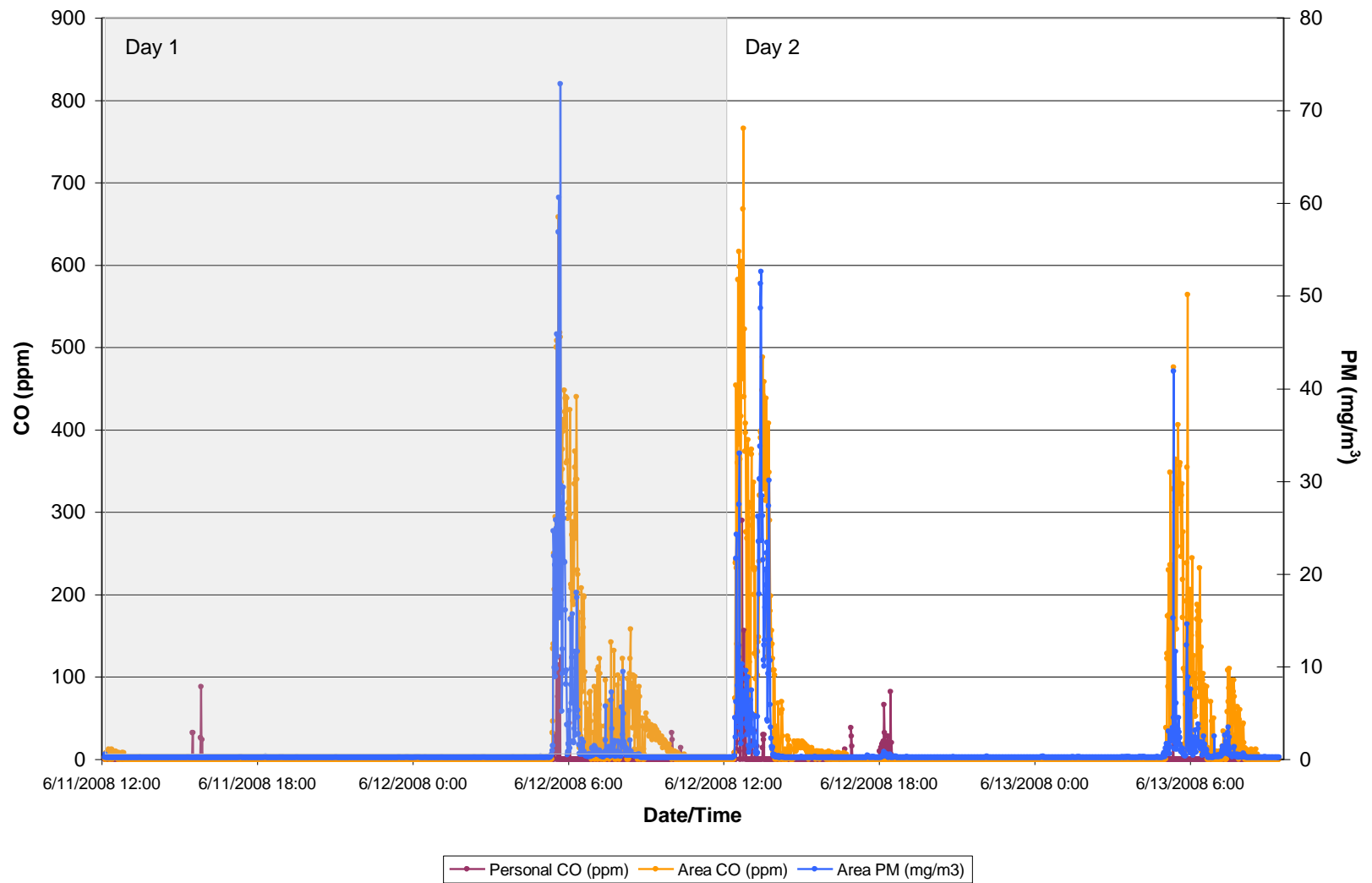
House 43 and Participant Exposure Data



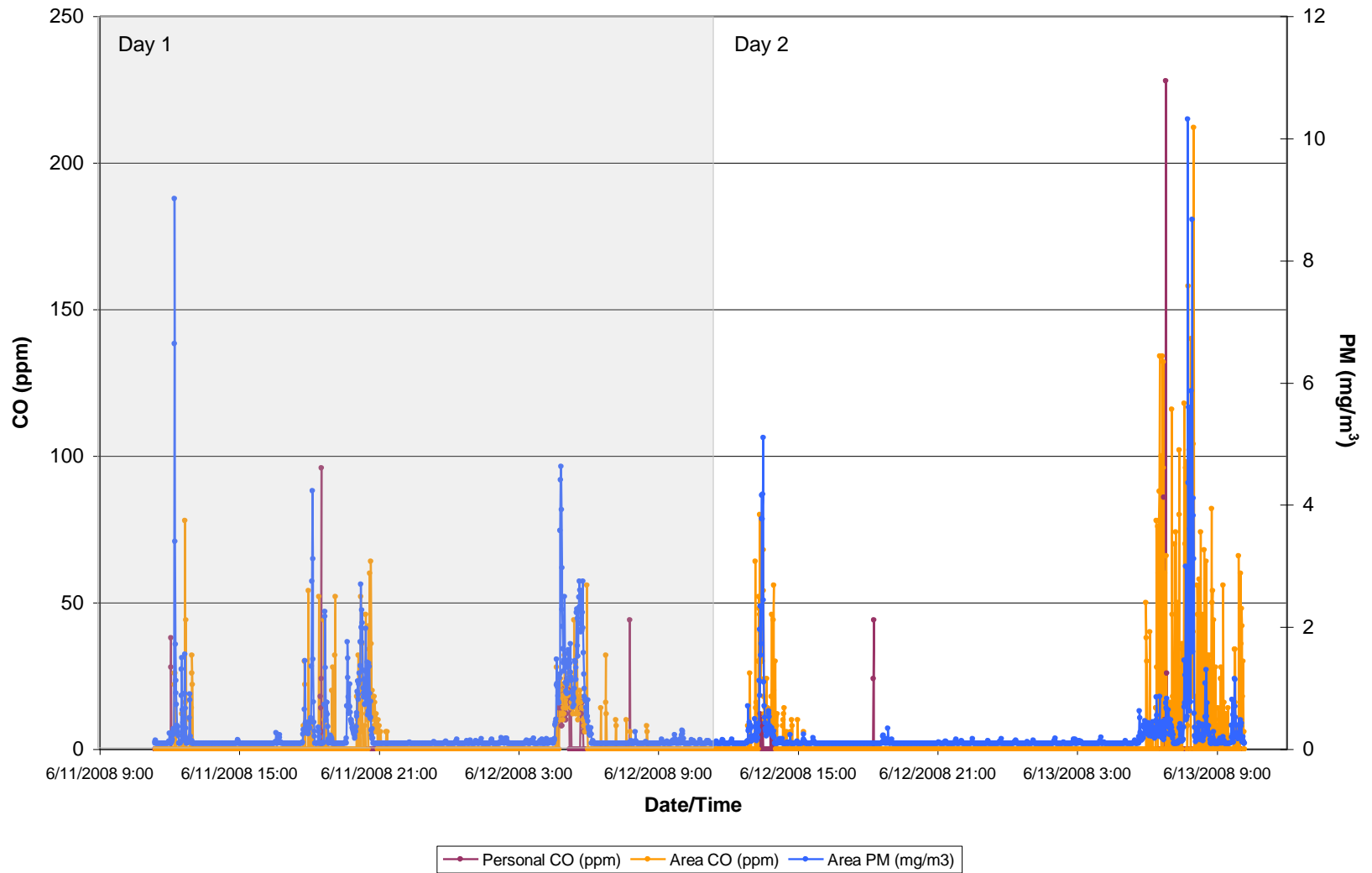
House 44 and Participant Exposure Data



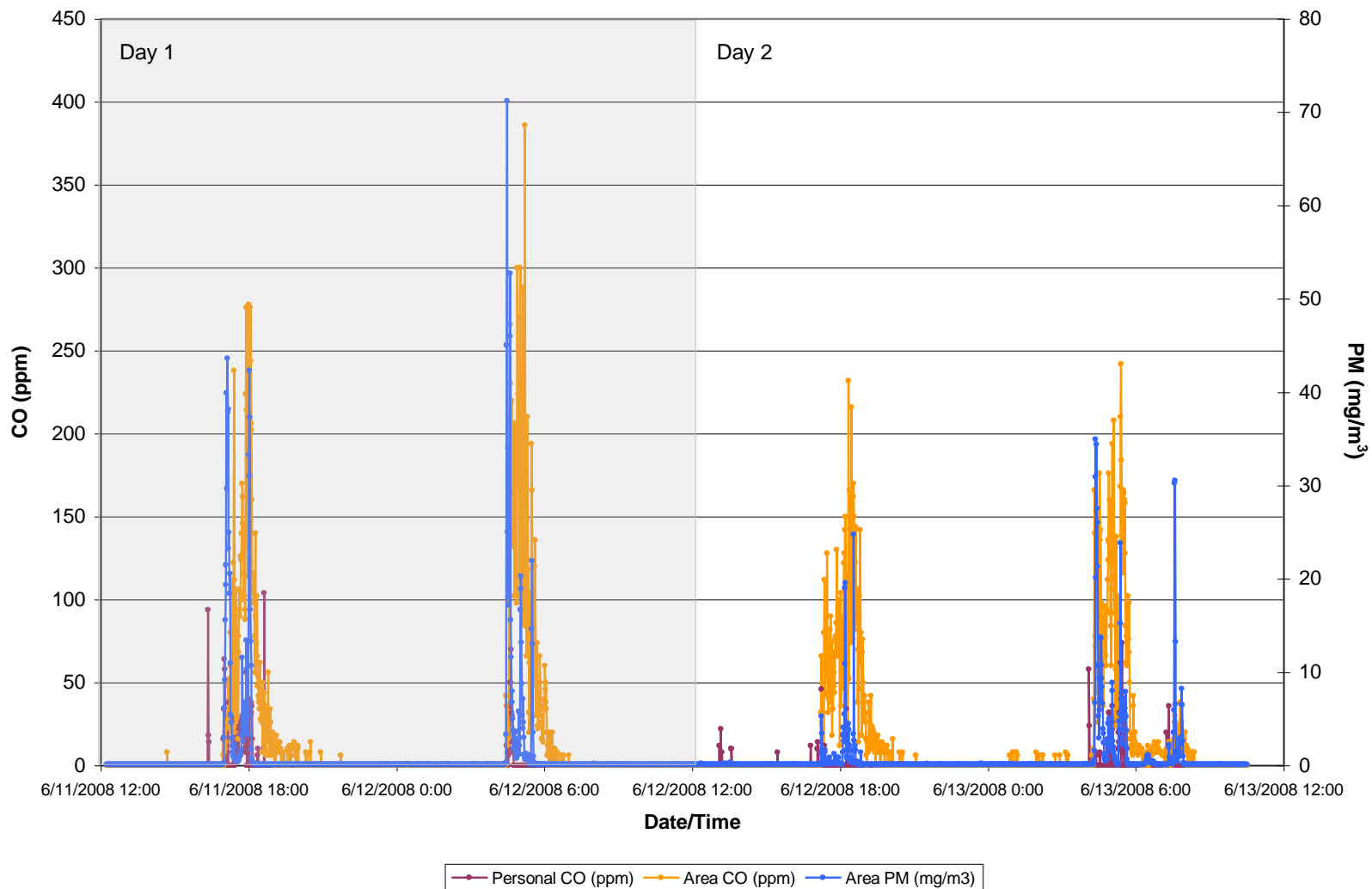
House 45 and Participant Exposure Data



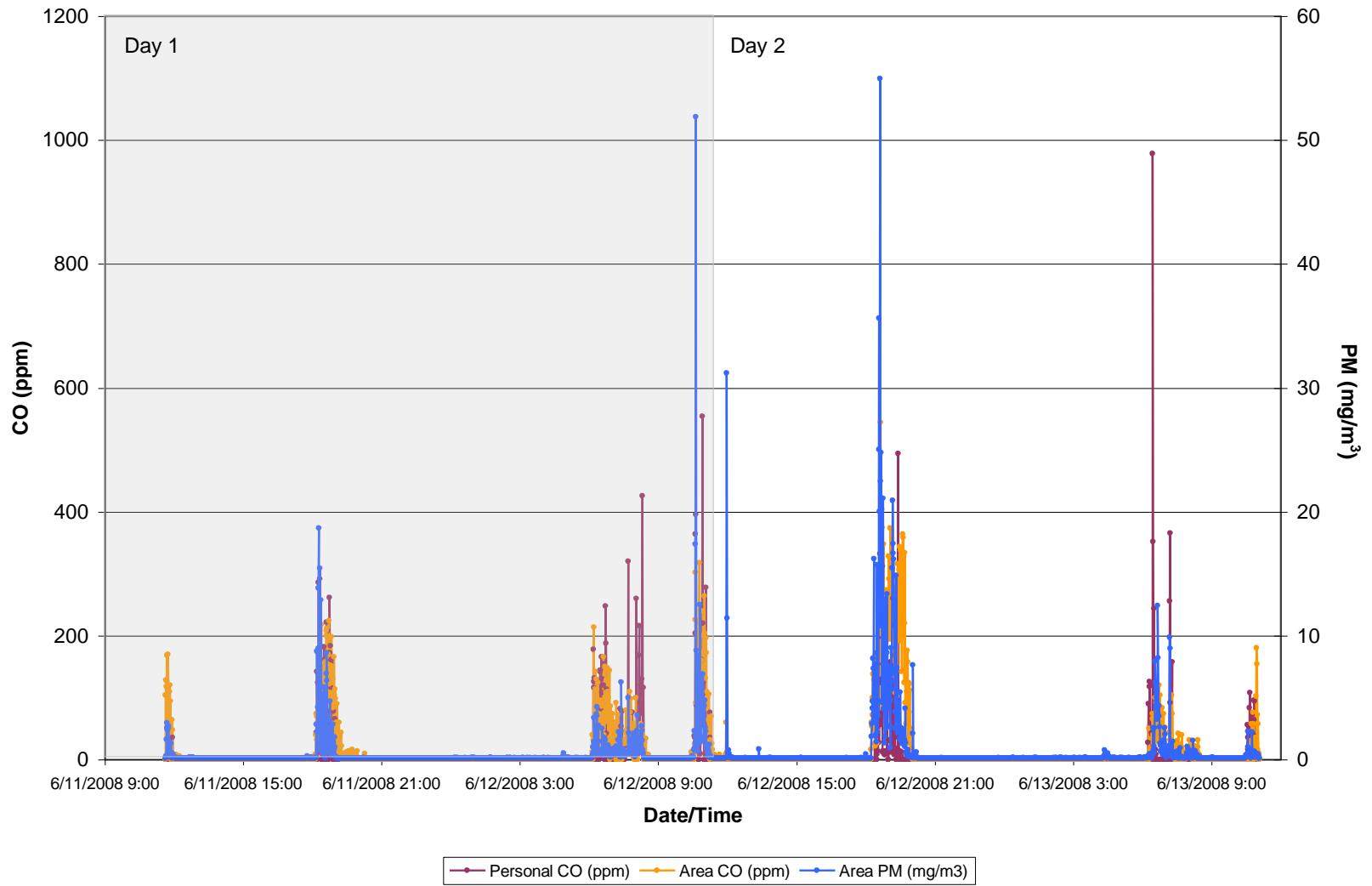
House 46 and Participant Exposure Data



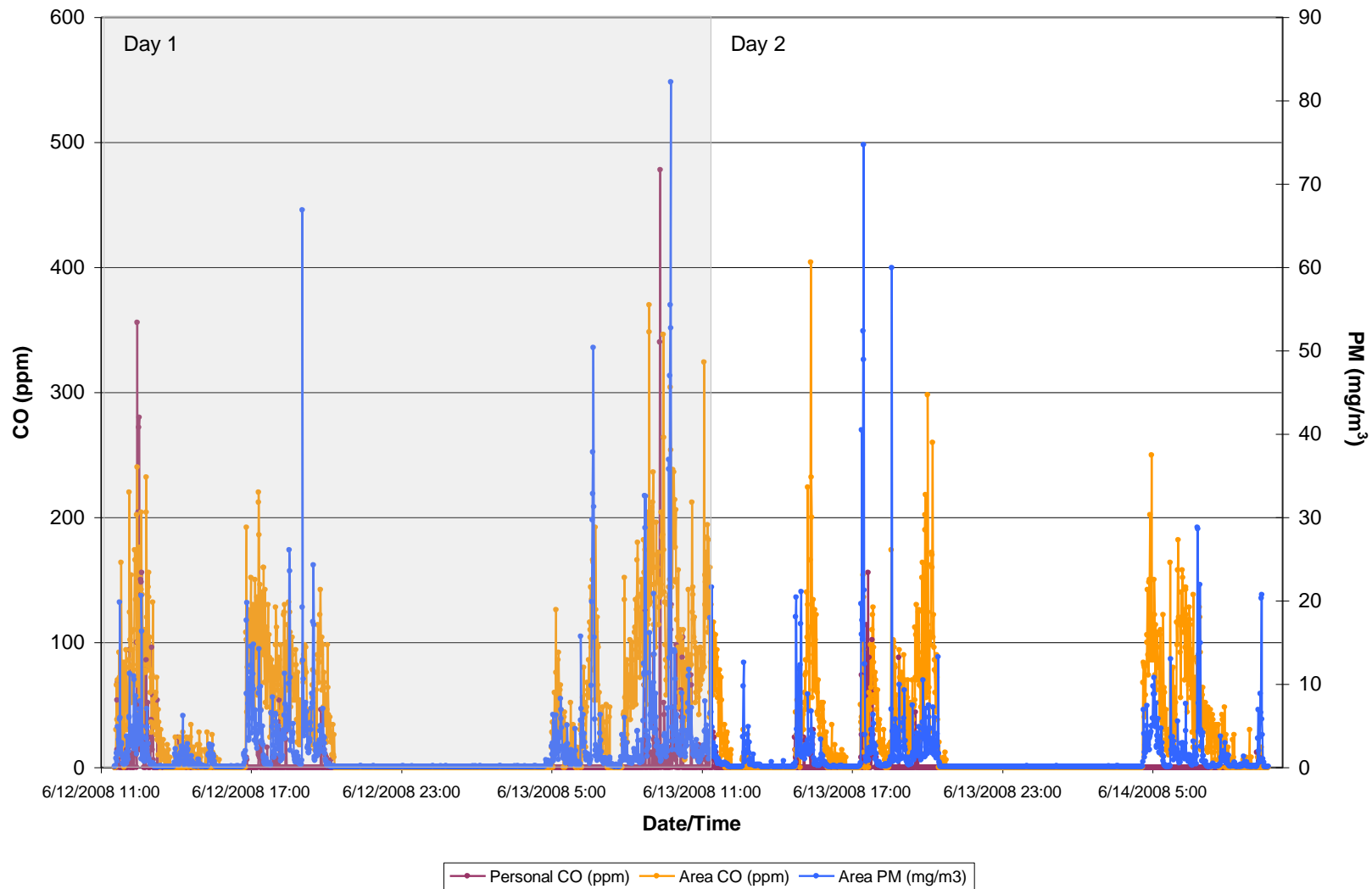
House 47 and Participant Exposure Data



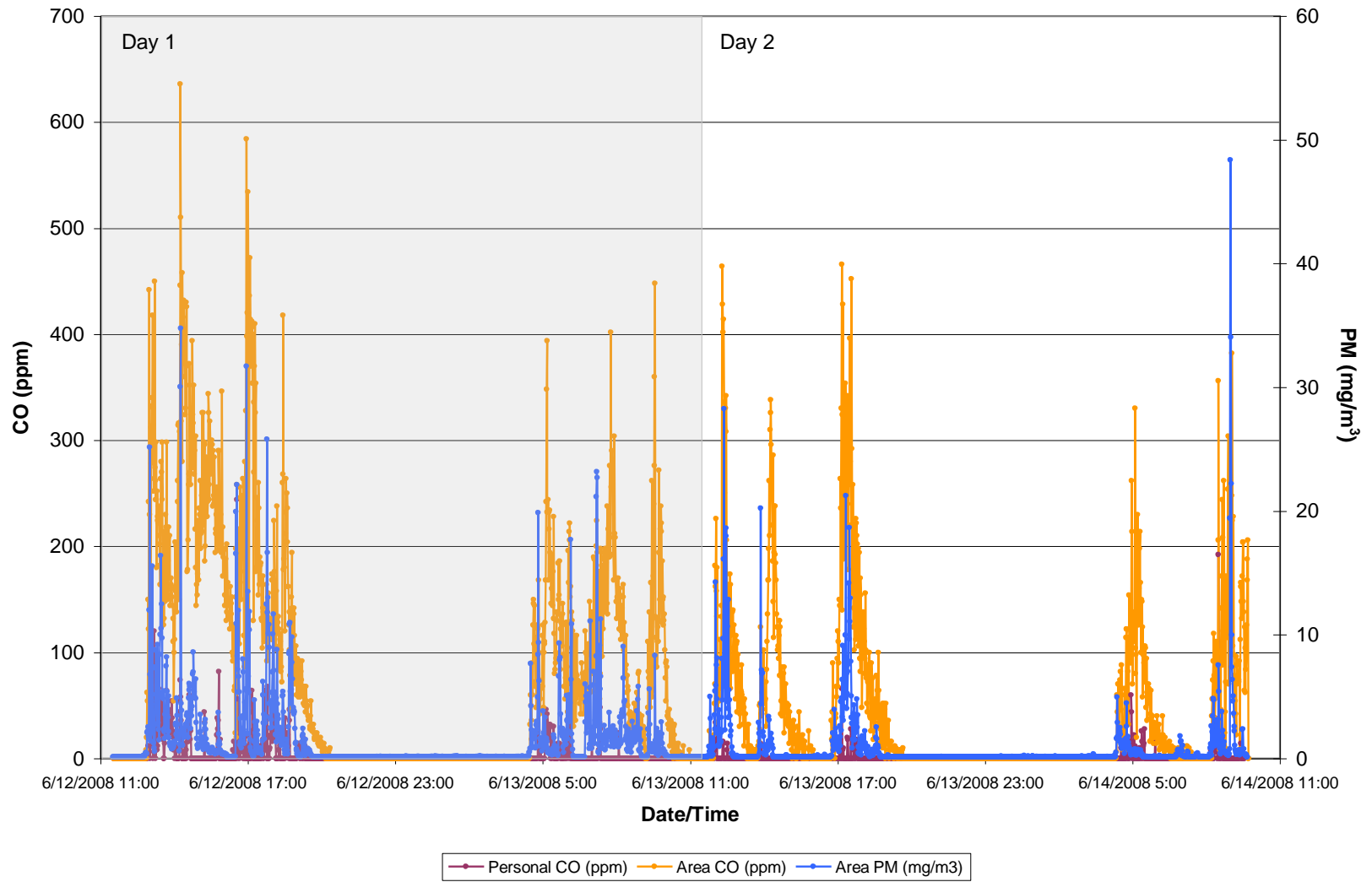
House 48 and Participant Exposure Data



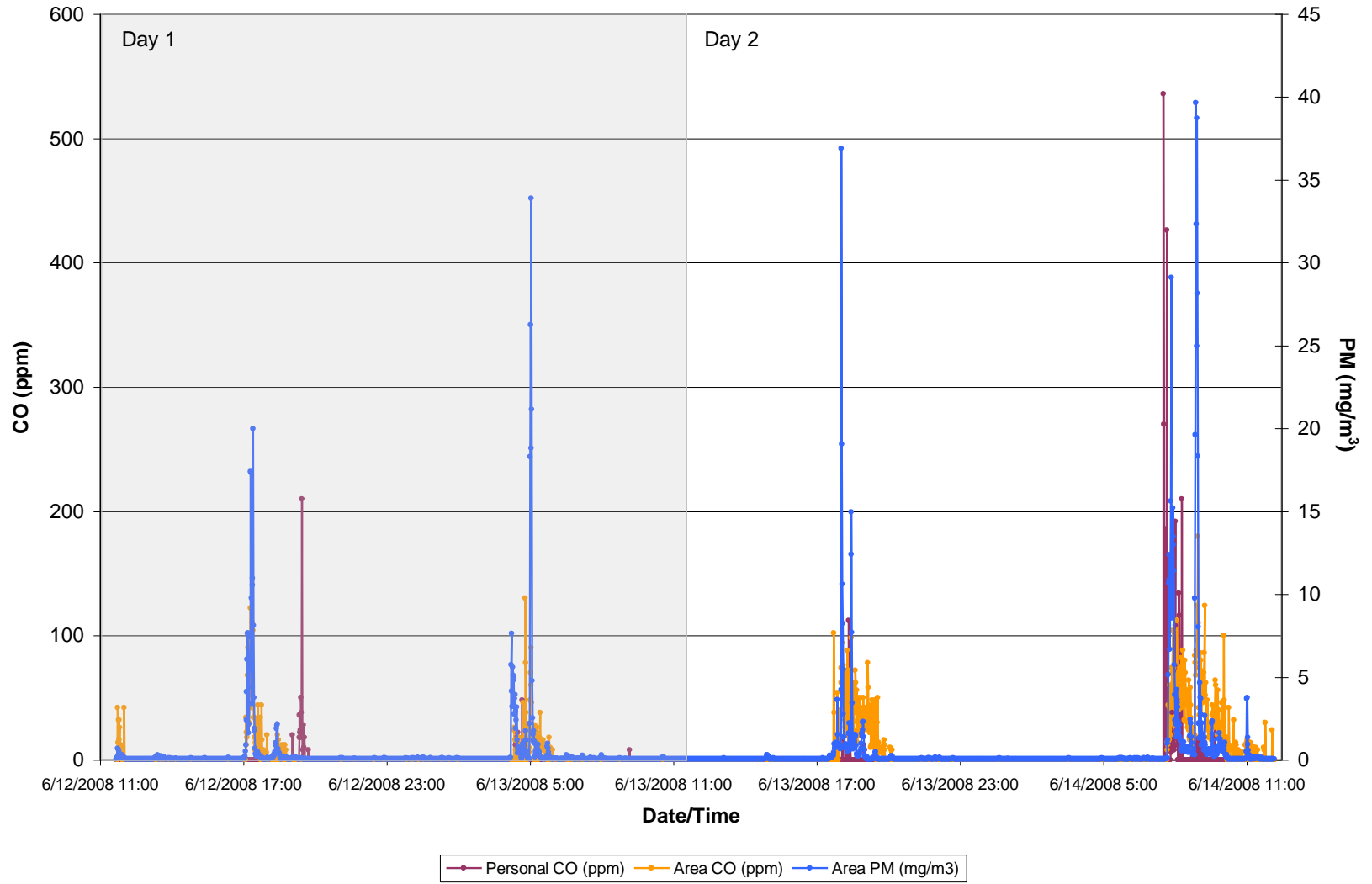
House 49 and Participant Exposure Data



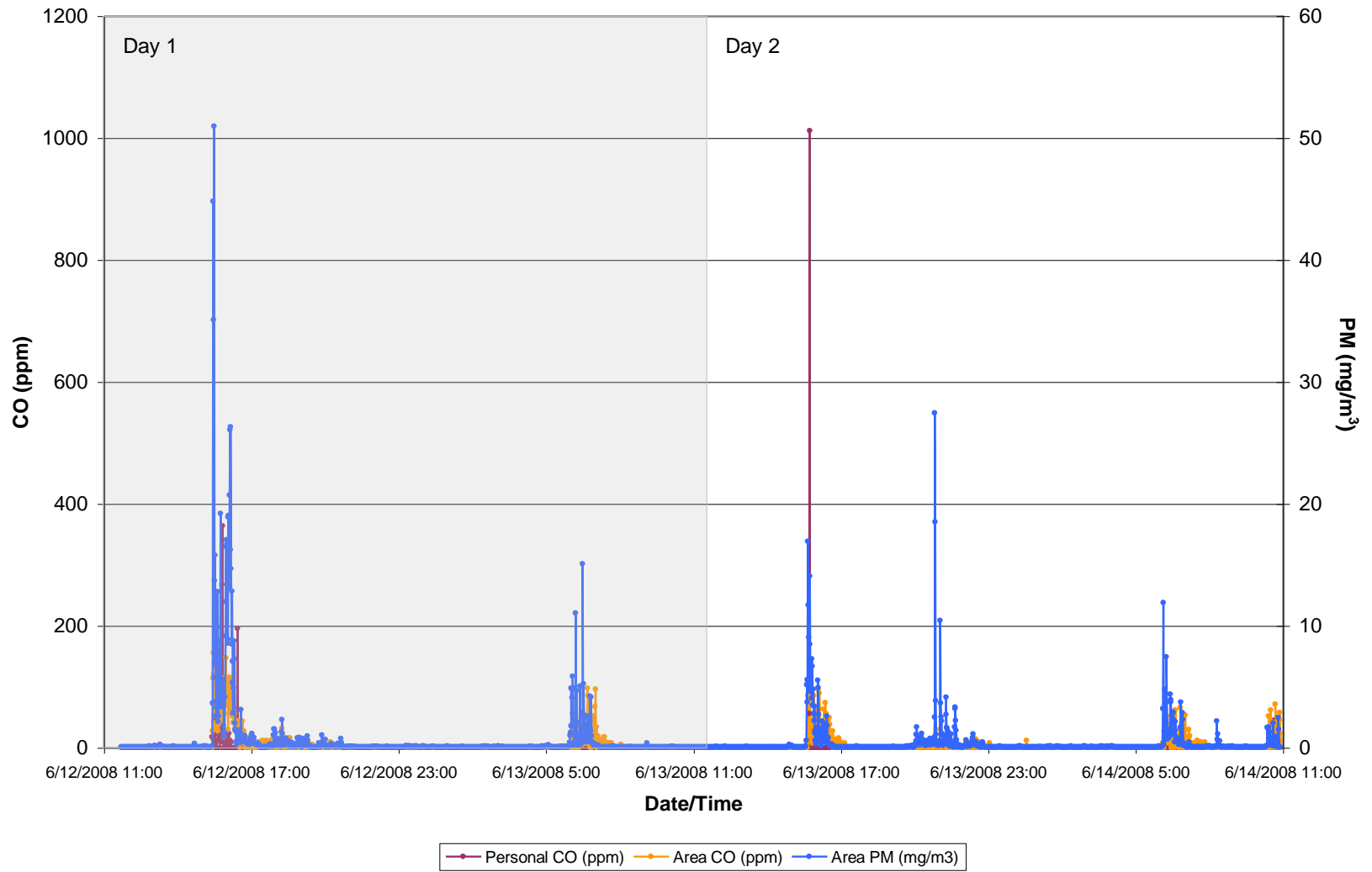
House 50 and Participant Exposure Data



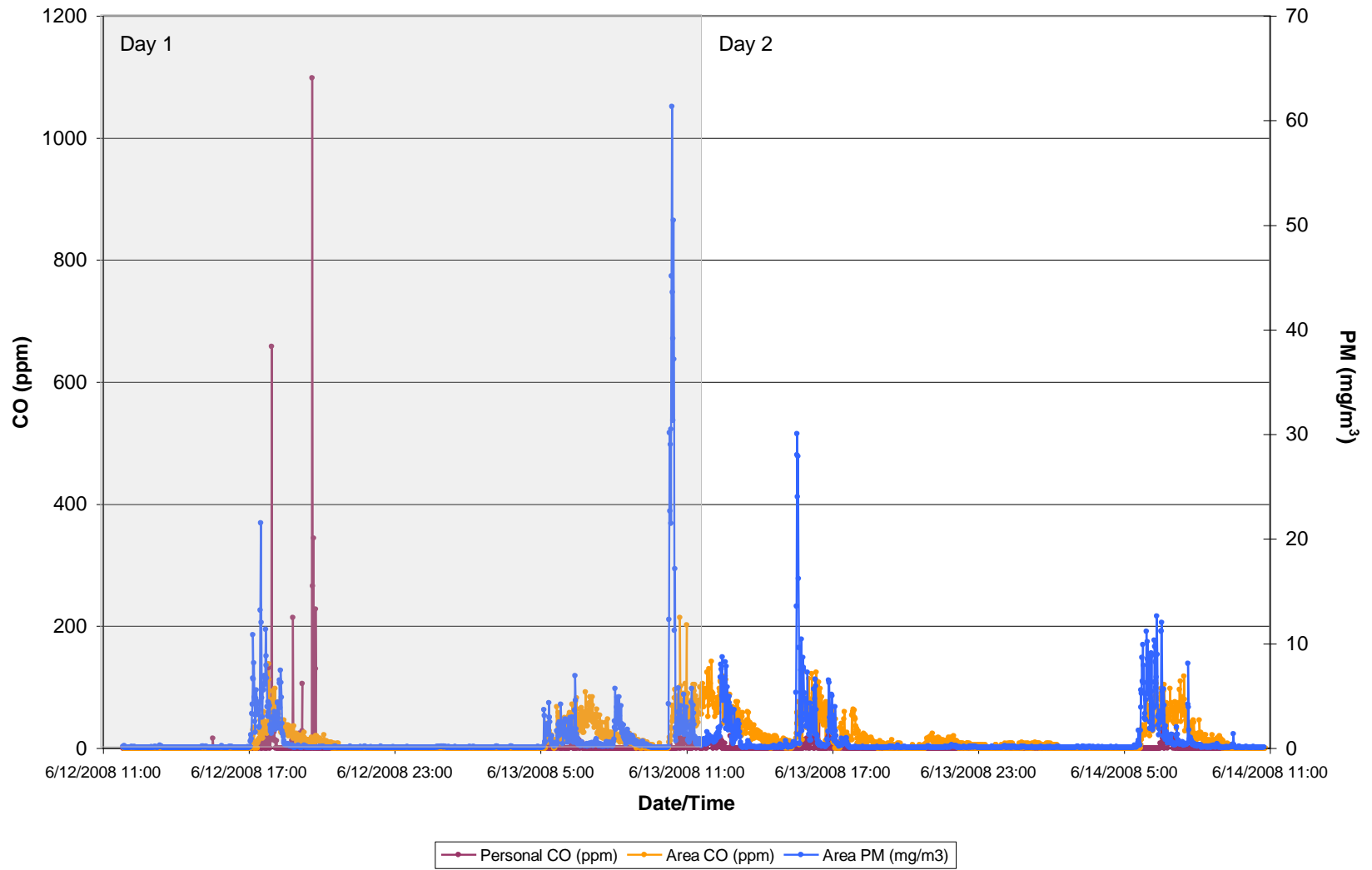
House 51 and Participant Exposure Data



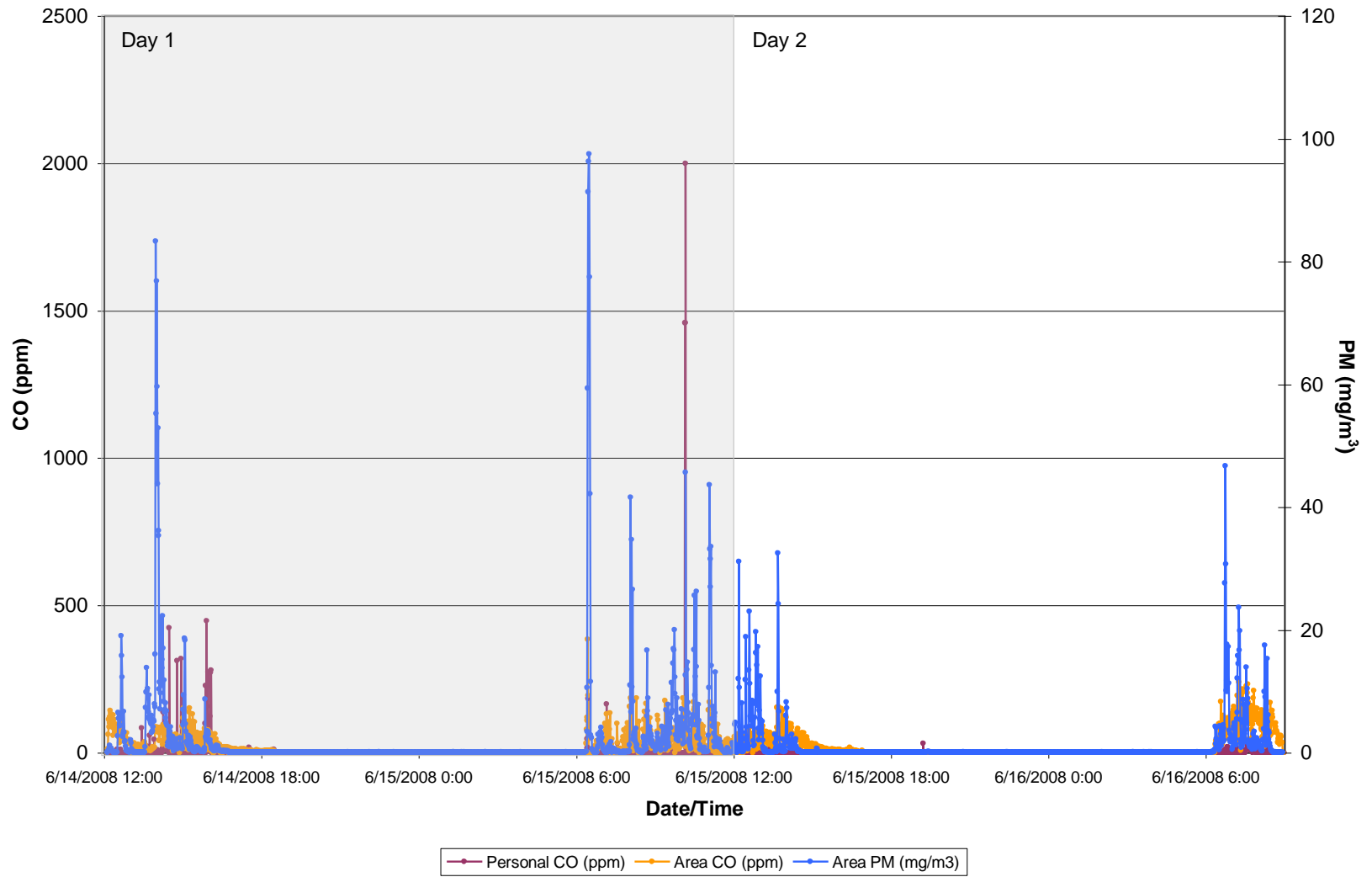
House 52 and Participant Exposure Data



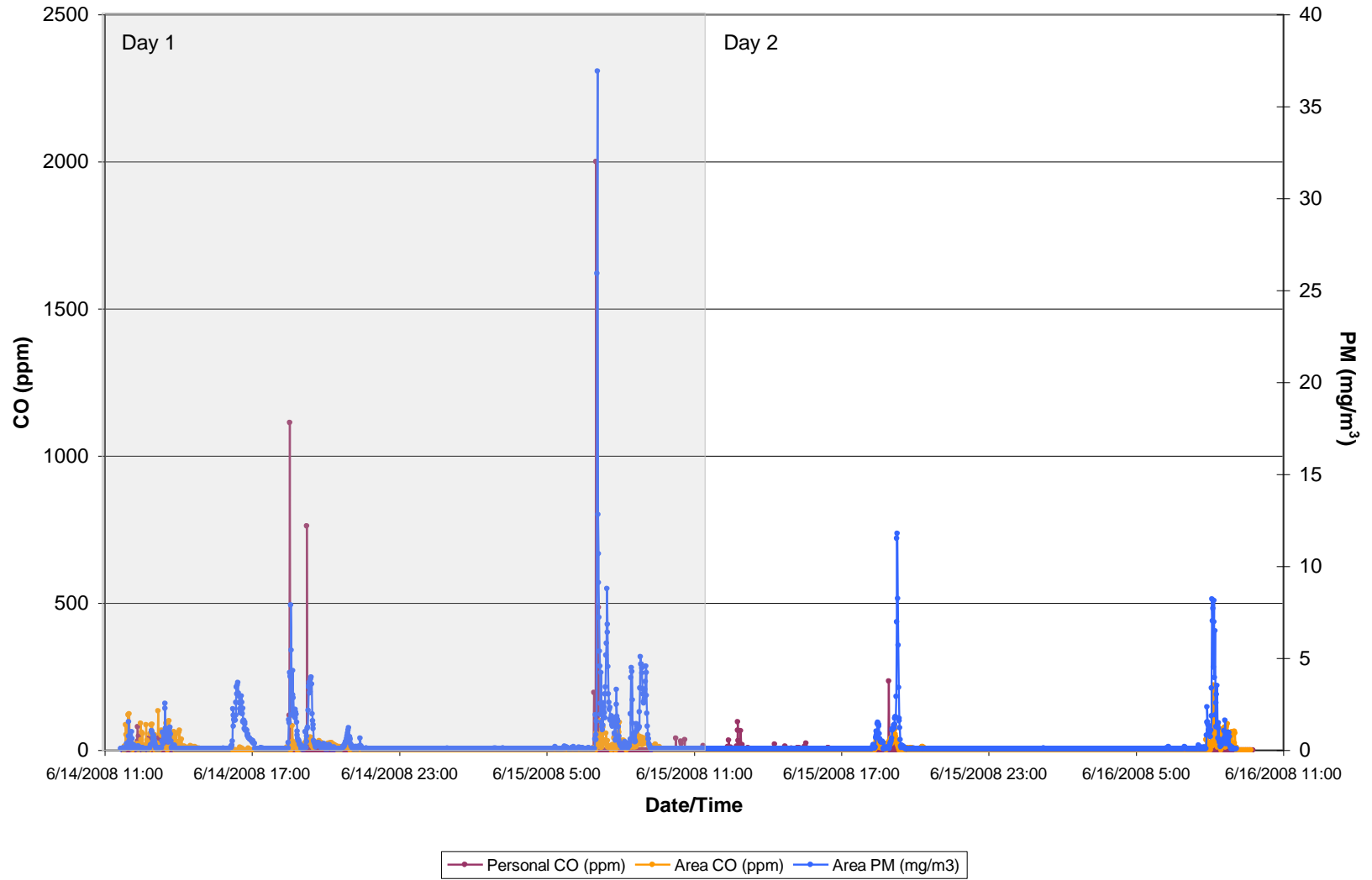
House 53 and Participant Exposure Data



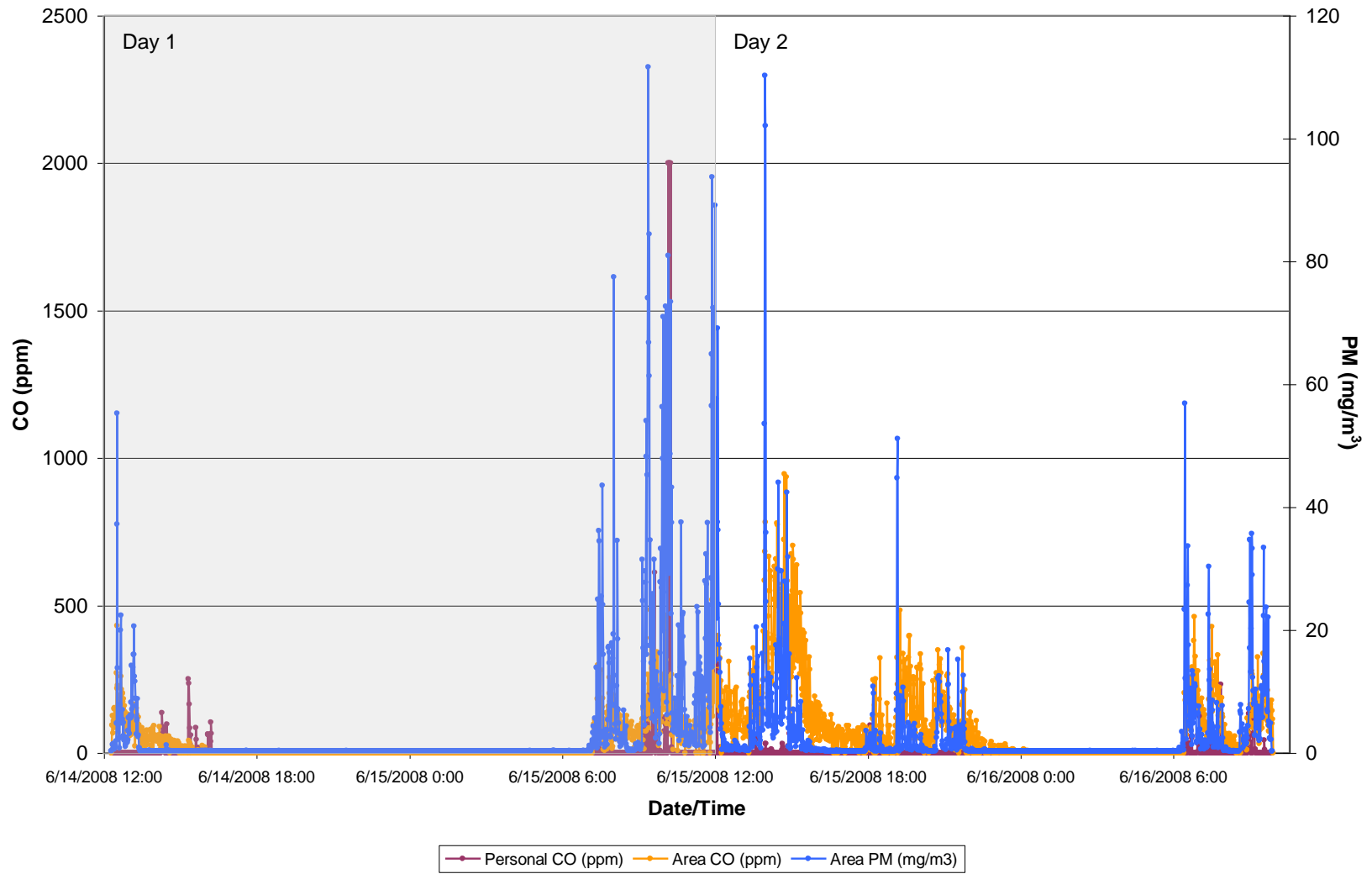
House 54 and Participant Exposure Data



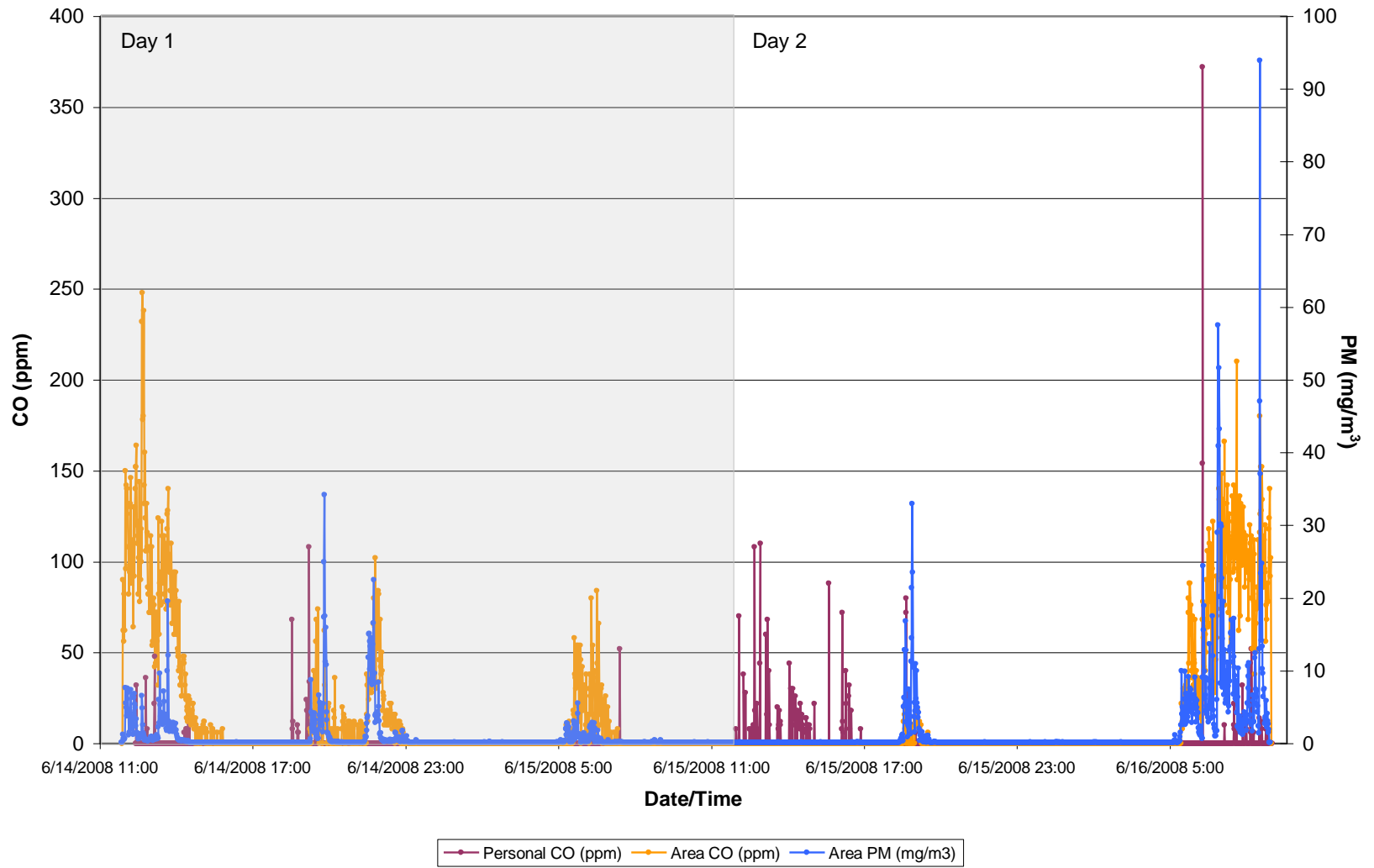
House 55 and Participant Exposure Data



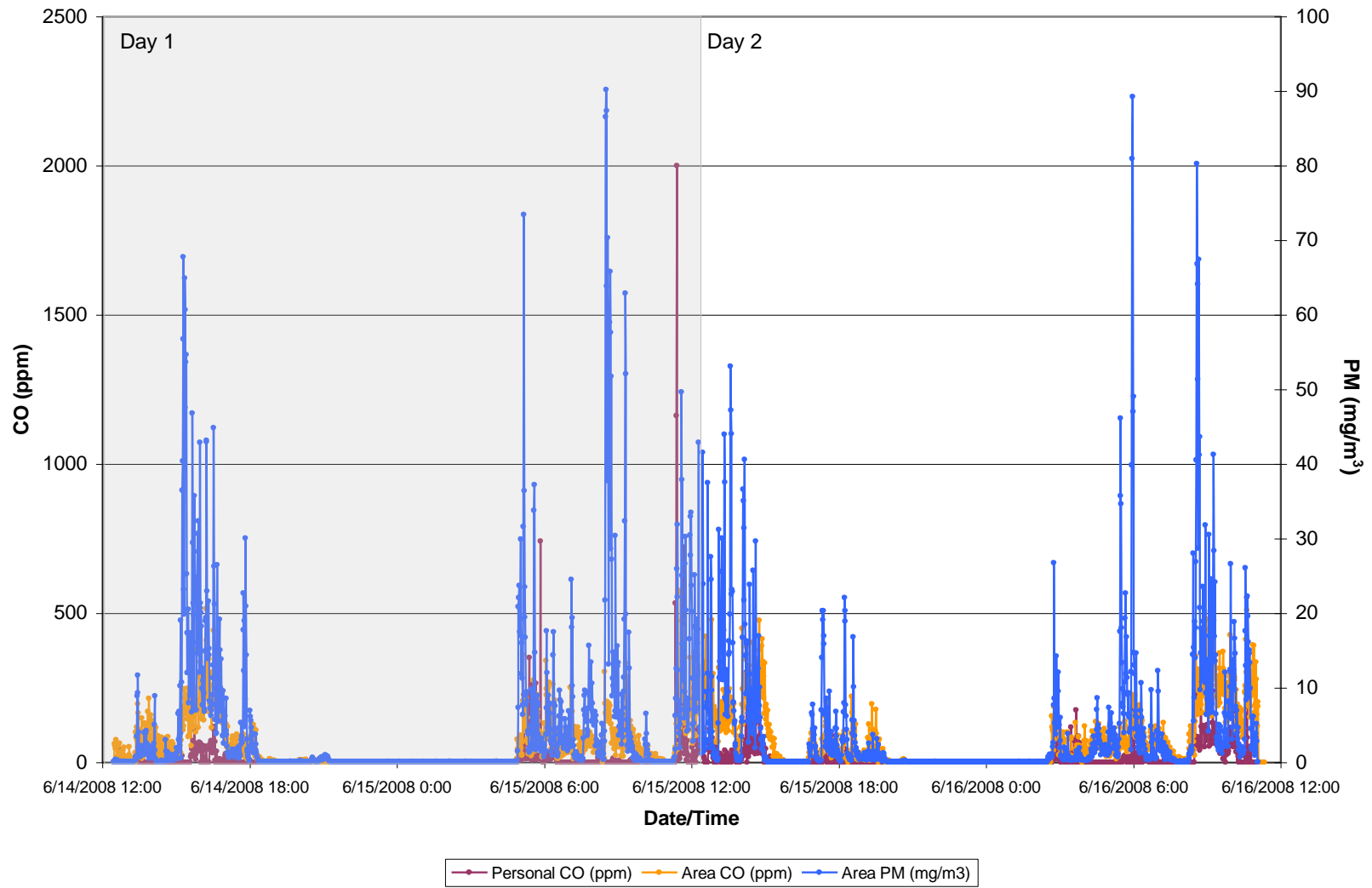
House 56 and Participant Exposure Data



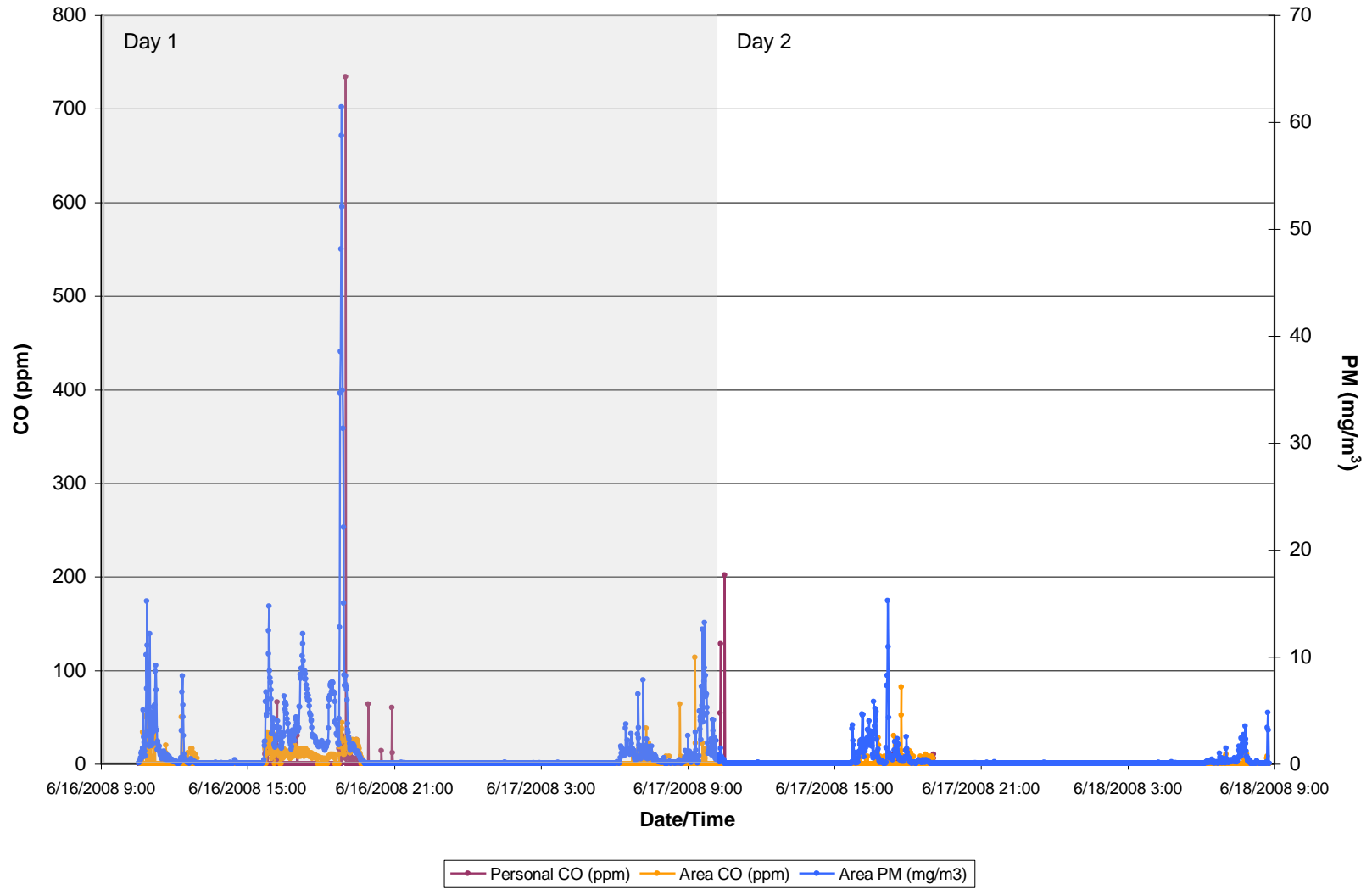
House 57 and Participant Exposure Data



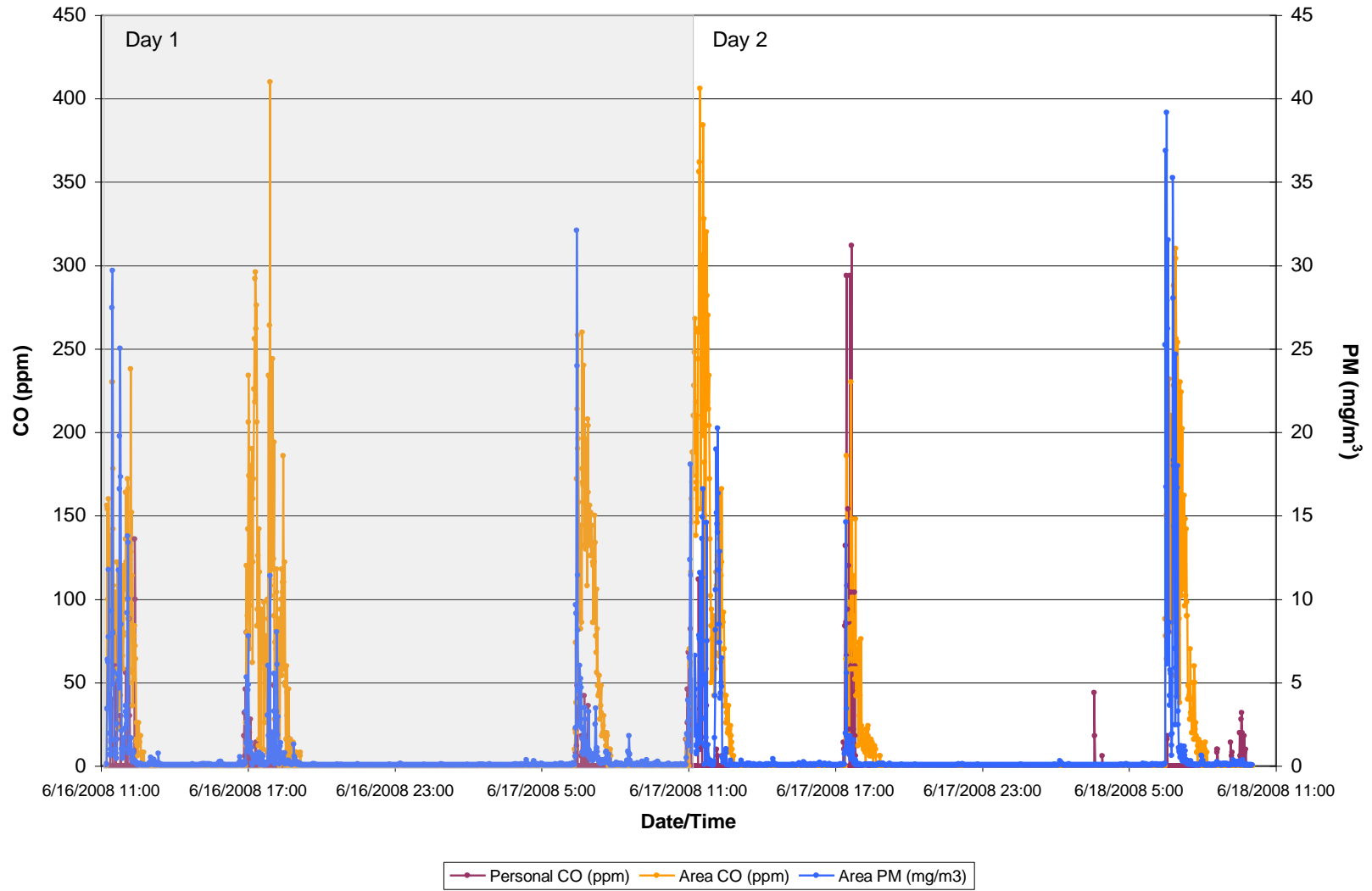
House 58 and Participant Exposure Data



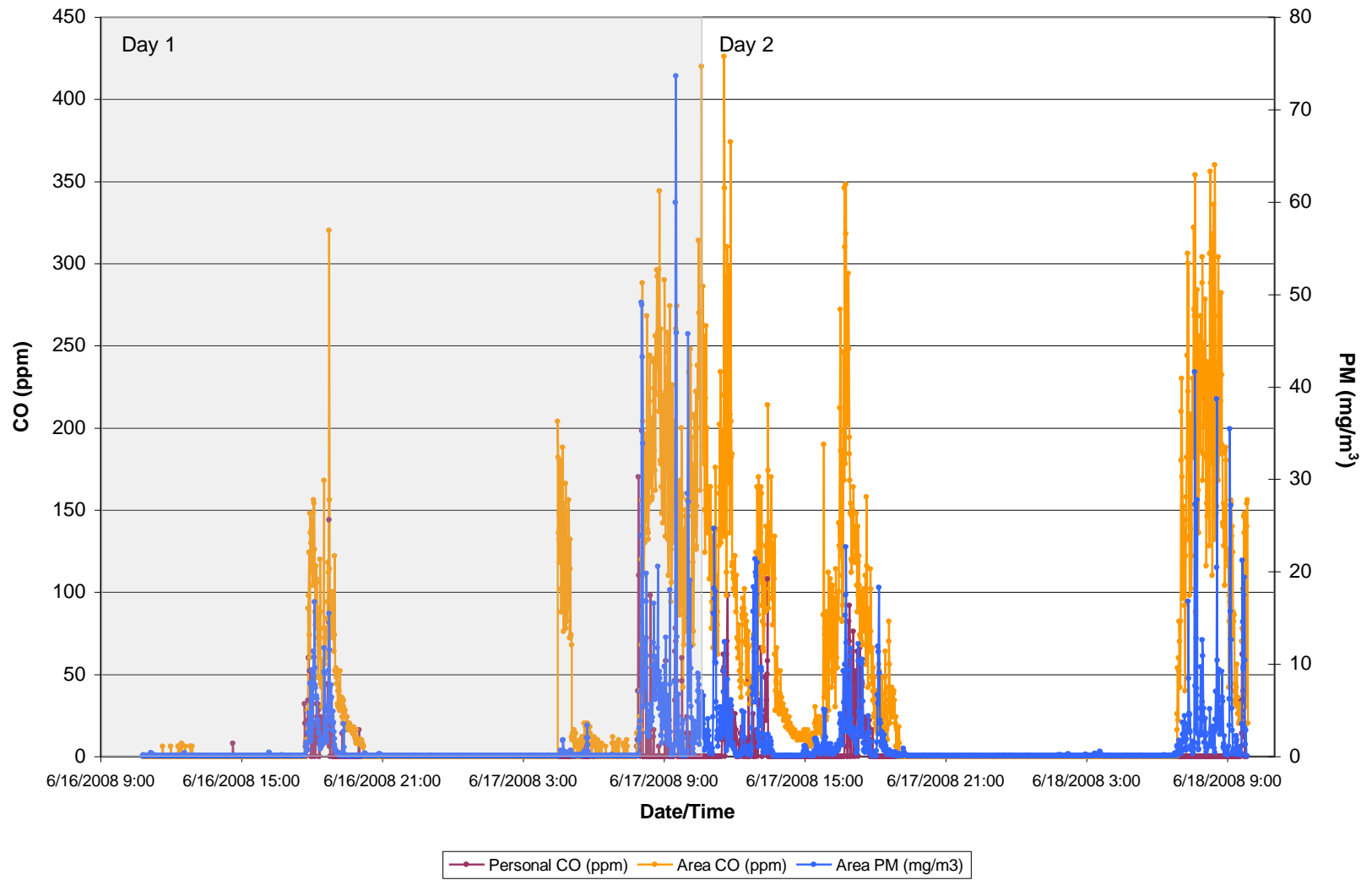
House 59 and Participant Exposure Data



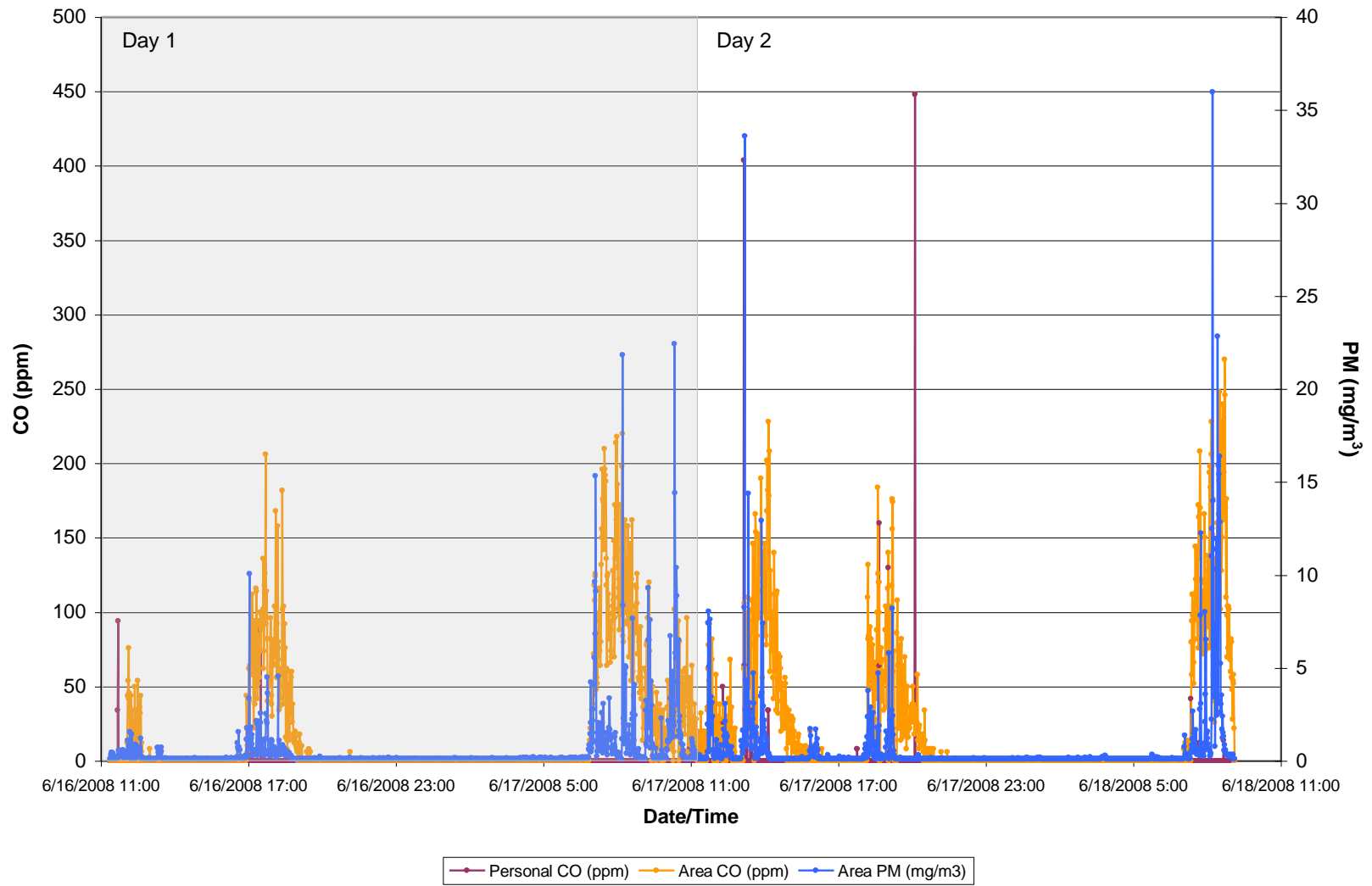
House 60 and Participant Exposure Data



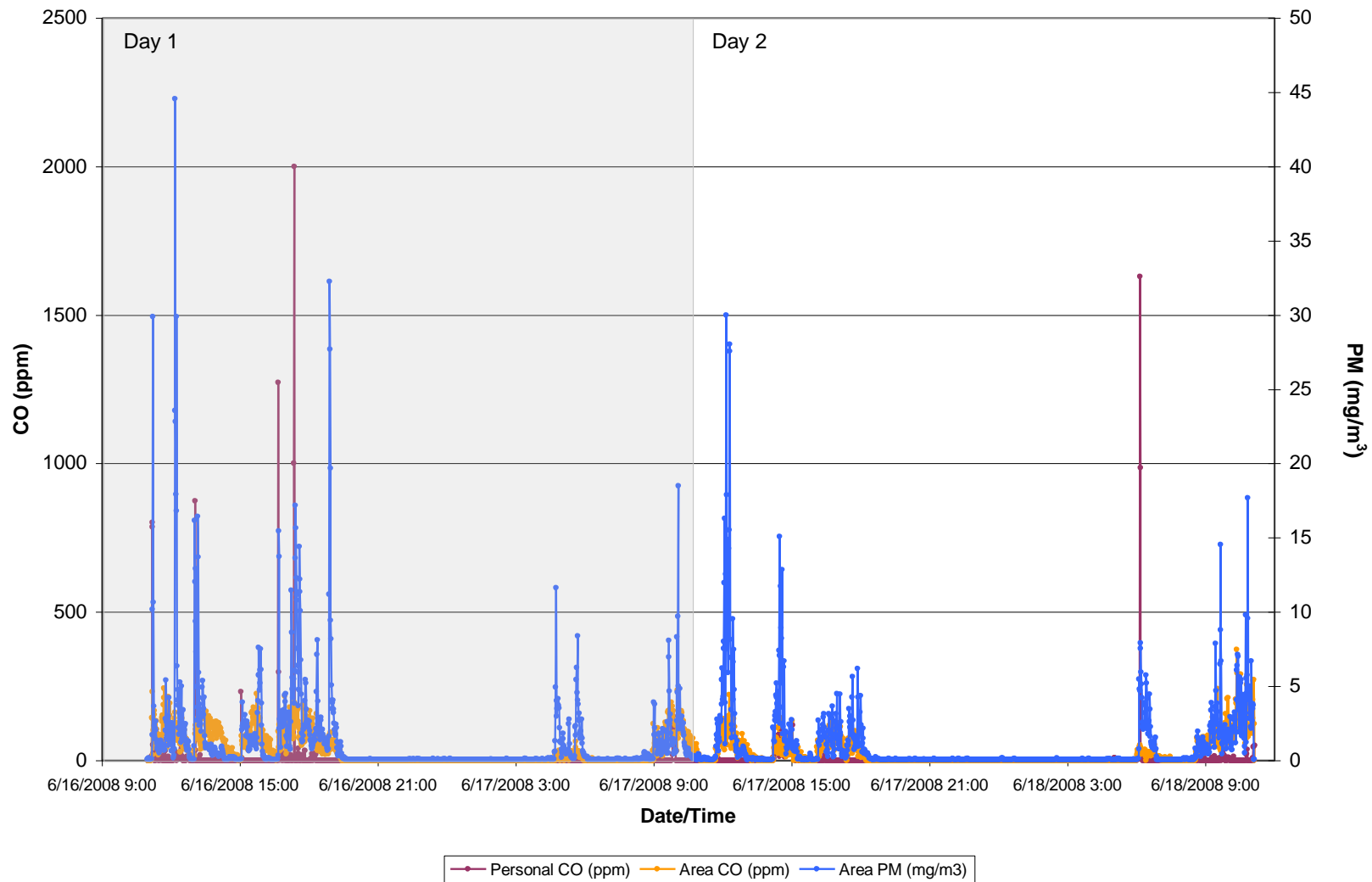
House 61 and Participant Exposure Data



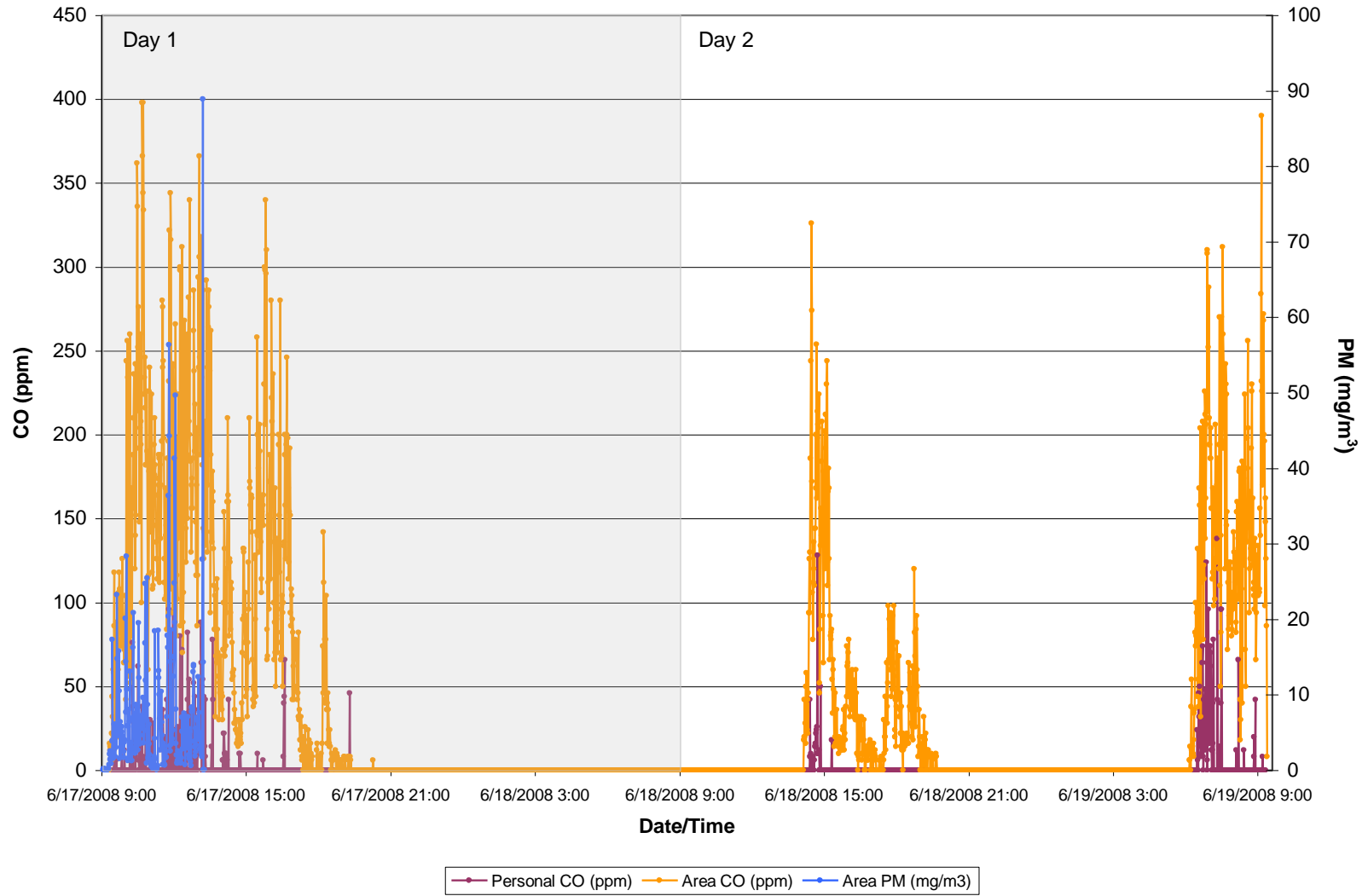
House 62 and Participant Exposure Data



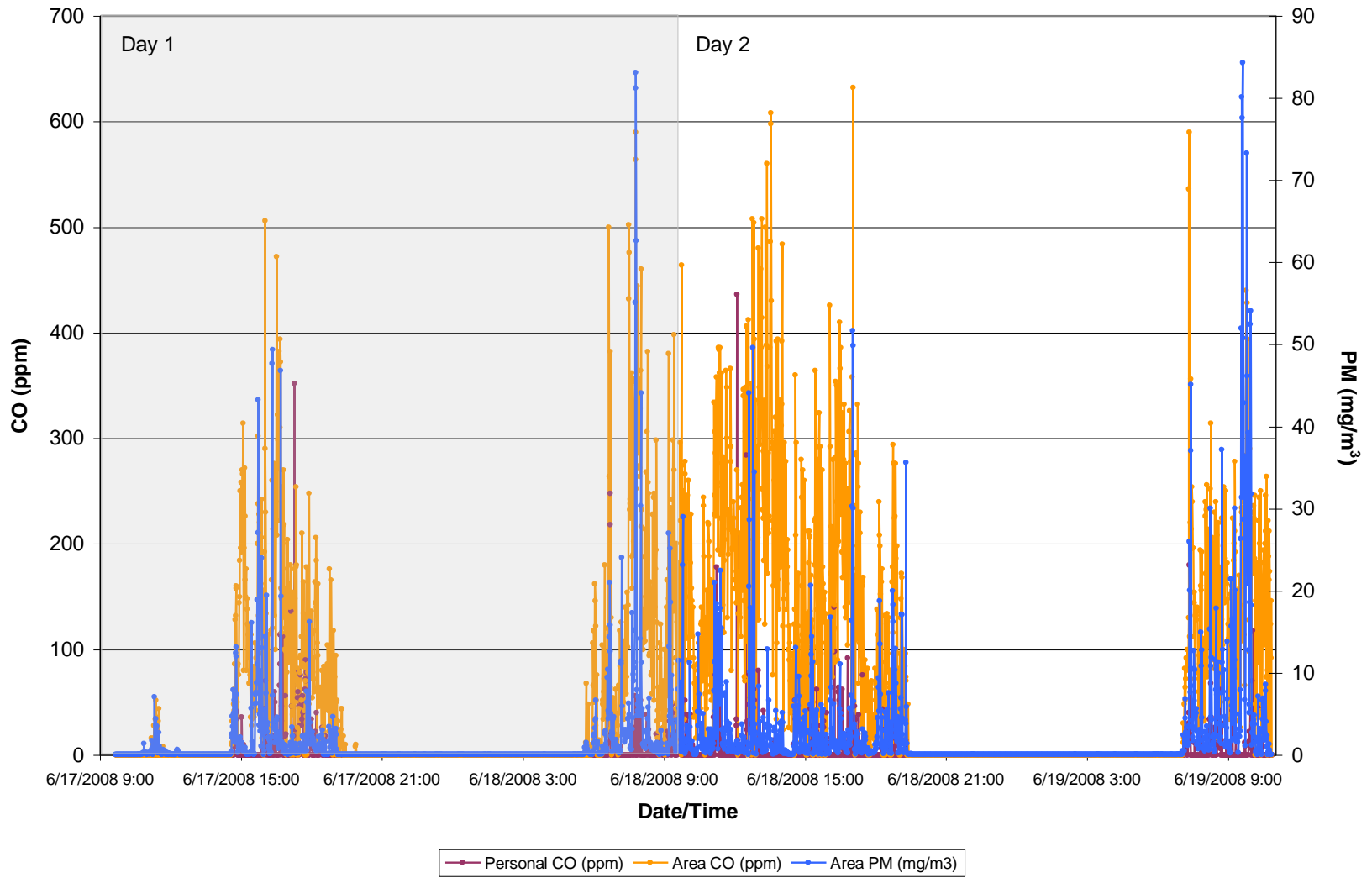
House 63 and Participant Exposure Data



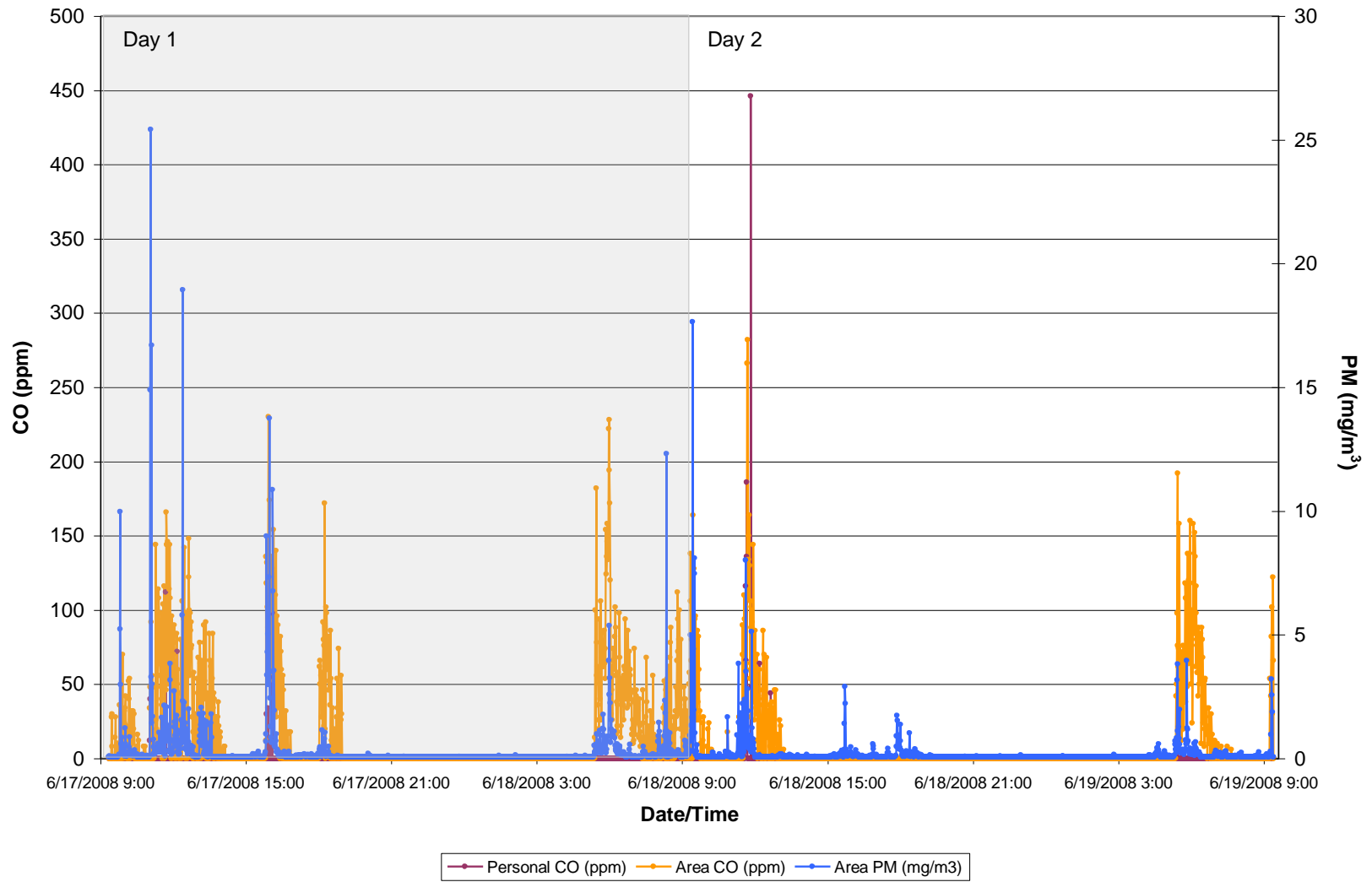
House 64 and Participant Exposure Data



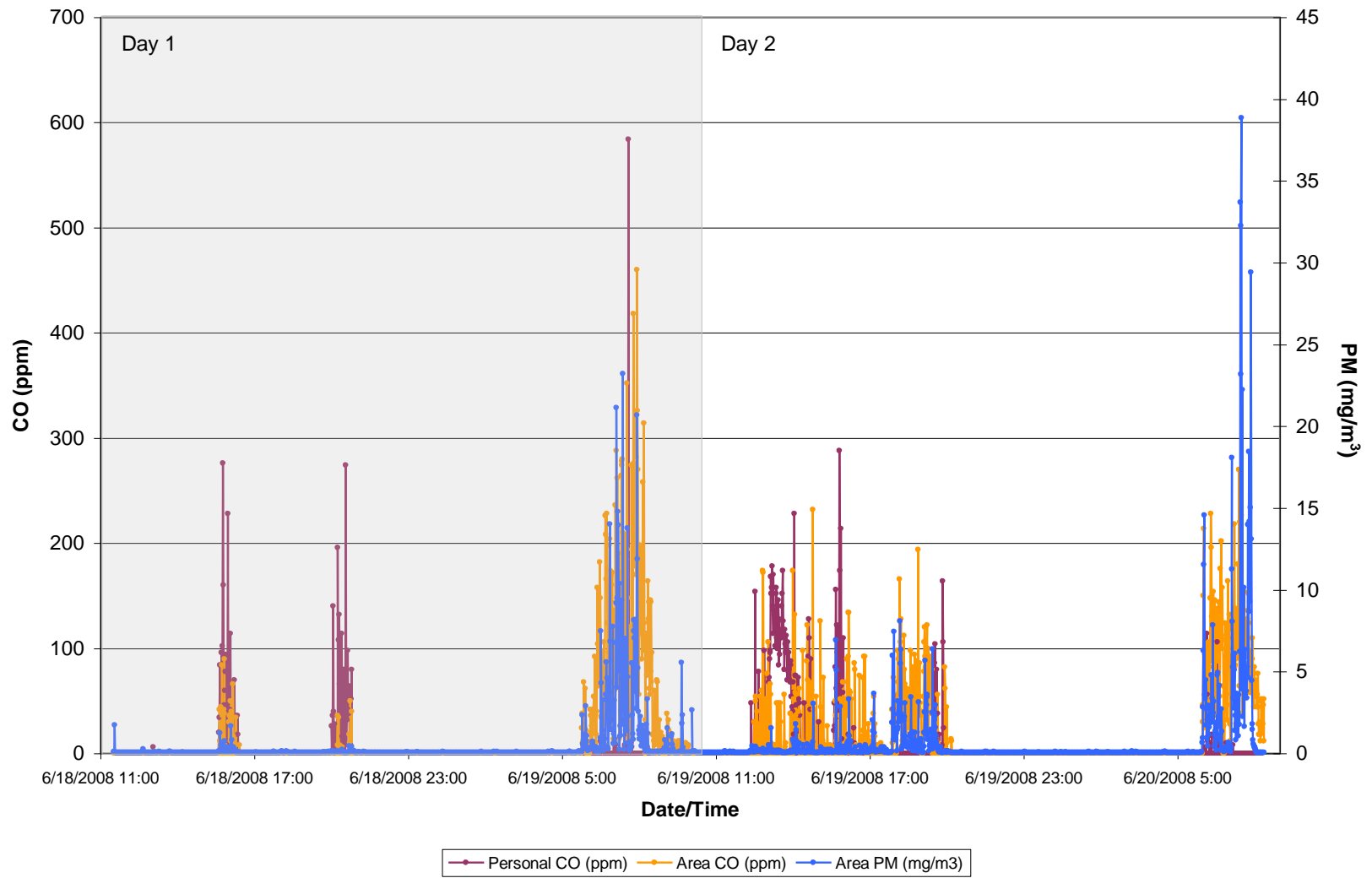
House 65 and Participant Exposure Data



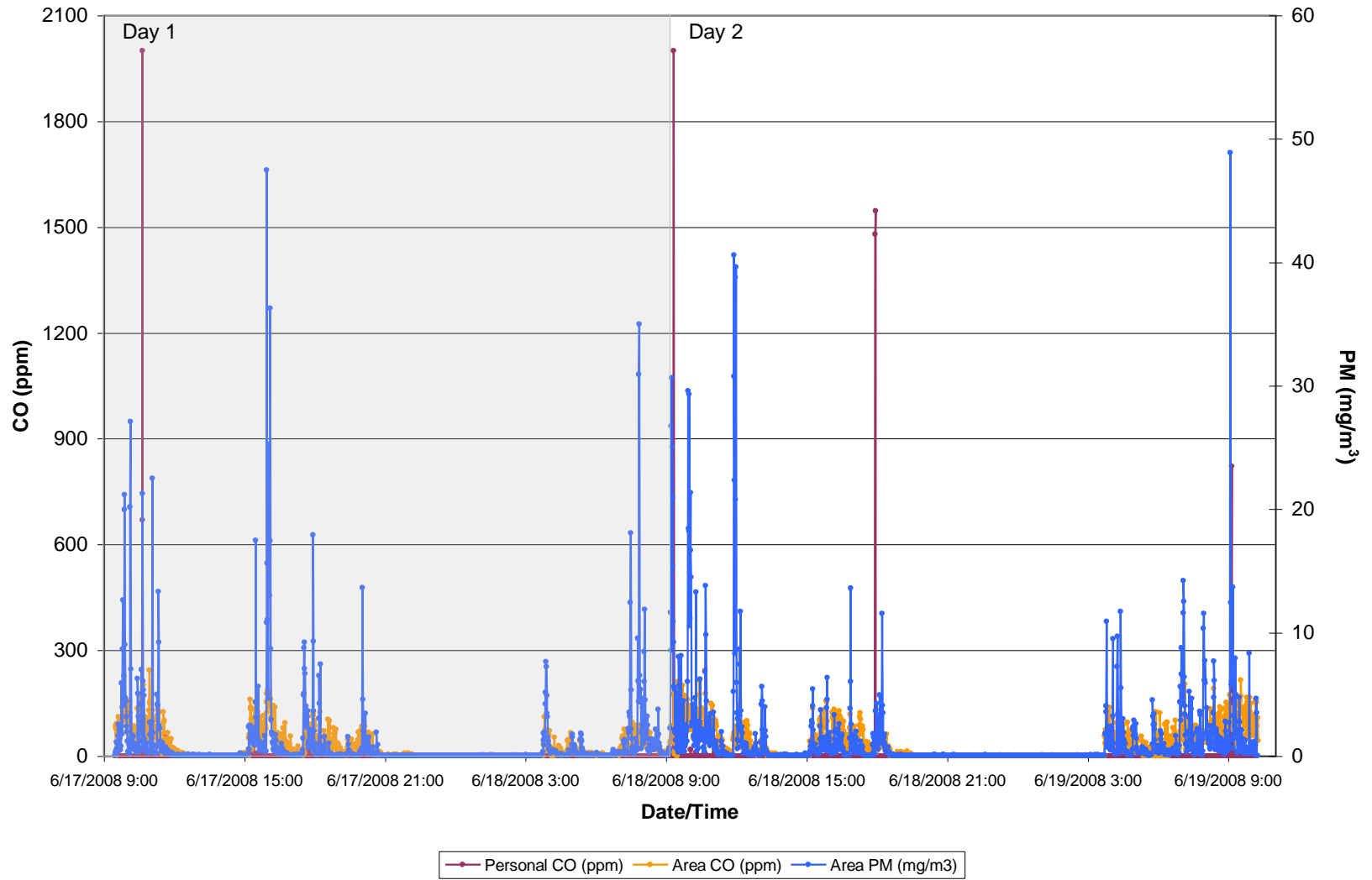
House 66 and Participant Exposure Data



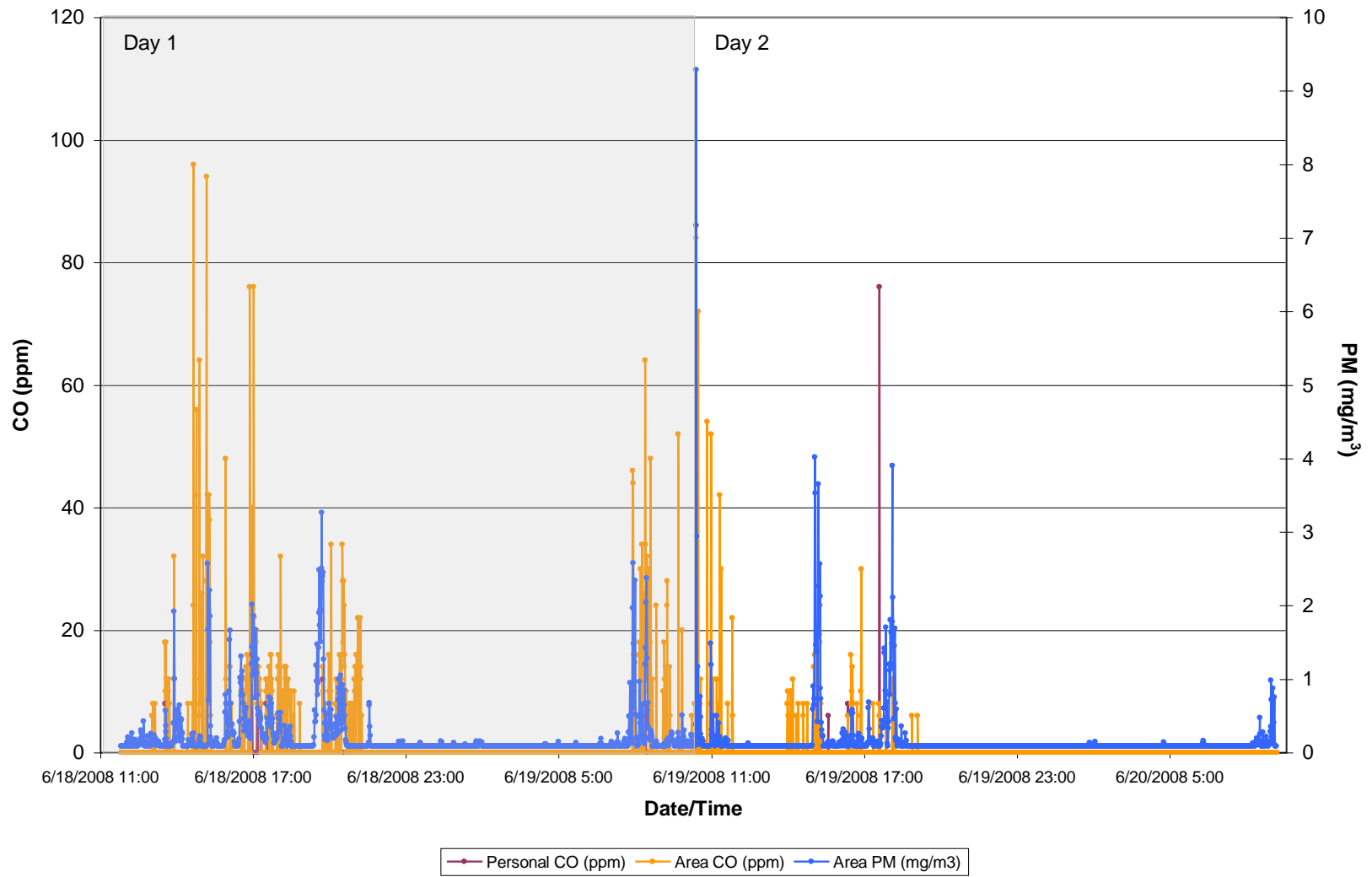
House 67 and Participant Exposure Data



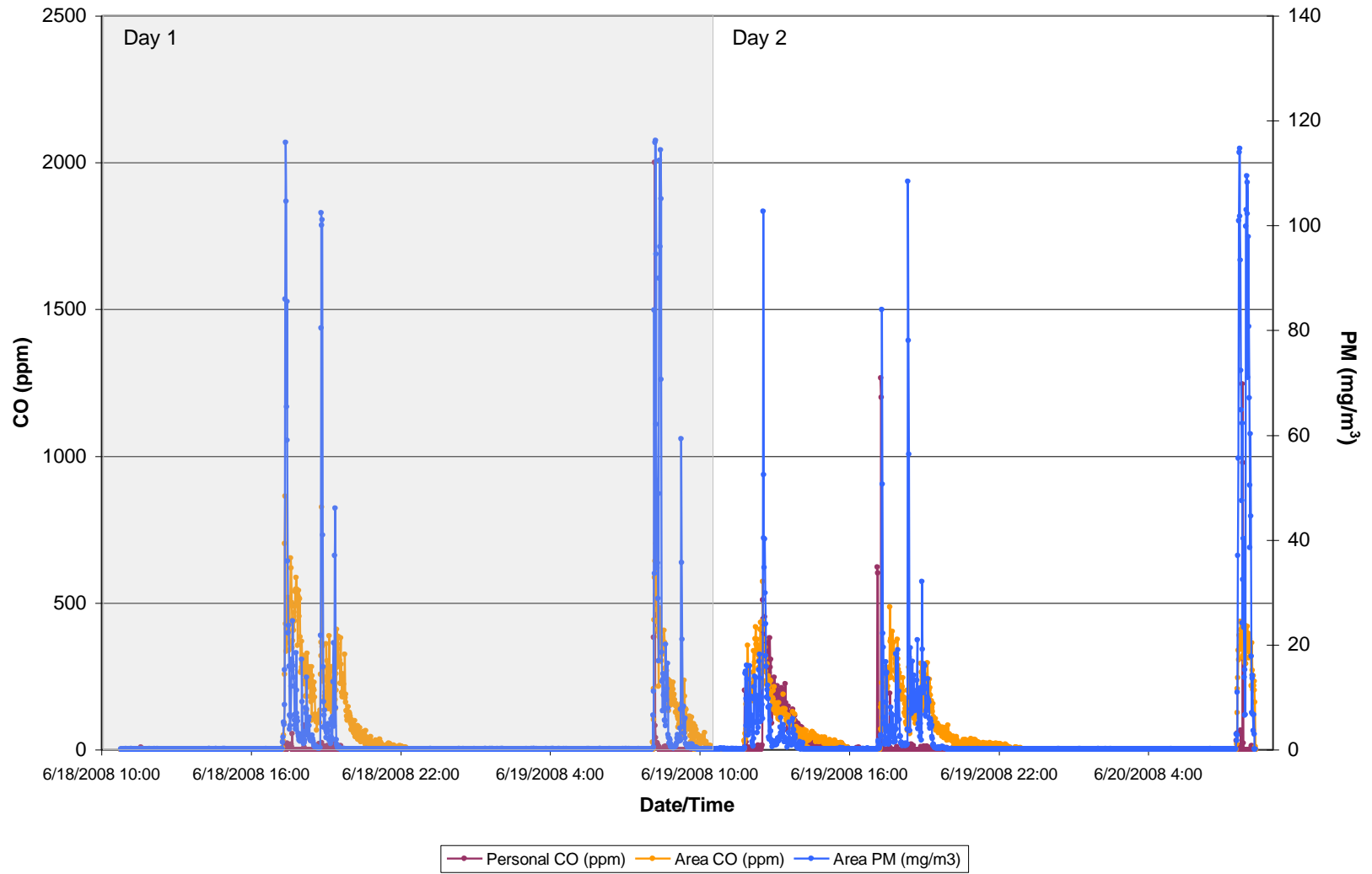
House 68 and Participant Exposure Data



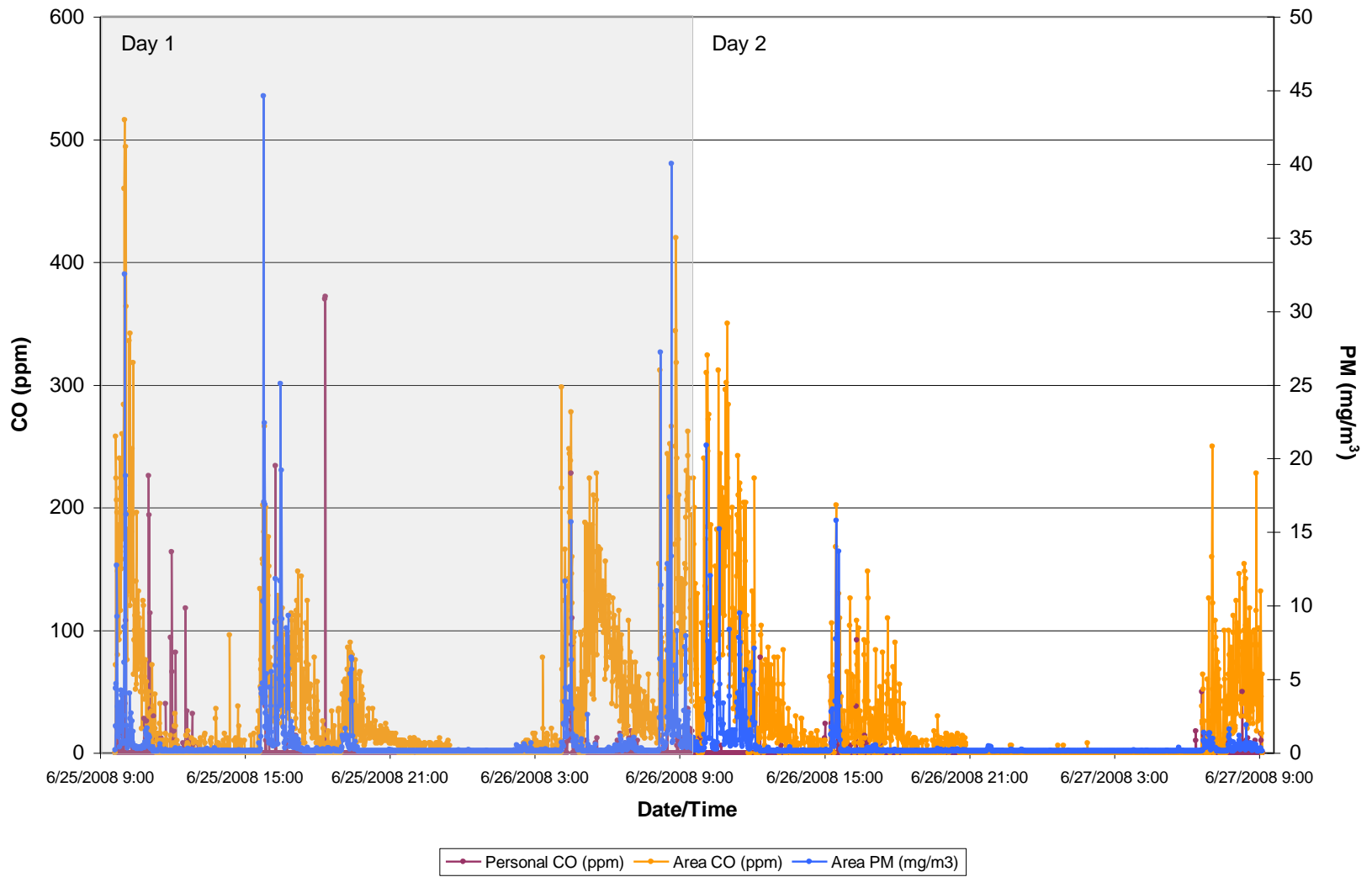
House 69 and Participant Exposure Data



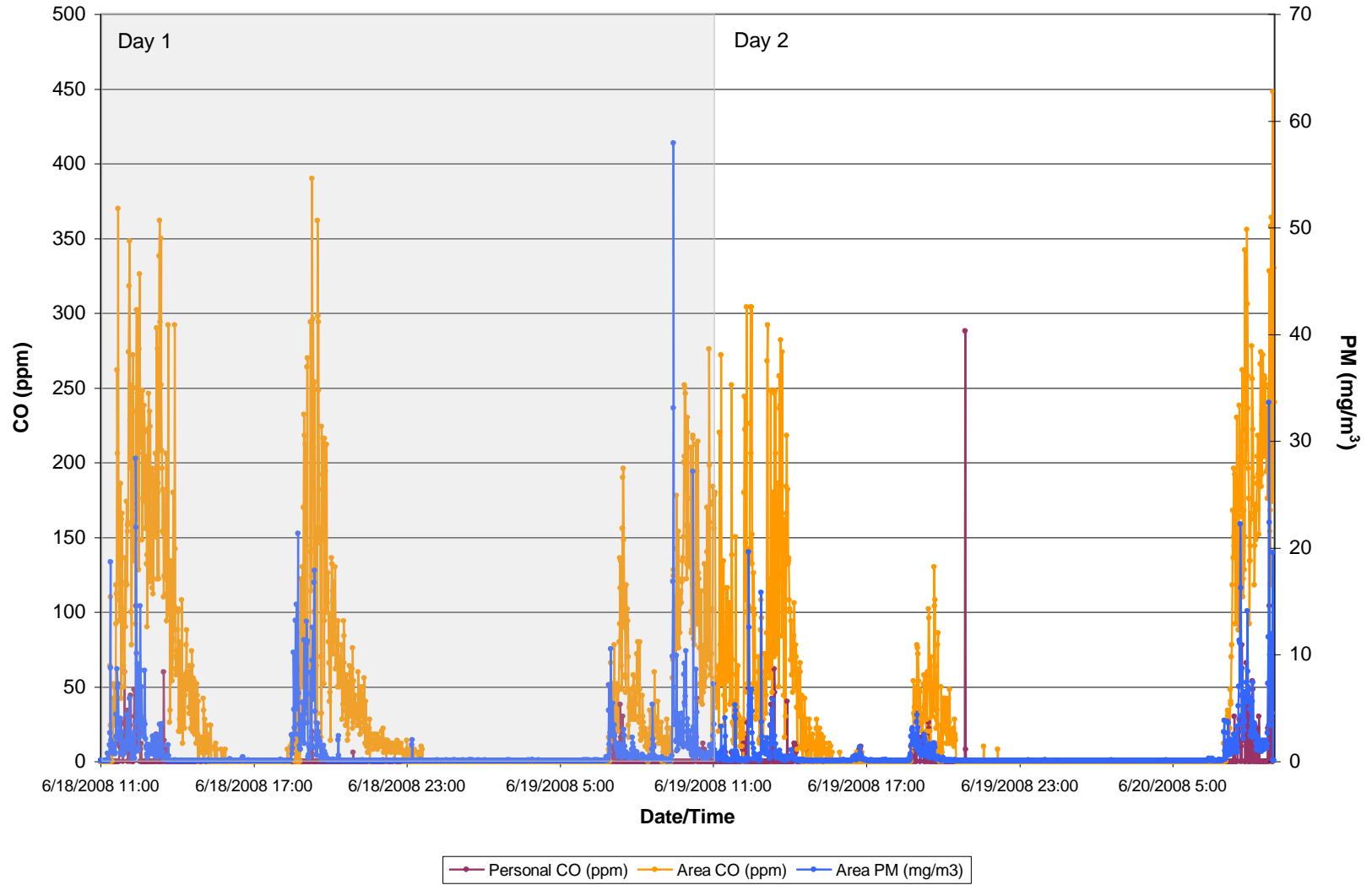
House 70 and Participant Exposure Data



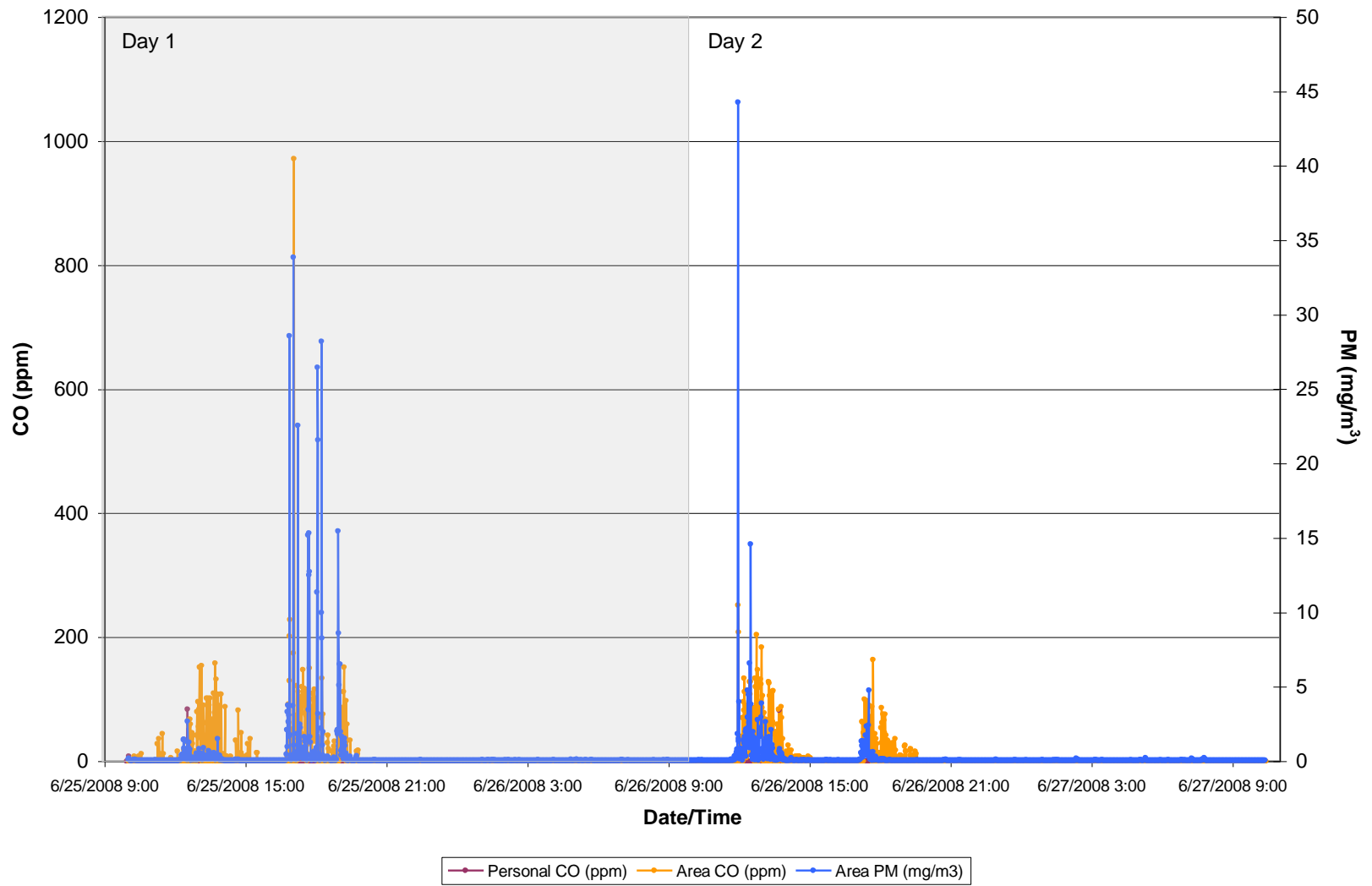
House 71 and Participant Exposure Data



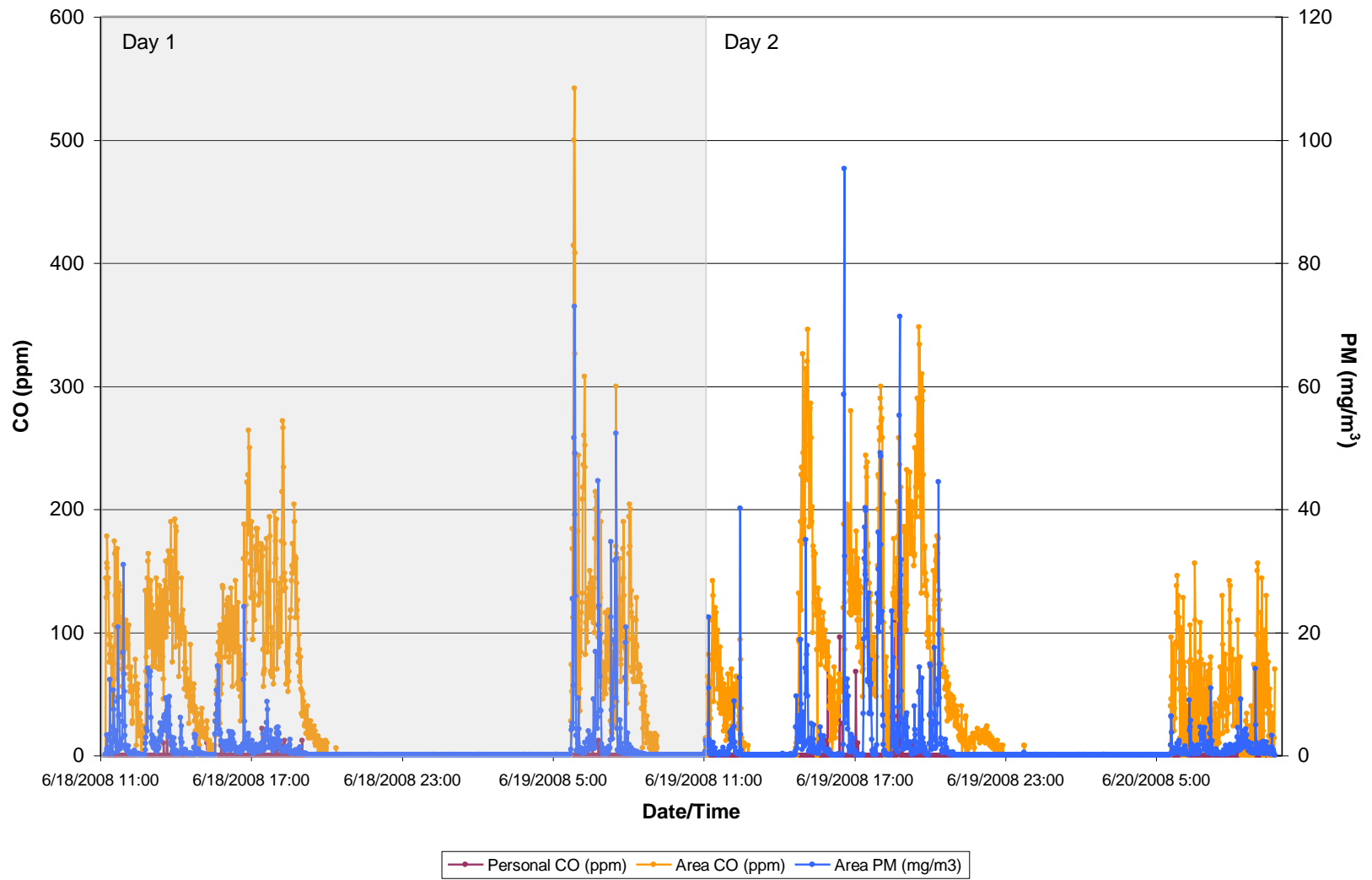
House 72 and Participant Exposure Data



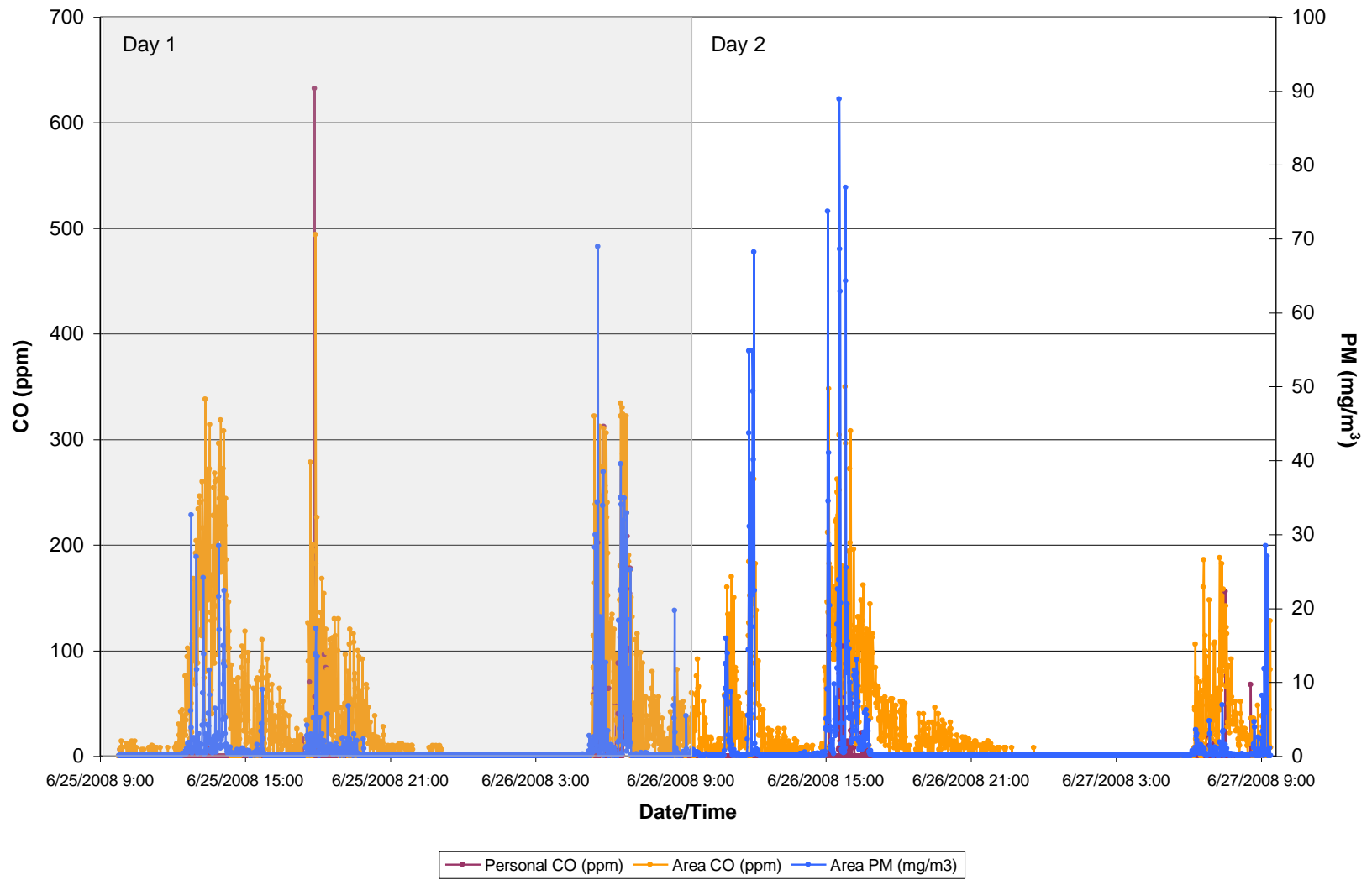
House 73 and Participant Exposure Data



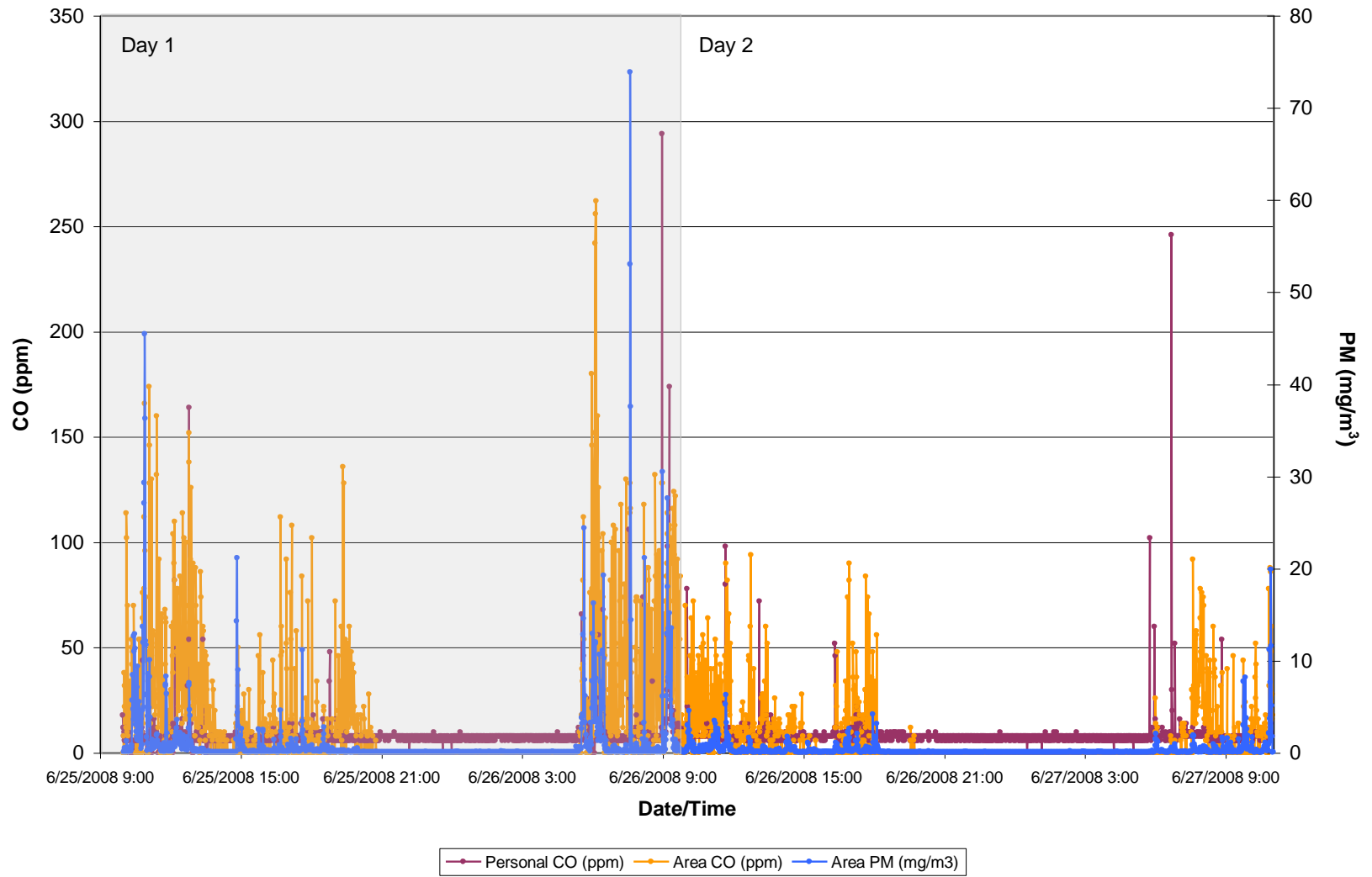
House 74 and Participant Exposure Data



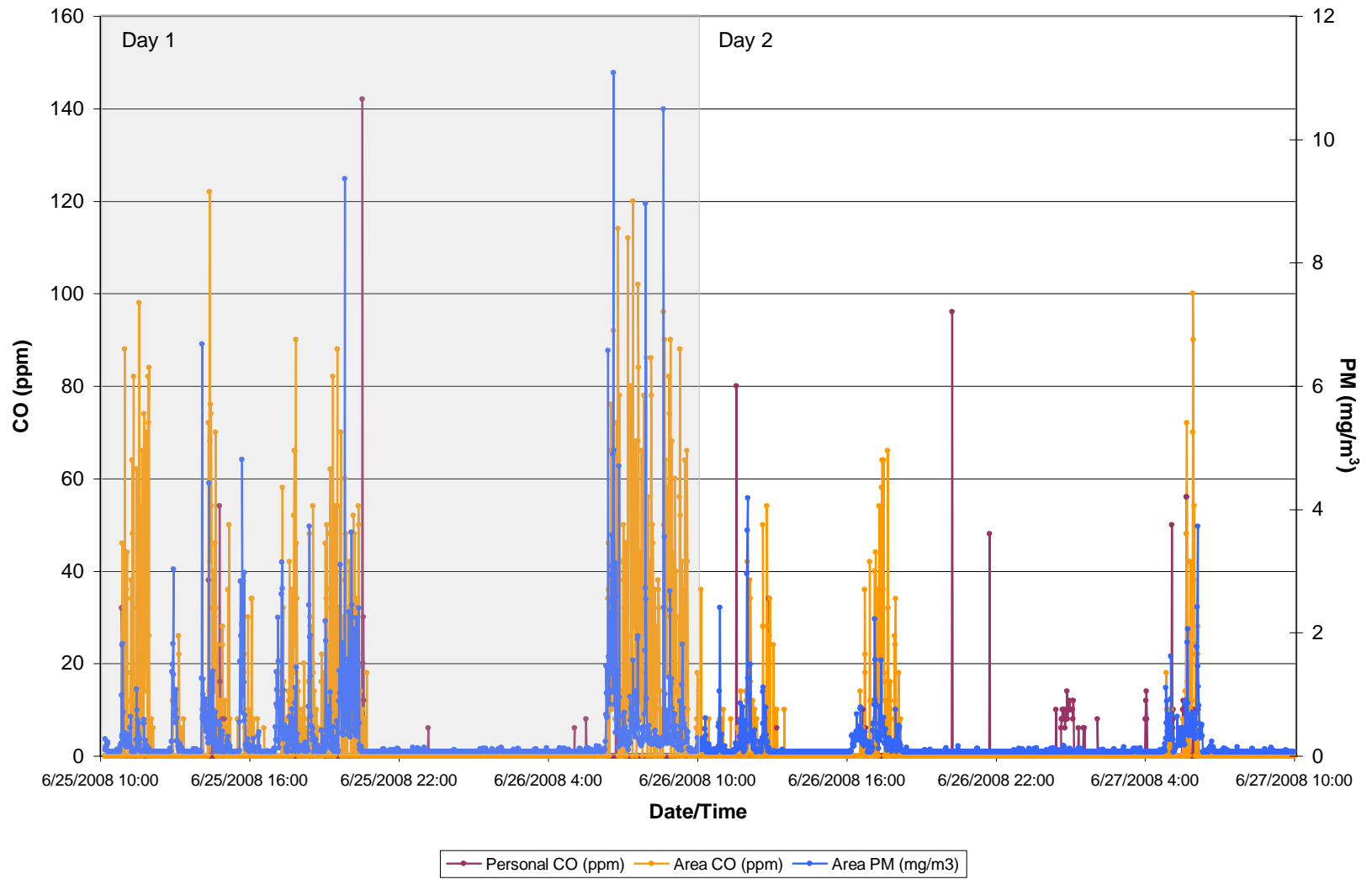
House 75 and Participant Exposure Data



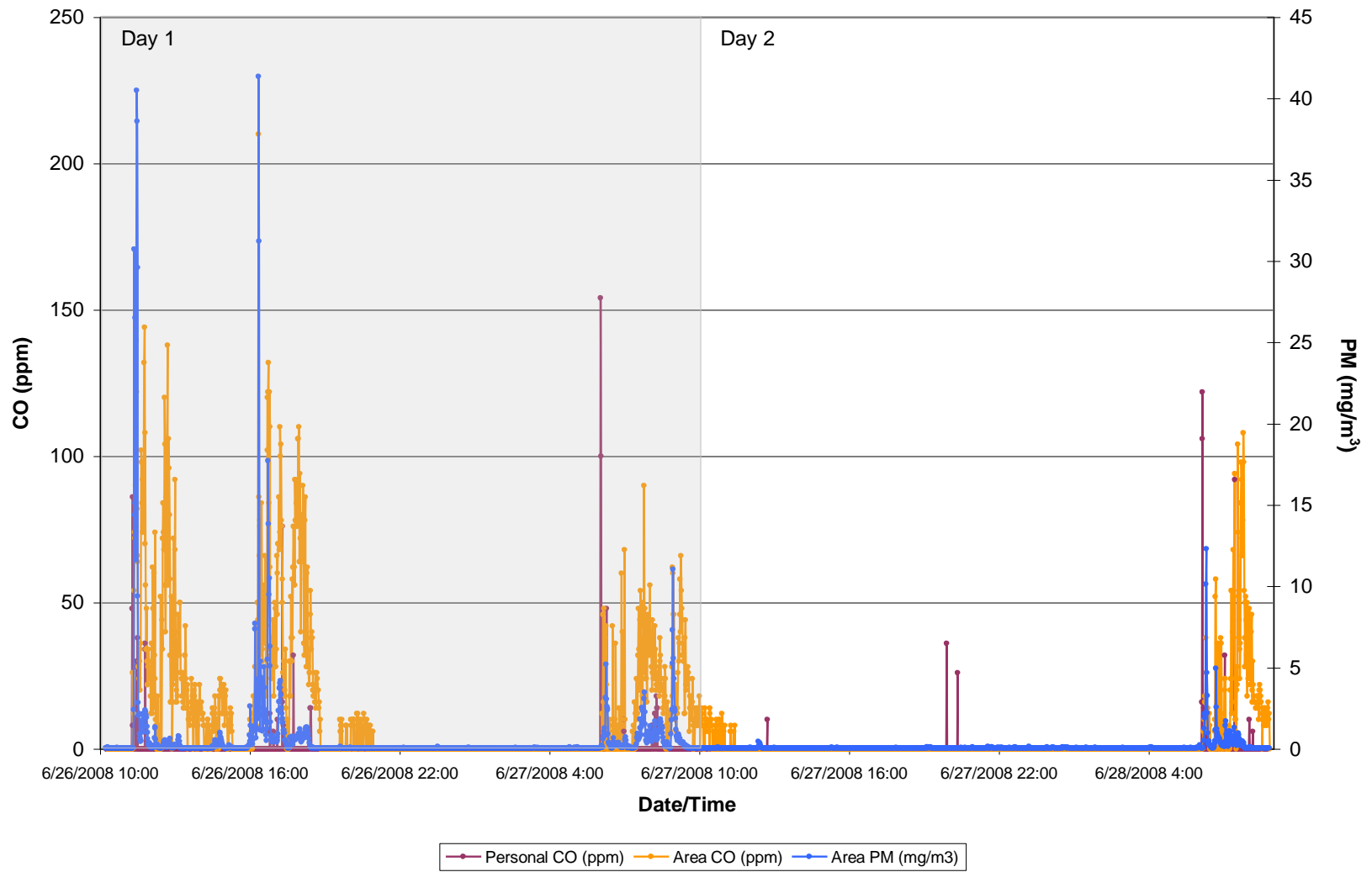
House 76 and Participant Exposure Data



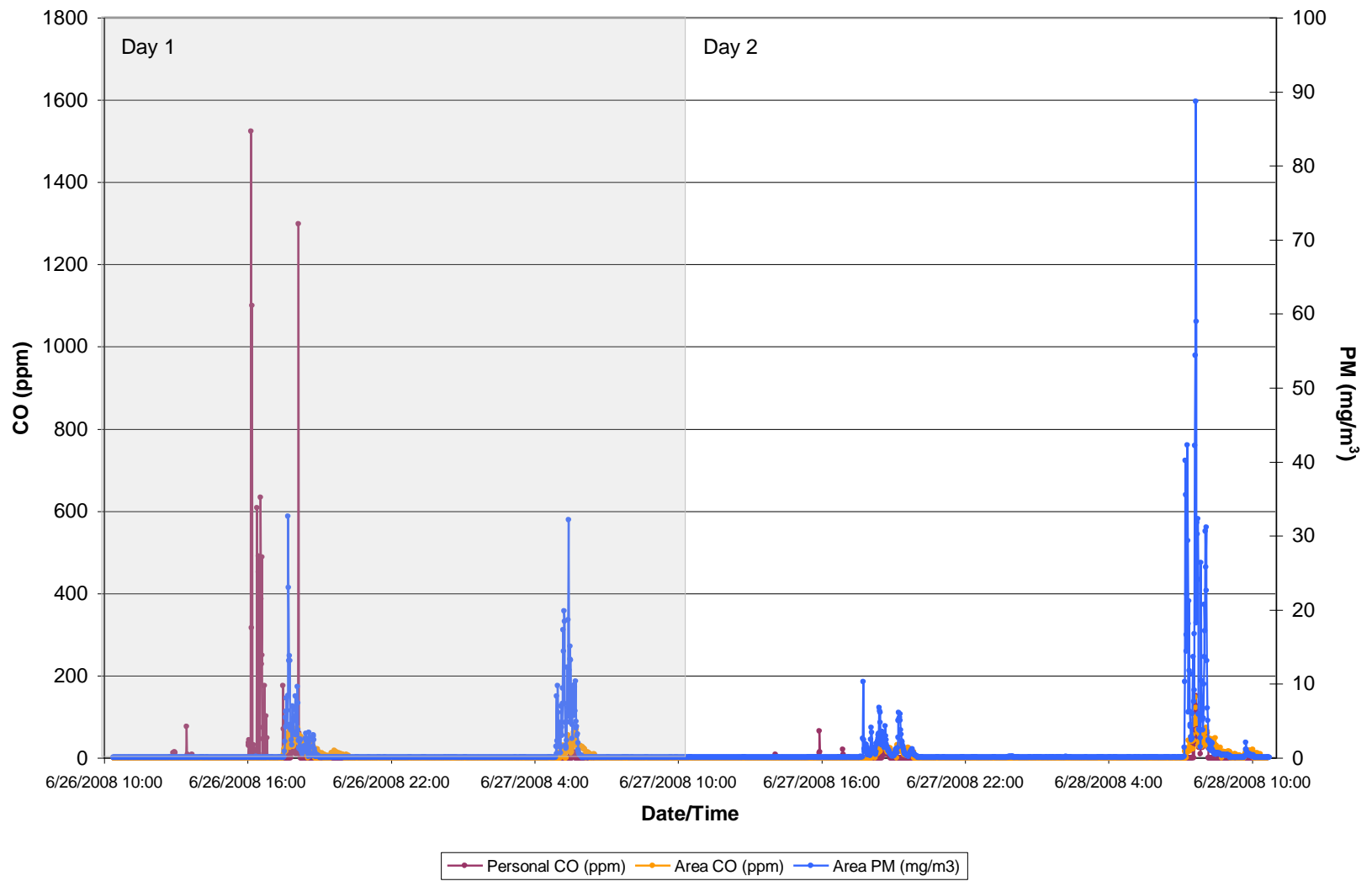
House 77 and Participant Exposure Data



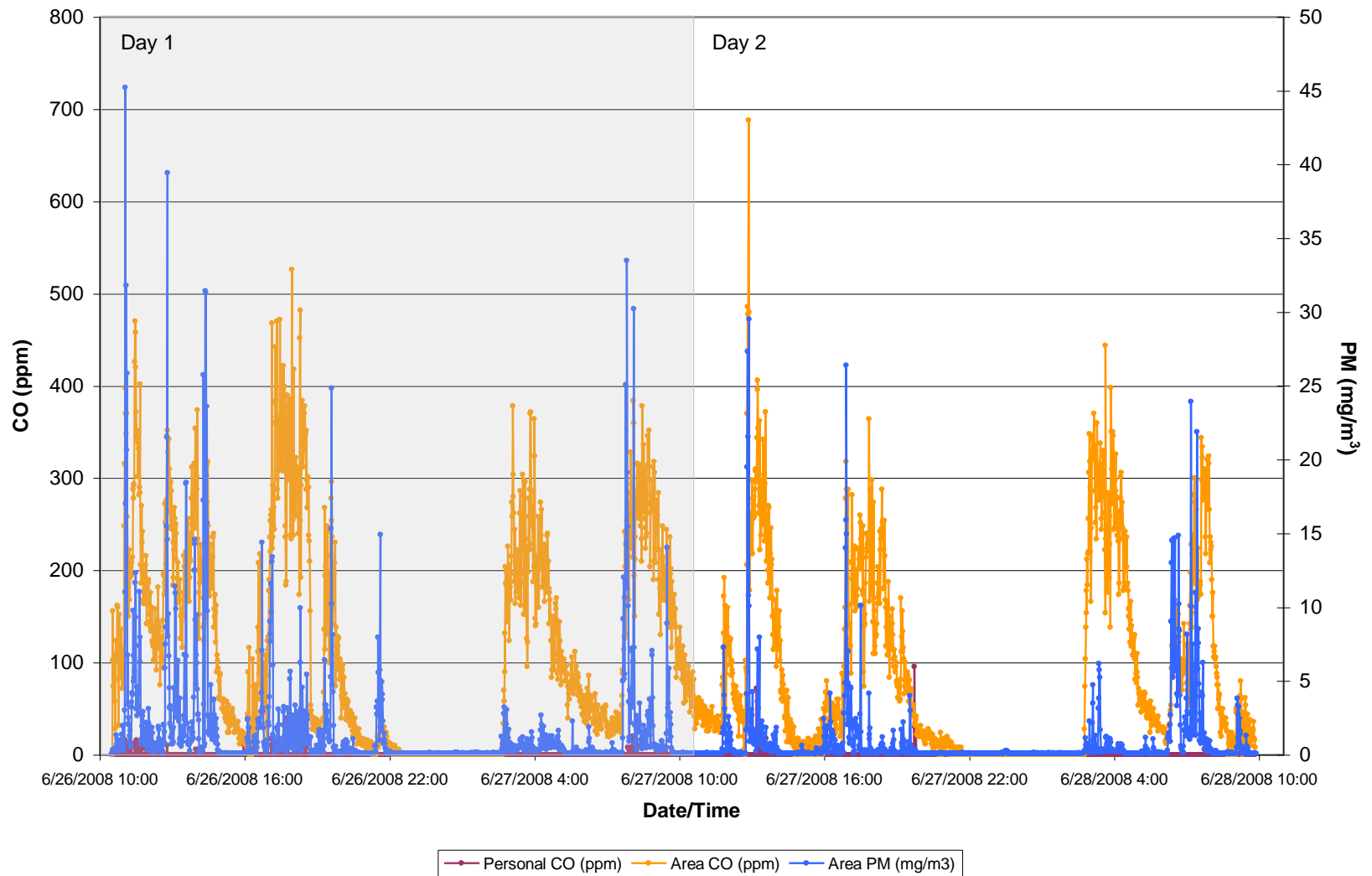
House 78 and Participant Exposure Data



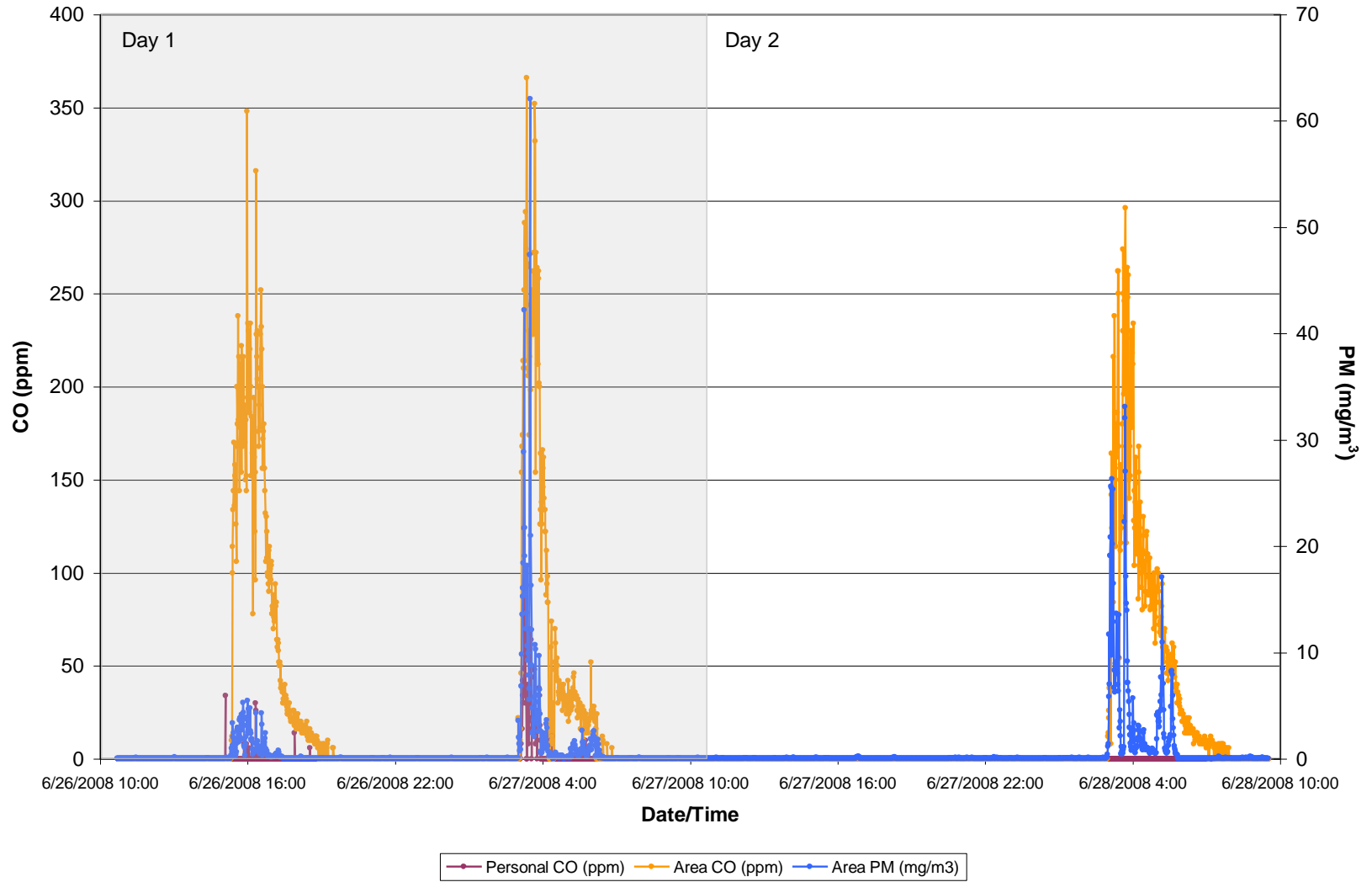
House 79 and Participant Exposure Data



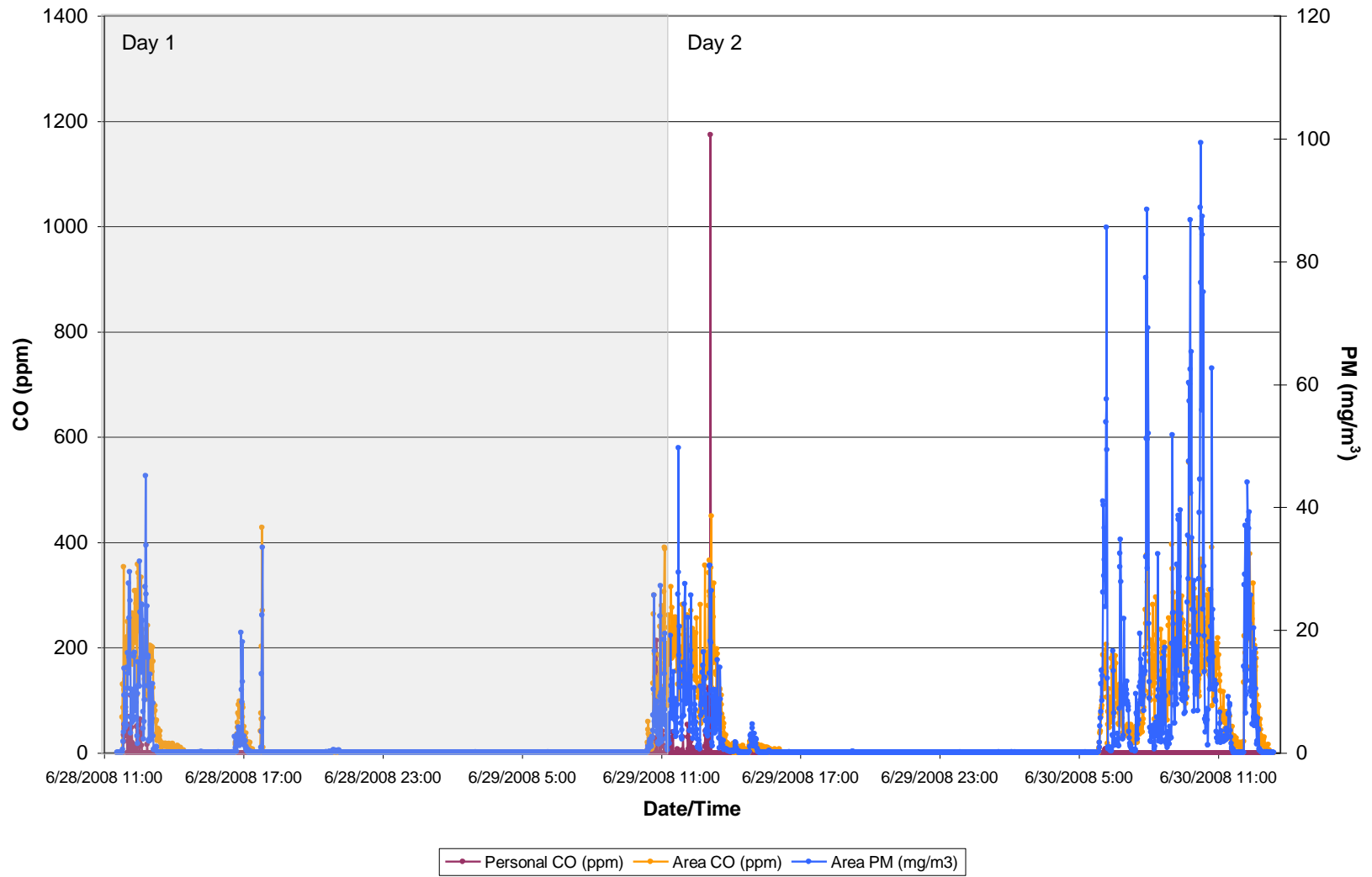
House 80 and Participant Exposure Data



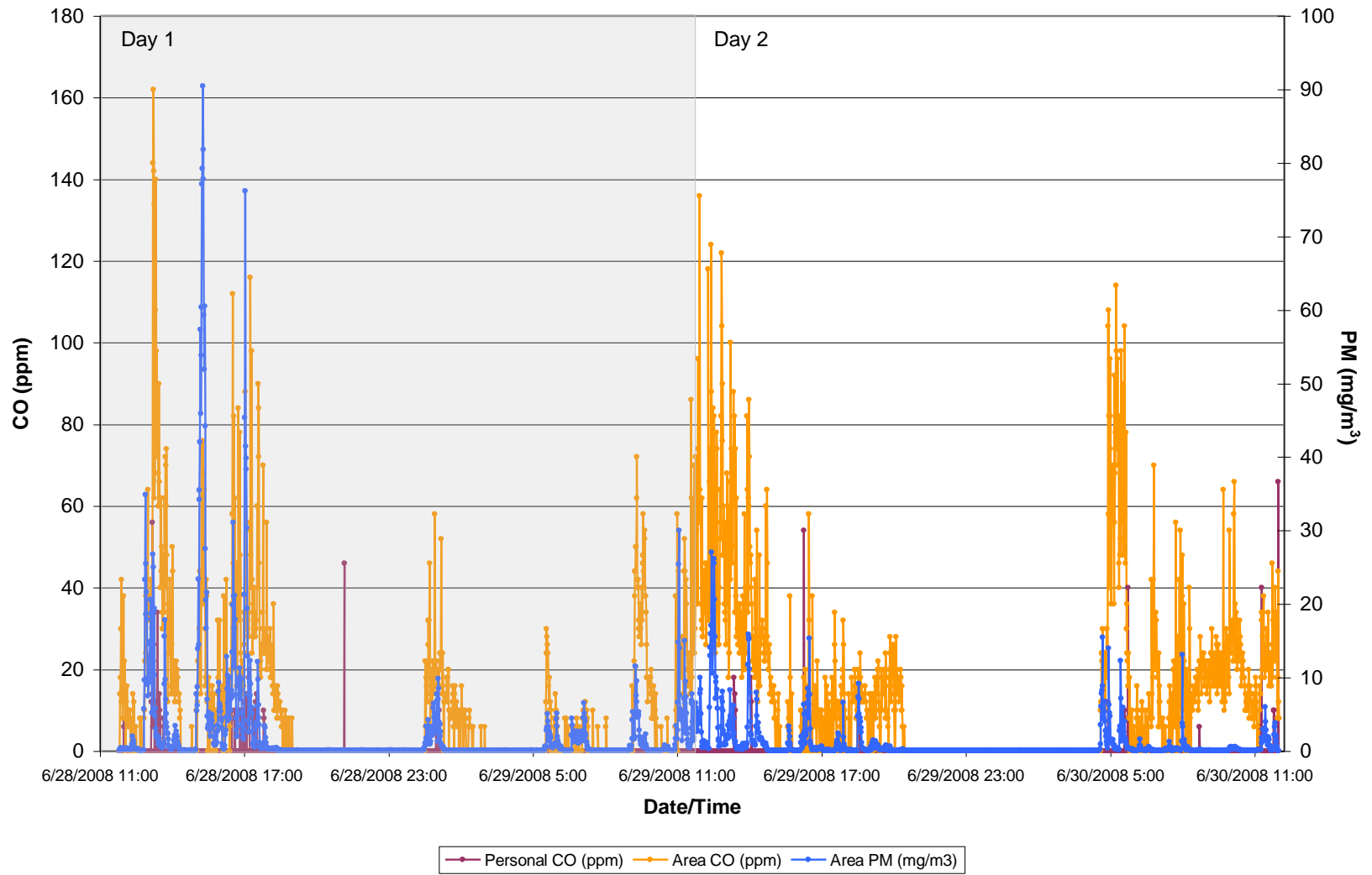
House 81 and Participant Exposure Data



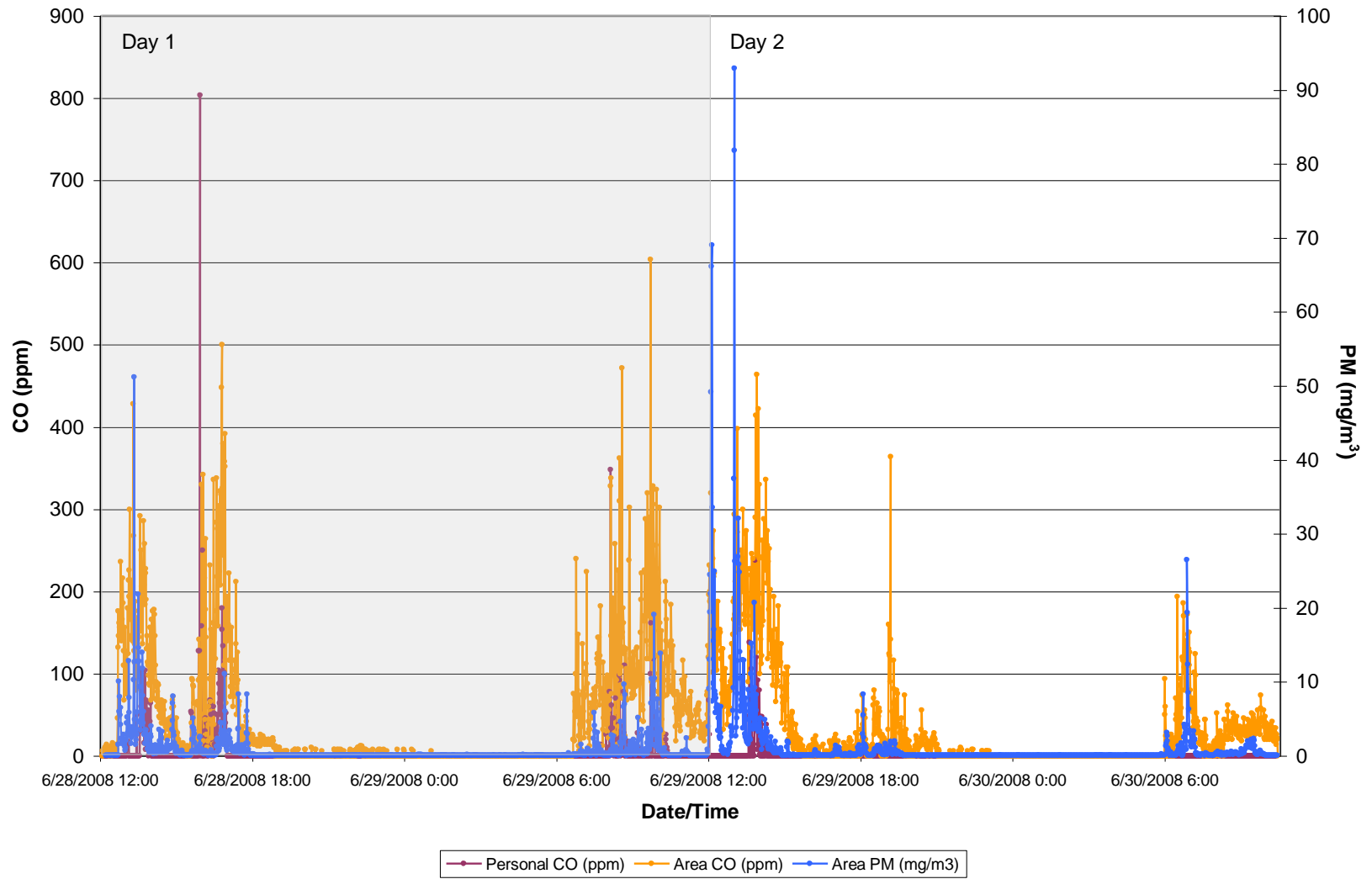
House 82 and Participant Exposure Data



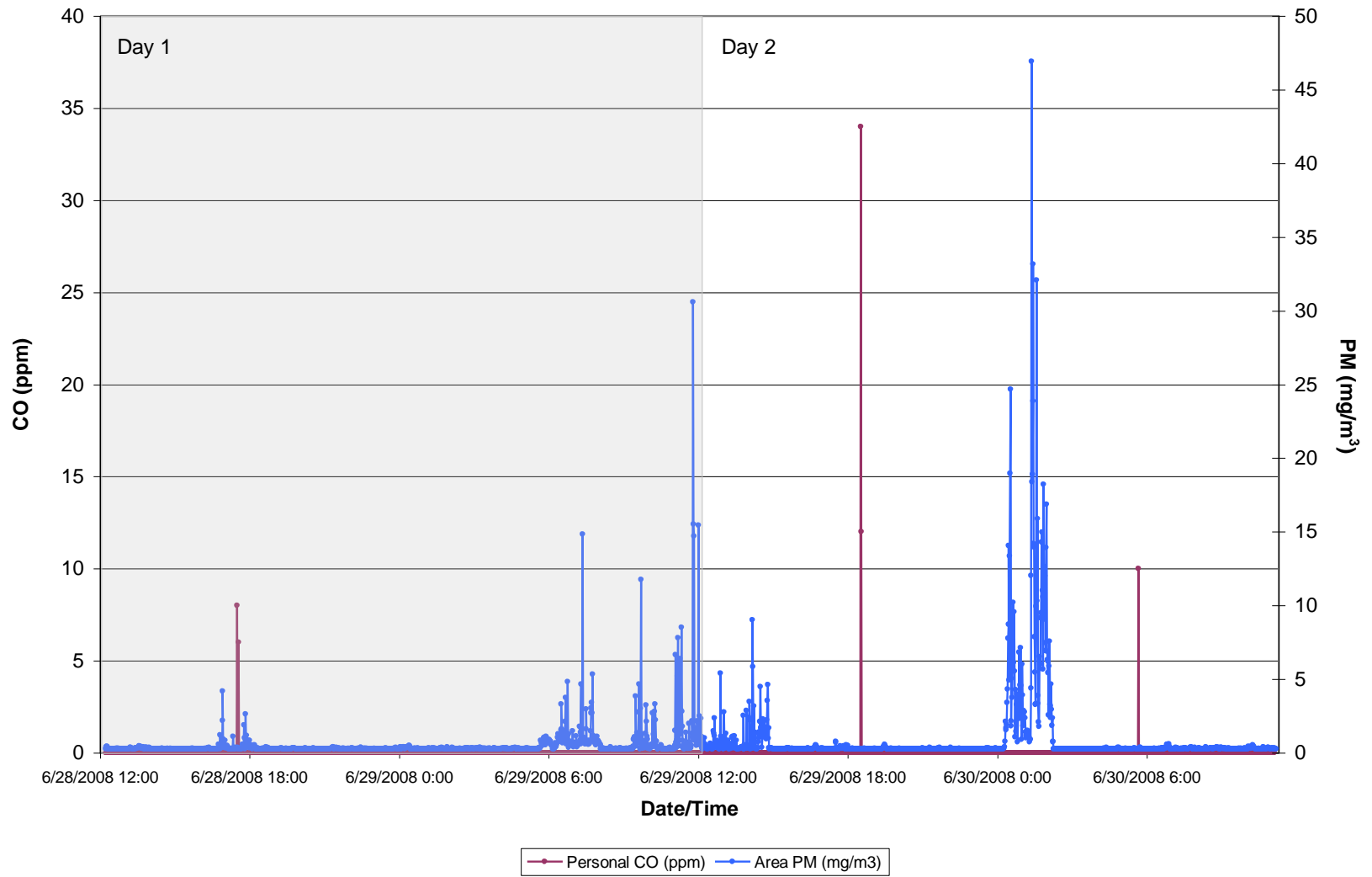
House 83 and Participant Exposure Data



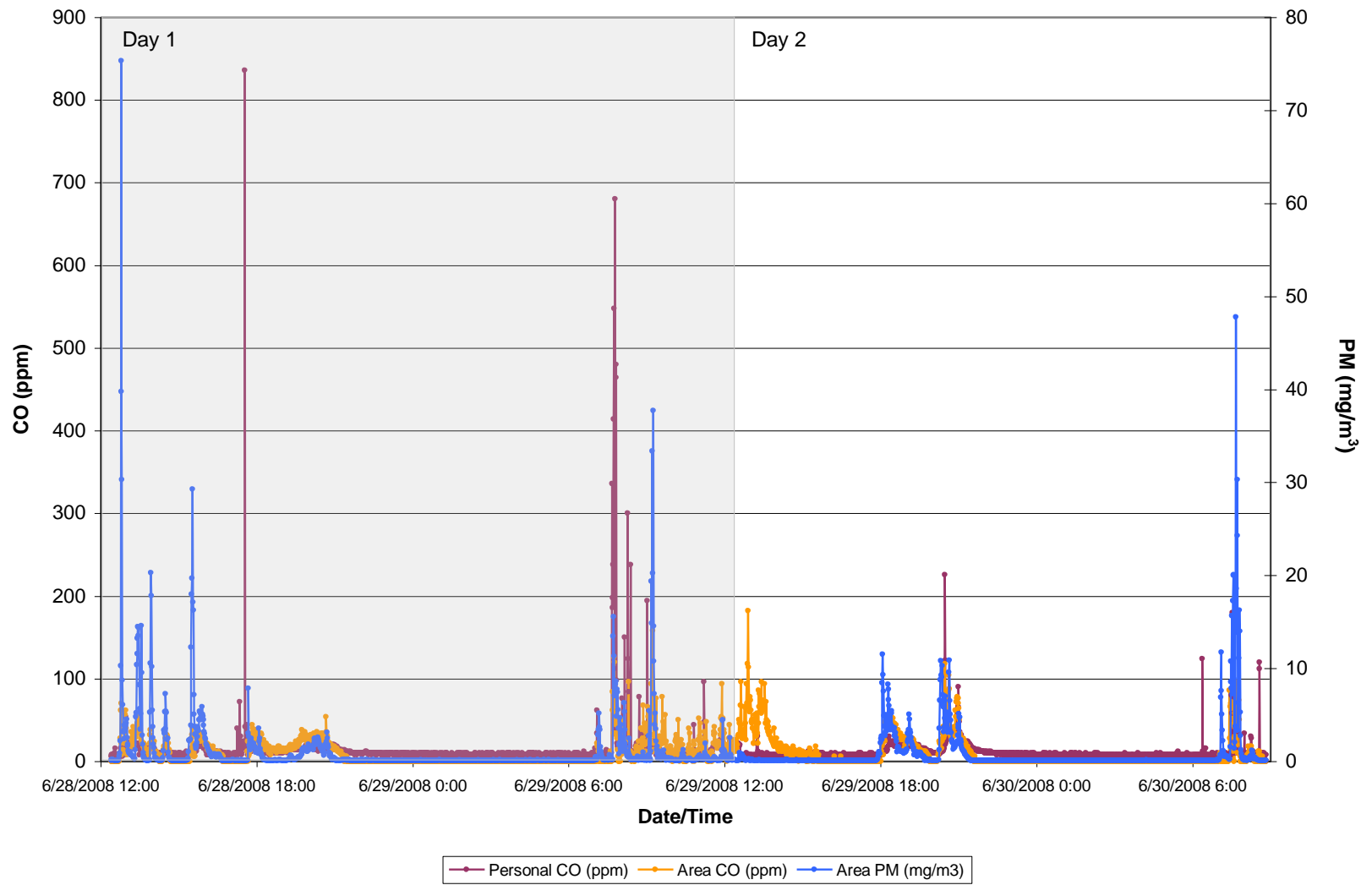
House 84 and Participant Exposure Data



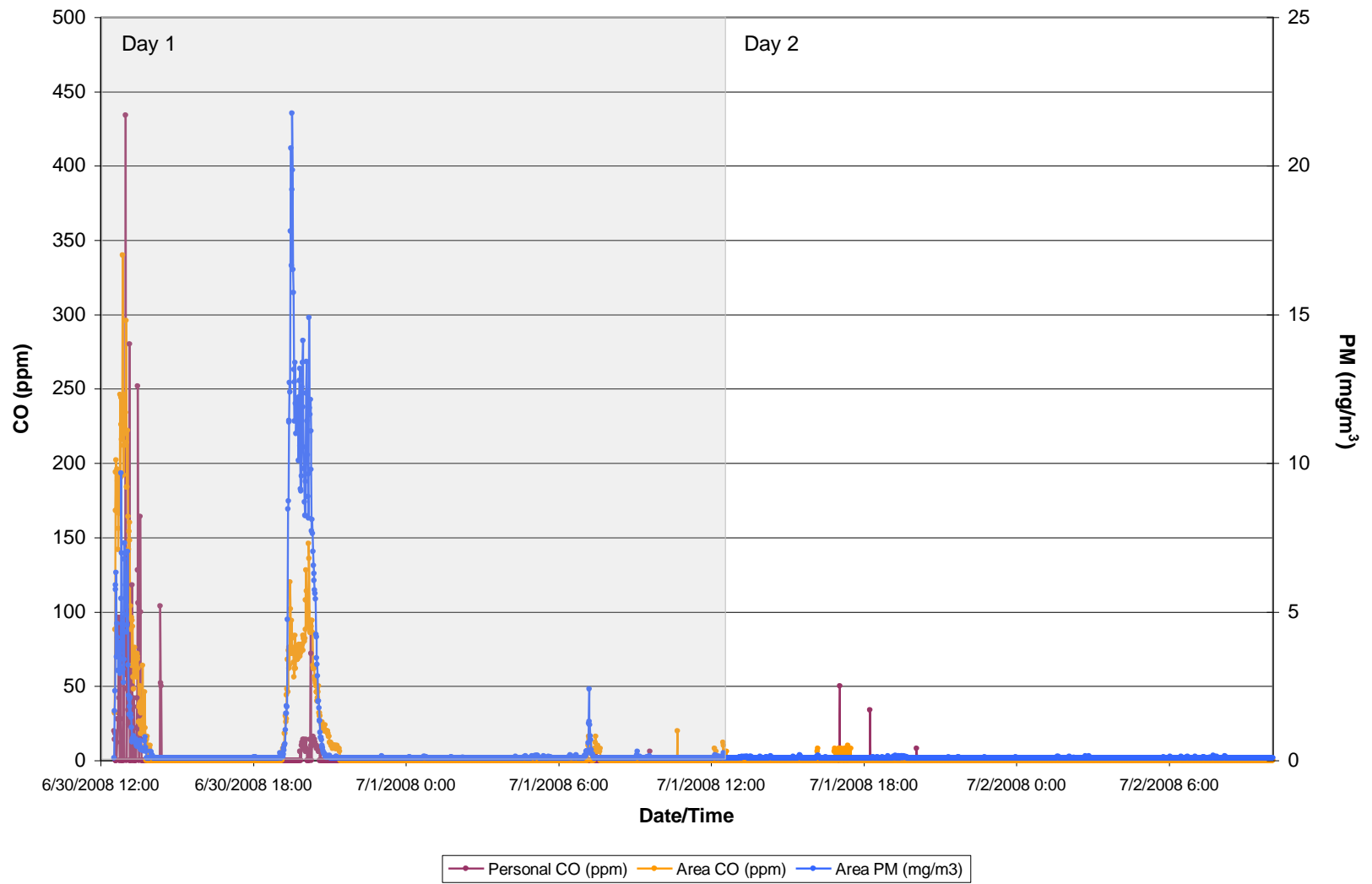
House 85 and Participant Exposure Data (Area CO Data N/A)



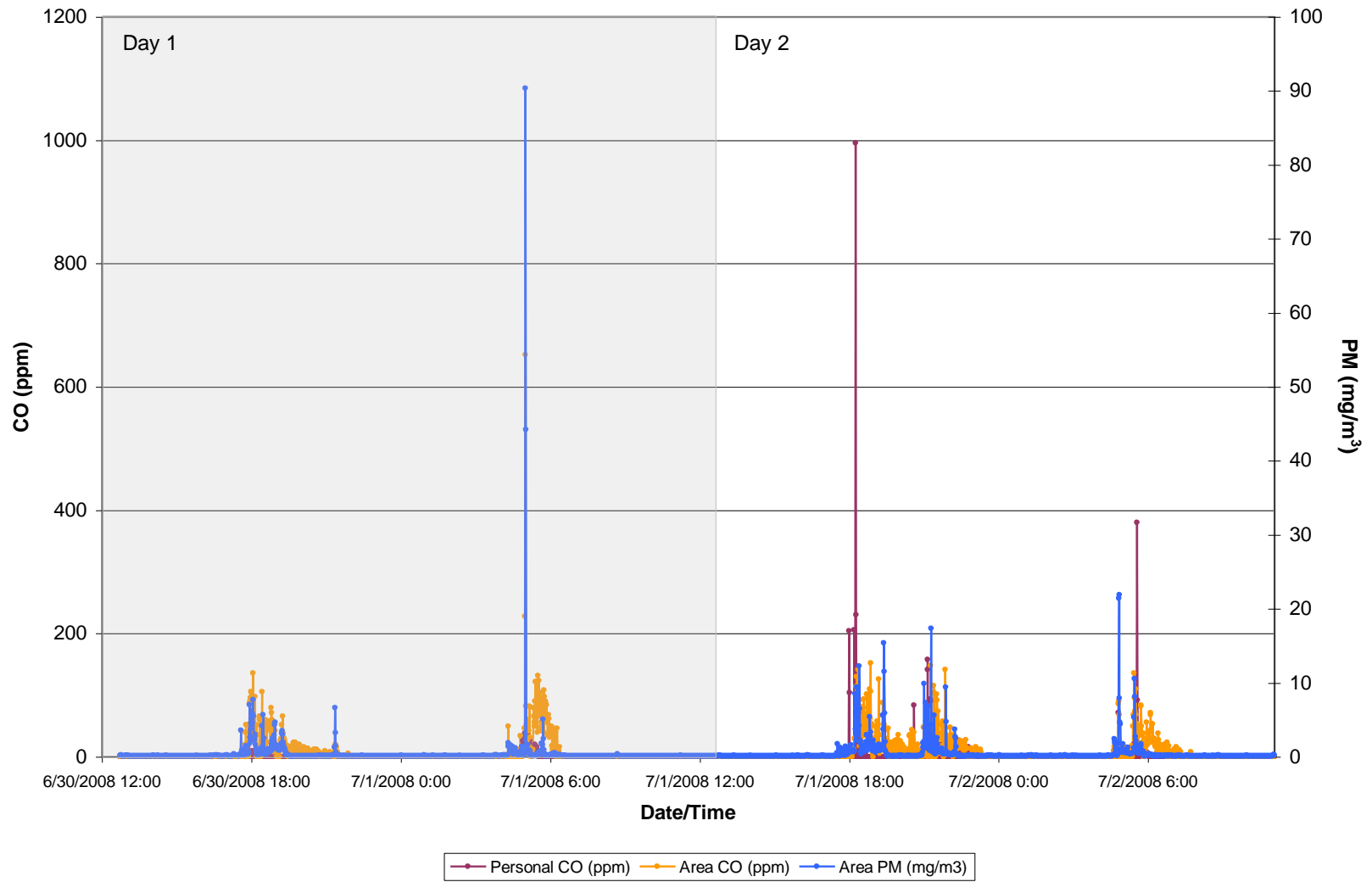
House 86 and Participant Exposure Data



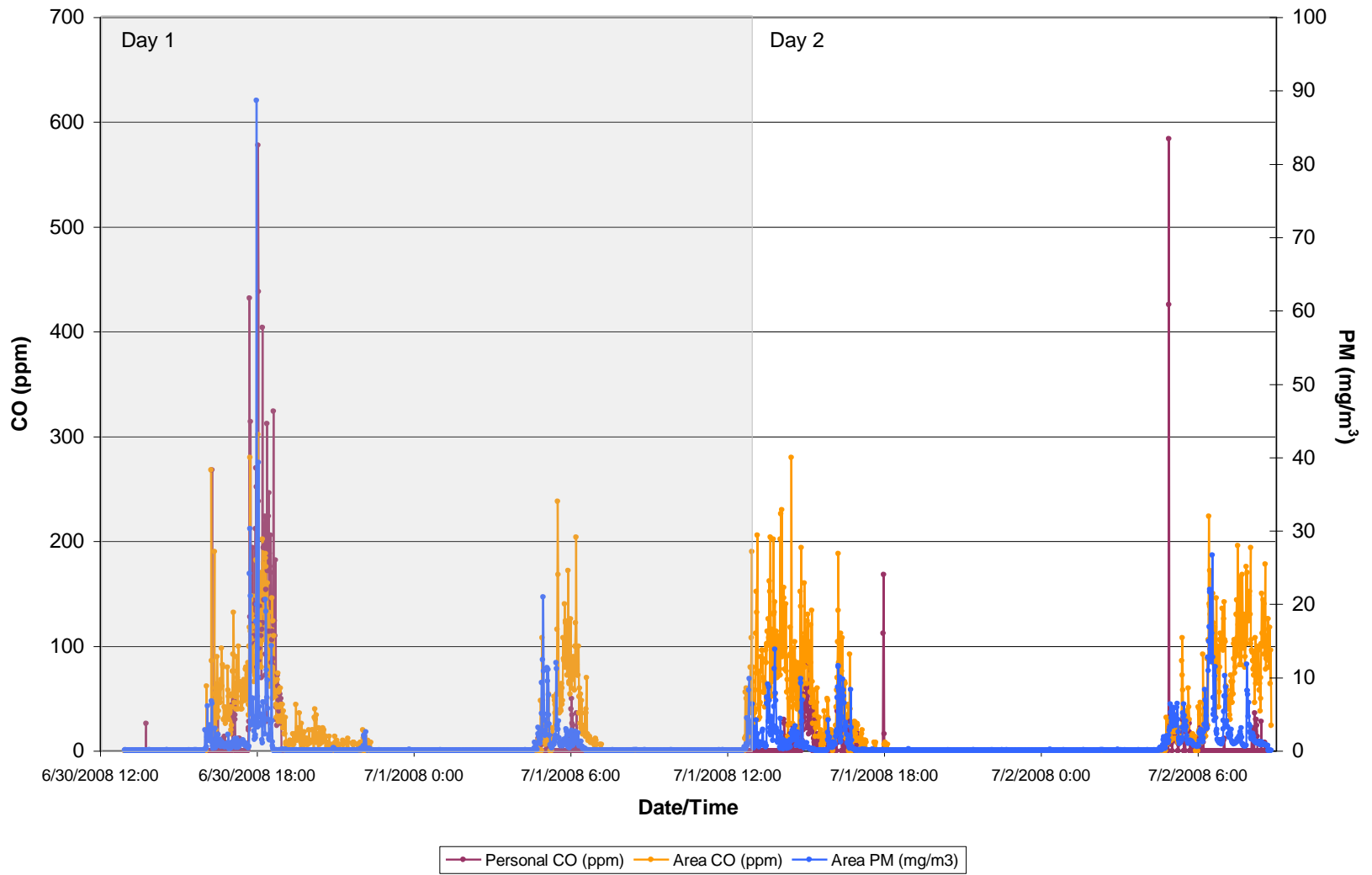
House 87 and Participant Exposure Data



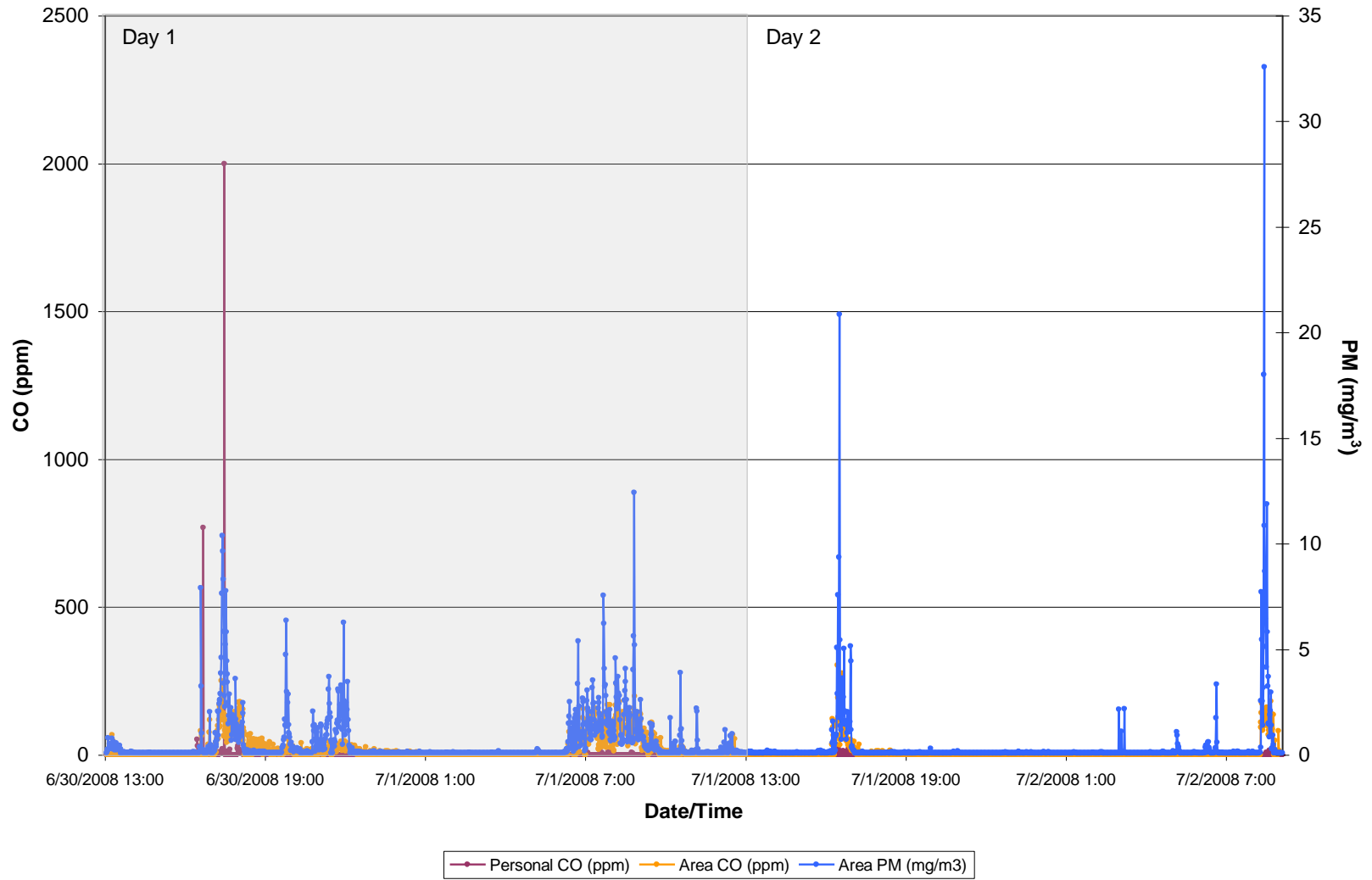
House 88 and Participant Exposure Data



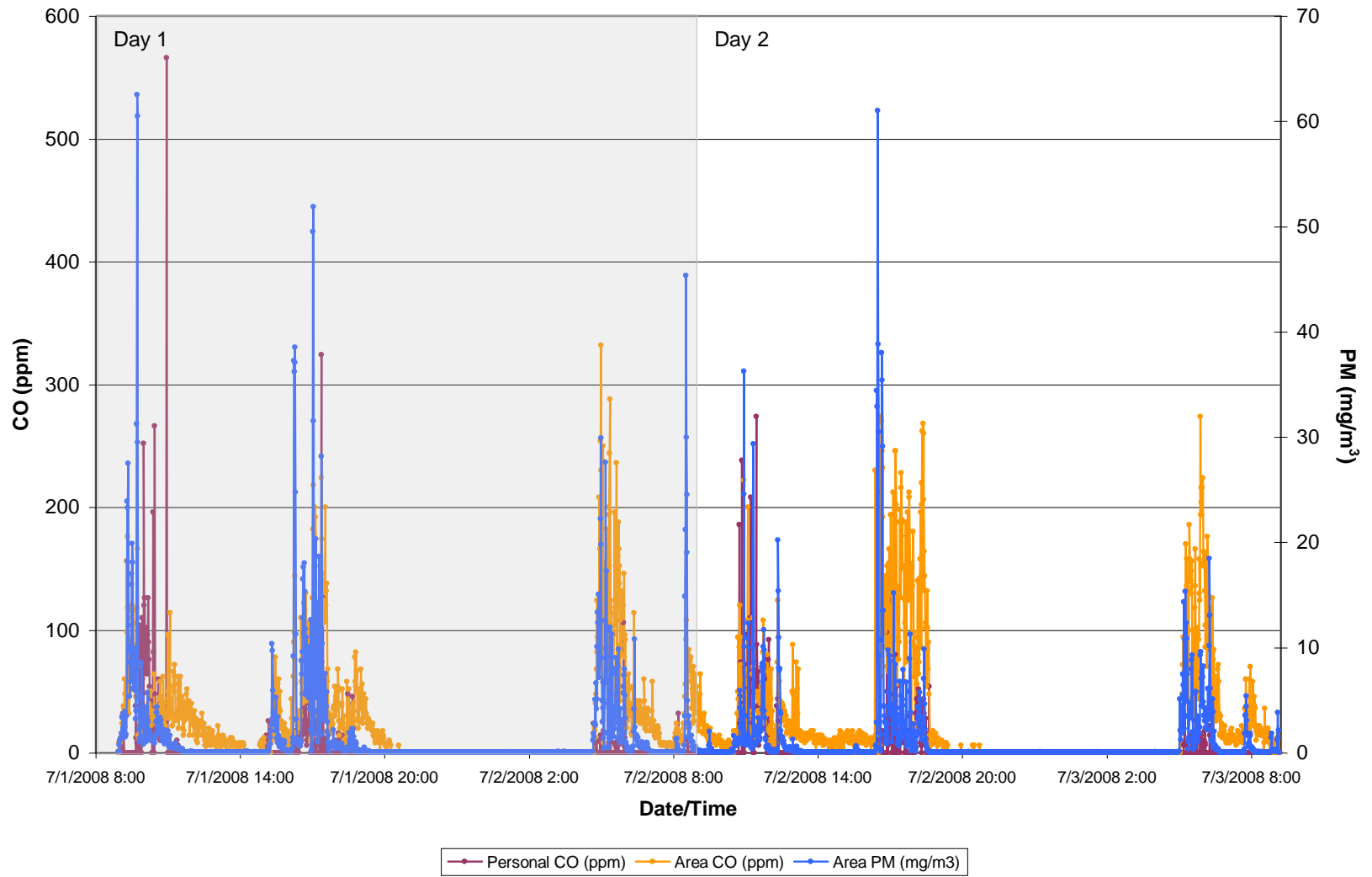
House 89 and Participant Exposure Data



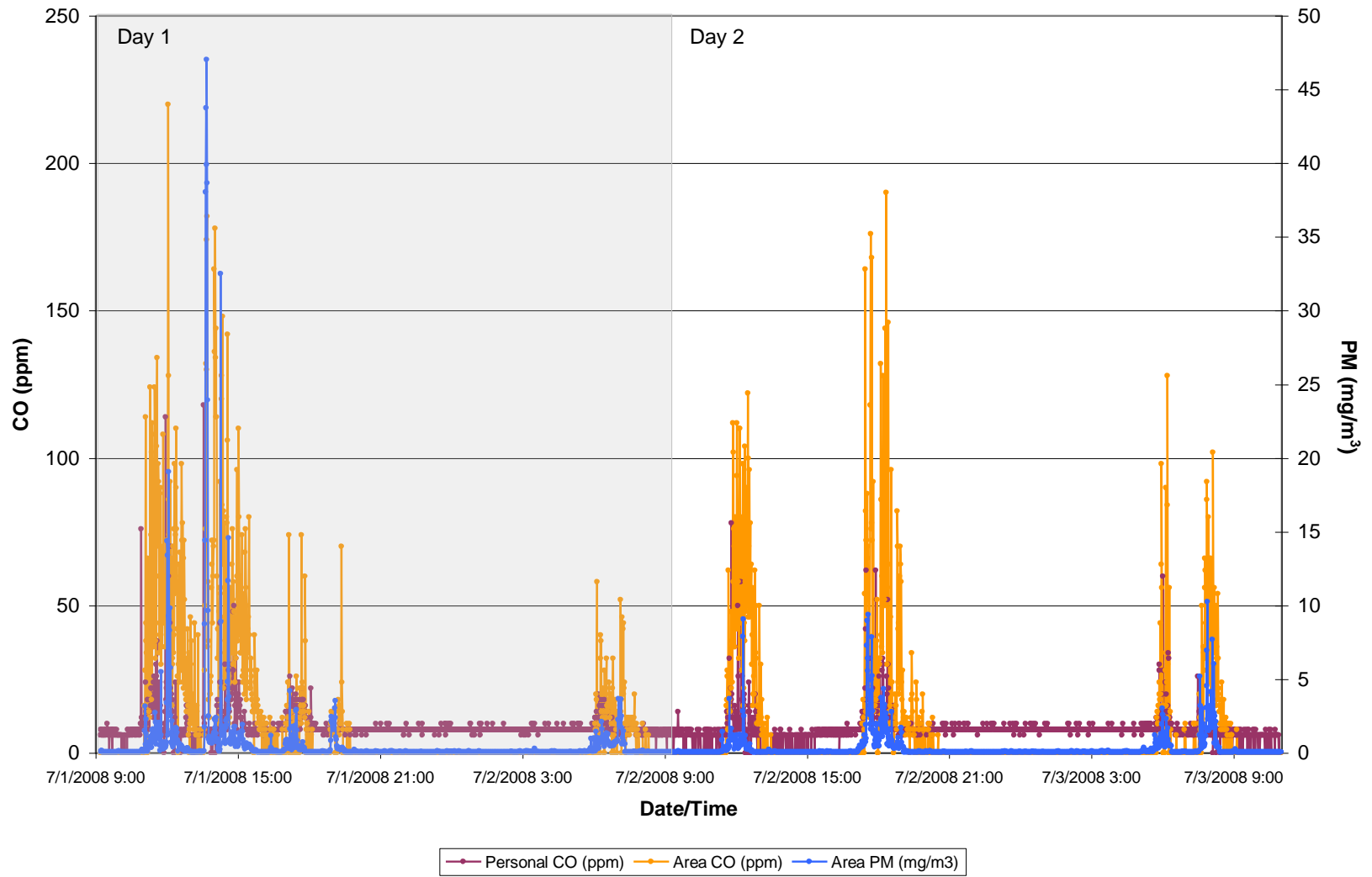
House 90 and Participant Exposure Data



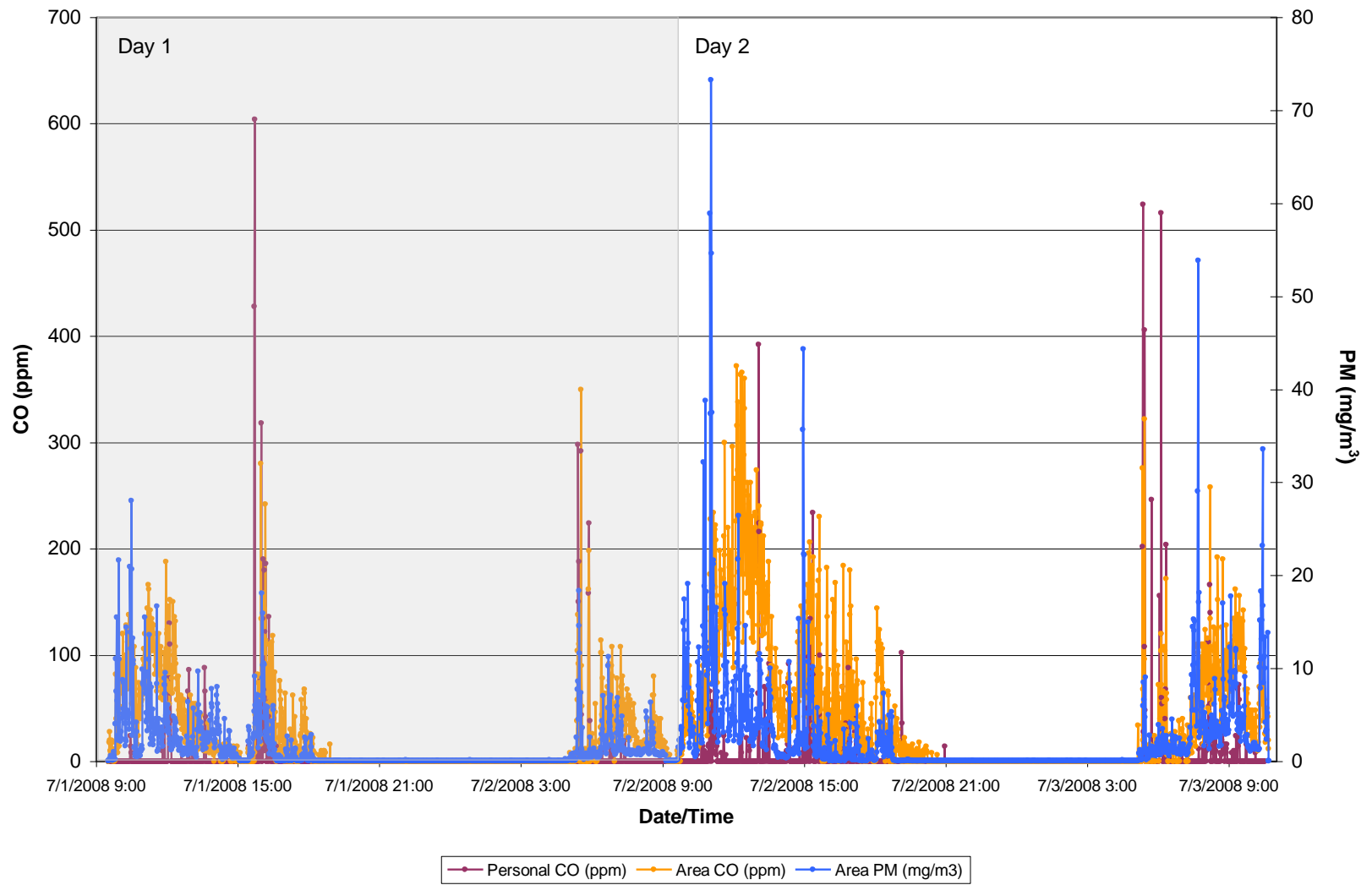
House 91 and Participant Exposure Data



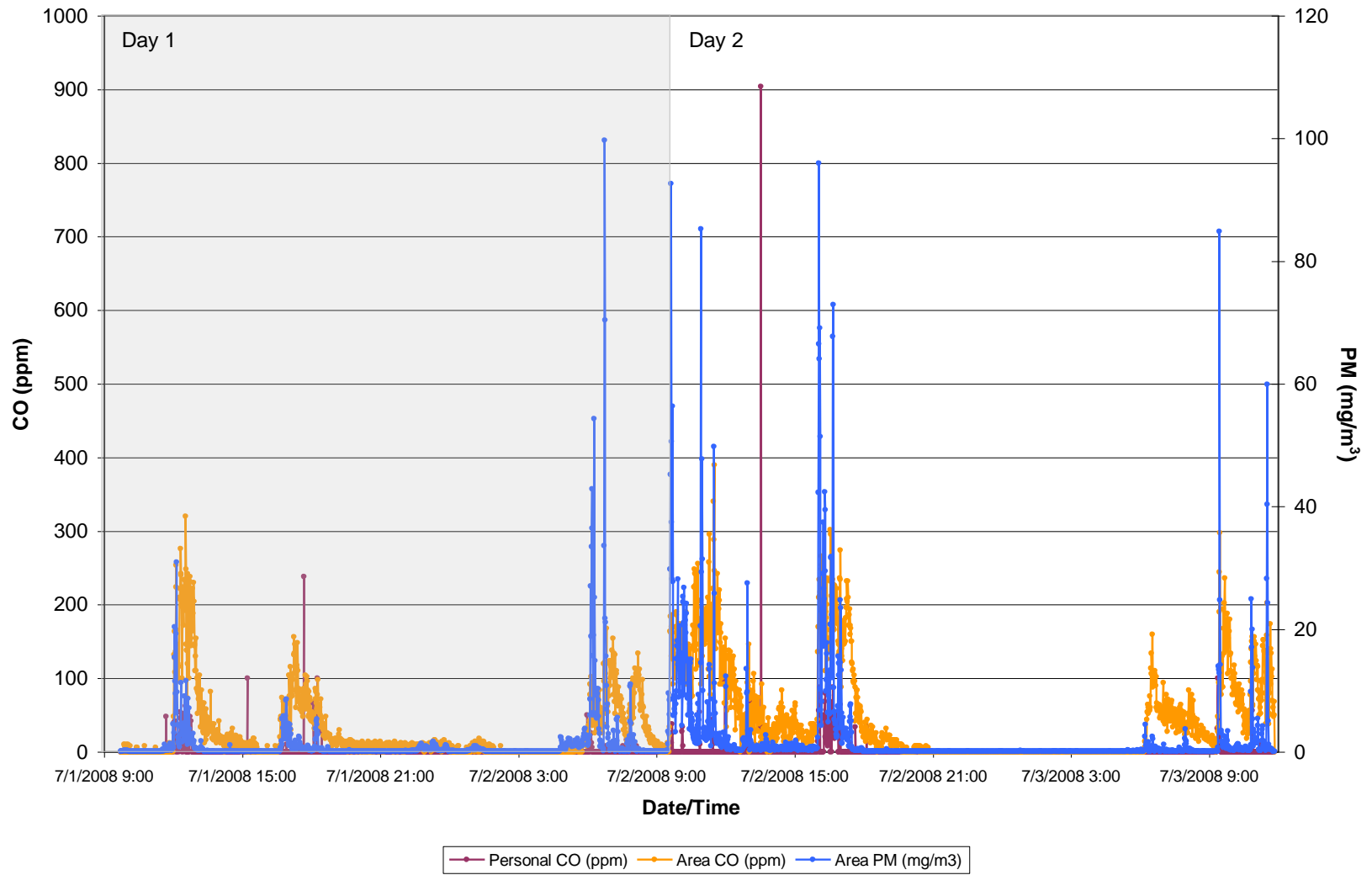
House 92 and Participant Exposure Data



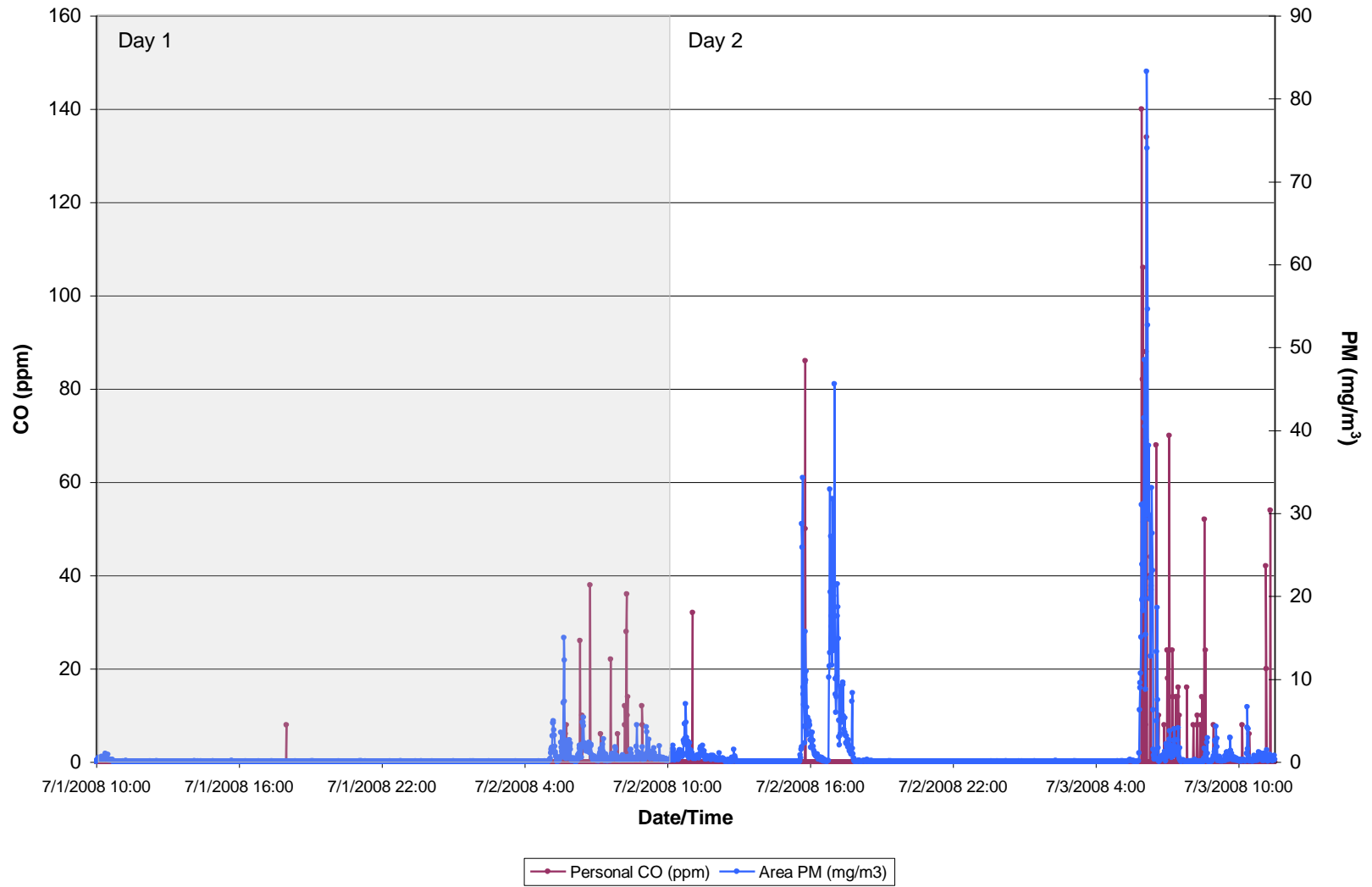
House 93 and Participant Exposure Data



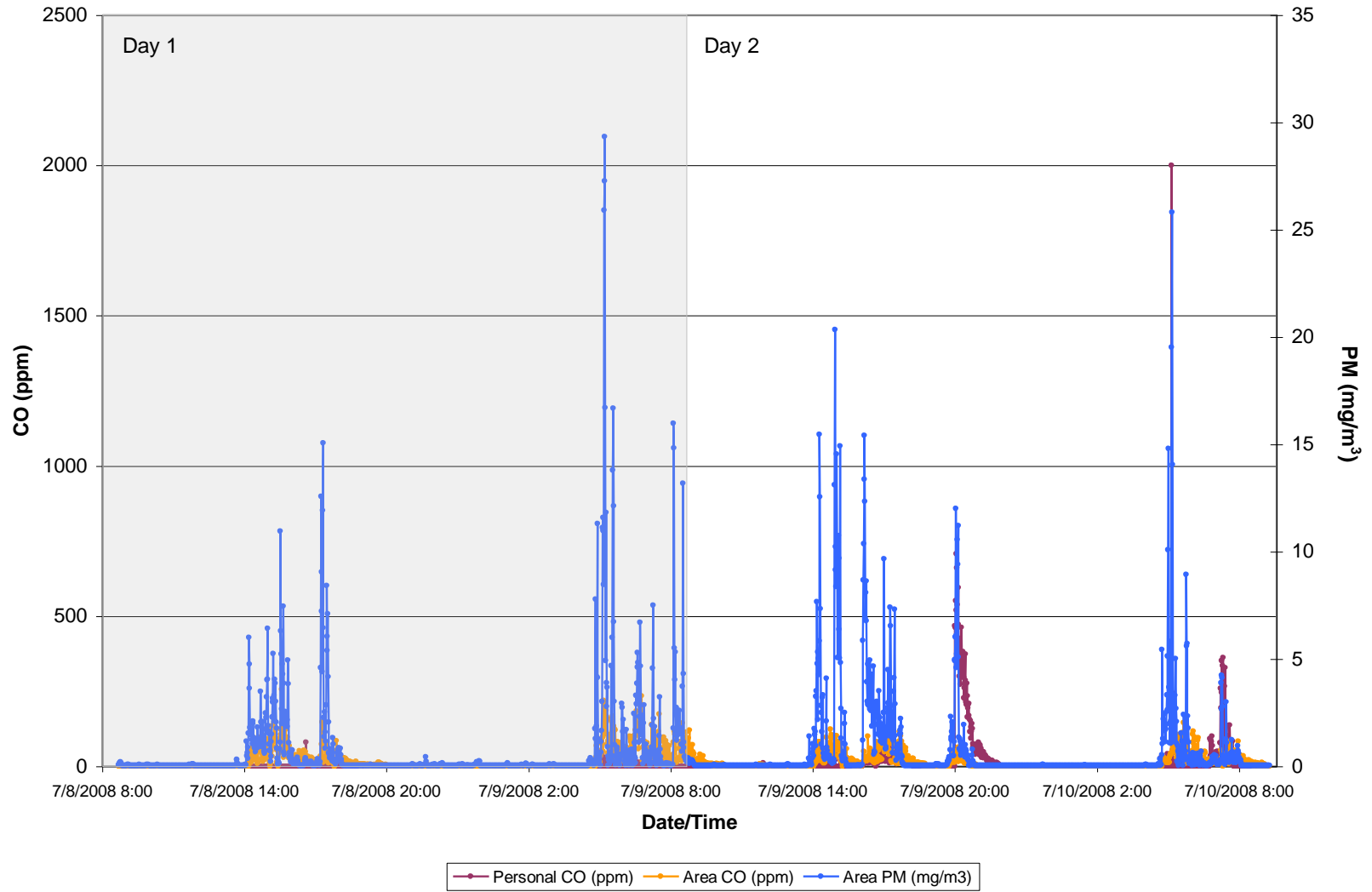
House 94 and Participant Exposure Data



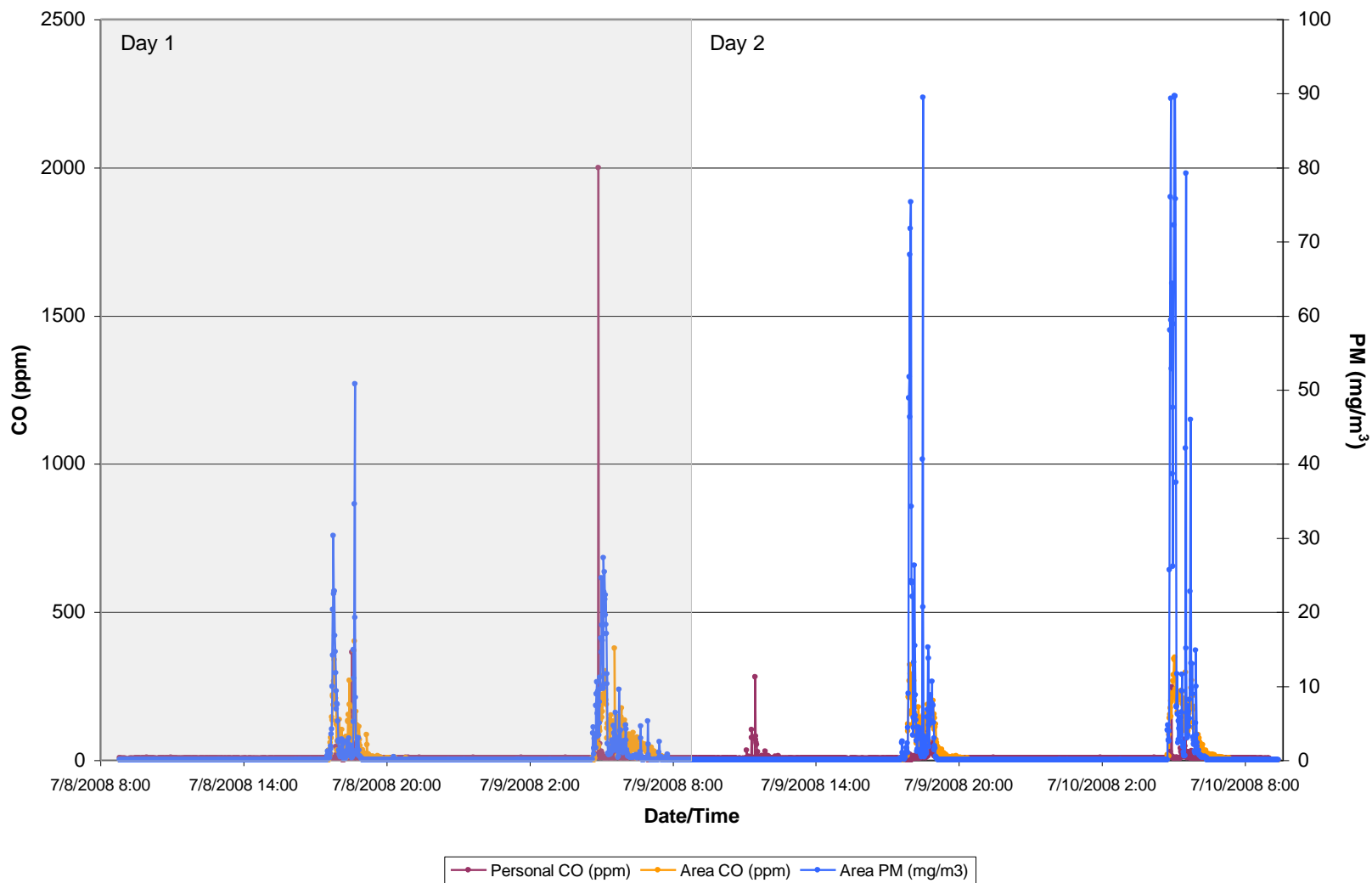
House 95 and Participant Exposure Data (Area CO Data N/A)



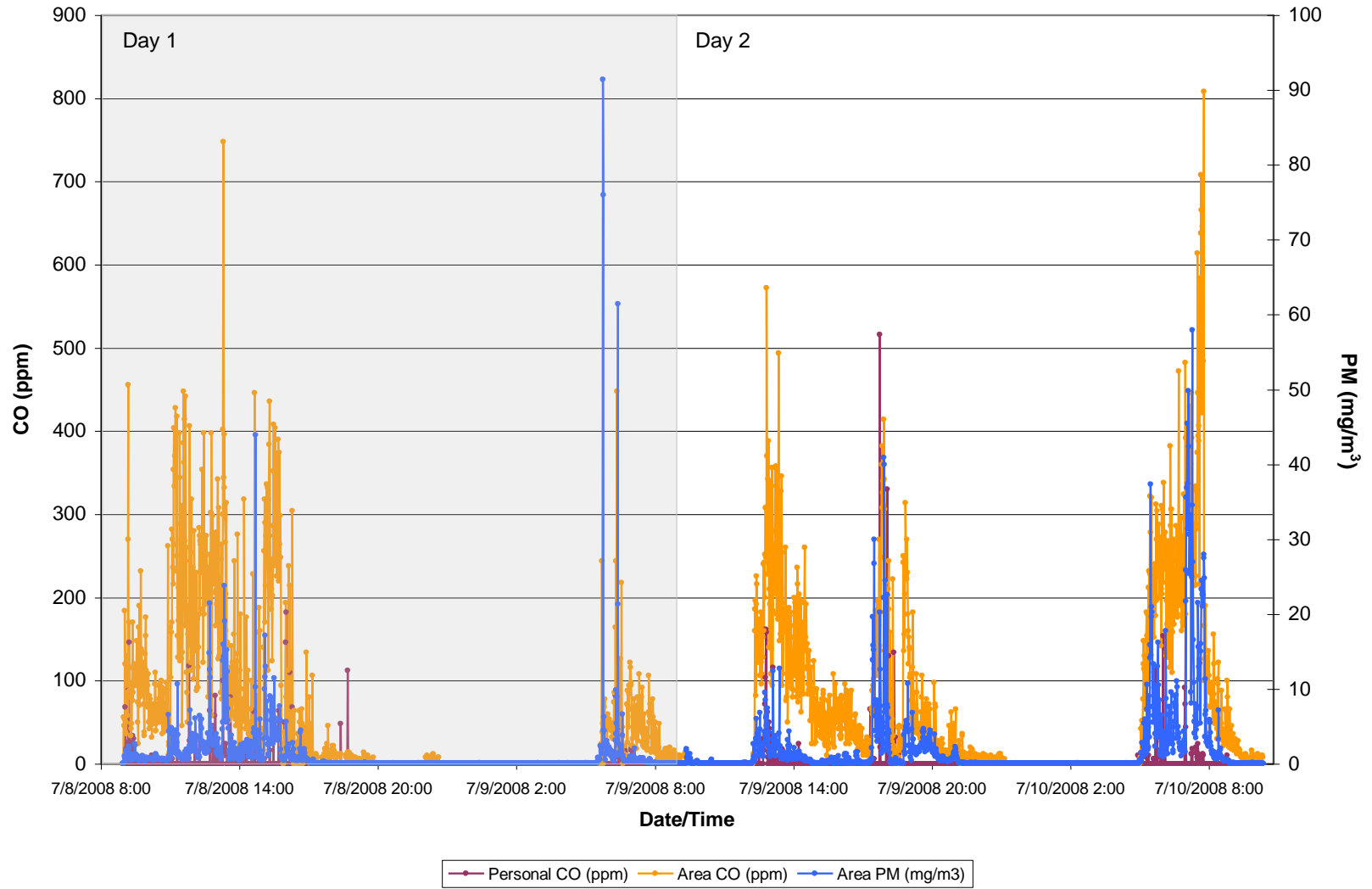
House 96 and Participant Exposure Data



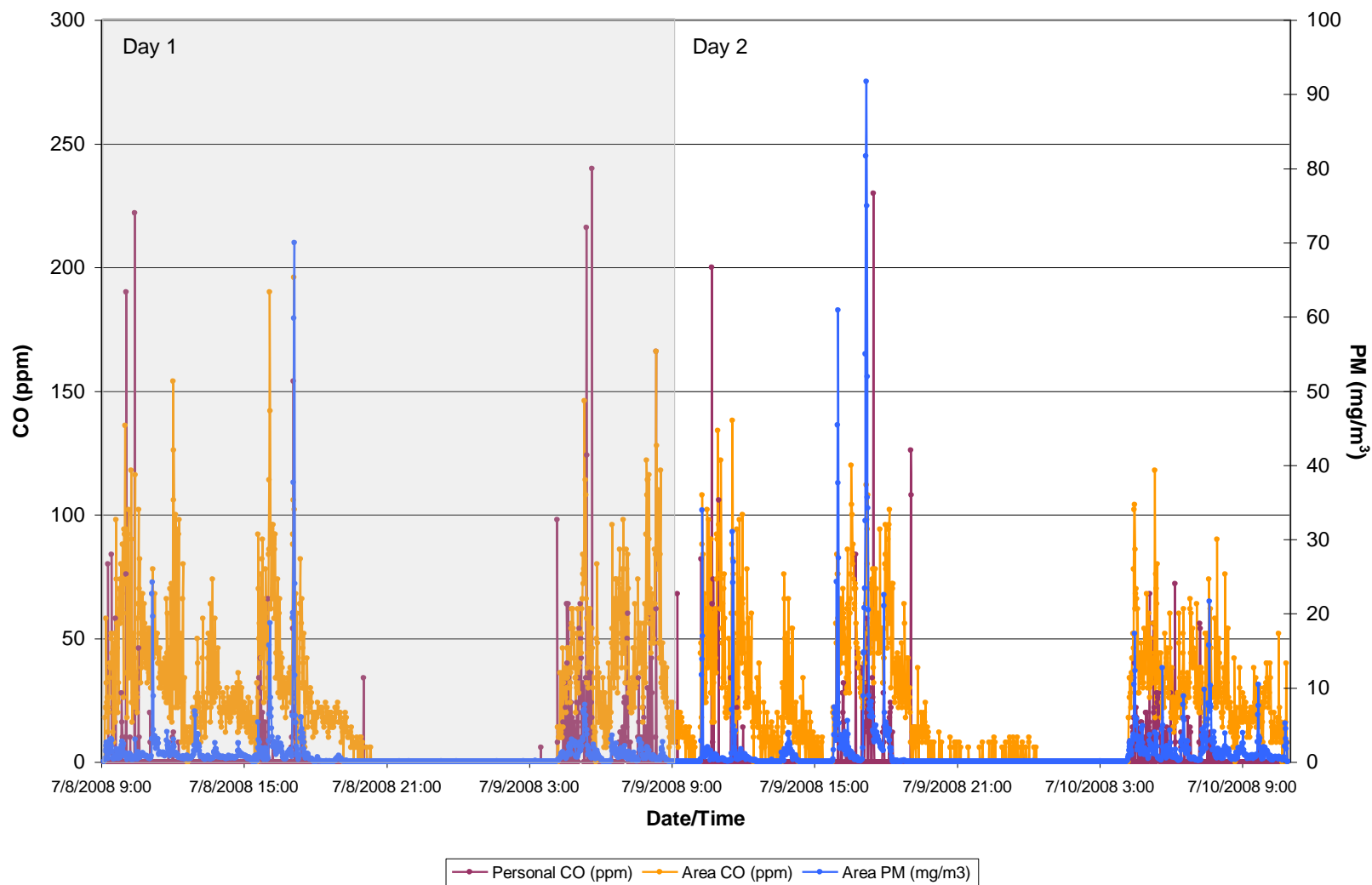
House 97 and Participant Exposure Data



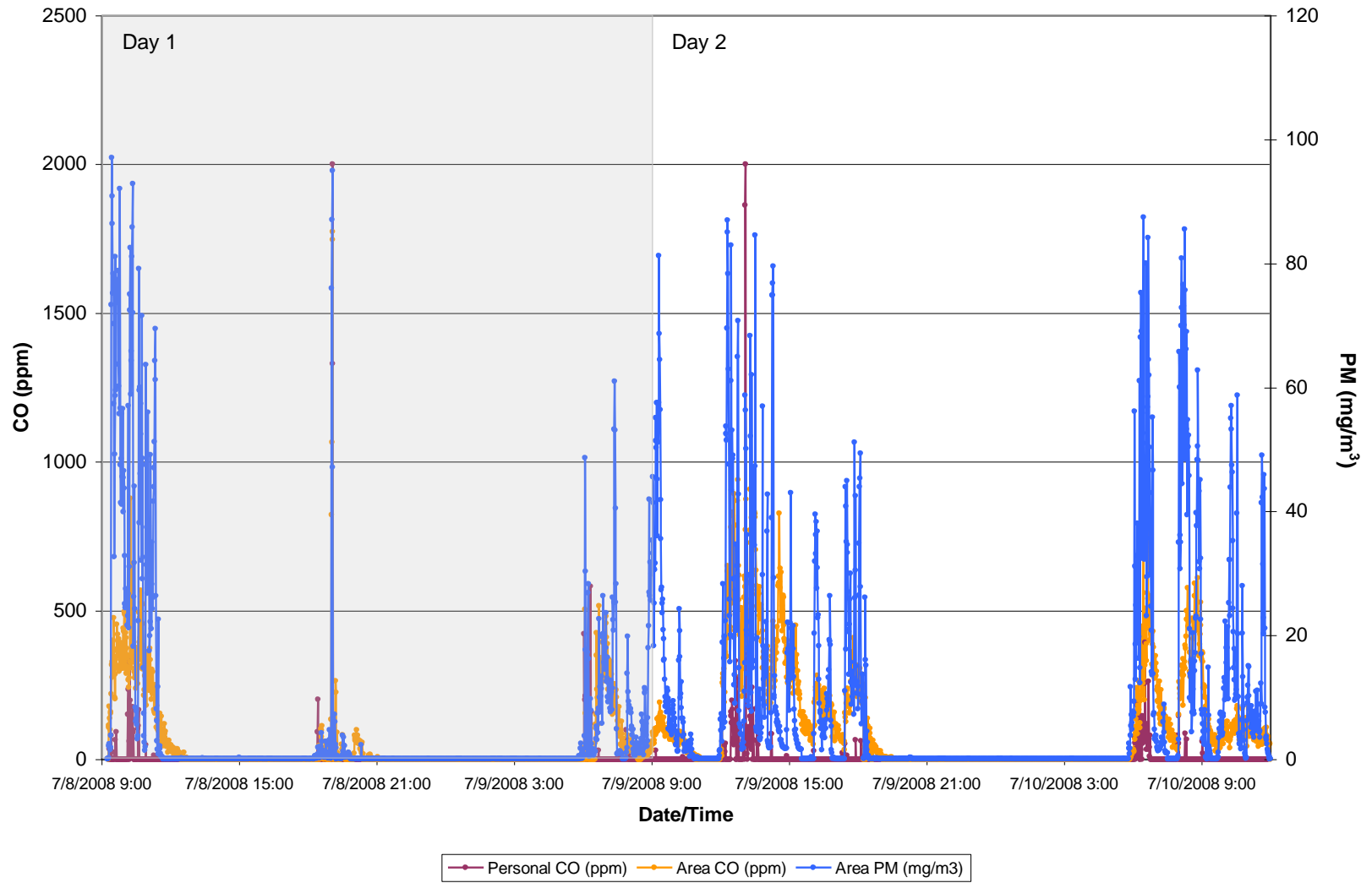
House 98 and Participant Exposure Data



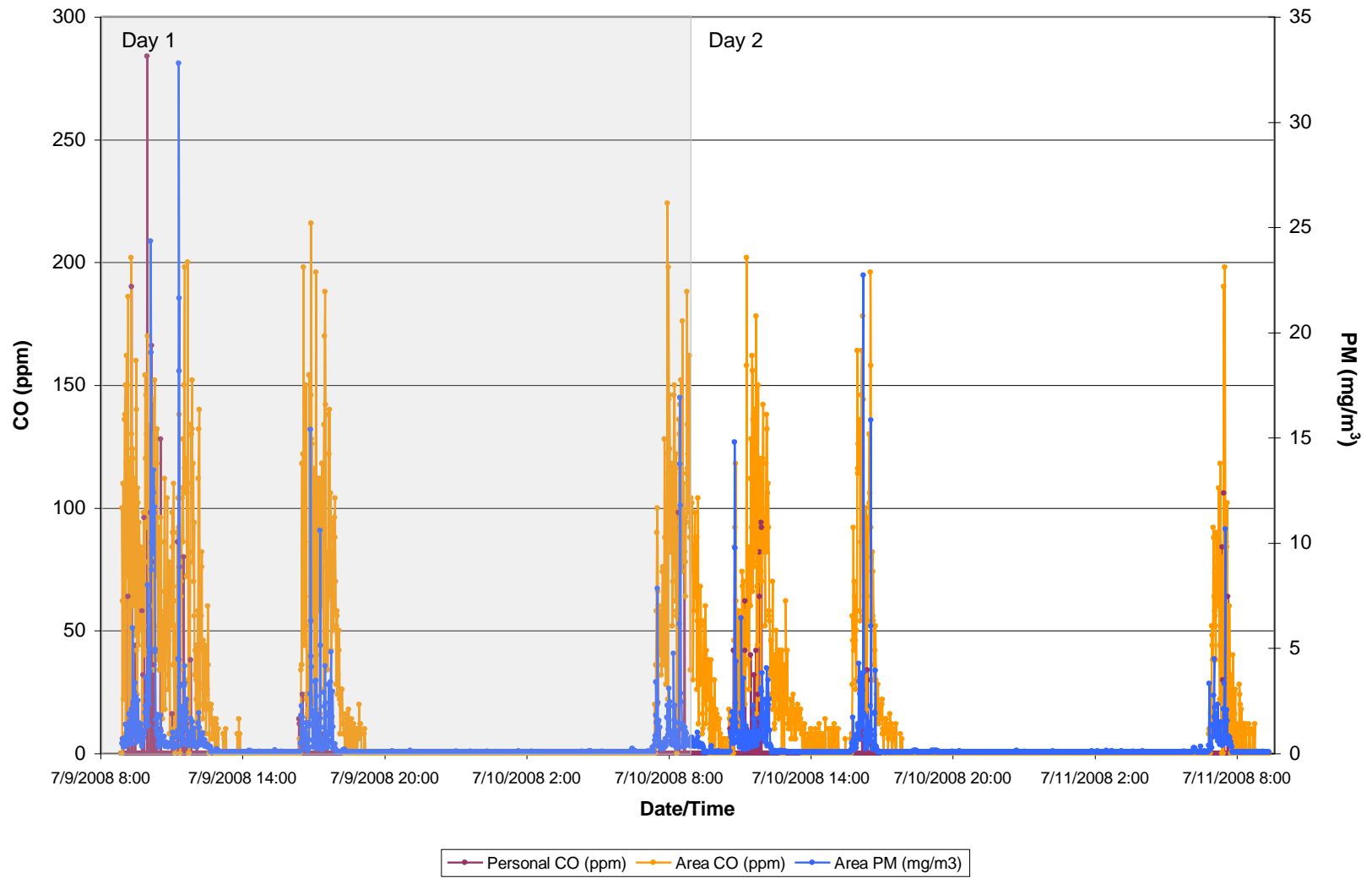
House 99 and Participant Exposure Data



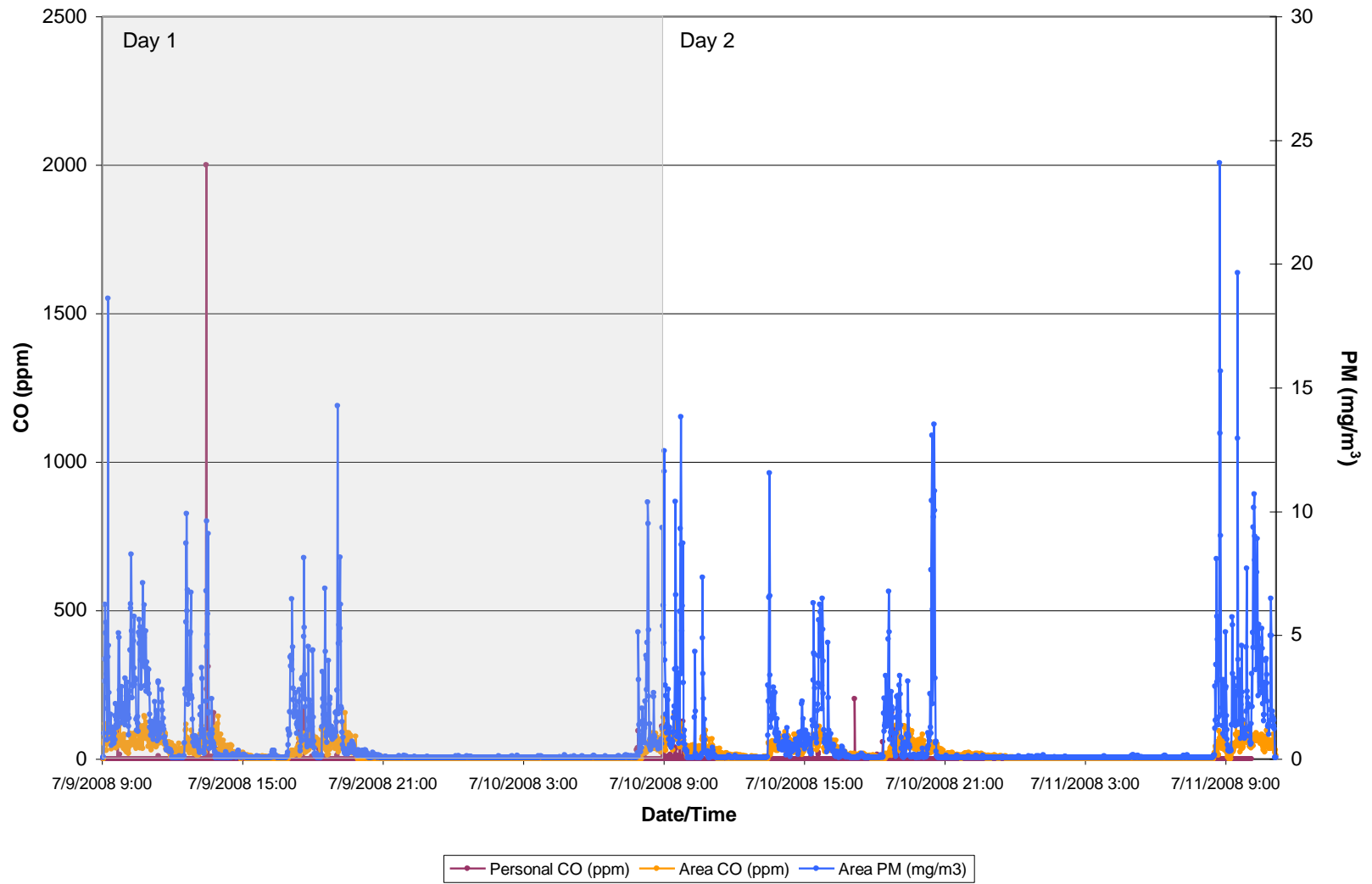
House 100 and Participant Exposure Data



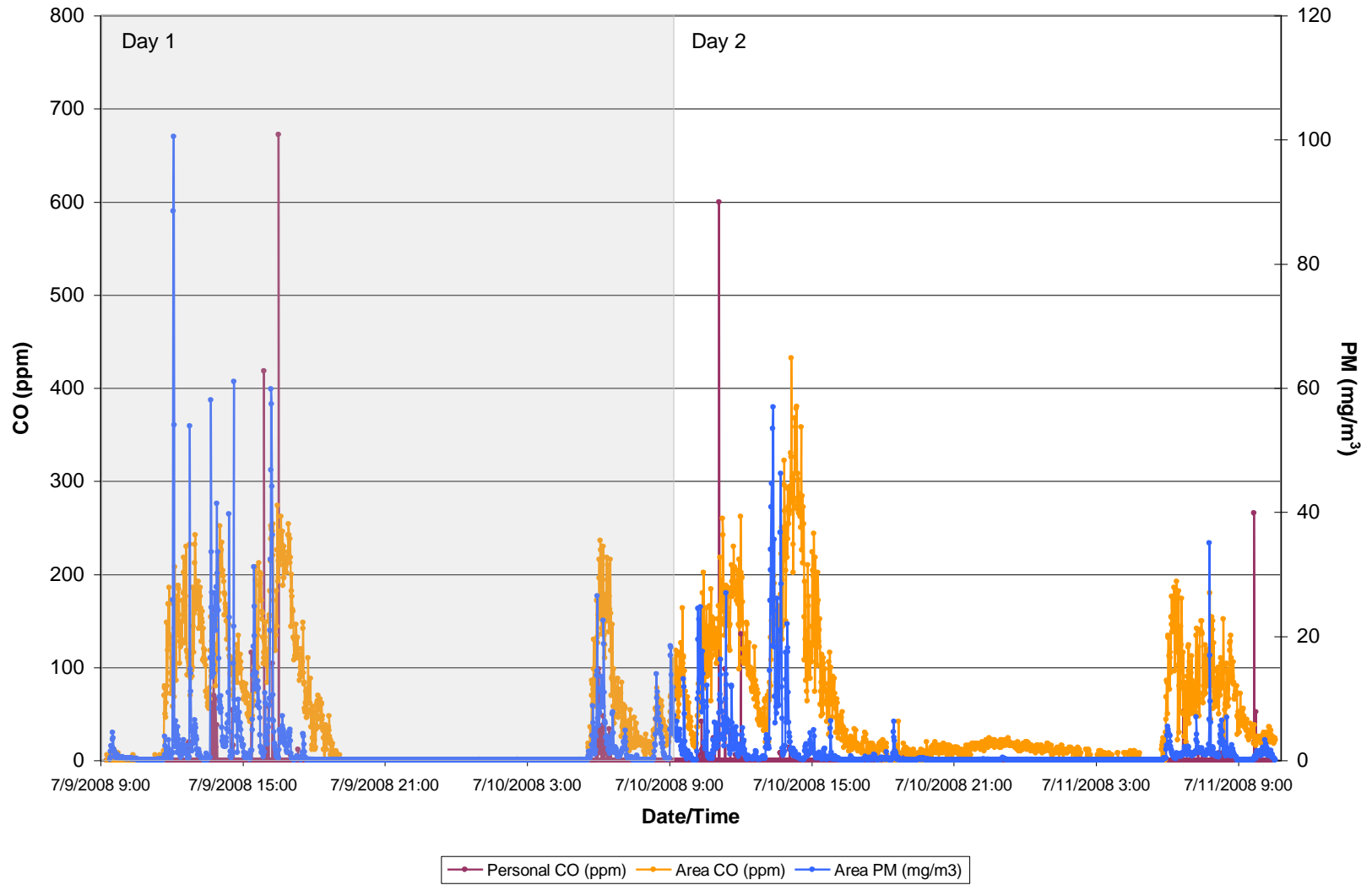
House 101 and Participant Exposure Data



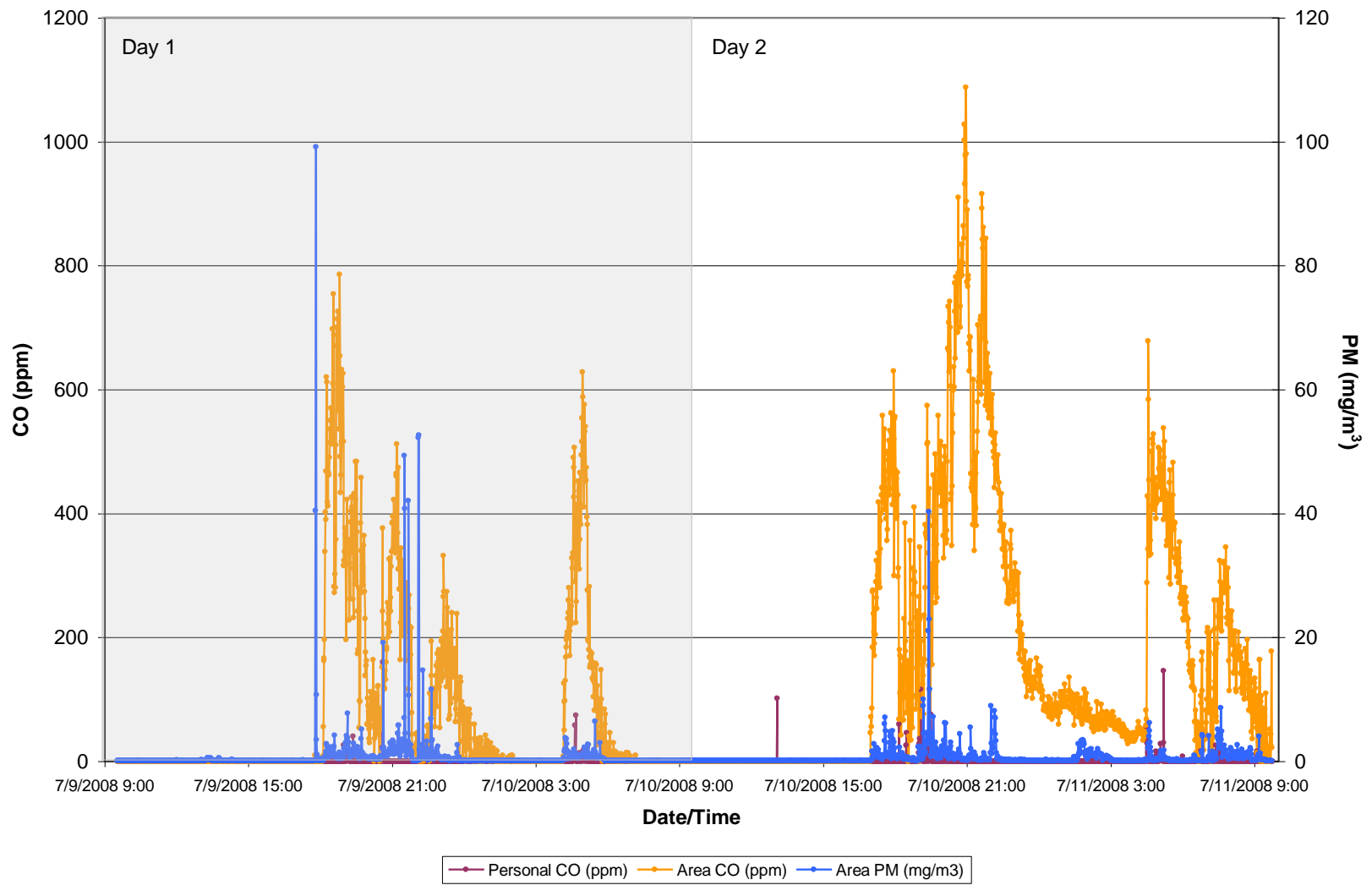
House 102 and Participant Exposure Data



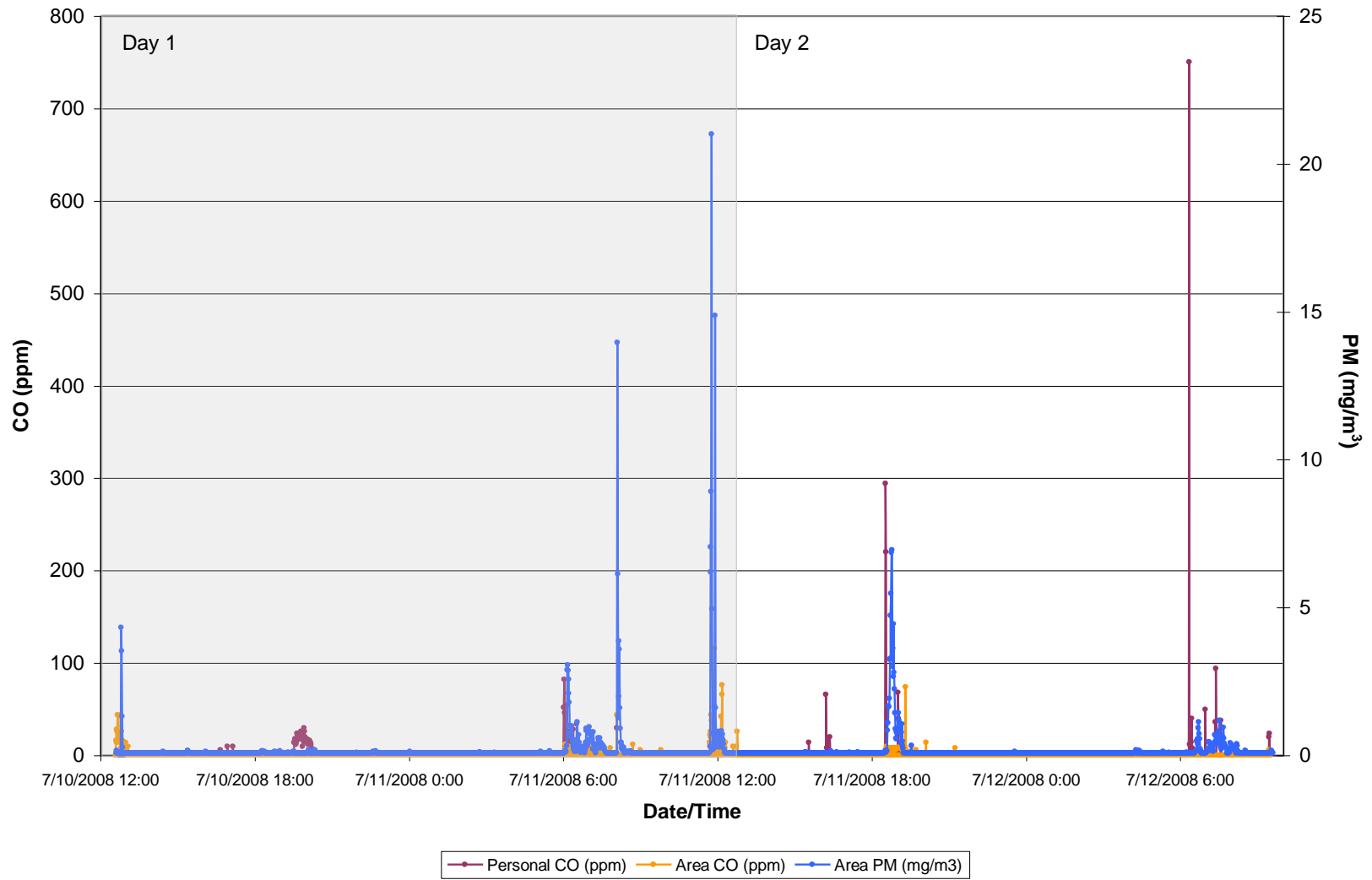
House 103 and Participant Exposure Data



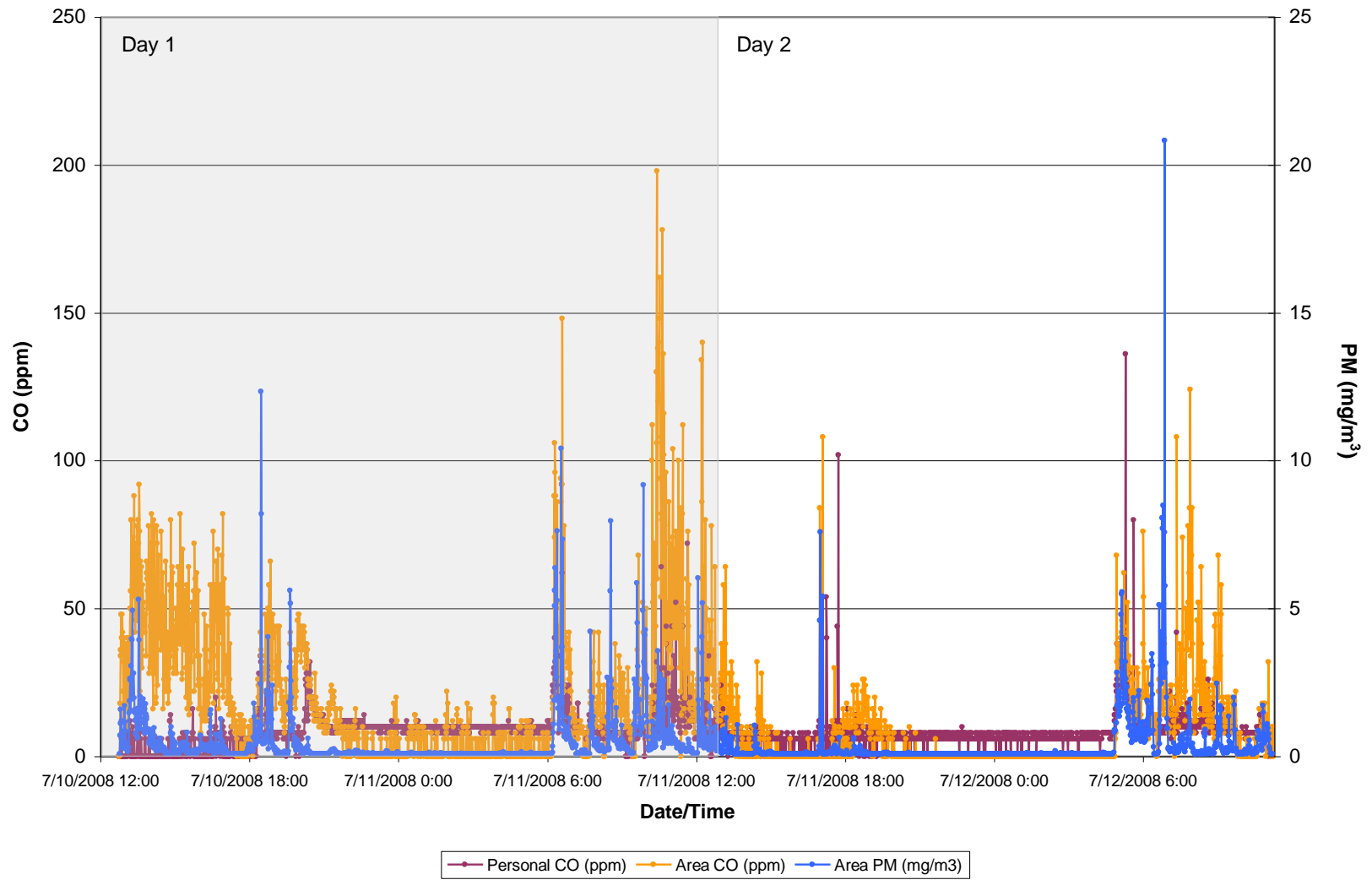
House 104 and Participant Exposure Data



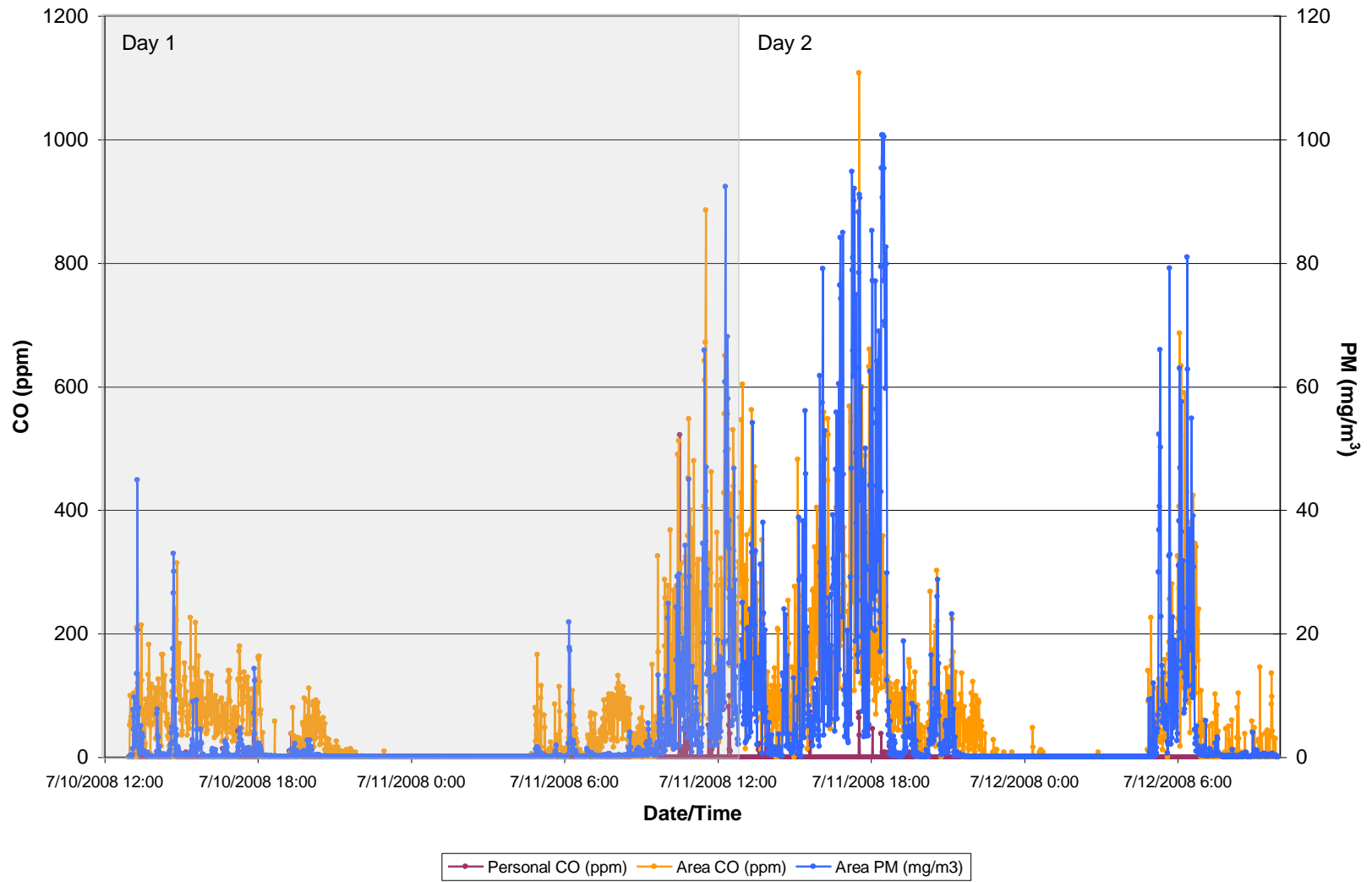
House 105 and Participant Exposure Data



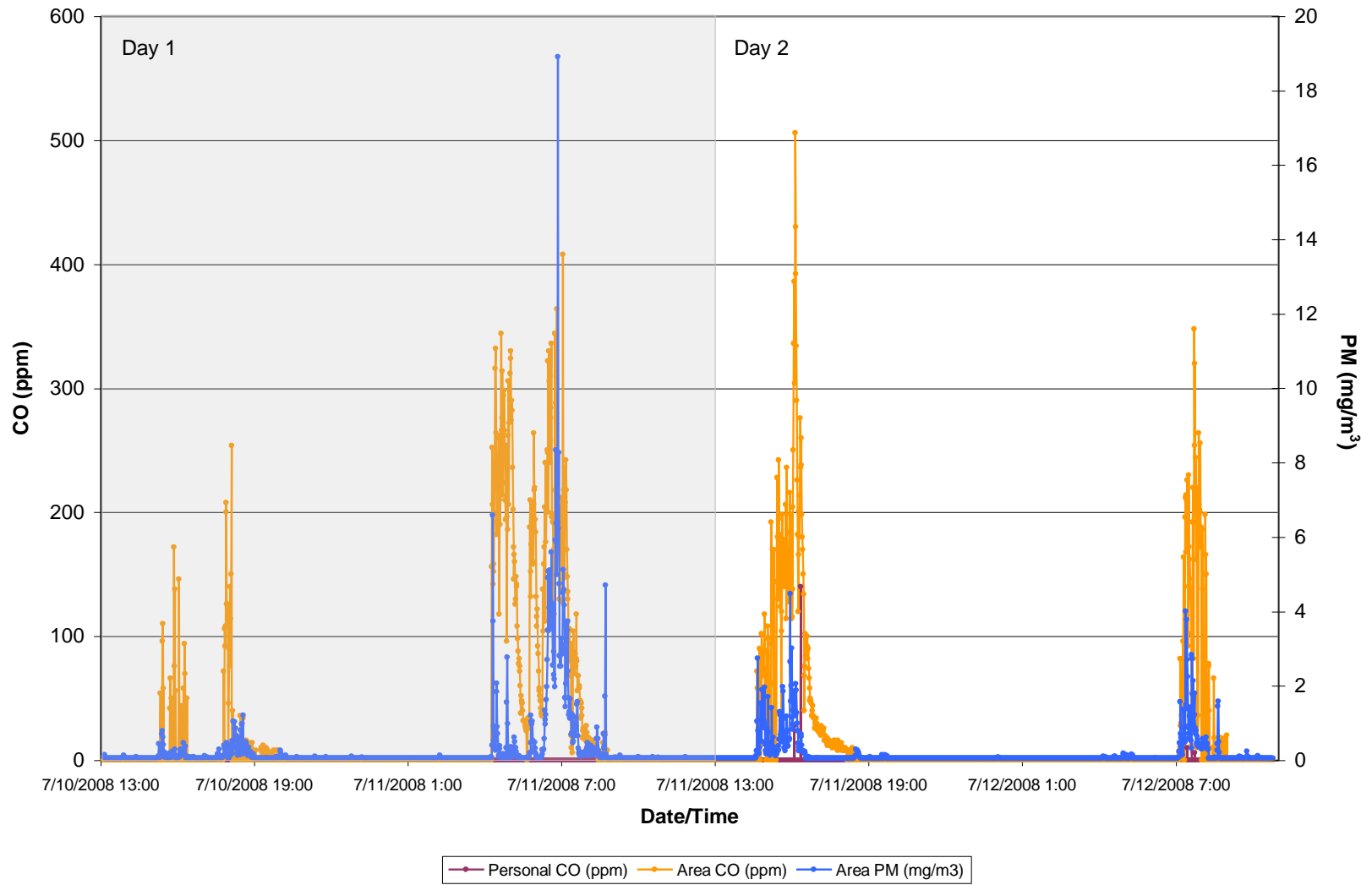
House 106 and Participant Exposure Data



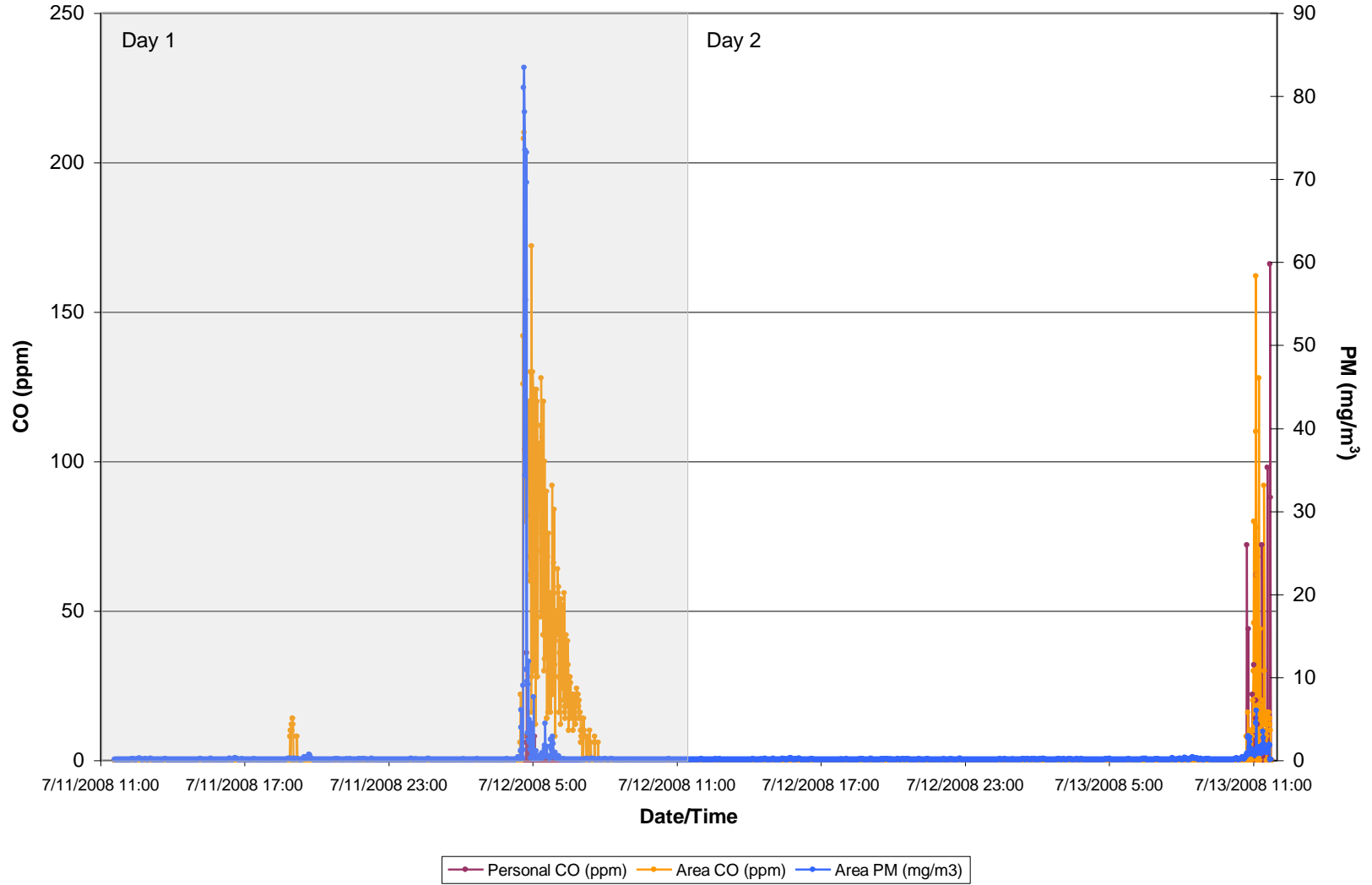
House 107 and Participant Exposure Data



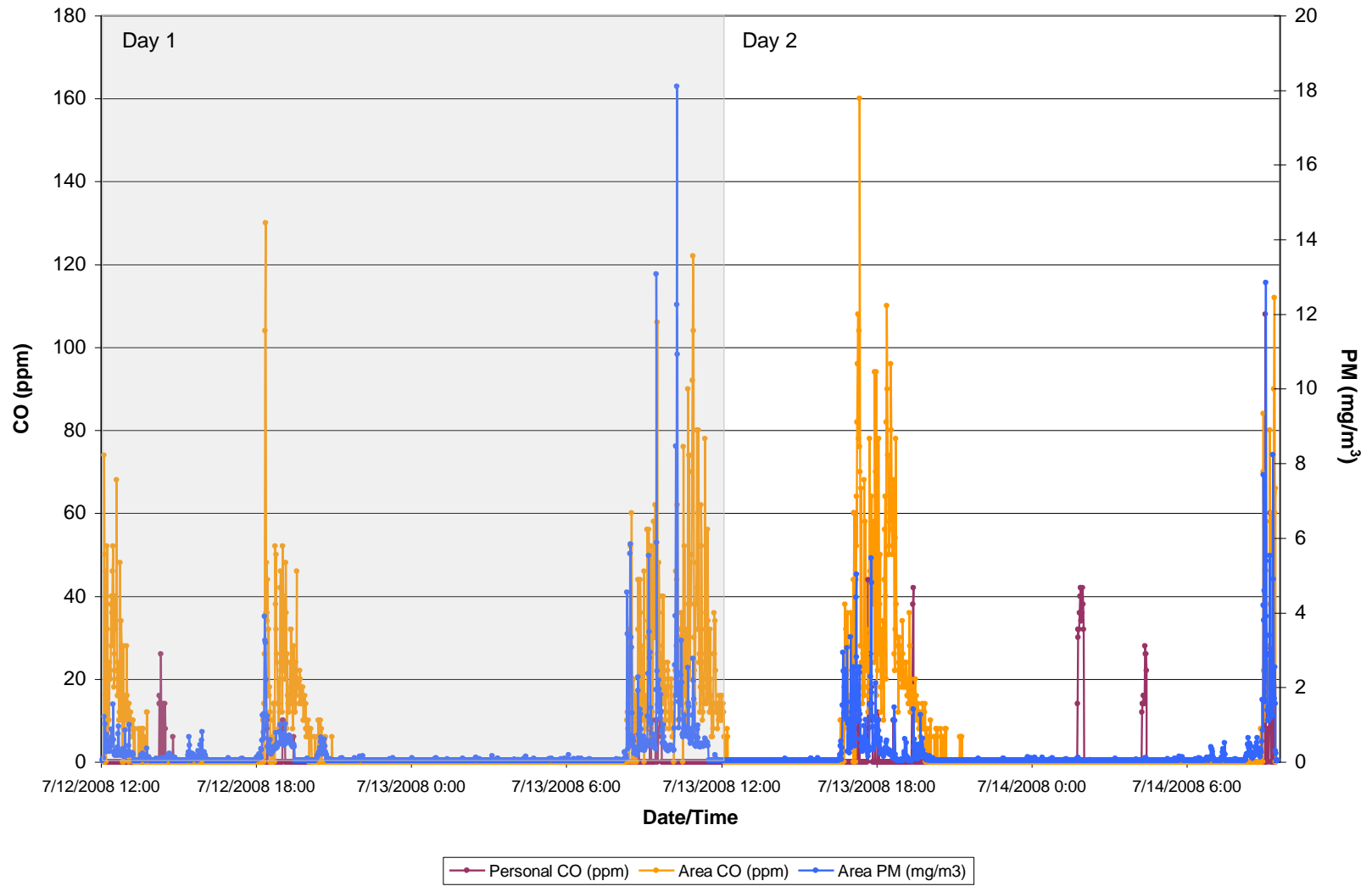
House 108 and Participant Exposure Data



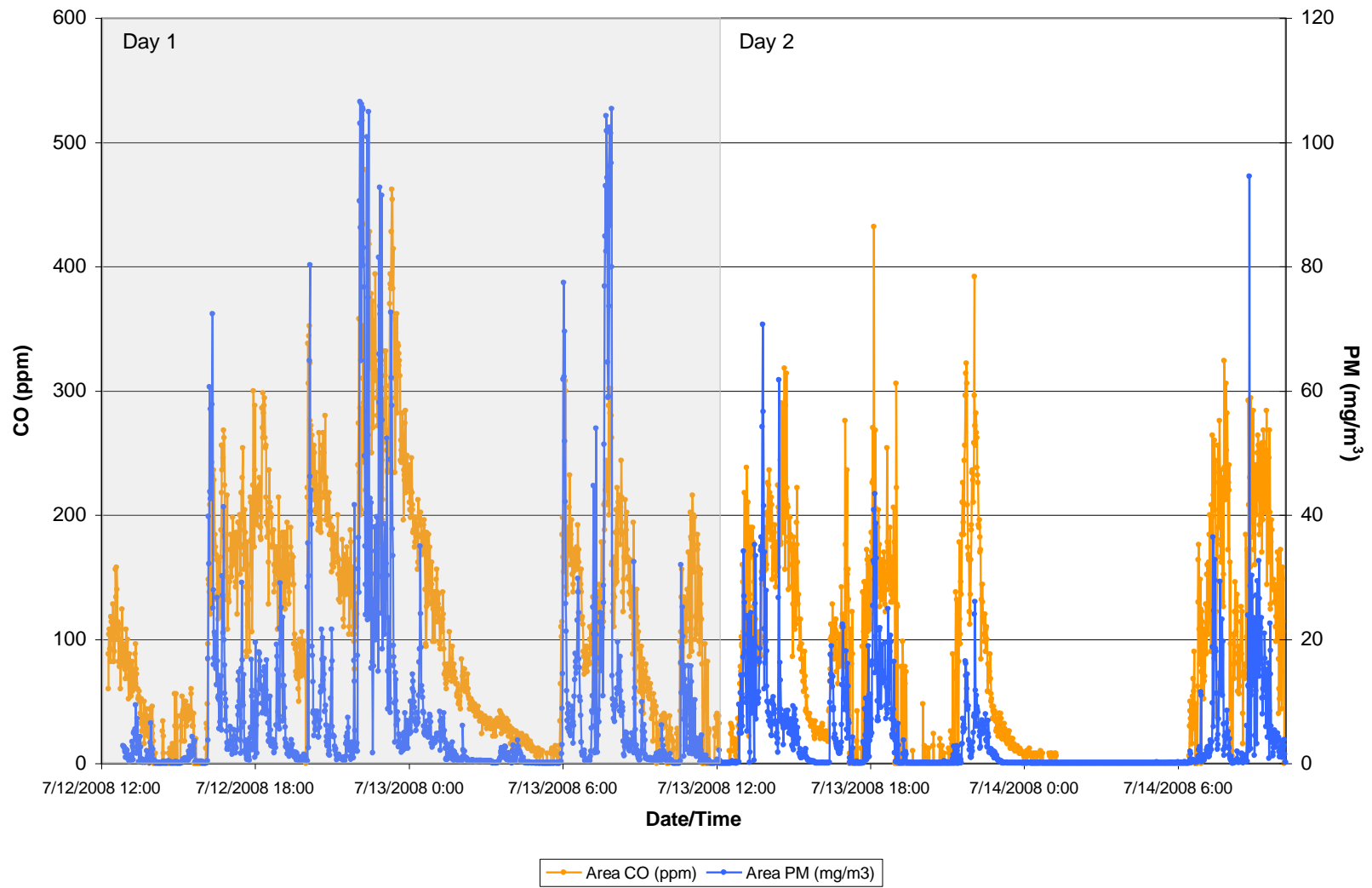
House 109 and Participant Exposure Data



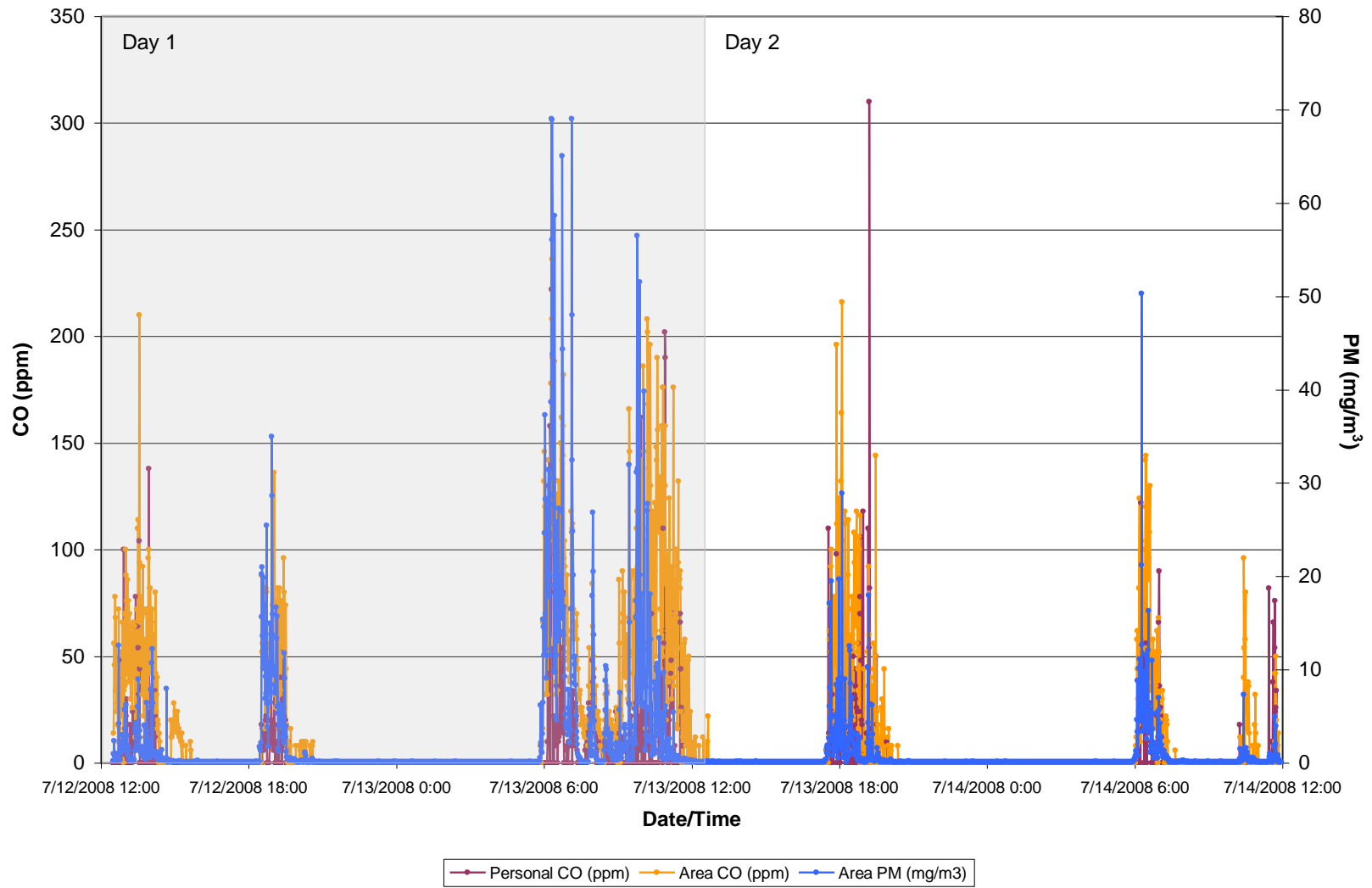
House 110 and Participant Exposure Data



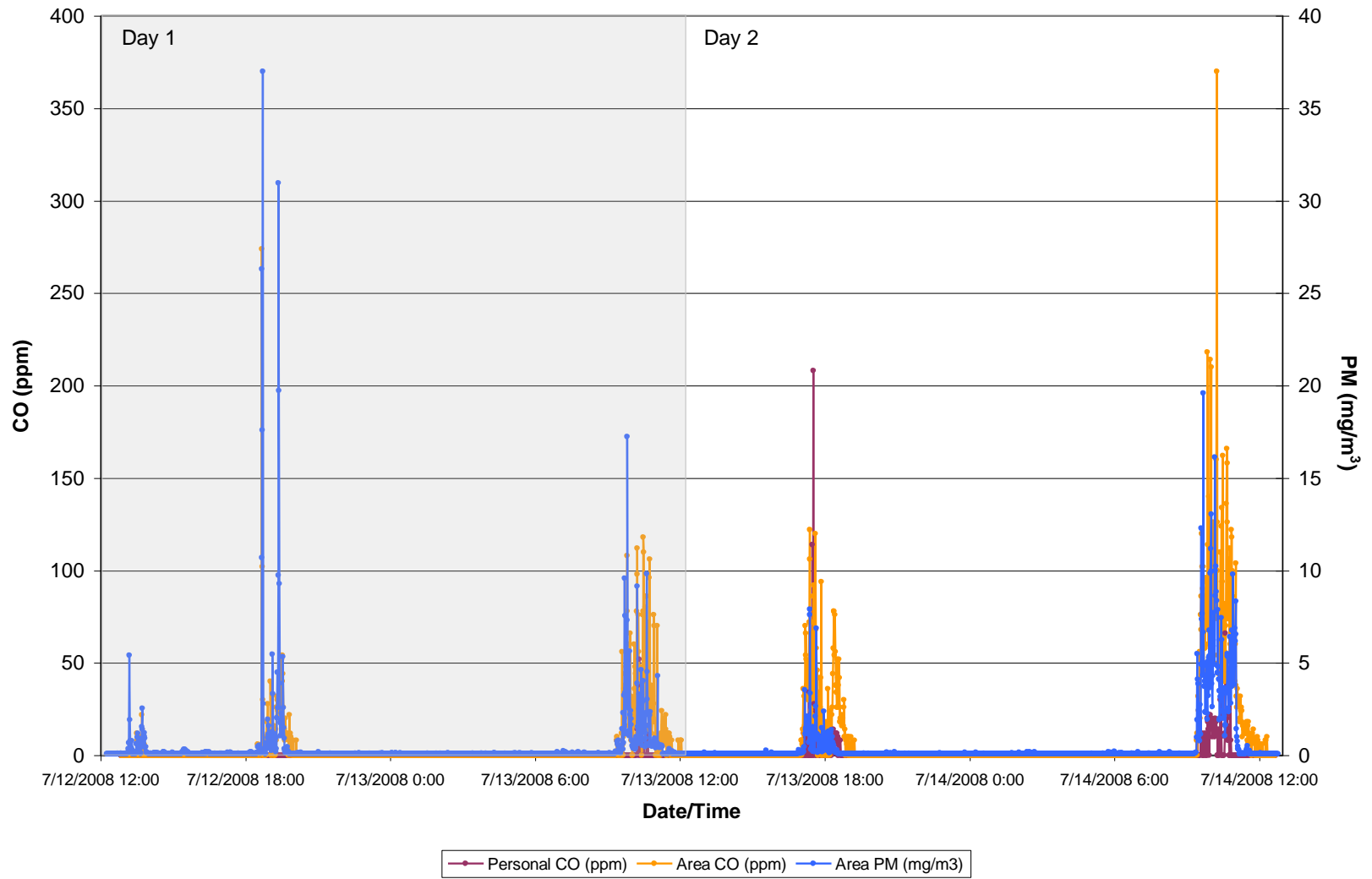
House 111 Exposure Data (Personal CO Data N/A)



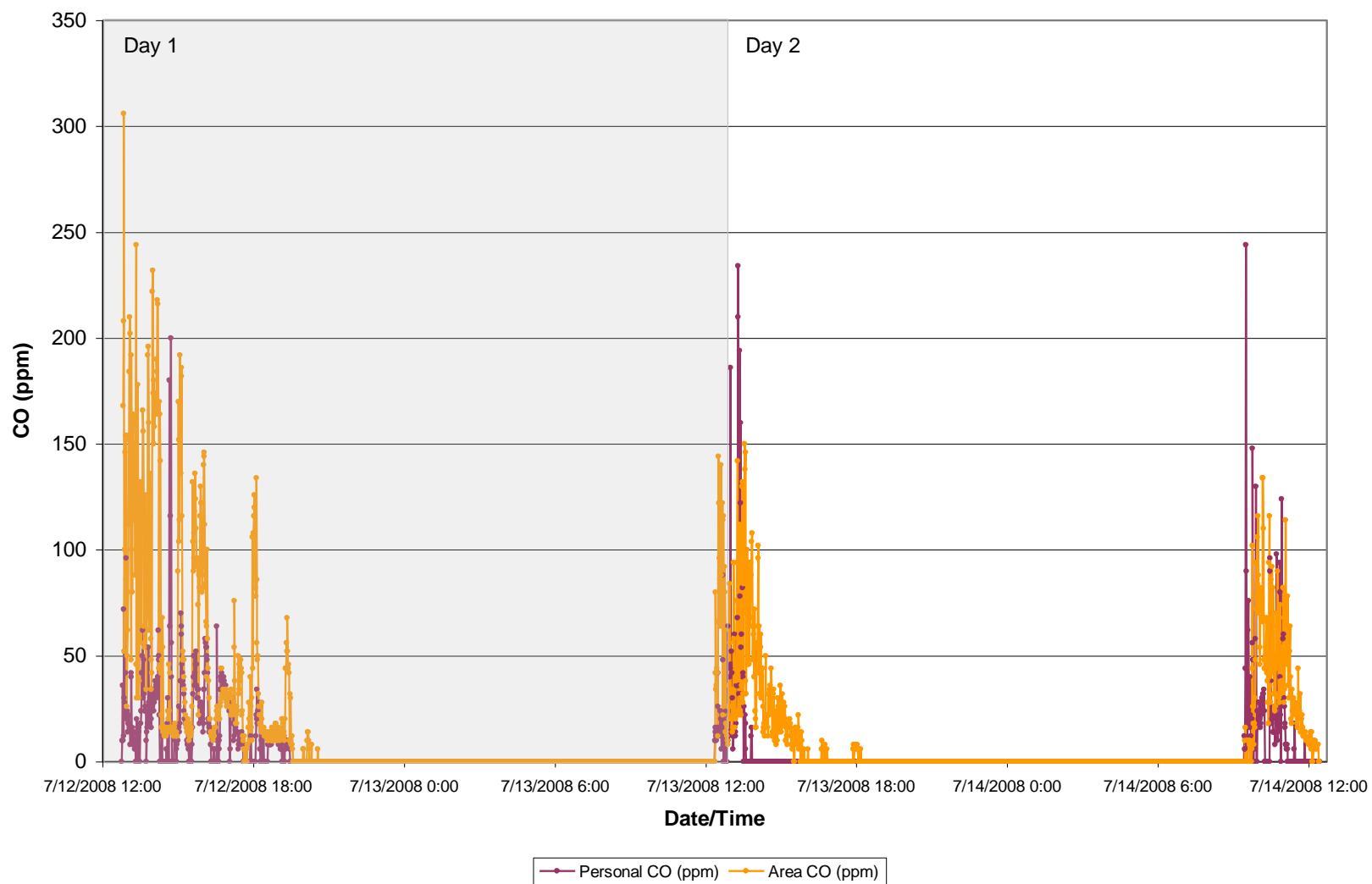
House 112 and Participant Exposure Data



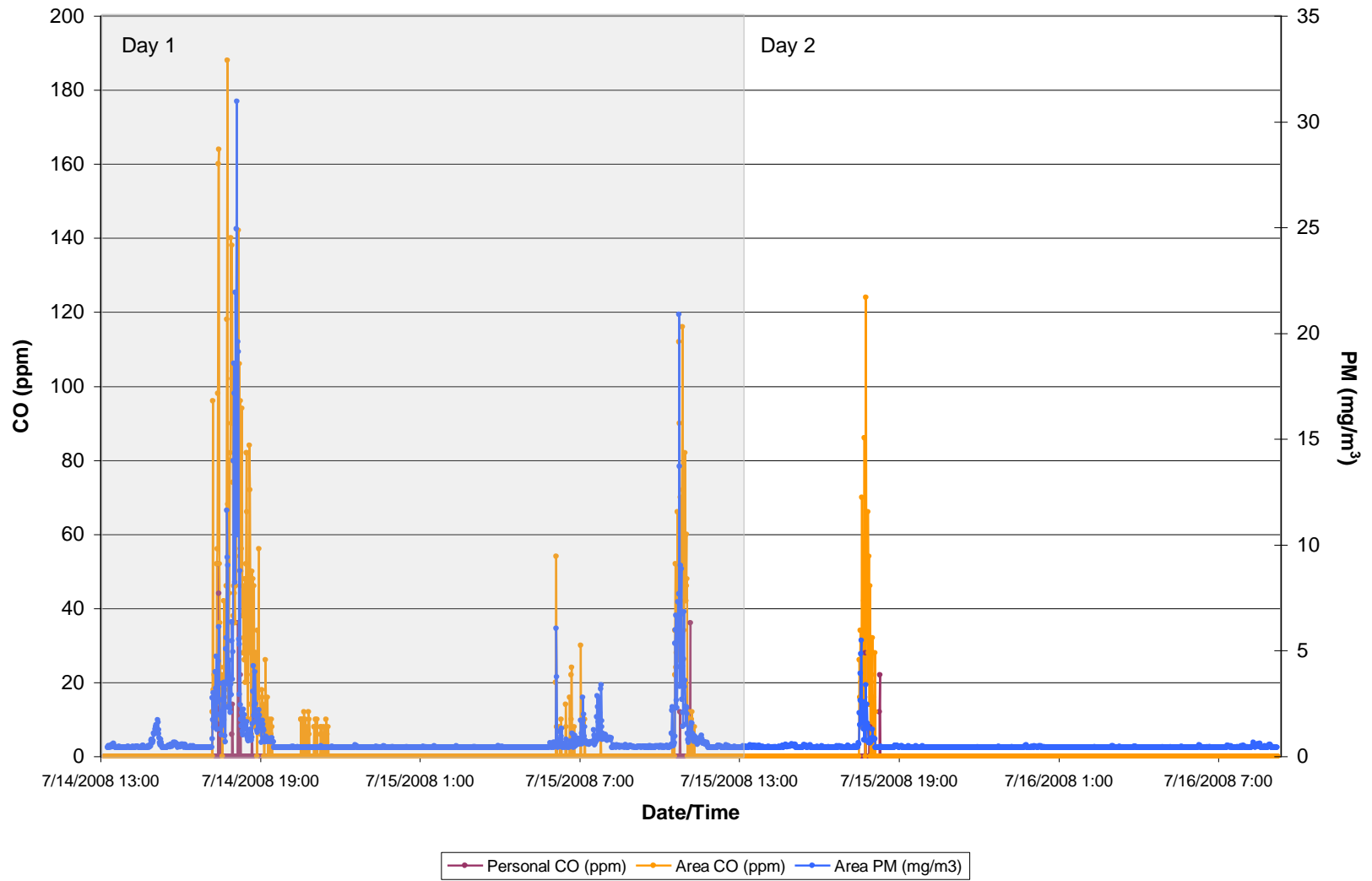
House 113 and Participant Exposure Data



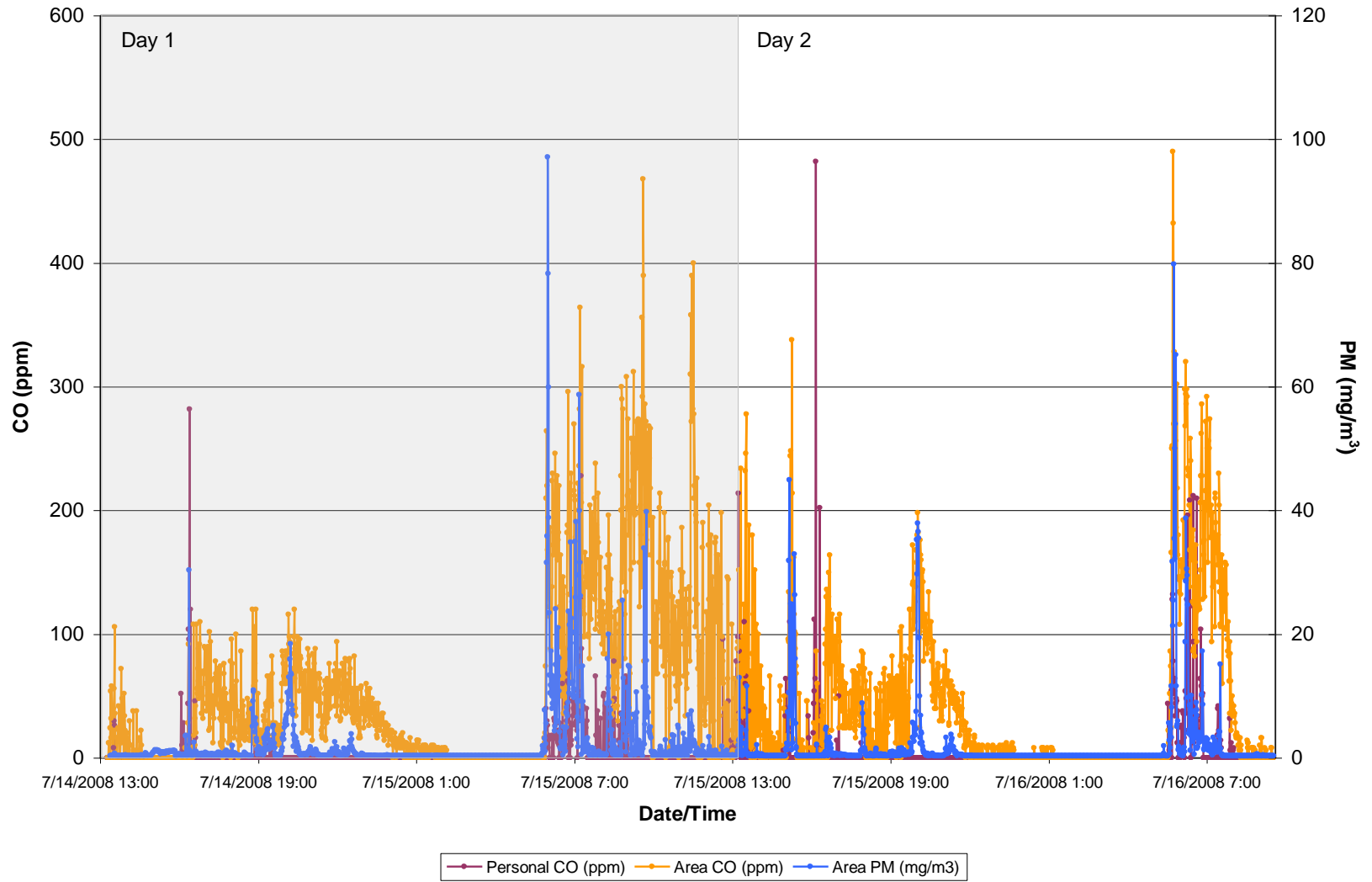
House 114 and Participant Exposure Data (PM Data N/A)



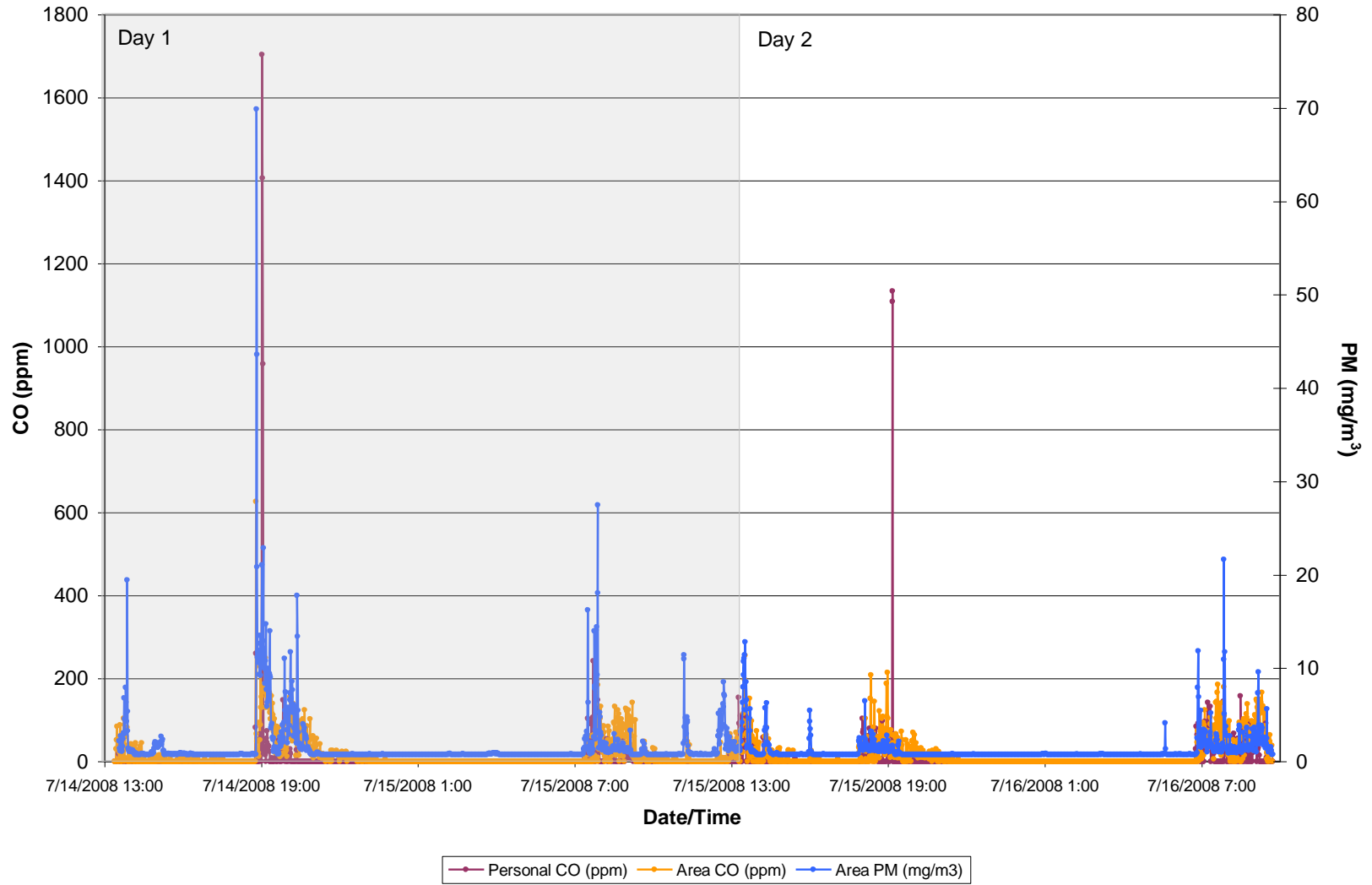
House 115 and Participant Exposure Data



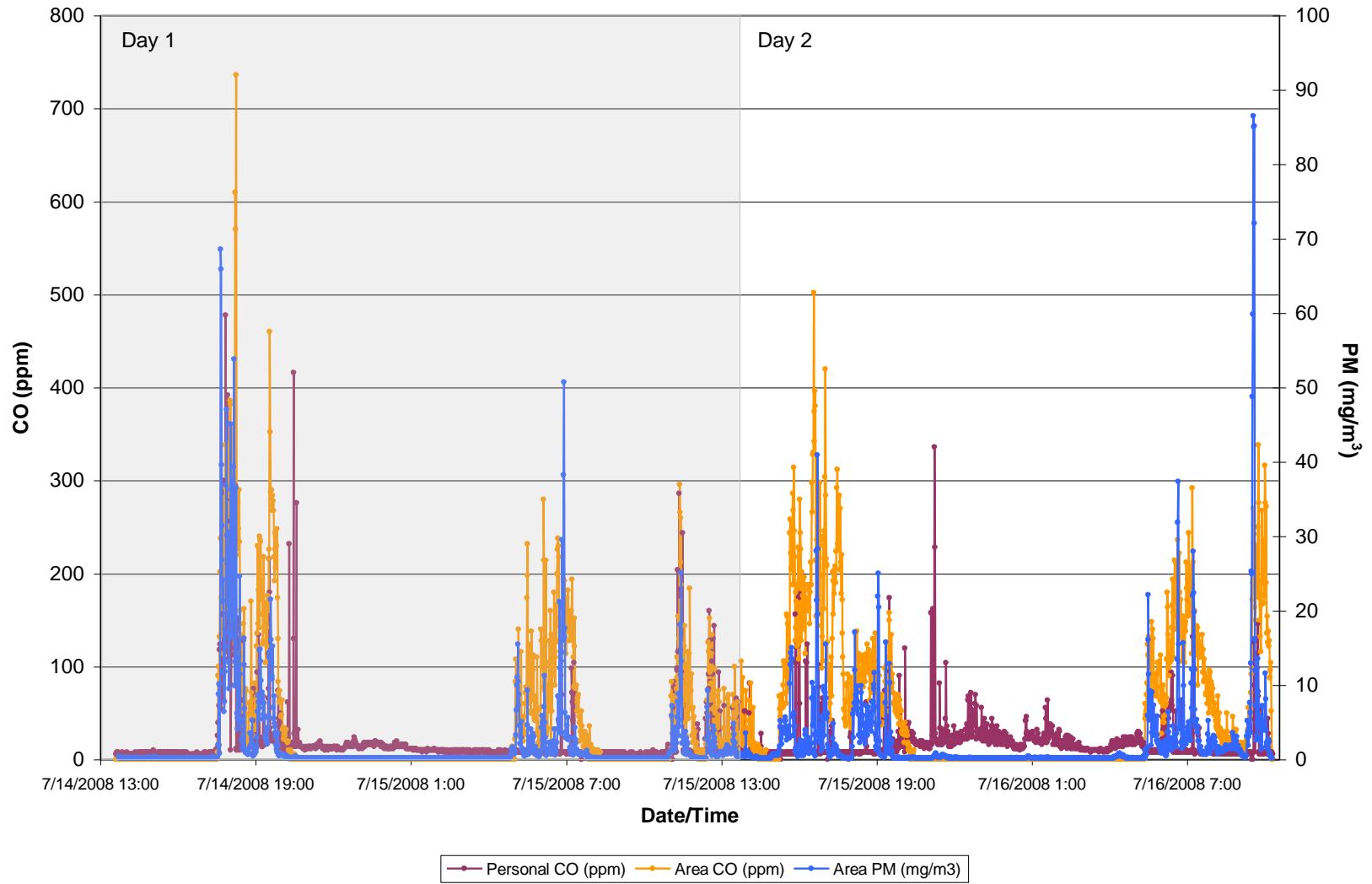
House 116 and Participant Exposure Data



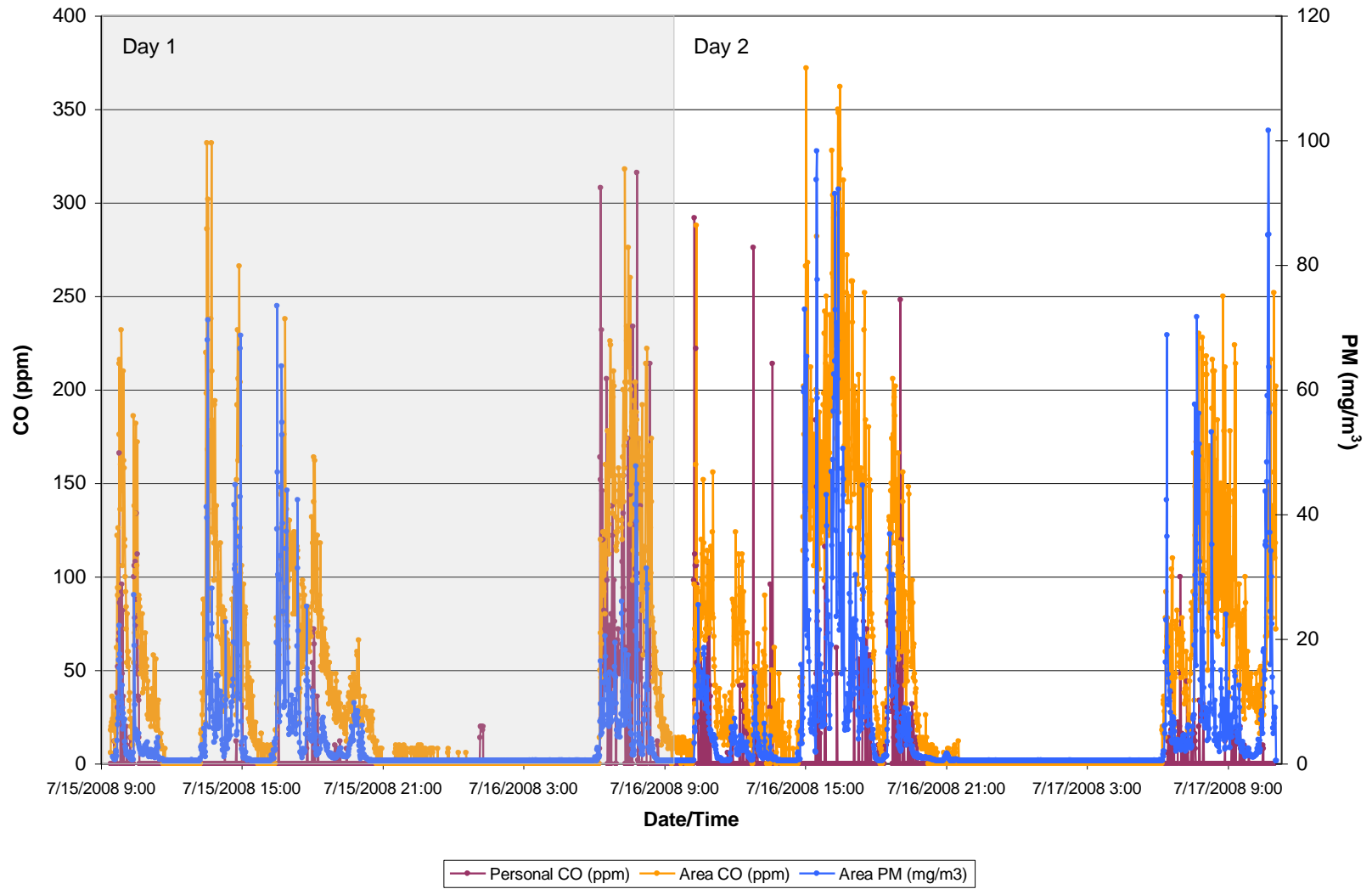
House 117 and Participant Exposure Data



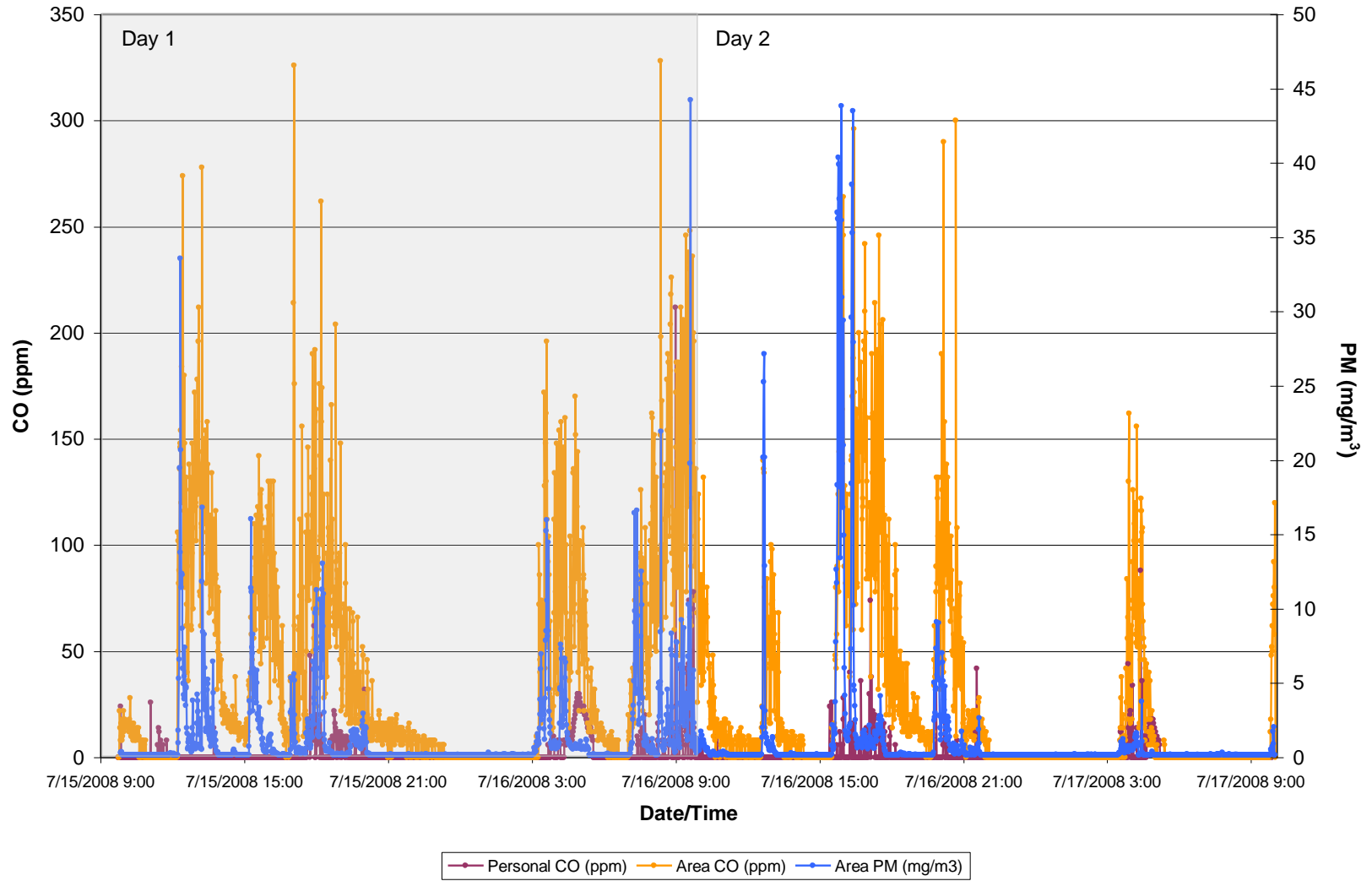
House 118 and Participant Exposure Data



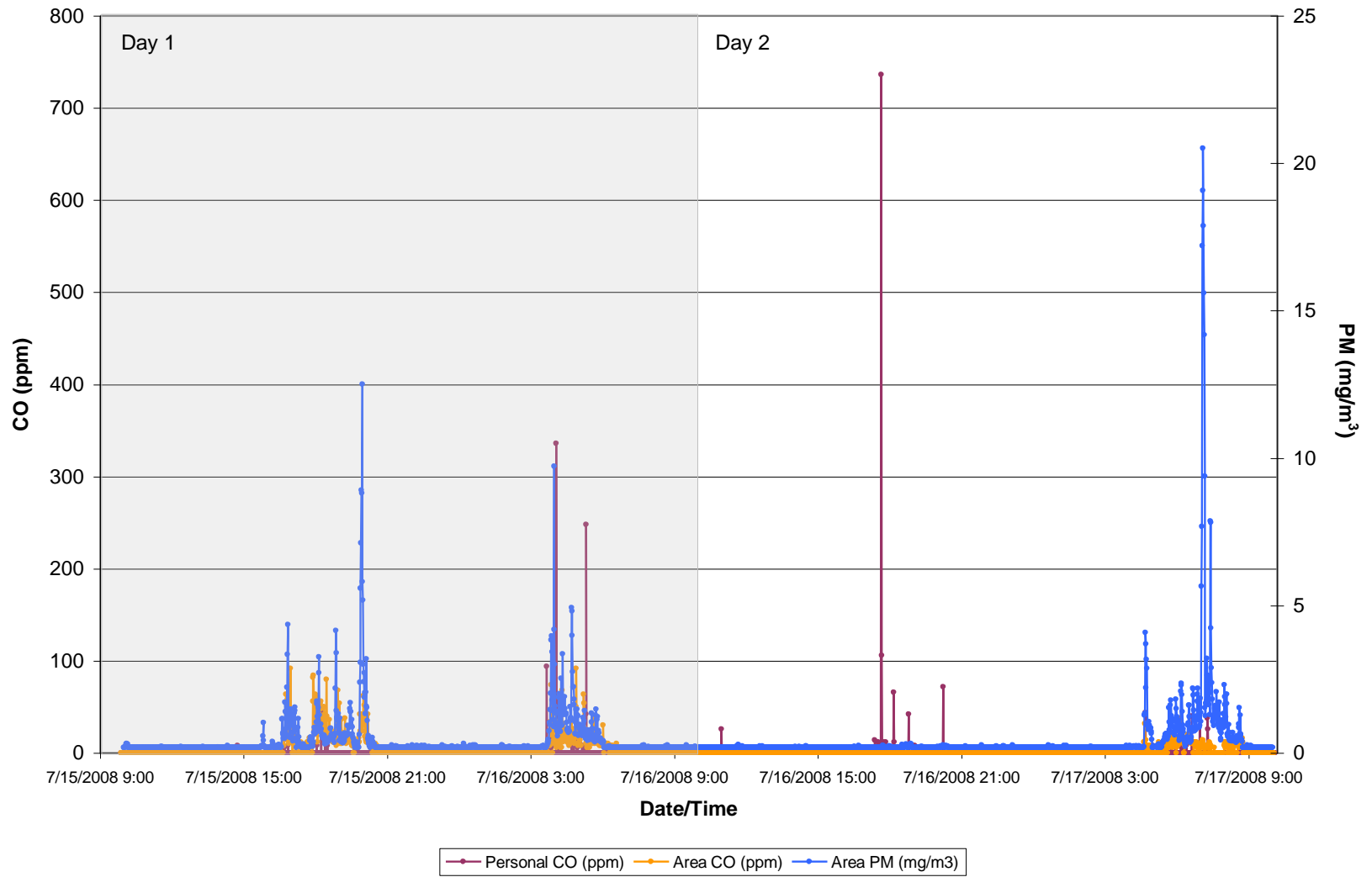
House 119 and Participant Exposure Data



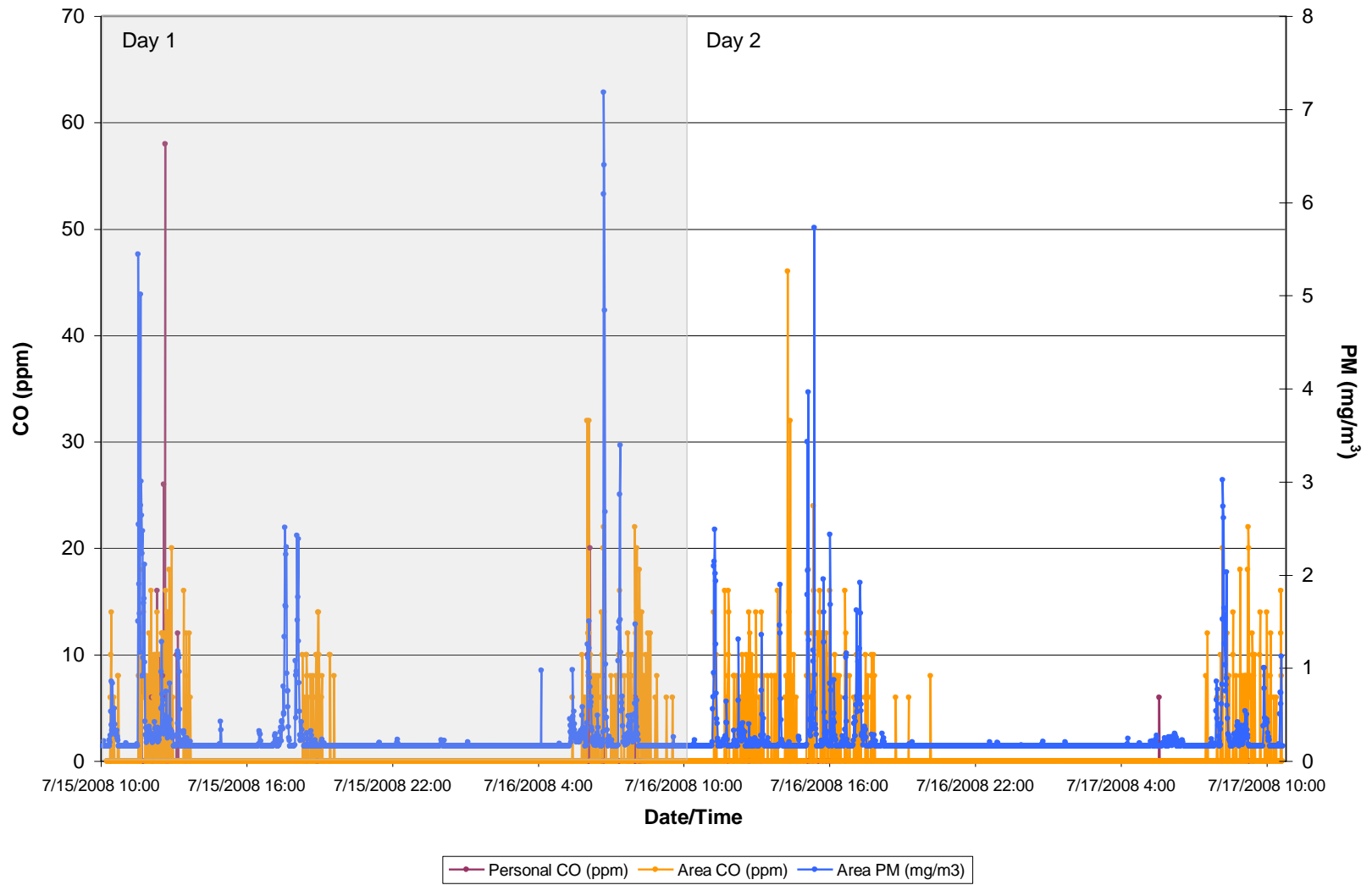
House 120 and Participant Exposure Data



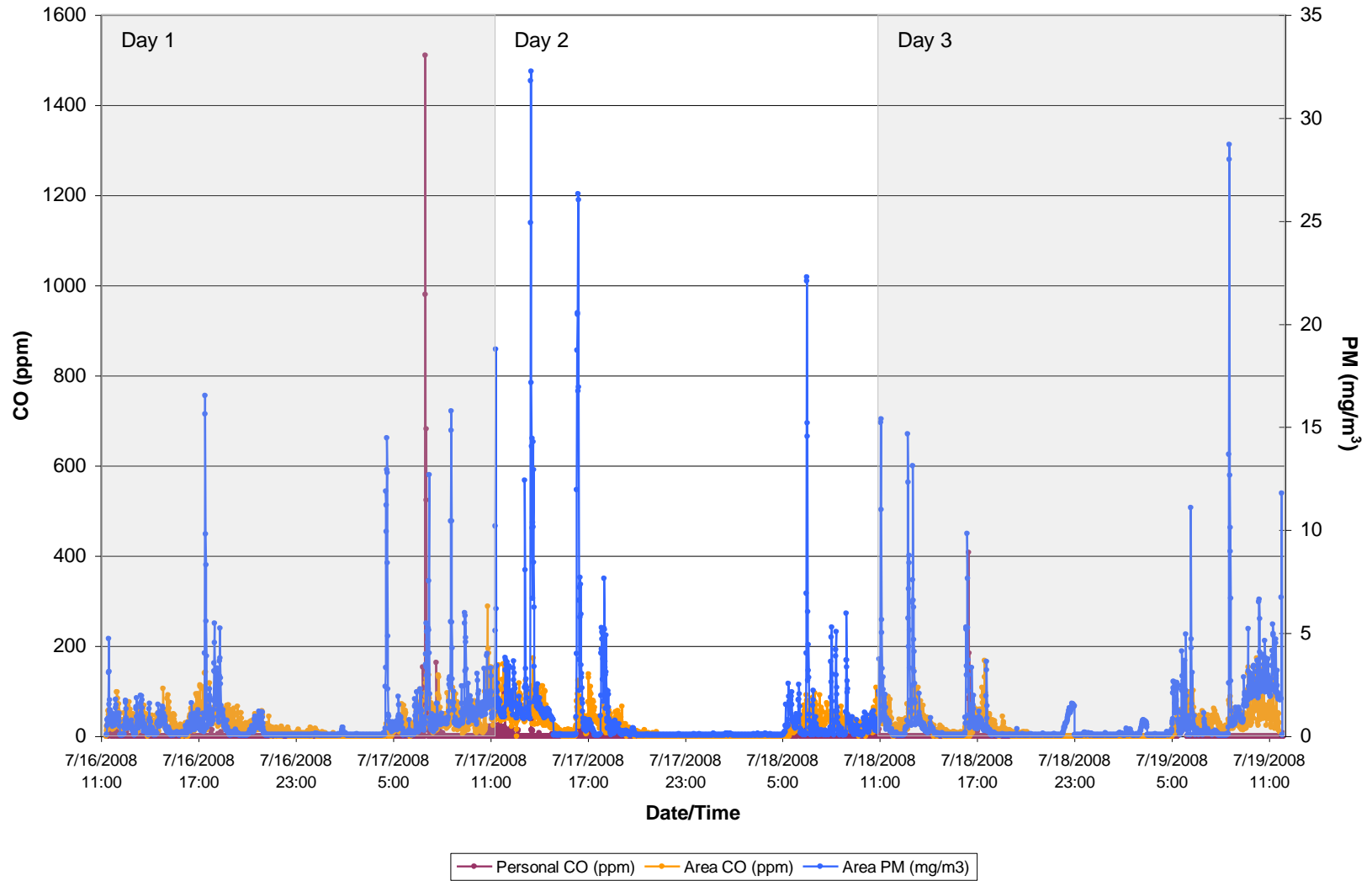
House 121 and Participant Exposure Data



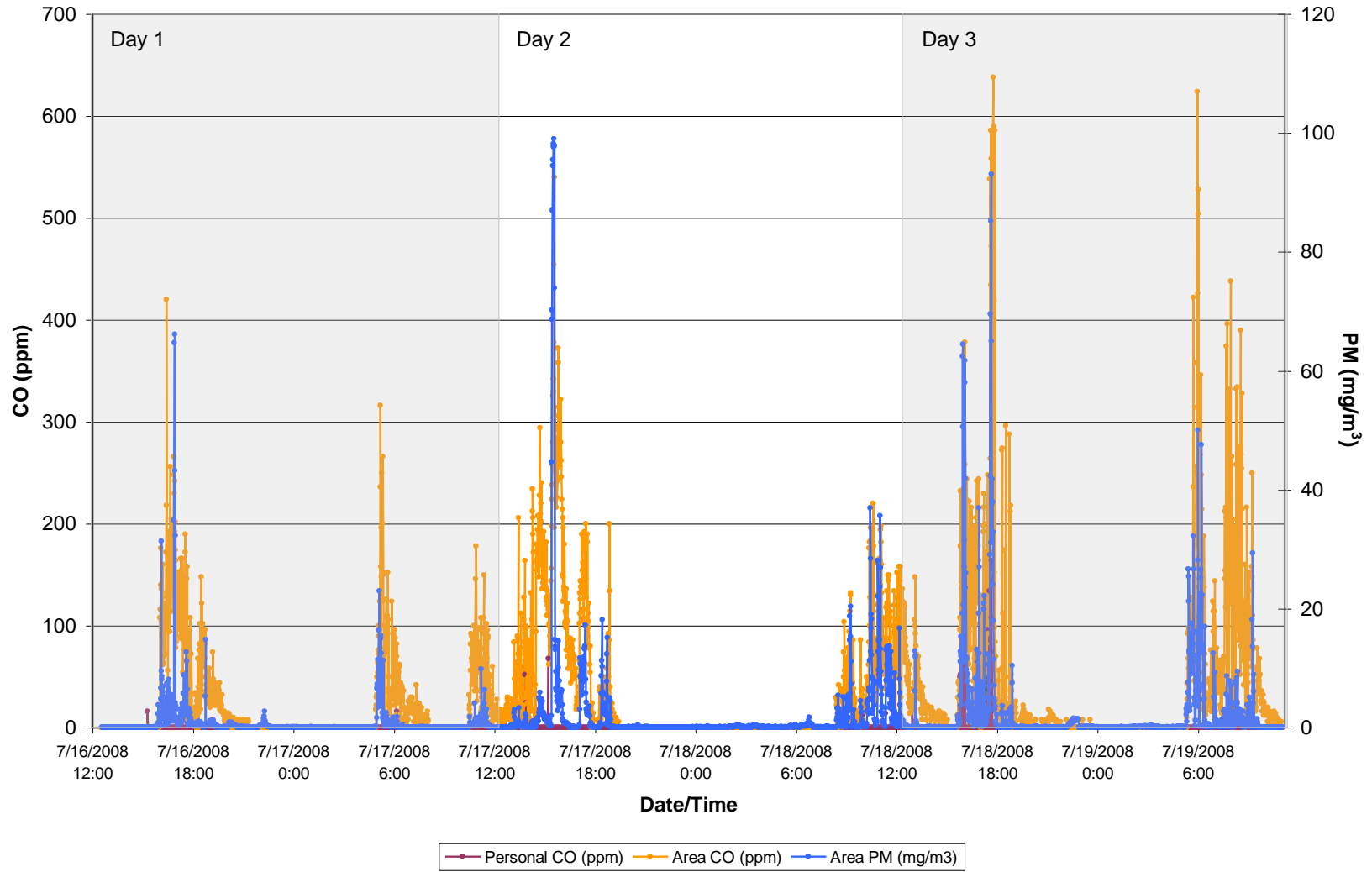
House 122 and Participant Exposure Data



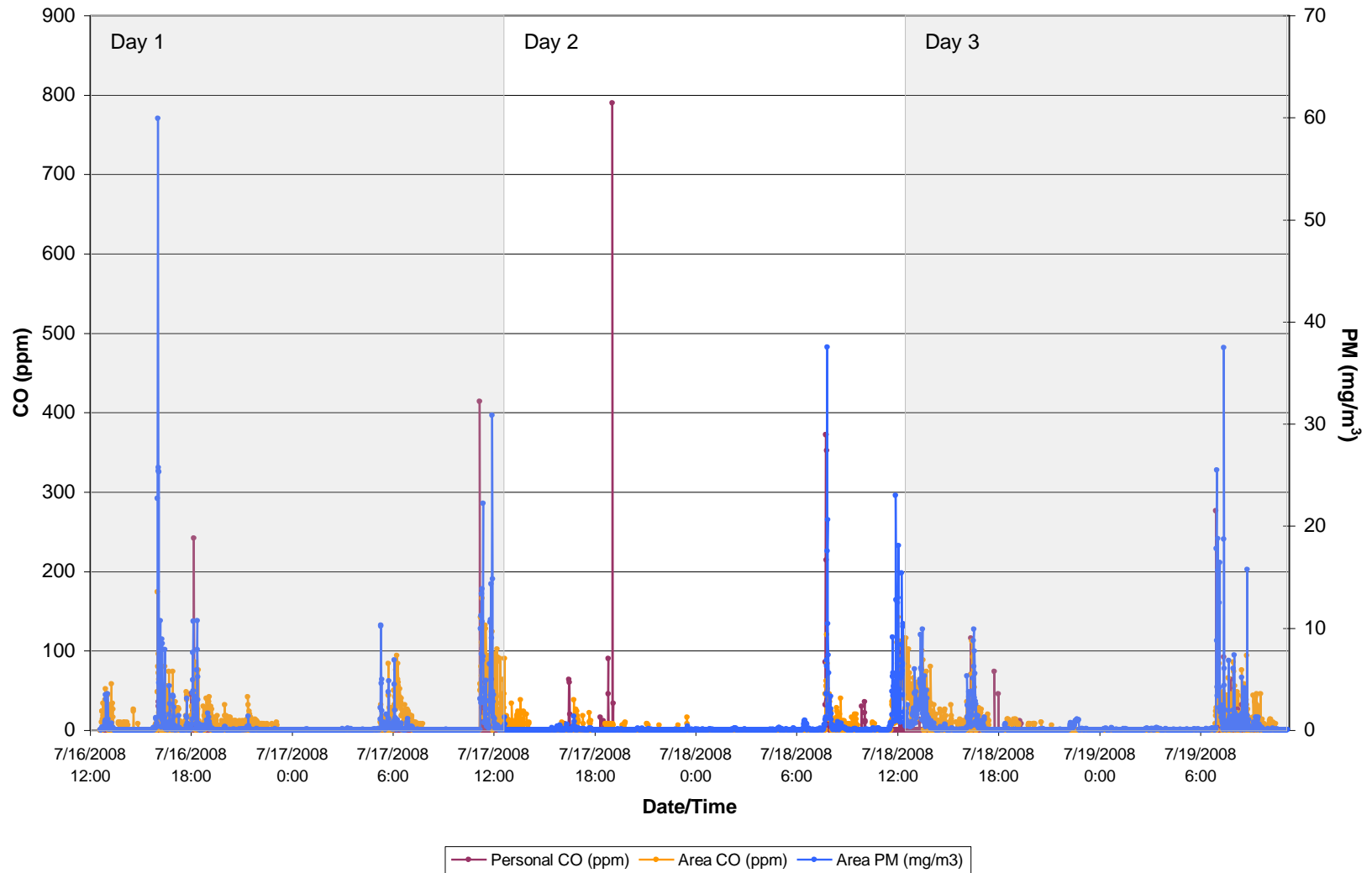
House 123 and Participant Exposure Data



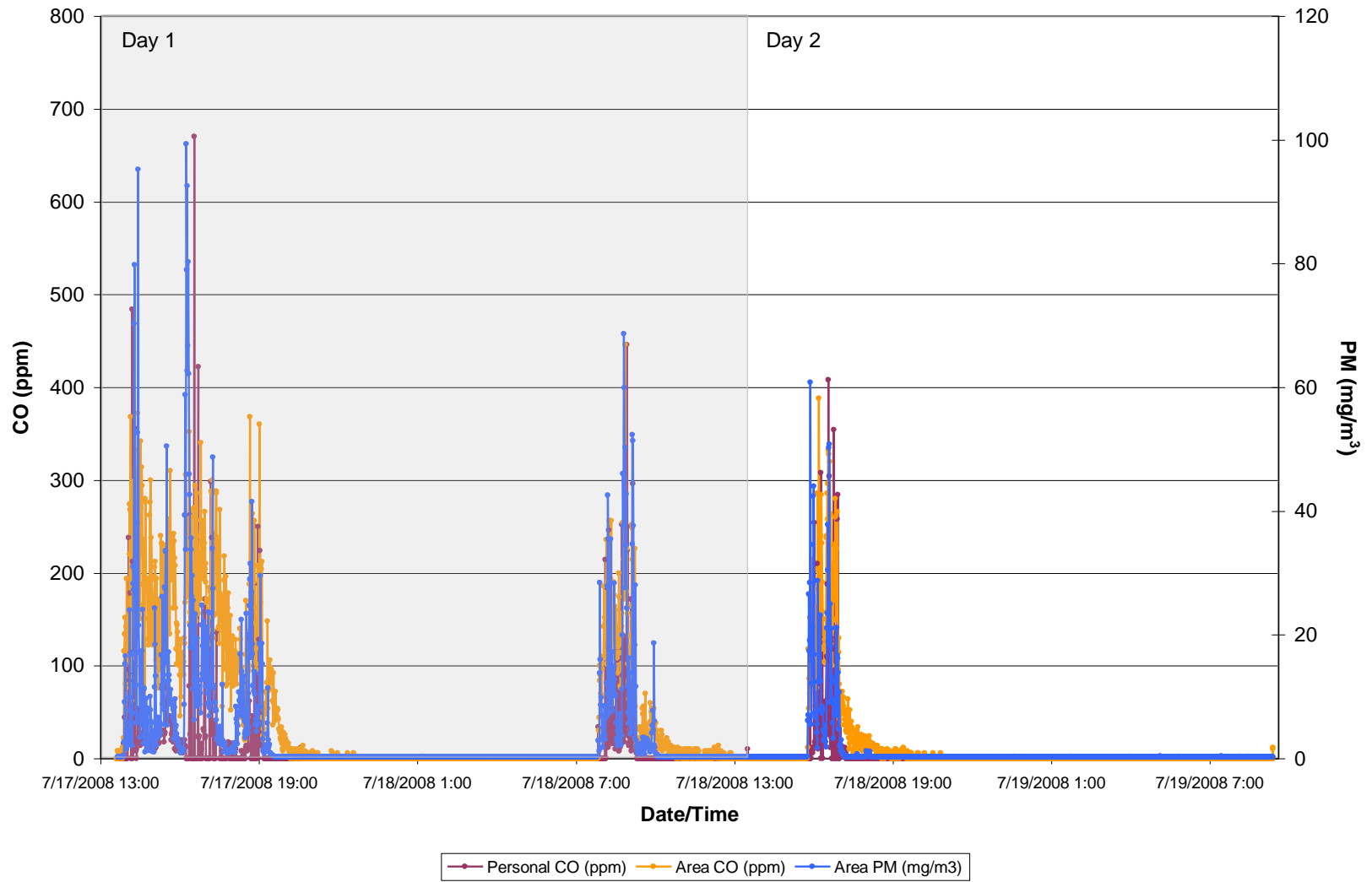
House 124 and Participant Exposure Data



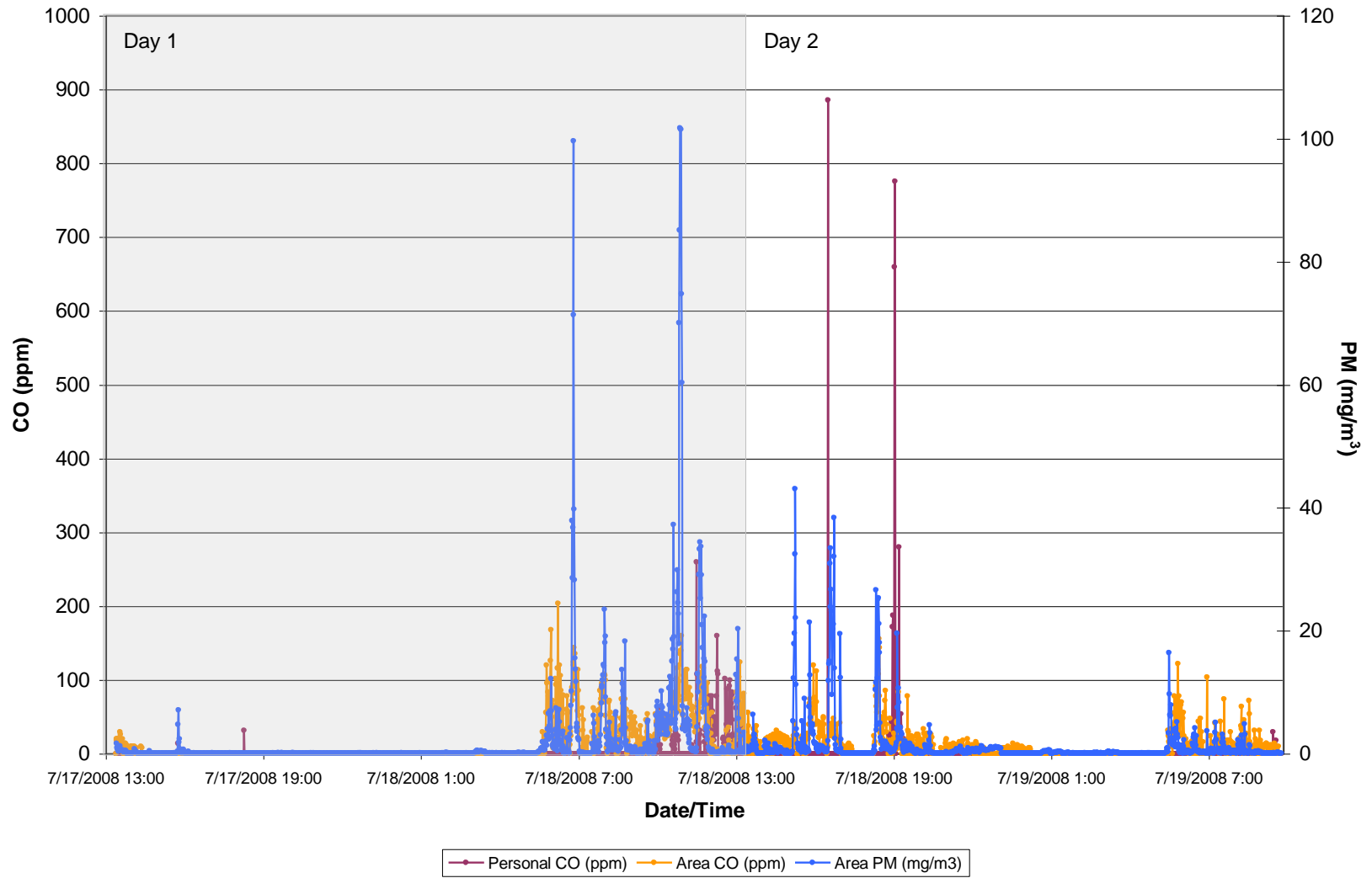
House 125 and Participant Exposure Data



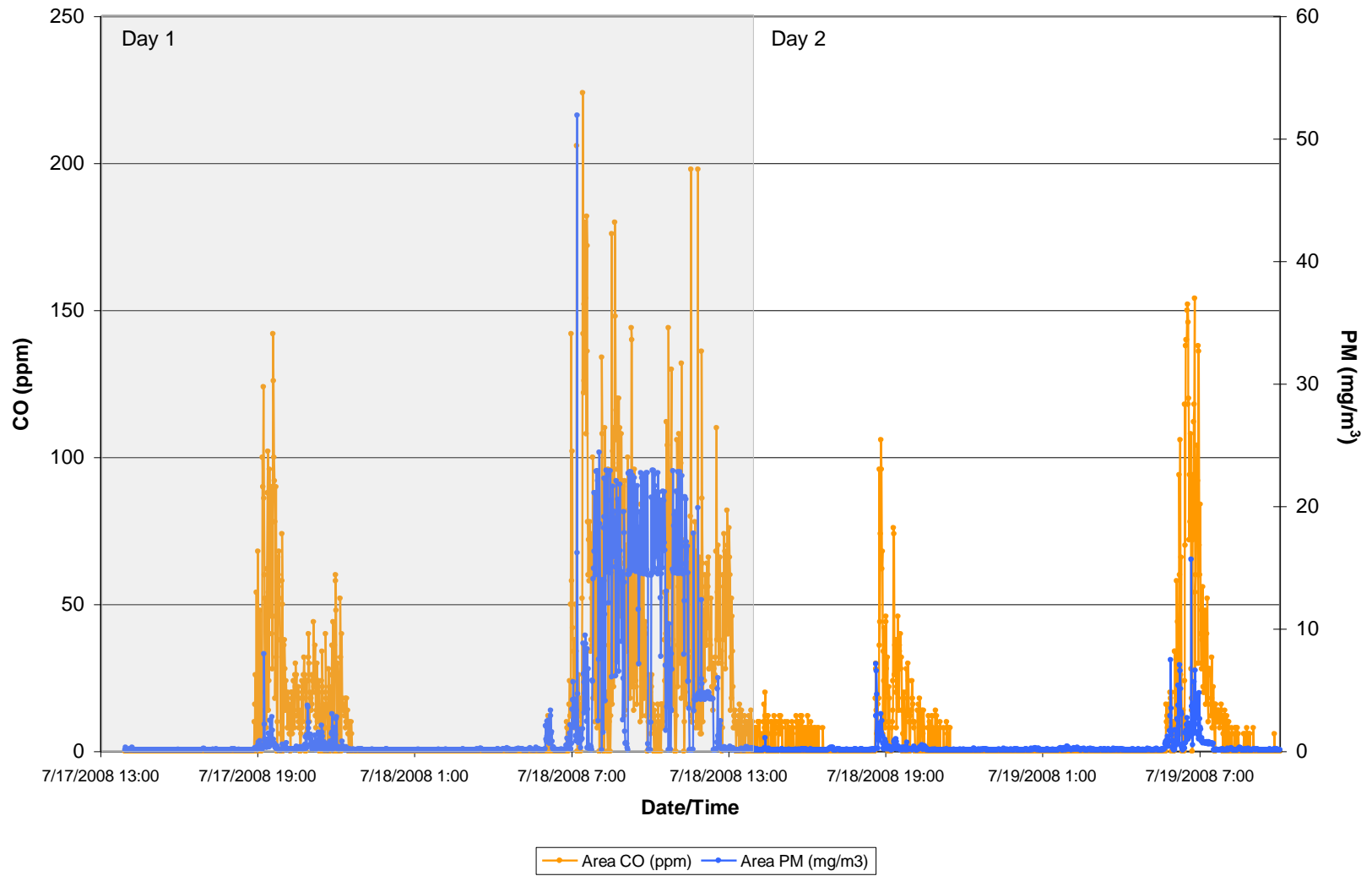
House 126 and Participant Exposure Data



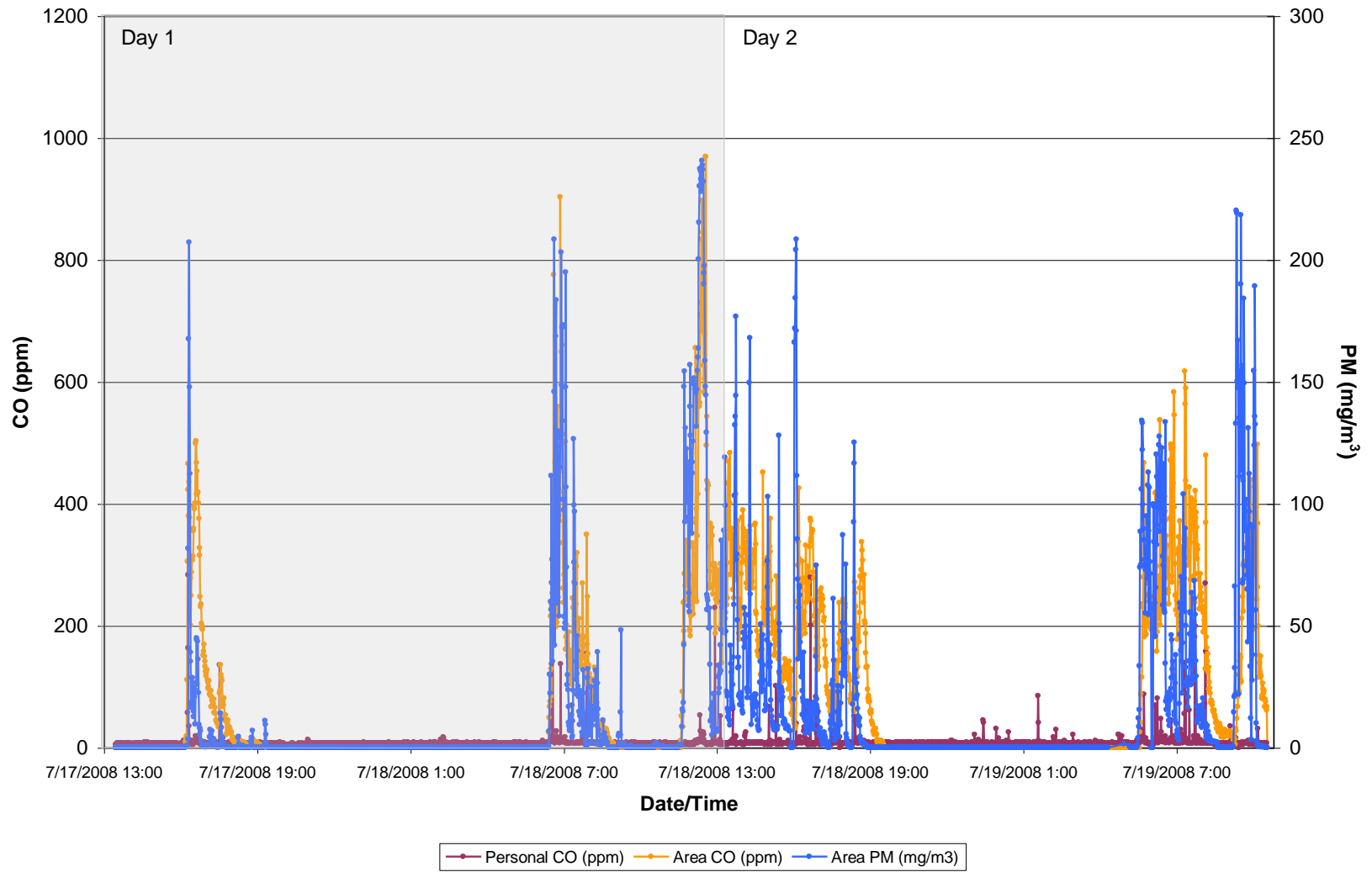
House 127 and Participant Exposure Data



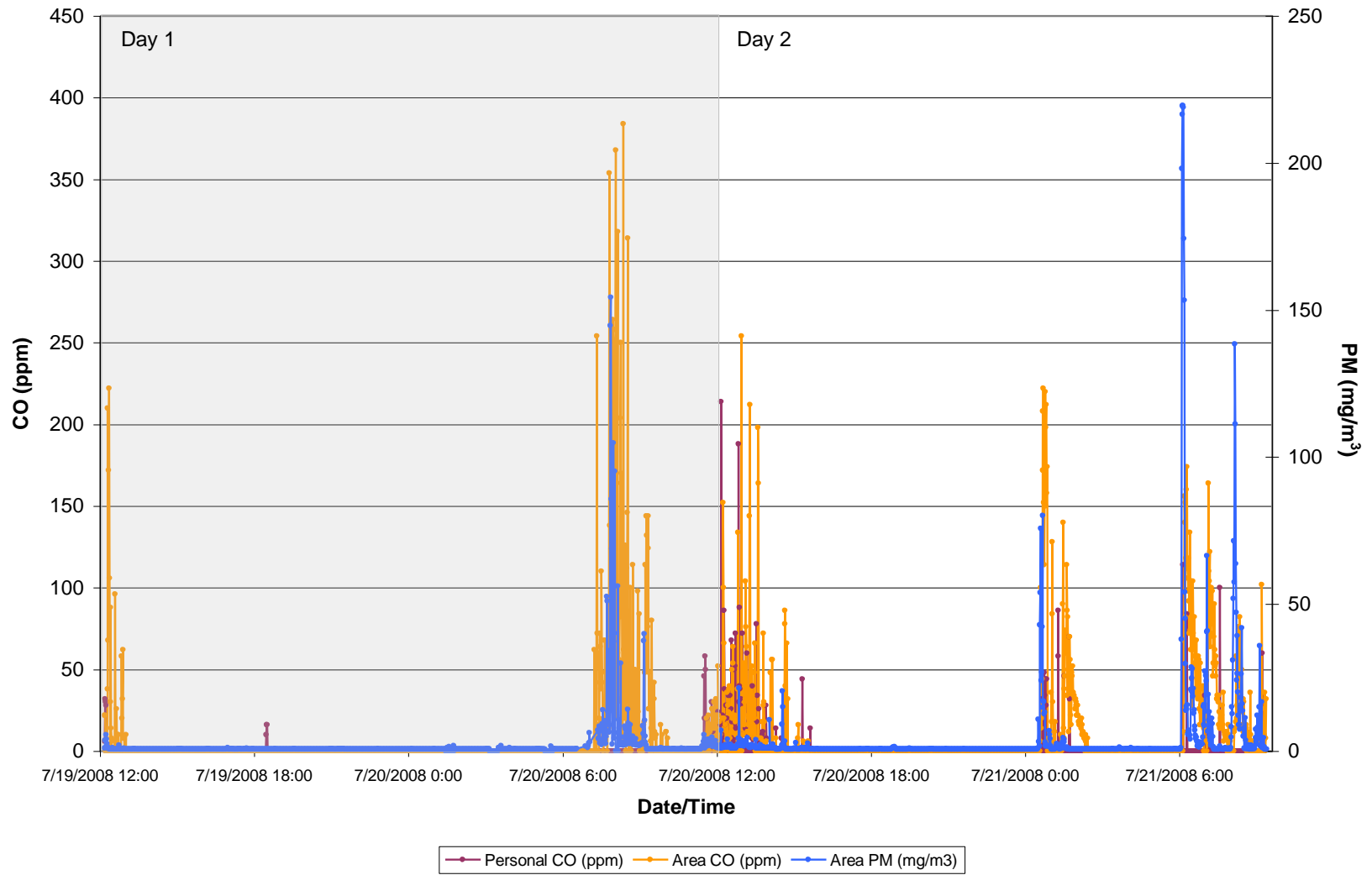
House 128 and Participant Exposure Data (Personal CO Data N/A)



House 129 and Participant Exposure Data



House 130 and Participant Exposure Data



APPENDIX E

Decisions made for Data

Decisions made for Data

UCB data:

- Used initial zeroing period only due to software glitch with using both initial and final zero periods

Dropped Houses:

- 105 – reported fire burning for 24 hours/day but had very low CO levels
- 129-130 – investigator recording error
- 7, 37, 61, 88 – self-reported, current smokers

Dropped Exposures:

- 76, 86, 92, 97, 106, 118, and 129 – personal CO monitor needed recalibration (gave baseline “zero” readings as 6-8 ppm); personal CO readings deleted

Creation of pollutant database:

- Used readings 1-2880 (minute counts) for creation of metrics; no data after the 2880th minute was used

Collapsing of Variable Categories:

- Number of walls – 1, 2, 3, or 4
- Number of doors – 0, 1, 2 or more
- Number of windows – 0, 1, 2 or more
- Primary type of wall material – wood, sheet metal, or brick/cement (15); dummy variables were created
- Exposure to environmental tobacco smoke – 0=none reported in home or kitchen, 1=reported yes or occasionally in home or kitchen
- Dummy variables were created for primary type of wall material; sheet metal was used as the reference since it had the highest prevalence, thus producing wood and brick/cement dummy variable columns in dataset

APPENDIX F

Correlations among Predictor Variables

Spearman correlation coefficients comparing dependencies among quantitative predictors:

Number of Windows, Spearman Correlation Coefficient (p-value)	
Number of doors	0.10 (0.25)
Number of walls	0.10 (0.26)
Amount of eave space	-0.01 (0.90)
Kitchen volume (log-transformed)	0.21 (0.02)
Hours spent cooking	0.08 (0.40)
Hours fire burns per day	0.04 (0.69)
Hours spent in room with fire burning	0.03 (0.75)
Exposure to ETS	0.12 (0.19)
Number of Doors, Spearman Correlation Coefficient (p-value)	
Number of walls	0.34 (0.0001)
Amount of eave space	0.20 (0.03)
Kitchen volume (log-transformed)	0.36 (<0.0001)
Hours spent cooking	-0.23 (0.01)
Hours fire burns per day	0.06 (0.52)
Hours spent in room with fire burning	-0.21 (0.02)
Exposure to ETS	-0.01 (0.93)
Number of Walls, Spearman Correlation Coefficient (p-value)	
Amount of eave space	0.15 (0.10)
Kitchen volume (log-transformed)	0.25 (0.01)
Hours spent cooking	-0.12 (0.17)
Hours fire burns per day	-0.01 (0.93)
Hours spent in room with fire burning	-0.09 (0.30)
Exposure to ETS	-0.05 (0.58)
Amount of Eave Space, Spearman Correlation Coefficient (p-value)	
Kitchen volume (log-transformed)	0.0003 (0.997)
Hours spent cooking	0.003 (0.97)
Hours fire burns per day	0.05 (0.58)
Hours spent in room with fire burning	-0.02 (0.83)
Exposure to ETS	-0.03 (0.78)

Spearman correlation coefficients comparing dependencies among quantitative predictors (page 2):

Kitchen Volume (log), Spearman Correlation Coefficient (p-value)	
Hours spent cooking	0.01 (0.90)
Hours fire burns per day	0.20 (0.03)
Hours spent in room with fire burning	0.07 (0.48)
Exposure to ETS	-0.05 (0.60)
Hours Spent Cooking, Spearman Correlation Coefficient (p-value)	
Hours fire burns per day	0.36 (<0.0001)
Hours spent in room with fire burning	0.70 (<0.0001)
Exposure to ETS	0.17 (0.07)
Hours Fire Burns per Day, Spearman Correlation Coefficient (p-value)	
Hours spent in room with fire burning	0.39 (<0.0001)
Exposure to ETS	0.15 (0.10)
Hours Spent in Room with Fire, Spearman Correlation Coefficient (p-value)	
Exposure to ETS	0.13 (0.15)