Study of Air Pollution and Noise Impact on the Community Surrounding DeKalb Peachtree Airport, Chamblee Georgia.

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Summary

In 2012, DeKalb County contracted P. Barry Ryan, PhD, Emory University, to conduct a study of the impact of DeKalb Peachtree Airport on air pollution and noise on the community surrounding the airport. Guided by the contract and the goals described in it, Ryan developed a plan to monitor air and noise pollution at DeKalb Peachtree Airport (PDK) and in the surrounding neighborhoods. This document is a Summary of results associated with the study.

Nitrogen dioxide and BTEX concentrations, while higher nearer the Airport, are not clinically significantly different than levels found anywhere else in the urban community of Atlanta. The concentrations of contaminants found both on the Airport grounds and in the surrounding community are consistent with those found in metropolitan Atlanta as a whole and in other metropolitan areas around the country. Health standards such as the National Ambient Air Quality Standards (NAAQS) offer a comparison measure. NAAQS exist for nitrogen dioxide and PM. In neither case are the levels measured at any location close to standard for nitrogen dioxide of 53 ppm. Average concentrations for this contaminant are in the 10-20 ppm range, well below the annual average health standard, and show only weak association with the Airport. Particulate matter measurements show potential violations of the PM standard on the Airport grounds. These measures are consistent with other measures of PM throughout the Atlanta Metropolitan Area that suggest Atlanta is in violation of the new 12 $\mu g/m^3$.

One issue of potential concern is the concentration lead particulate matter on the Airport grounds. The NAAQS for lead is 150 ng/m^3 based on a three-month rolling average. The concentrations of lead on the Airport grounds are higher than in typical locations in the urban, metro Atlanta area and the West site is often above this value. It should be noted that no level is considered acceptable for children. PDK may well be a source of lead contamination, primarily in the nearby community, but also for the region as a whole. This observation should be put in context, however, by noting that the highest levels on the Airport ground may only just exceed the NAAQS standards at one location and that dispersion and dilution are significant even over 100-200 m downwind, but still on the Airport grounds. Further, the phase-out of leaded aviation fuel products planned by the FAA in the coming years will likely mitigate this problem. The Airport Director reports that since 2014 all of the Airport's motorized vehicles (other than aircraft) now use unleaded fuel.

Analysis of real-time air pollution data from the airport grounds indicates the black carbon particulate matter and total fine particulate counts are associated with Maximum Take Off Weight (MTOW) of aircraft, but in an opposite sense. For black carbon particulate data, higher MTOW aircraft, particularly those over 66,000 lbs MTOW, are more likely to produce a transient air pollution increase than lighter aircraft. For total fine particulate matter, smaller aircraft, those less than 25,000 lbs MTOW and those with UNKNOWN MTOW characteristics are more likely to produce and air pollution transient event.

The Airport does contribute to the noise pollution levels in the surrounding community. There are a significant number of events for which Airport traffic results in noise level exceedances that most would find troublesome. There is an association with the noise levels of jet aircraft with MTOWs greater than 25,000 lbs, above 66,000 lbs and those with MTOWs greater than 75,000 lbs at the fixed noise monitoring sites. Identification of these aircraft offers the potential for mitigating the noise effects on the surrounding community Additionally, specific aircraft were associated with multiple noise threshold exceedances and often these tail numbers were not associated with the largest aircraft that used at PDK.

Introduction

Peachtree DeKalb Airport (PDK) located in DeKalb County is the second busiest airport in Georgia with PDK staff reporting as many as 150,000 and 200,000 airport operations per year. Approximately 40% of the flight operations at the Airport (landings and takeoffs are separate flight events) are by general aviation, small, piston engine aircraft. The other 60% of the operations at PDK are by business jets with the largest jet regularly using the Airport a Gulfstream V.

The principal runway at PDK is 5001 feet in length, with an additional 1000 feet on one end to be used as a touchdown apron (known in Federal Aviation Administration – FAA- parlance as a "displaced threshold.") The principal runway handles all of the jet traffic due to it being longer than the other runways. It runs nearly due N/S, and currently provides takeoff and landing for individual aircraft up to 75,000 lbs, with heavier aircraft allowed with special permission. All agree that the current practice at PDK is to permit all aircraft up to 75,000 lbs. to use the facility without having to obtain permission to do so.

DeKalb County and the organization Open DeKalb, Inc. (Open DeKalb) agreed on the need to study the impact of aircraft emissions and aircraft noise events with specific goals in mind. These goals are attached to the contract between the County and Ryan/Emory and provided below. The goals may be summarized by stating that both groups are fundamentally interested in the public, the Airport, and DeKalb County government having information about the potential health impacts of aircraft operations at PDK on the surrounding community so they can make informed decisions regarding Airport operations and management.

Goals*

The goal of the study is to collect hard data on the impact of PDK aircraft operations on air quality and noise over the geographic area reasonably impacted by the Airport. The study must to the greatest extent possible:

1. Analyze the air and noise pollution impacts of three categories of aircraft, (a) those with certified maximum takeoff weights of 66,000 pounds or less, (b) those with certified maximum takeoff weights in excess of 66,000 pounds but less than 75,000 pounds, and (c) those with certified maximum takeoff weights of 75,000 pounds or more;

2. not include air and noise pollution impacts from major vehicular highways near the Airport;

3. not include air and noise pollution impacts from air traffic in and out of Hartsfield-Jackson Airport;

4. provide analysis of PDK's relative impact on air quality in the area, so that PDK emissions can be understood as one contributor to the area's air and noise pollution, rather than with static figures for PDK's emissions without any qualifying context for the figures; and

5. provide comparative analysis of similar airport's(s') emissions.

The intent is to provide the DeKalb County Board of Commissioners, DeKalb CEO's Office and the Airport Staff, and the public with the ability to make informed decisions about Airport operations. As the County moves toward a Master Plan for the airport, policymakers, those who execute policy and those persons regularly impacted by the Airport either due to the location of their homes, offices or other regular physical contact with the Airport's operations, must be able to weigh costs and benefits of Airport operations intelligently.

*Per contract provided by PDK Airport/DeKalb County, April 22, 2011

Data Collection

The data collection effort was developed to achieve Goals 1-4. Data collection fell in two separate areas: air sampling and noise event monitoring. Prior to initial data collection, we undertook modeling exercises to determine the most appropriate locations for taking air samples and monitoring noise potentially associated with the PDK. Data collection commenced in March 2013 and concluded October 2014. Additional noise data were provided by PDK administration from their own recording devices. Transponder ID's and associated MTOW along with takeoff and landing times for aircraft were provided by PDK.

Air Sampling

Based on known emissions from aircraft, Emory researchers selected a number of air contaminants for collection. These contaminants were selected as contaminants of direct concern for environmental health and as overall markers of contamination associated with combustion such as that associated with aircraft fuels. Each air contaminant selected for analysis is described below. Air sampling was performed in the community to establish the impact that PDK may have on its neighbors. Prior to selecting locations for community-based sampling, we performed dispersion modeling using the modeling system AERMOD, developed by the United States Environmental Protection Agency (USEPA) using ten years (2003-2012) of meteorological data to locate the local areas most likely impacted by air pollution from PDK. These modeling results suggested that predominant wind directions for over the course of a year were from west to east during most of the year and from the south during the summer. This is consistent with the primary direction for the principal runways at PDK. With this knowledge, we sought community settings primarily to the east and north of the PDK, but placed several monitors in the upwind directions for comparison.

Air Pollutants Measured

Nitrogen Dioxide

Nitrogen dioxide is produced whenever there is an ongoing high-temperature combustion process, such as the burning of fuels in internal combustion engines. From a health effects perspective, nitrogen dioxide is a lung irritant. Aircraft produce nitrogen dioxide upon taxiing, take off, and landing. Vehicular traffic on the airport ground also produces this compound. In addition, typical vehicular traffic on roads, e.g., cars, trucks, busses, diesel trains, etc., also produce nitrogen dioxide. In addition to health implications, this compound was also studied because nitrogen dioxide acts as a general tracer for combustion-related processes, helping us determine the relative magnitude of sources of combustion-related contamination in and around PDK. By noting the concentrations around PDK and in the high-traffic highways and surface streets nearby, one can determine the relative impact of the Airport as a source of nitrogen dioxide potentially impacting the surrounding community.

Specific Volatile Organic Compounds (VOCs)

Volatile organic compounds (VOCs) are produced by incomplete combustion of fuels and by evaporation of fuels from storage, for example, fuel tanks in cars and in aircraft. Emory researchers chose to monitor the so called "BTEX" compounds, benzene, toluene, ethyl benzene, *o,p*-xylene, and *m*-xylene because, in addition to being precursors of ozone pollution, for which Atlanta is often in violation of EPA standards during the summer, and a contributor to smog, they act as tracers for automotive emissions and for aircraft emissions. Further, other investigations have monitored for these compounds affording direct comparisons with other studies (Goal 5.) Benzene is an EPA-recognized carcinogen that used to be present in most fuels including automotive gasoline, general-aviation fuels (AVGAS), and jet fuel. It has largely been removed from these fuels, although trace levels remain. Toluene is a significant component of gasoline, while the other compounds, ethyl benzene, *o,p*-xylene, and *m*-xylene*,* are present in somewhat lower concentrations in these fuels. In much the same way that nitrogen dioxide is used as a tracer to try to differentiate aircraft emissions from car and truck emissions, these compounds are as well. Concentrations of these compounds have been collected in numerous other studies of both airport-related air pollution and urban background pollution. Knowledge of their concentrations affords us the opportunity to study the impact of PDK on the local community relative to other sources.

Fine Particulate Matter

Particulate matter (PM) is an important contaminant in the Atlanta metropolitan area, with violations of the EPA standards common during the winter months and present during summer months as well. Fine particles (FP), particles with aerodynamic diameter less than 2.5 µm (about 1/40th the diameter of a human hair), penetrate deeply into the lungs and can produce myriad health effects including respiratory, cardiovascular, and neurological effects. Epidemiology suggests that both acute and long-term exposure to particles on the smaller end of this scale, less than 1.0 µm or even less than 0.2 µm may be principally responsible for the damage in the human body. Various measures of these particles are available and Emory researchers have selected from among them for this study.

Fine Particulate Mass

Some health outcomes are thought to relate to the total mass of FP inhaled by an individual. Towards this end, researchers have developed the so-called "pump and filter" method of FP collection. Using the physics of particle movement in an airstream, it is possible to collect particles that are in the FP size range by passing air scrubbed of larger particles through a filter to collect them. Sampling for a 24-hour period allows us to collect sufficient mass to determine mean concentrations for that day, but also to collect enough material to afford analysis of the samples for their speciated content, that is the content of certain metals, most notably lead, within the general particulate matter collected. We use this method to do both; 1) determine the concentration of FP in the air; and, 2) determine the concentration of fine particulate metals, e.g., lead, in the air. EPA regulates fine particle in the air due to perceived health effects associated with population exposures. Lead is regulated separately as it has multiple known health effects and no benefit to health.

Particle Number

As we have noted, very fine particles (less than 1.0 µm) are currently thought to be of concern in terms of health outcomes. Small particles contribute little to the mass, but, because of their small size, have a substantial surface area and can adsorb materials onto the surface. For these particles, mass does not give us the total picture. We need to address the number of particles to ascertain likely health impact. Further, combustion-related PM starts off as very small particles that agglomerate to form larger ones. Identification of such particles can guide our thinking regarding potential health effects and to identify sources that are “new” in the sense that the very small particles have not yet had time to “grow” into larger particles.

Black Carbon

The combustion of certain types of fuels occurs with a substantial amount of unburned hydrocarbon emission. Diesel trucks are noted for this in that they emit black smoke, especially when under load. Less-efficient combustion in certain older aircraft also produce this “black carbon” emission. Such particles are very small, often in the less than 1.0 µm size range. Further, the emissions themselves, especially in the case of diesel exhaust, are identified as carcinogens. The so-called “black carbon” measurements identify these types of emissions and give a signal as the background concentrations in the urban area and the contribution made by PDK.

Metals

As noted under particle mass, a component of that measurement is metal concentrations. Lead, in particular, is regulated separately. Since the removal of lead anti-knock agents from gasoline in the 1980s, few sources of lead emissions are left in the urban setting. However, AVGAS (used in small, general aviation aircraft) is one important remaining source. Lead, thus, may be used as a tracer for the emissions from General Aviation aircraft in settings like PDK.

Sampling Methods

Monitoring data were of five types: passive, time-integrated air pollution data taken in the community, active, real-time (one- and five minute averaged) particulate data taken on the airport grounds, integrated particulate data (24-hour data taken on a six-day cycle) taken on the airport grounds, fixed-site noise data taken from existing stationary monitors operated by airport personnel, and mobile noise data taken at various sites in the community on a rotating schedule.

Volunteers were solicited for community-based passive monitoring and portable noise monitoring. There were few requirements for the passive air pollution monitoring; samplers are small and are placed inside an aluminum paint can, which is then placed in an out-of-the-way location on the volunteer’s property where it is left for a two-week sampling period, then retrieved and replaced with new samplers. These monitors allowed us to assess the levels of nitrogen dioxide, a common air contaminant associated with combustion sources, using one type of monitor, and a set of volatile organic compounds (VOCs).

Selection of real-time data sites was done with the need for secure locations, electrical power, and access for servicing technicians. Integrated particulate sampling also required electrical power and thus was done in the same location as the real-time particle sampling.

Real-time data were collected at four locations on the airport grounds: at either end of the principal runway, and both east and west of the principal runway and the approximate mid-point. Two types of data were collected. With one monitor called a condensation particle counter, or CPC, we collected data on total particle count for fine particles- those thought to produce the majority of health effects. The other monitor, the microAeth, also looked at fine particulate matter, but focused on what is referred to as “black carbon”, which is essentially unburned hydrocarbons associated with diesel exhaust and aviation fuel. These instruments collect data on a real-time basis and average over adjustable time period ranging from a few seconds to five minutes.

In an effort to understand potential particulate metal contamination, we outfitted each of the airport sites with pump-and-filter monitors that drew air through a filter that collected particulate matter less than 2.5 µm in aerodynamic diameter. When breathed in, such particles penetrate deeply into the lung and present the greatest potential for produce adverse health effects. This monitoring protocol produces data for one 24-hour period during each monitoring phase; it is not a real-time monitor. However, it does collect enough material to afford analysis of the chemical content of the particulate matter, unlike the CPC or the mircoAeth. By weighing the filter both before and after placement, we can determine the mass of particulate matter collected. Further, by knowing the air flow rate during sampling, we can determine the mass concentration (mass collected divided by the volume of air passed through the filter). Finally, by extracting the filters and performing analysis in the laboratory, we can determine the total amount of metal collected and its concentration. Our focus in this study was on lead in that general aviation aircraft, and potentially vehicles used only on airport grounds, use leaded fuel and could be a source of contamination in the community.

Passive, Time-integrated Air Pollution Sampling in the Community

The community-based passive sampling program began on March 13, 2013 and continued through the end of the investigation with the final samplers being collected on October 16, 2014 covering 19 months. There were 41 two-week monitoring periods. Samples were collected at 14 sites as depicted in Figure 1.

Noise Monitoring

Noise monitoring was effected using two different strategies: fixed-site stationary noise monitoring, and mobile portable noise monitoring. These two strategies offer differing strengths. Through discussions with PDK personnel as well as representatives of the community, noise monitoring was thought to be most important along the glide paths to the north and south of the Airport essentially along an extension of the principal runway as it is the only runway that can handle larger jets.

Stationary, fixed-site noise monitors have been placed about the community by airport personnel to ascertain the noise levels experienced in the community that might be associated with aircraft. These monitors record information on a continuous basis. Data can be readily downloaded and reports are available if the noise level exceeds certain levels (e.g., 90 or 93 dBA depending upon the site), a level that is likely to be noticed by individuals in their homes. These devices are maintained by the airport, are regularly calibrated, and record data on events including time of the event, and information on aircraft in the vicinity at that time. In this investigation, we obtained data at noise levels of 60 dBA and above.

Airport staff offered us the use of a portable noise monitor. As the name suggests, the monitor can be moved from location to location to ascertain noise levels, for example, in the community. The portable noise monitor required access to electricity and thus we were more limited in location than the passive air monitoring sites. Further, the noise and air pollution monitoring locations had differing requirements. Hence the sites for the two forms of community monitoring, air pollution and noise, were generally distinct, although two sites did monitor both. The portable noise monitor was rotated among the noise sites. The monitor stayed in one location for two weeks, then was moved to the next. Over the approximately one-and-a-half-year monitoring period, each of the noise monitoring sites was monitored for three two-week periods. Please refer to Figure 1 for the locations of the Community Noise Monitoring Sites.

In order to tie noise events and air samples to specific types of aircraft as anticipated by Goal 1, we identified aircraft using their transponder signals using FAA radar feed information. That was possible for approximately 60% of the aircraft using the airport because they aircraft can be identified by tail number, and thus specific aircraft types, through their transponder signals. The remaining 40% of the aircraft do not send out unique transponder signals, but rather a general signal that precludes unique identification of the aircraft. For aircraft with unique, identifiable, transponder signals, we researched each aircraft to ascertain its certified maximum takeoff weight to attempt to achieve Goal 1 of the study (comparing three categories of aircraft grouped by weight/size). For the remainder of the aircraft, specific identification of aircraft type was not possible. However, the vast majority of such aircraft have low MTOW, certainly less than 25,000 lbs. These can be categorized separately or, as decided, combined with aircraft in the <25,000 lb MTOW category..

While the noise monitors may indeed note and a high noise event defined as a noise event exceeded a particular threshold (see analysis), the aircraft type, call letters and other identifiers are not registered. In the databases thus obtained, these aircraft are listed as UNKNOWN. High noise events produced by such aircraft are indistinguishable from other noise sources in the community setting, including motor vehicles, landscape maintenance equipment, and other noise-producing devise.

Similarly, except under very unusual circumstances, Hartsfield-Jackson would not contribute to the noise burden in the community surround PDK and, again, are considered part of the urban background for this pollutant.

In addition to the noise and air pollution monitoring, we undertook the task of identifying individual aircraft participating in airport operations at PDK. We were able to identify over 8,000 unique aircraft that took off and landed at PDK during the monitoring period and to associate with each one a maximum take-off weight. Coupling these data with information from the noise monitors allows us to assess the relationship between noise levels and the weight of the aircraft. In addition, coupling these data with the Flight Event Data supplied to us in early 2018 affords direct correlation between specific-aircraft MTOW and flight event timing.

The “fleet mix” defined as the ratio of aircraft types participating in airport operations at PDK has changed substantially over the years. In the past, as many as 250,000 airport operations occurred annually at PDK. At that time, the fleet mix was dominated by general aviation aircraft, consisting of primarily single engine small aircraft, generally privately owned. These aircraft comprised as much as 80% of operations historically. These aircraft use aviation fuel (AVGAS), which is a leaded fuel specially formulated for such aircraft. Since the fuel is leaded, general aviation aircraft are a source of lead in the environment, similar to automobiles built prior to about 1980.

Currently, the fleet mix has shifted substantially towards jet aircraft, which now comprise about 60% of airport operations. Further, total airport operations have decreased to about 110,000 during our one-year monitoring period with the most recent calendar year increasing to almost 160,000 operations. Jet aircraft use unleaded fuel similar to kerosene and produce essentially no lead emissions. In contrast to the general aviation aircraft, essentially all jet aircraft, from the smallest to the largest are specifically identifiable. This affords analysis of aircraft-specific threshold violations as described above.

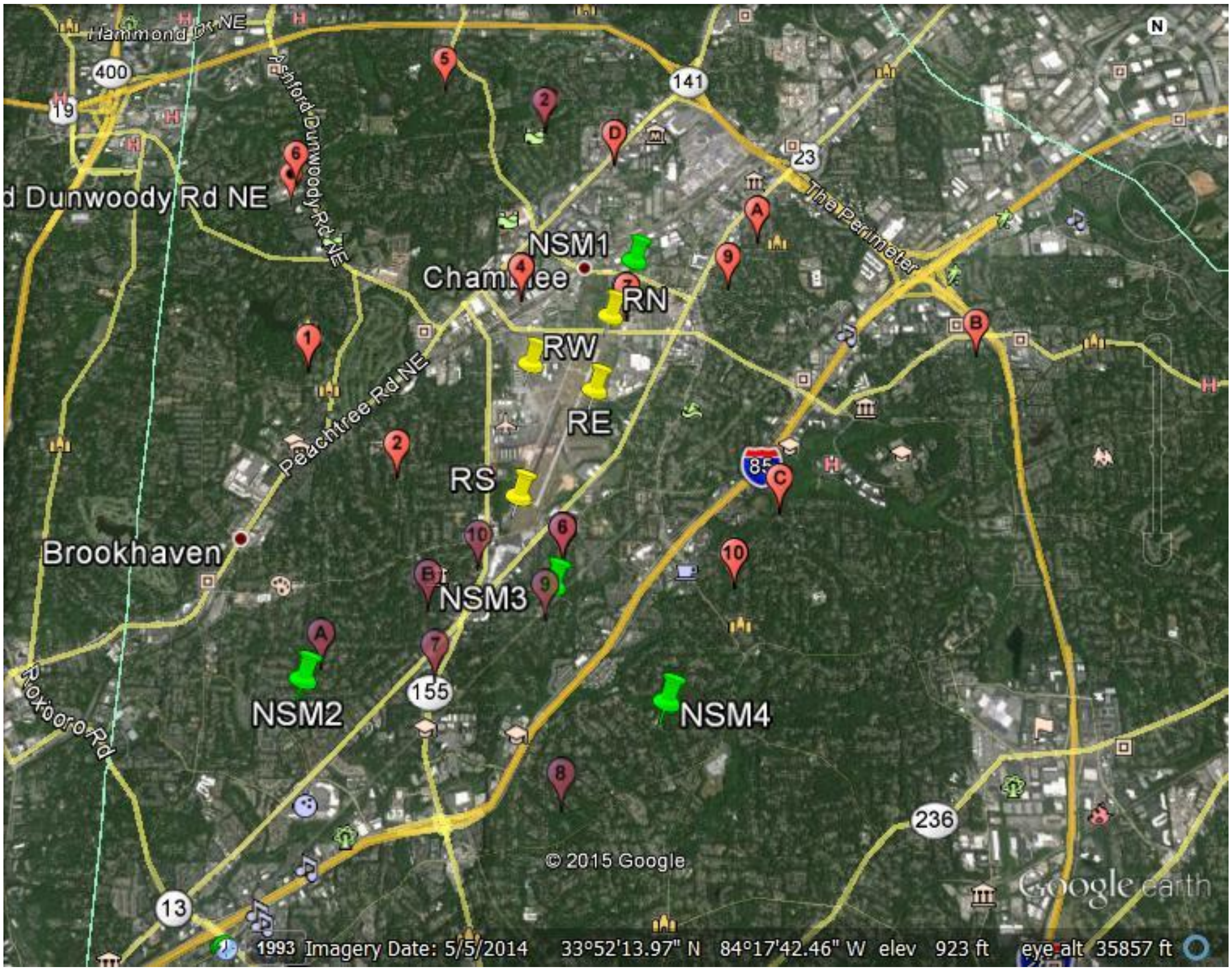


Figure 1- ***Sampling locations for PDK Noise and Air Pollution Study.***

Legend: Yellow push pins are the monitoring locations for the real-time air particle monitors,
integrated particle mass sampling, and lead (Pb) sampling.
Pink balloons are the community air monitoring sites
Green push pins are the stationary noise monitor sites.
Purple balloons are the community noise monitoring sites.
Note that Air Site 7 and Noise Site 2 are monitored for both air pollution and noise (See text)

The map spans a radius of approximately five kilometers from the center of PDK in all directions.

Parameter Monitored	**Beginning Date**	**End Date**	**Notes**
Passive Nitrogen Dioxide- Community	15 March 2013	15 October 2014	Approximately 95% Data Recovery
Passive Volatile Organics- Community	15 March 2013	15 October 2014	Greater than 95% Data Recovery
Noise- Community	15 March 2013	25 October 2014	Approximately 80% Data Recovery[1]
Real-Time Particles- Airport, Multiple Sites	15 October 2013	15 October 2014	Approximately 80% Data Recovery[2]
Real-Time Black Carbon- Airport, Multiple Sites	15 October 2013	15 October 2014	Approximately 80% Data Recovery[2]
Particle Mass- Airport, Multiple Sites	15 October 2013	15 October 2014	Approximately 90% Data Recovery
Airborne Metals- Airport, Multiple Sites	15 October 2013	15 October 2014	Approximately 90% Data Recovery
Noise- Airport Run[3]	15 March 2013	15 October 2014	Data Recovery Not Known

Table 1. Parameter Monitored, the Start Date, End Date, and any Notes including data recovery percentages.

Parameter Monitored, the Start Date, End Date, and any Notes including data recovery percentages.

1. Monitor failed in May 2014 and required recalibration twice
2. Particle monitors required refurbishing during sampling periods
3. The airport runs four monitoring sites in the vicinity of the airport which also provided data for this study

Results

Air Pollution

Community Nitrogen Dioxide

The National Ambient Air Quality Standard (NAAQS) for nitrogen dioxide is 53 ppb averaged over one year. This standard applies to any location within a metropolitan area; if a single location exceeds the NAAQS then the entire region is in violation. Since the NAAQS are themselves averages over time, we used these same time averages in our assessment. It is worthy of note that the NAAQS is designed to afford essentially a no-effect level for health effects. Observed values below this level are assumed to have no adverse health effects. No site in this study exceeded this standard for an annual average, or even for a single monitoring period.

For nitrogen dioxide, data recovery was excellent. Data from one two-week monitoring period in August 2014 was lost. Other than this data loss, only a small number of individual samples were lost. Overall, 97% data recovery was achieved. Averaging all of the data for all 14 sites across the 40 available monitoring periods results in an average concentration of 13.7 ppb. Therefore, the average concentration is well below the standard, which is, again, designed to afford essentially a no-effect level for health effects.

There is some variability from site to site and across sampling periods with the highest two week-average concentration of 24.6 ppb with the lowest two-week average concentration at 5.4 ppb. Since the NAAQS specified an annual average, a comparison with the 53 ppb standard requires a similar averaging process. We note that averaging over the entire time period Sites B and D displayed the highest overall average of 16.9 and 16.4 ppb respectively, well below the Standard. We note that Sites B and D are the closest to the Airport while Site C is the farthest away, near the intersection of I85/I285, called “Spaghetti Junction” by locals. The lowest site was Site C, which averaged just under 10 ppb. These observations may suggest that PDK is a distinct source of Nitrogen Dioxide. However, this observation must be tempered by noting that Sites B and D (and also 7, the next highest site) are located in an industrial area. Site B, in particular, is an automotive repair facility that may be expected to have elevated combustion-related concentrations.

We also noted seasonal variability in nitrogen dioxide concentrations with winter values being somewhat higher than summer values. Averaging over all Sites, we note that the sampling period ending on January 2, 2014 displayed the highest average concentration at 20.7 ppb while the sampling period ending on July 10, 2014 had the lowest average concentration across all Sites of 9.7 ppb. This trend of higher values in the winter and lower values in the summer is reflected in both sampling years. This observation is somewhat unusual as other, non-Atlanta locations typically see the reverse trend. However, this trend in Atlanta has been observed by other studies. We should note that PDK operations are typically somewhat lower during the winter months when compared with summer months.

Our general conclusion for nitrogen dioxide sampling is that PDK may be contributing to nitrogen dioxide exposure in the near-field vicinity of the Airport (Sites 7, B, and D), but that the contribution is small. Once removed from the Airport by a little as 500 m, the contribution is not detectable above the urban background. Further, the levels for this pollutant are low overall, with no expected adverse health outcomes. Finally, the variability across the community is low- only a few ppb.

Industrial areas, including those near the airport, have higher levels of this pollutant as do residences near major roadways. However, Site C, near the intersection of two major highways, displays the lowest values. We note little evidence of PDK as a major source of this contaminant.

Our general conclusion for nitrogen dioxide sampling is that the results are consistent with observations made in the Atlanta metro area for this time period. Concentrations for this contaminant are associated with vehicular traffic and this is reflected in our observations; sampling locations close to major roadways (within 50 m of a major road) display somewhat higher concentrations- perhaps 2-3 ppb, than those more removed or in residential, low-traffic settings.

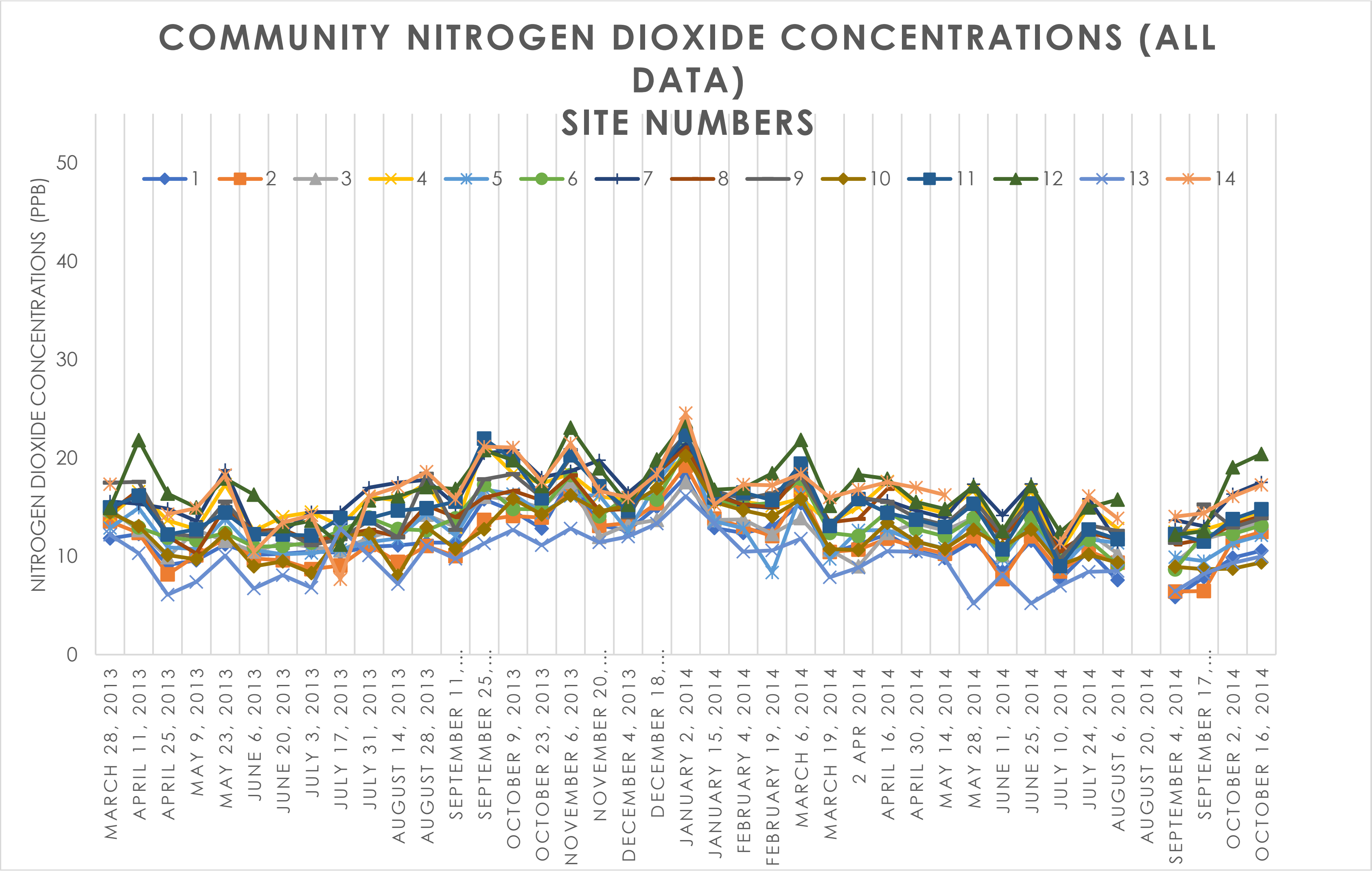


Figure 2 Community-based Nitrogen dioxide data. Note that the National Ambient Air Quality Standard (NAAQS) of 53 PPB can be seen as the horizontal line connecting the Site Number Legend at the Top of the Graph.

Community Volatile Organic Compounds (VOCs)

The results for passive VOC sampling for the BTEX compounds reflects those found for nitrogen dioxide with some important differences. Data recovery for all compounds, other than benzene, was excellent with only a small handful of missing samples, exceeding 95% for all and approaching 99% for toluene. However, there were contamination problems in the first batch of samplers analyzed causing us to consider data through sampling ending on May 9, 2013 to be suspect. If these samples are discarded, out data recovery drops to about 90%, still in excess of the 75% data recovery expected by USEPA. Further, it gives us 17 months of BTEX data from the study. Only a small number of samplers had benzene levels exceeding the limit of detection. These occurred primarily at the automotive repair site and only very occasionally elsewhere. This may be expected as benzene, now considered a carcinogen by EPA, has been removed from many products and is present only in very small quantities in automotive and aviation fuel.

Typical concentrations for these compounds were as follows: Benzene < LOD (0.1 $\mu g/m^3$); Toluene 1-3 $\mu g/m^3$; Ethyl benzene 0.1-0.5 $\mu g/m^3$; *m*-/*p*-Xylene 0.5-1.5 $\mu g/m^3$, and *o*-Xylene ~0.5 $\mu g/m^3$ (See Figure 3.) There are no appropriate standards for these compounds; however, the values reported here are consistent with those found in other urban areas. The Sites associated with higher nitrogen dioxide concentrations tended to have higher concentrations of these compounds as well. Again, the automotive repair facility was notable in being the highest Site consistently. This is in line with the presence of gasoline fumes at the site as gasoline can still contain trace quantities of this known carcinogen. Nevertheless, the values reported here were only on the high end of a continuum in the ranges noted throughout the rest of the community; they were not outliers. Further, variability within Sites across time and variability between Sites for each monitoring period or in averages was only about 50%. This is compared with the factor of roughly 2 variability for nitrogen dioxide.

Seasonal patterns were less pronounced in these compounds, however, summer was higher than winter. This is consistent with expected volatilization of these compounds from gasoline and other fuels. The formulation of automotive fuels is modified in the summer to reduce the amount of very volatile compounds, but these compounds, e.g., butadiene, do not fit into that category and are not measured effectively by passive sampling. Nevertheless, elevated temperature results in greater volatilization of BTEX in the summer. Our observations are consistent with this fact.

The Sites nearest the airport do display higher concentrations than those further away. This may be due to the airport being a local source or, as discussed under nitrogen dioxide results, may result from the industrial facilities that serve as the monitoring Sites. Regardless, the differences are small between these sites and more residential areas and, again, reflect the concentrations of these contaminants found in other studies of urban areas.

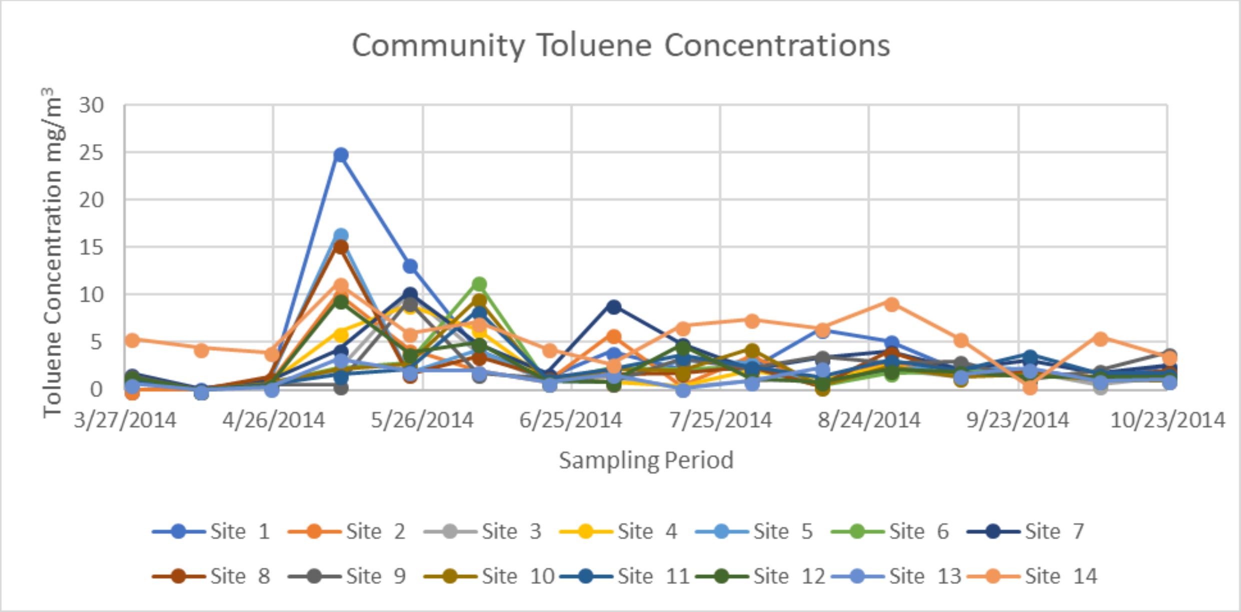


Figure 3- Community-based Toluene Concentrations. There are no National Ambient Air Quality Standards for Toluene. Typical values found nationwide are in the 1-10 mg/m^3 range across the United States.

Similar figures for Ethyl Benzene , *o*-Xylene, *m,p*-Xylene

Integrated Lead and Particle Sampling

Integrated lead and particle sampling occurred at each of the locations on the airport grounds on a six-day cycle beginning October 10, 2013 and continuing through the end of the study data collection effort in October 2014. A total of 59 samples were taken at each site. Overall data recovery was 94%, but data from the North site was problematic due to pump flow difficulties. Several samples at that site had to be voided yielding at 83% recovery at that site alone. Data recovery at the remaining three sites exceeded 97%.

Particle Mass

Mean particle concentration for the duration of sampling were 19.3, 11.8, 13.3, and 11.9 $\mu g/m^3$ for the North, East, South, and West sites respectively. The North location displayed not only the highest concentration, but also substantially more variability than the other sites. We note that the NAAQS standard for this contaminant is 12 $\mu g/m^3$ based on an annual average and that the Atlanta metropolitan area is in violation of this standard. PDK grounds show similar values to the rest of Atlanta (13-16 $\mu g/m^3$ annual average depending on location within the Atlanta metro area) with the North monitoring station, closest to the industrial area discussed previously, showing the highest values. Seasonally, there was a slight tendency for particulate matter concentrations to be higher in the spring and summer months and lower in the fall and winter months. This observation is consistent with Atlanta as a whole, but also may represent an effect of increased Airport operations during the warmer months, relative to the colder months. However, this effect is not large with spring/summer values only 1-3 $\mu g/m^3$ higher during those months as compared with cooler seasons. One can conclude that the Airport, or perhaps the nearby industrial areas, contribute to particulate matter concentrations and that these concentrations exceed the NAAQS of 12 $\mu g/m^3$. It is noteworthy that the North and South sites exceed the standard while the East and West sites are slightly below the standard suggesting that Airport activity, with the major N/S runway, may be contributing to particulate matter concentrations in these directions.

Lead Aerosol

We have analyzed these samples for a series of metals typically found in both combustion-related aerosol concentration and in windblown dust. In this Report, we report only the results for lead (Pb). Only lead has an NAAQS health-based standard. This value is 150 ng/m^3 = 0.150 $\mu g/m^3$, based on a three-month rolling average. Measured values of lead concentration in the air ranged from below our detection limit to approximately 300 ng/m^3. The North and South sites displayed somewhat lower concentrations centering on about 50 ng/m^3. The East monitoring station averaged somewhat higher, nearing 100 ng/m^3. The West monitoring station reported the highest average values with typical values ranging between 100 and 200 ng/m^3 to as high as 300 ng/m^3.This is consistent with our observation that general aviation aircraft, which use AVGAS, a leaded-fuel, are often parked, cleaned, and serviced around the West sampling location. Further, prevailing winds would tend to come from the west toward the east, transporting lead-containing aerosol from the western edge of the airport toward the east. Sampling locations at the ends of the principal runways would likely be lower in that aircraft spend less time at this location. There is seldom a queue for takeoff as there might be for larger airports, hence aircraft taxi to the end of the runway and leave shortly thereafter. It is also relevant that no sampling site was near a common landing location resulting in dispersion of aerosol and concomitant reduction in concentrations at the North and South sampling locations. There is little vehicular traffic near the sites other than the West location, suggesting that ground transport vehicles have little impact on the community with regard to lead.

The values found at the Airport are higher than those generally found in metropolitan Atlanta. This suggests that PDK may be a source of lead contamination in the surrounding community. The local area around the West site may approach the 150 ng/m^3 value on occasion. It is unlikely that the other sites approach this value in any three-month period and did not do so during our monitoring. More study is needed to evaluate the lead dispersion from the airport into the surrounding community.

Real-time Particle Data

Real-time sampling occurred only on the airport ground in four secure Sites located and the two ends of the principal runway and perpendicular to the principal runway and a distance of between 50m and 100m from the centerline at roughly at its midpoint. Sampling began on beginning October 10, 2013 and continuing through the end of the study data collection effort in October 2014 (See Figure 1 for Locations.)

Data recovery for the real-time monitors was good, exceeding 75% when the monitors were in place. Each of the monitors had to be taken offline for software updates, repairs, and maintenance. Typical updates, maintenance, and repairs required shipping the instruments back to the manufacturer with a loss of sample collection for roughly two weeks each time. For the black carbon instruments (the microAeth), we elected to purchase two additional devices to ensure that backups were available. This was not possible for the particle counting apparatus (CPC) as the cost for the instruments was prohibitive. When only three CPCs were available, we rotated them around the four Sites on the airport grounds so that all Sites received approximately the same number of days of monitoring.

Data from the continuous monitoring does not lend itself well to summary presentation as the data collected are averaged of very short durations (30 seconds to 300 seconds) for an entire year. Most of the data are low and constant, reflecting urban background concentrations, as no sources are present. However, spikes in levels of particulate matter are associated with airport operations, whether a take-off, landing, or running an aircraft engine for maintenance purposes. Further, we can correlate spikes occurring in the four instruments located at different locations around the airport to identify events unique to one location, or perhaps influenced by meteorology, i.e., affected by which way the wind is blowing. Since all air data are time stamped, we can correlate individual events with specific aircraft by noting if an airport operation occurred at that time and, especially, if such events can also be correlated with a noise event in a time window of a few minutes. We have been less successful with this type of analysis to the present. See Appendix 2 for an example of data output from the real-time monitors.

What they do give, however, is an indication of when an "event" occurs where we define an event as when particulate matter counts increase substantially or "spike." Spikes can be associated with airport operations of aircraft, maintenance activities on aircraft, or other activities that produce a large number of small particles in the air. Further, we can correlate spikes occurring in the four instruments located at different locations around the airport to identify events unique to one location, or perhaps influence by meteorology, i.e., affected by which way the wind is blowing. Finally, and most usefully, since all data are time stamped, we can correlate individual events with specific aircraft by noting if an airport operations occurred at that time and, especially, if such events can also be correlated with a noise event in a time window of a few minutes. We will discuss this below in regard to noise monitoring.

The time-resolved data do net lend themselves to assessing particulate impact on the surrounding community in the same way as other measures. For nitrogen dioxide and BTEX compounds, the compound does not change after emission. This is not the case with particles. Aerosol particle-size distributions change with "aging" of the aerosol as smaller particles as measured by these devices change into larger particles due to accumulation and aggregation. As discussed above, such data are useful in assessing the impact of specific aircraft on fine particle concentrations closest to the airport. In order to determine the impact of ultrafine particulate matter as measured by these two instruments, we must make assumptions about the composition of the aerosol and of the rate at which it accumulates and aggregates. The differences we see between the upwind (generally the west site) and the downwind site (generally the east site) allow us to say that the concentrations of these ultrafine particles diminishes as we go across the airport grounds. However, we can identify aircraft as they land through the short-duration (a few minutes) spikes seen at the monitors.

Air pollution monitoring was designed to assess the impact of PDK on the local community keeping in mind Goals 2 and 3 that required removing the effect of both noise and air pollution associated with the surrounding highway system (Goal 2) and the impact of Hartsfield-Jackson Atlanta International Airport (Hartsfield-Jackson) (Goal 3). Since the concentrations of the air pollutants we have measured show no relationship with highway proximity (indeed the community site in closest proximity to the Interstate highways shows low contaminant levels) our results suggest that the surrounding highway system, while contributing to the general background pollution levels, does not offer direct impact into the community surrounding PDK.

With regard to Goal 3, modeling work showed that air pollution associated with Hartsfield -Jackson would not be distinguishable by any measures utilized but, rather, would be part of the metropolitan urban air pollution background.

Analysis of Air Pollution Event Data Using Maximum Takeoff Weight (MTOW) Levels

The community surrounding DeKalb Peachtree Airport (PDK) considers the potential for air pollution impact on the region to be one of the major problems associated with proximity to the airport. As part of their investigations, Open DeKalb, a citizen’s action group, has requested information regarding the association of air pollution levels with aircraft operations, particularly with larger aircraft. Earlier work on this study focused on air pollution data collected at various sites within the community. These community-based data, suggested that, with the possible exception of the location approximately 100 m north of the PDK grounds, pollutant concentrations indistinguishable from other regions about metropolitan Atlanta. However, these data could give no information on the impact of aircraft as a function of Maximum Takeoff Weight (MTOW) as they represented data integrated over a two-week period. This document describes approaches to assessing the differential impact of MTOW of aircraft on air pollution levels in the vicinity of the airport runways.

Initial Analytical Attempts

During the study design phase of this investigation, it was assumed that information was available that would specify the timing of airport operations, i.e., take offs and landings, with some precision. Emory researchers designed an investigation that would monitor in real-time, particulate matter concentrations at four locations on the airport grounds using sophisticated monitors that measure particulate matter concentration on a minute-by-minute basis. By design, these monitors were placed at either end of the principal north-south runway approximately 50 m past the north and south ends as well as approximately mid-runway, perpendicular and approximately 100 m east and west of the principal runway (See Figure 1.) Aircraft, identified by transponder signal would be identified and, using a database developed by Emory researchers, the MTOW of the aircraft assigned. These data would then be correlated with air pollution measurements taken by the instrumentation described above.

While this design would have yielded information appropriate to the goal of this investigation, the data initially made available were not what was originally envisioned. Aircraft transponder data, that is, the information needed to identify individual aircraft and thus their MTOW, were available to us from Noise Monitor data. Noise monitors are located 2-5 km from the airport, not on the airport grounds. The portable noise monitor, which also supplies similar information, was moved from location to location in the community and was at distances from about 100 m north of the airport, to distances up to 3 km away from the airport grounds (See Figure 1.) As these data were not optimum, modification of the original plan was necessary.

In January 2018, some 18 months after completing analysis using the limited noise monitor data on aircraft, we were given data on airport operations- the original data we had expected that would have allowed the analysis originally proposed. However, by that point, we had fully developed algorithm based on the air pollutant data and elected to continue with that analysis rather than abandon that process and revert to the original algorithm. We were satisfied that the analysis done in this fashion would afford quality results equivalent to what we would have obtained from the original analysis. We report here on the implementation of the alternative algorithm using the full Flight Event List data for the monitoring period.

For a discussion of data processing for Real-Time Particle Data See Appendix 2- Data Processing of Real-Time Particle Measures- A Detailed Description of the Algorithm Used with Illustrative Example

General Information for Particle Analysis

Table AP-1 presents a summary of aircraft operations during the monitoring period parsed by MTOW. The are two points of note. First, we have combined Aircraft with known MTOW less than 25,000 lbs and those with UNKNOWN characteristics into a single Weight Class, i.e., Weight Class 1.. This is consistent with the information supplied by PDK staff that most such aircraft, perhaps 95%, are likely General Aviation aircraft that fit into to this weight classification. This classification includeds nearly 88% of all airport operations at PDK. The second point of note is that we identified 137 airport operations for non-fixed wing aircraft. These included 135 helicopter operations and two blimp operations. These operations have not been included in these analyses.

Weight Class	Criteria	Number of Events	Percent	Cumulative Frequency
-1*	**Non-Fixed Wing**	137	0.13	137
1	**UNKNOWN and <25,000 lbs**	89,749	87.76	89,886
2	**25,000 – 66,000 lbs**	9,645	9.43	99,531

3	**66,000 – 75,000 lbs**	1,786	1.75	101,317
4	**>75,000 lbs**	948	0.93	102,265

*Not Considered in further analyses

Table AP- 1 *Summary of Airport Operations during the monitoring period commencing on October 10, 2013 and continuing through October 10, 2014.*

Data Analysis- microAeth Black Carbon Data

In the data collected at PDK Airport we used two different real-time monitors that measured particulate matter in the air. The first of these is the Black Carbon Aethelomoter sold under the name micrAeth ® (we refer to these data as Black Carbon or BC) that measures fine particles focusing on the component of these fine particles that are made up of finely divided , primarily unburned, carbon, which is a material consisting of very fine particles, general < 1.0 µm in diameter. Further, these particles are typically associated with diesel exhaust, and exhaust from the burning of kerosene and similar compounds, associated with jet fuel. The physics of how these instruments work is covered in some detail in the report above. The second is the Condensation Particle Counter (CPC) measured particles in the respirable (<2.5 µm in diameter) range. It is particles of this size that are of importance in human health effects.

For the Black Carbon data, and subsequent Condensation Particle Data, we collect information at each of our sites on a real-time basis and average the results over 60 seconds to give concentrations (for BC data) or particle counts (for CPC data). Please refer to *Appendix 2 Data Processing of Real-Time Particle Measures- A Detailed Description of the Algorithm Used with Illustrative Example* for the details of the algorithm used. In brief, much of time, these instruments are measuring background concentrations typical of the Atlanta urban environment. Intermittently, the monitors identify Transient Particle Peaks or TPPs during which time the particle concentration increases substantially above background. Because of the large number of data gathered, we use a statistical determination of a TPP to identify when as a change from the average Black Carbon is “significant” in some sense. The instruments used are “counting instruments” in that the attenuation of a light beam associated with the presence of colored particle (BC) or the count the number of particles procedure (CPC). Background, urban air pollution results in a variable signal for these instruments. This signal, on average, varies slowly with time, but displays very short term variability that is statistical in nature. TPPs are observed, then, reflect a sudden change in BC levels increasing 10- or even 100-fold above the background level. These changes are transient; they last for only a very short period of time, generally less than five minutes. The key is identifying such peaks in the large amount of data available thereby addressing the question: How do we distinguish events from naturally occurring background variability. Let us examine a particular TPP to illustrate the process.

Our algorithm identifies peaks as observations that differ from background level in a statistical sense. As pointed out, the concentrations vary slowly over time, and typically fluctuate within a range of a few ng/m^3. However, excursions from this occur. The slowly varying concentrations are characterized by a *mean level*, that is the average levels observed, and a variation from this level that we can assess in a statistical sense through the *standard deviation*, a measure of the variability in the concentration over time of the background levels. We use the following definition. We define a TPPx as occurring when we identify a concentration that exceed the mean concentration by x standard deviations. A TPP1 event occurs when the measured concentration exceeds the mean value by one standard deviation. A TPP5 event occurs when the measured concentration exceeds the mean level by five standard deviations. A TPP15 event occurs when the measured concentration exceeds the mean background level by 15 times the standard deviation, and so on. If we assume normally distributed data, a TPP1 event would occur about 16% of the time by chance. A TPP2 event would occur less than 5% of the time. A TPP3 event, would be an exceeding rare event not likely to be observed by random chance and likely represents a true source of pollution. Higher level TPPx events are even less likely to occur by chance.

Our process involves identifying TPP events and assessing whether such events are more likely to occur when specific Weight Classes of aircraft are evident through airport operations via the Flight Event Data describing airport operations at PDK. We present two different analytical schemes referred to as *Heuristic Analysis* and *Logistic Regression Analysis*. We describe each below and discuss the results obtained from these analyses.

Heuristic Analysis

Our Heuristic Analysis proceeds as follows. If air pollution events were not associated with aircraft MTOW, we would expect to see TPP percentages in line with the percentage of aircraft taking part in airport operations that fit into that category. This is most easily seen by an example. Consider a case in which we had 100 airport operations and two classes of aircraft. Suppose that a record of airport operations indicates that 65 of the aircraft were of Class A and 35 of the aircraft were of Class B. We then monitor air pollution events, say by the mechanism of TPP indicators discussed above. If the Class of the aircraft were not associated with TPP, then we would expect that the fraction of air pollution events associated with Class A aircraft would be about 65% and the fraction air pollution events associated with Class B aircraft would be about 35%. This is a “null” result; there is no association between aircraft class and air pollution events and the preponderance of events “associated” with Class A aircraft simply reflects the fact that more of those aircraft are present.

Imagine now that we measure air pollution events and note that 70% of the time they are associated with Class B aircraft. Since this is twice the expected frequency if there were no fundamental association of such events with aircraft class- we would expect 35%- then we assert that there is an association of aircraft class and air pollution levels.

We note here that we have 34,536 15-minute Time Segments in our study BC study. Inspection of Table BC-1 indicates that no aircraft is present during 10,374 or approximately 30.34% of the Time Segments. This reflects reduced frequency of airport operations during, for example, night hours. We further note that smaller aircraft (<25,000 lbs MTOW) and UNKNOWN aircraft (combined to give Weight Classes 1) are operational during the largest fraction of Time Segments. Weight Class 1 Aircraft are evident in 69.96% of the total number of Time Segments and 96.88% of the Time Segments for which an aircraft is present. The other Weigh Classes follow on. We note that larger aircraft, Weight Classes 3 and 4 are present in smaller fractions of Time Segments. By way of explanation, the total number of Time Segments parsed by Weight Class exceeds the total number of Time Segments overall as multiple aircraft can be present in the same Time Segment.

Weight Class	Time Segments with Aircraft in Class	Percent of Total Time Segments	Percent of Time Segments with Aircraft Present

No Aircraft	**10,374**	**30.34**	**-**
Weight Class 1	**24,162**	**69.96**	**96.88**
Weight Class 2	**7,566**	**21.91**	**30.34**
Weight Class 3	**1,689**	**4.89**	**6.77**
Weight Class 4	**918**	**2.66**	**3.68**

Table HBC-1- Time Segments with Aircraft with Specific Weight Class present. Black Carbon.

During the Black Carbon monitoring period, there were 34,536 15-minute Time Segments monitored. During this period 24,162 of the Time Segments had one or more aircraft present, while 10,374 Time Segments had no aircraft present.

Transient Level	**Number**	**Percent**
TPP 1	**6,860**	**27.73**
TPP 3	**1,954**	**7.90**
TPP 4	**1,390**	**5.62**
TPP 5	**1,050**	**4.24**
TPP 10	**452**	**1.83**
TPP 15	**258**	**1.04**
TPP 20	**160**	**0.65**
TPP 25	**107**	**0.43**

Table HBC-2- Number of Transient BC Particle Events occurring when Aircraft is Present. There are 24,742 Time Segments with aircraft present out of total of 35,040 time segments. The total number of Time Segments with TPP events with aircraft- perhaps from more than one Weight Class present- is 6,860 or 27.73%.

For Black Carbon (BC), TPP events do not occur in every Time Segment. Most Time segments are characterized by urban background levels with no transient peaks noted anywhere on the airport grounds. Using the loose criterion of a transient excursion of one standard deviation from the background (TPP1), only 27.73% of the Time Increments show any excursion. As we look at exclusions of larger magnitude (TPP3, TPP5, etc.), the percentage of Time Segments where such excursion occur diminish to less than 10%, less than 5%, and less for higher TPPx respectively; these events are unusual. Transient events occur approximately 39.72% of the time when aircraft are present.

As a comparison, we present data showing the number of TPP events occurring when <u>no aircraft are present.</u> Of the 10,374 Time Segments when no aircraft are present, 3,326 or 32.06% display transient events with the distribution of TPP events across the three levels that is similar to those for which aircraft were present.

Transient Level	Number	Percent
TPP 1	**2,088**	**20.13**
TPP 3	**761**	**7.34**
TPP 5	**477**	**4.60**

Table HBC-3- Number of Transient Particle Events occurring when no Aircraft is Present. There are 10,374 Time Segments with no aircraft present out of total of 35,040 time segments. The total number of Time Segments with TPP events with no aircraft present is 3,326 or 32.06%

We now examine the association of transient events with the weight class of the aircraft present during such an event. Tables BC-5a and BC-5b present these results. Note that the numbers on the Total row of BC-5a do not quite match the ones due to the presence of multiple aircraft of a given classification in the same Time Segment. The data are presented in numbers of such events in BC-5a and in percentage in BC-5b.

	Aircraft	**TPP1**	**TPP3**	**TPP4**	**TPP5**	**TPP10**	**TPP15**	**TPP20**	**TPP25**
WC1	70.36%	61.90%	64.64%	66.04%	67.52%	68.81%	67.44%	63.75%	68.22%
WC2	22.03%	27.64%	25.54%	23.74%	22.86%	21.46%	22.48%	23.75%	22.43%
WC3	4.92%	6.21%	5.83%	5.97%	5.33%	5.53%	5.81%	6.88%	5.61%
WC4	2.68%	4.11%	3.99%	4.24%	4.29%	4.20%	4.26%	5.63%	3.74%

Table HBC-4- A Comparison of the fraction of aircraft by Weight Class contributing to Transient Particle Peaks at various levels.

A number of features stand out in this analysis. First, going across the columns in Table BC-4, we note that the percent, the fraction of all TPP for a given Weight Class does not vary greatly. Further, Weight Class 1 (<25,000 lbs and UNKNOWN) dominate the various TPP values. Larger aircraft, Weight Classes 2, 3, and 4 make up smaller percentages of the TPP values. However, one does note that the fraction of aircraft in Weight Class 1 is consistently lower for the various TPP levels when compared to the number of aircraft of that type observed. For example, only 61.90% of TPP1 events are associate with Weight Class 1 while 70.36% of the aircraft observed are in this category. The opposite is true of Weight Classes 3 and 4; a larger percentage of all TPP level events are associated with these aircraft when compared with the fraction of aircraft in the fleet mix during this monitoring period. The trend is less clear for Weight Class 2 aircraft although most of the TPP event levels also exceed the expected levels, with the Exception of TPP10. A graphical depiction of these data can be found in Figure BC-1. Visually we note the same trends, and note that they are more clearly represented in this visual display.

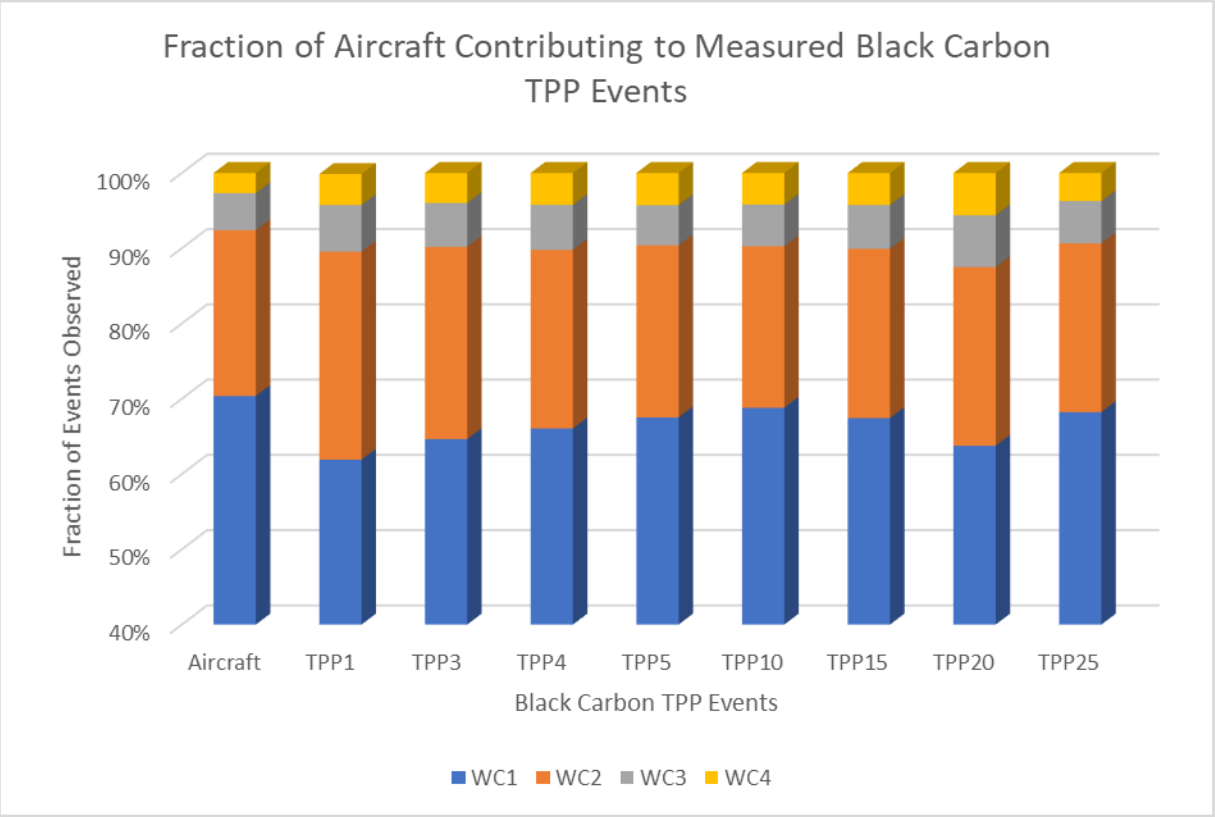


Figure HBC-1- A comparison of the fraction of each Weight Class associated with BC TPP events.

The results of this analysis is compelling. In each case, there is a suggestion that larger aircraft may be producing a disproportionate fraction of TPP events, and again by analogy, air pollution on the airport grounds. Specifically, this Heuristic Approach suggests that larger aircraft may be contributing more to TPP events and, by analogy, to particulate air pollution, than smaller aircraft. This suggest the need for more sophisticated and detailed analysis.

Logistic Regression Approach

Logistic regression is a statistical method that puts what we have done in the Heuristic Approach on a firm statistical footing. The methods asks the question: Is the outcome of interest more likely to occur in one class of a variable than in another? In our analysis, the outcome of interest is the occurrence of a TPP event. The class of variables in our analysis is the Weight Class of the aircraft. We ask a series of questions, again similar to what we did in the Heuristic Approach: Is there any difference among the Weight Classes with respect to the probability of seeing a TPP event? Is Weight Class = 1, different from Weight Class 2, or Weight Class 3, etc.? In particular, we are interested in the relationship between Weight Classes 3 and 4, and the other classes. We explore all of the possible interactions. Further, we explore them for TPP1, TPP3, TPP4, TPP-5, TPP10, TPP15, TPP20, and TPP25 to see if there is a magnitude dependence, i.e., are there differences for larger peaks that may not be evident for smaller peaks.

The results will be presented separately for the eight levels of TPP. We will present this in a series of tables showing the statistical results., which I will explain in detail for the first set describing the outcome of analysis for TPP1. In all of these analyses, the outcome variable is the probability that a TPP event occurs given knowledge of the Weight Class. Further, we present separate analyses for the microAeth Black Carbon data for the Condensation Particle Counter (CPC) data.

TPP1

Our discussion begins with TPP1, transient peaks identified as being one or more standard deviations above the mean background level. Table LRBC1-1 presents the overall statistical significance of the model. We ask the statistical question: "What is the probability that we would have achieved a results such as the one we saw had there been, in truth, no effect associated with Weight Class We use the common statistical criterion that the probability, listed as p-Value, must be less than 0.05 in order to interpret the results as statistically significant and not due to random chance. In this case, we see that there is only a 2.15% chance that we would have seen an effect relating Weight Class to the presence of a TPP at the TPP1 level had there been no such relationship. Since our observed value is less than 5%, we deem this a statistically significant effect; Weight Class is associated with TPP-1.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.0215

Table LRBC1-1. The overall statistical significance of a the model relating TPP-1 at Weight Class.

This is an important result, but one that should be viewed with some caution. Recall that the criterion for TPP-1 is that a peak is defined as being present if the BC concentration exceeds the mean by one standard deviation. This is a very loose criterion as , if the statistical variability in the background levels was normally distributed, 16% of the time such a peak would occur just due to normal statistical fluctuation of the background levels. Nevertheless, such a result is suggestive of moving forward with the analysis, so we continue onward.

The next analysis we present is to compare the probability ratios between each of the Weight Classes with the highest Weight Class. Here we are looking at the probability of a TPP1 level peak occurring with air craft in, say, Weight Class 1 (< 25,000 lbs MTOW or UNKNOWN) with the probability of a TPP1 event occurring with aircraft in Weight Class 4 (MTOW > 75,000 lbs). The "Point Estimate" is the best "guess" for this ratio. A value of 1.000 would imply that there is equal probability of noting a TPP1 event in Weight Class 1 and in Weight Class 4. This is a null result; there is no difference. What we note in this table is that all of the Point Estimates are less than 1.000 indicating that it is less likely to see a TPP1 event in Weight Class 1 than in Weight Class 4. But this is the "average" result. In looking at all of the data for the two weight classes, we can make further statements. This is expressed in the "95% Confidence Limits." The data we have collected allow us to say with 95% confidence (we would be wring 5% of the time) that the true ratio lies between the two values. For the comparison of Weight Class 1 with Weight Class 4, we are 95% confidence that the true ratio lies between 0.728 and 0.972. It is important that this 95% confidence limit does not cover the null value of 1.00 as this implies that this, too, is a statistically significant result and adds credence to the overall significance displayed in Table LRBC1-1.

Examining the rest of Table LRBC1-2, we note that two of the three comparisons indicate differences between the lower Weight Classes and Weight Class 4, i.e., in particular, Weight Class 4 is more likely to give rise to a TPP1 event than Weight Class 1, as we have said, but also Weight Class 3. On the other hand, from a statistical point of view, we cannot say that Weight Class 2 differs from Weight Class 4.

Odds Ratio Estimates

Effect	**Point Estimate**	**95% Confidence Limits**	
wgtclass 1 vs 4	0.841	0.728	0.972
wgtclass 2 vs 4	0.901	0.776	1.047
wgtclass 3 vs 4	0.820	0.686	0.981

Table LRBC1-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

At this point, we have established that Weight Class 4 is more likely to give rise to a TPP1 event than some of the other classes. We would like to compare all of the weight classes to each other, and group them in an appropriate way. We do this by "contrasting" the Weight Classes and determining whether they differ from one another. These data are presented in Table LRBC1-3. We note that for the pairwise comparisons only Weight Classes 1 and 3 differ, as well as the previous information noting a difference between With Classes 2 and 4. Using these data and the data from Table LRBC1-2, we can establish a hierarchy of pairs. While Weight Class 4 is most likely, relative to the number of aircraft in this category, to produce a TPP-1 event, Weight Class 2 is next most likely, although is does not differ appreciably from Weight Class 1 or Weight Class 3.

But this simply says they are different; it does not give an ordering. Combining data from the two tables allows us to infer that in terms of probability of a TPP-1 event occurring, we rank the weight Classes as Weight Class 4 > Weight Class 2 > Weight Class 1 > Weight Class 3 This non-monotonic behavior may be due to differs of the fleet mix between Weight Class in terms of aircraft age, etc., but also may be due, at least in part, to the loose criterion associated with TPP1 as we will discuss presently.

Contrast Test Results

Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	0.0590
WgtClass=1 vs WgtClass=3	0.0165
WgtClass=2 vs WgtClass=3	0.0532
WgtClass 1, 2, 3	0.0341

Table LRBC1-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios.

TPP3

As mentioned above, TPP1 is a very loose criterion for the establishment of a true peak. Because of this, we repeated analyses for several other criteria and present the data sequentially. As we increase the magnitude of the peak, i.e., increase the value x in the TPPx definition, we have more confidence that these criteria would result in more meaningful associations as they provide a definition of a “peak” that is larger in magnitude and more likely to be impactful on the larger community. However, this is tempered by the fact that each time we make the criterion more stringent, we reduce the number of sample peaks we have to contribute to our statistical analyses. Note that any TPPx with a lower value for x must contain all of the peak at the higher values. For example, a peak identified as TPP5, would also be identified as TPP3 since it would also exceed the criterion for inclusion in that category. So as we increase the value of x in TPPx, we reduce, often substantially, the number of peaks identified.

We now examine TPP3, i.e., using a definition of a “peak” that requires a deviation from the mean of three standard deviations. In Table LRBC3-1, we note that the p-value does not meet out statistical significance criterion. We would see an effect this large approximately 30% of the time if there was, indeed no effect present through statistical variability.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.3066

Table LRBC3-1. The overall statistical significance of a the model relating TPP-3 at Weight Class.

The overall model results are borne out again by the results given in Table LRBC3-2. We note a series of comparisons results comparing Weight Class 4 with the other Weight Classes. While all of the estimates are less than 1 suggesting that Weight Class 4 is more likely than the other Weight Classes to produce a TPP3 event, in all of the cases, the confidence limits span the null value of 1.000. We cannot conclude that the effect is statistically significance. We are forced to conclude that there is no difference in the likelihood of producing a TPP3 event that can be attributed to Weight Class

Odds Ratio Estimates

Effect	**Point Estimate**	**95% Confidence Limits**	
wgtclass 1 vs 4	0.944	0.743	1.199
wgtclass 2 vs 4	0.875	0.682	1.123
wgtclass 3 vs 4	0.828	0.613	1.118

Table LRBC3-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

The results given in Table LRBC3-2 are borne out by the Contrasts displayed in Table R3-3. We note here that no pairwise comparisons nor any of the group comparisons even approach statistical significance. Hence we cannot infer that any of the Weight Classes is more likely than the others to give rise to a TPP-3 than any of the others; there is no effect of Weight Class on TPP-3 and thus no inference of higher Weight Classes producing more BC air pollution.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.4322
WgtClass=1 vs WgtClass=3	0.3384
WgtClass=2 vs WgtClass=3	0.2150
WgtClass 1, 2, 3	0.3073

Table LRBC3-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-3.

TPP4

We now show results for TPP-4 for which the criterion for a peak is that it exceed the mean plus four standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP. Further, we chose TPP4 analysis because there appeared to be a break in the descriptive power at this level.

Table LRBC4-1 present the overall significance of the relationship of TPP4 probability of occurrence and Weight Class. The p-value is less than our criterion for statistical significance ($p<0.05$) indicting that there is an association between Weight Class and TPP-4probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP4 event increases steadily with Weight Class, as we shall see.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.0347

Table LRB4-1. The overall statistical significance of a the model relating TPP-5 at Weight Class.

The overall model results presented in Table LRBC4-1 are not readily borne out by the ensuing Tables. In Table LRBC4-2, we note the somewhat familiar pattern of point estimates being less than 1.000 suggesting that Weight Class 4 is more likely to result in a TPP4 event occurring than are the other Weight Classes. However, all of the confidence intervals span the null result of 1.000. But we do note that the upper confidence intervals are near the 1.000 value, particularly the comparison between Weight Classes 2 and 4. Had we chosen a 90% confidence interval (accepting a 10% chance of being wrong) we might well have reached significance.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	0.906	0.690	1.189
wgtclass 2 vs 4	0.761	0.572	1.014
wgtclass 3 vs 4	0.798	0.566	1.126

Table LRBC4-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

The other paired comparisons have probability values that also approach significant, especially the comparison between Weight Classes 2 and 3. All of these "near misses" together results in the model being overall significant.

Contrast Test Results

Contrast	Pr > ChiSq
WgtClass=1 vs WgtClass=2	0.1803
WgtClass=1 vs WgtClass=3	0.2696
WgtClass=2 vs WgtClass=3	0.0937
WgtClass 1, 2, 3	0.1595

TPP-5

We now show results for TPP5 for which the criterion for a peak is that it exceed the mean plus five standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRBC5-1 present the overall significance of the relationship of TPP-5 probability of occurrence and Weight Class. The p-value is less than our criterion for statistical significance ($p<0.05$) indicting that there is an association between Weight Class and TPP-5 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP-5 event increases steadily with Weight Class, as we shall see.

Effect	p-Value
wgtclass	0.0056

Table LRBC5-1. The overall statistical significance of a the model relating TPP-5 at Weight Class.

In Table LRBC5-2, we report the comparisons of lower Weight Class probabilities and those of Weight Class 4. We notice a steadily decreasing point estimate that suggest that the probability of observing a TPP5 event in a given Weight Class, *relative to Weight Class 4*, decreases. This implies that Weight Class 1 has a higher probability of producing a TPP5 than Weight Class 2, Weight Class 2 has a higher probability then Weight Class 3, etc., which may seem counterintuitive. However, we note that all of these estimates have 95% confidence limits that cross the null value of 1.00. We cannot say with confidence that any of these values are different from Weight Class 4.

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
wgtclass 1 vs 4	0.919	0.675	1.252
wgtclass 2 vs 4	0.728	0.525	1.008
wgtclass 3 vs 4	0.705	0.472	1.053

Table LRBC5-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Finally, we look at all of the paired and grouped comparisons for TPP5 (See Table R5-3). While none of the -values reach p<0.05, the comparison of Weight Class 2 and Weight Class 3 comes very close. Combining the results shown in Table LRBC5-2 and LRBC5-3 gives us confidence, despite the overall significance of the model, that there is not a monotonic increase in the probability of noting a TPP5 event related to Weight Class.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.2018
WgtClass=1 vs WgtClass=3	0.1978
WgtClass=2 vs WgtClass=3	0.0502
WgtClass 1, 2, 3	0.1206

Table LRBC5-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-5.

TPP10

We now show results for TPP-10 for which the criterion for a peak is that it exceed the mean plus ten standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRBC10-1 present the overall significance of the relationship of TPP-10 probability of occurrence and Weight Class. The p-value is less than our criterion for statistical significance (p<0.05) indicting that there is an association between Weight Class and TPP-5 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP-5 event increases steadily with Weight Class, as we shall see. Further, we see that the overall model probability is approaching the 0.05 cutoff for statistical significance. Extrapolating from the TPP3, TPP4, and TPP5 results, we might have expected the TPP10 results to be strongly significant. However, we now are beginning to lose statistical power as the total number of such events has dropped below 500.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.0460

Table LRBC10-1. The overall statistical significance of a the model relating TPP-10 at Weight Class.

In Table LEB10-2, we see a trend similar to that seen in the TPP5 results. We also not an expansion in the 95% confidence limits consistent with the reduced sample size a concomitant increase in statistical noise. Yet we continue to note the observation presented in Table LRBC10-1 that the model does show a statistically significant overall result.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	0.958	0.600	1.530
wgtclass 2 vs 4	0.702	0.427	1.153
wgtclass 3 vs 4	0.752	0.412	1.374

Table LRBC10-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

The results given in Table LRBC3-2 are borne out by the Contrasts displayed in Table R3-3. We note here that no pairwise comparisons nor any of the group comparisons even approach statistical significance. Hence we cannot infer that any of the Weight Classes is more likely than the others to give rise to a TPP-3 than any of the others; there is no effect of Weight Class on TPP-3 and thus no inference of higher Weight Classes producing more BC air pollution.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.4322
WgtClass=1 vs WgtClass=3	0.3384
WgtClass=2 vs WgtClass=3	0.2150
WgtClass 1, 2, 3	0.3073

Table LRBC10-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-10.

TPP15

We now show results for TPP15 for which the criterion for a peak is that it exceed the mean plus fifteen standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRBC15-1 present the overall significance of the relationship of TPP15 probability of occurrence and Weight Class. The p-value is greater than our criterion for statistical significance (p<0.05) indicting that there is an association between Weight Class and TPP-5 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP15 event increases steadily with Weight Class, as we shall see. We now begin to see steon effects of the reduction of sample size. We have cut the numberof TPP events by another factor of two below that observed in TPP10 events. The sample is now only 258 observations. It is unlikely that, given the statistical noise in these data, we would see an effect.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.4055

Table LRBC15-1. The overall statistical significance of a the model relating TPP-10 at Weight Class.

Wile we still seem the same pattern of point estimates in Table LRBC15 as in the results for TPP5 and TPP10, the confidence limits expand further and span 1.000 calling into questions the effectiveness of the model.

Odds Ratio Estimates

Effect	**Point Estimate**	**95% Confidence Limits**	
wgtclass 1 vs 4	0.926	0.502	1.709
wgtclass 2 vs 4	0.727	0.380	1.390
wgtclass 3 vs 4	0.782	0.357	1.709

Table LRBC15-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

The results given in Table LRBC15-2 are borne out by the Contrasts displayed in Table R3-3. We note here that no pairwise comparisons nor any of the group comparisons even approach statistical significance. Hence we cannot infer that any of the Weight Classes is more likely than the others to give rise to a TPP15 than any of the others; there is no effect of Weight Class on TPP15 and thus no inference of higher Weight Classes producing more BC air pollution.

Contrast Test Results

Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	0.5263

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=3	0.6263
WgtClass=2 vs WgtClass=3	0.4005
WgtClass 1, 2, 3	0.5025

Table LRBC10-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-15.

TPP20

We now show results for TPP-20 for which the criterion for a peak is that it exceed the mean plus twenty standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRBC20-1 present the overall significance of the relationship of TPP20 probability of occurrence and Weight Class. The p-value is greater than our criterion for statistical significance ($p<0.05$) indicting that there is not an association between Weight Class and TPP20 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP20 event increases steadily with Weight Class, as we shall see. Further, the small number of TPP20 events substantially diminishes the statistical power to assess this effect.

We report the same Tables for TPP20 and TPP25 here for completeness, but the reduction in sample size for TPP20 (N=160) and TPP25(N=107) makes it difficult for any statistically valid modeling results of this type to be undertaken.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.5347

Table LRBC20-1. The overall statistical significance of a the model relating TPP-20 at Weight Class.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	0.662	0.334	1.313
wgtclass 2 vs 4	0.581	0.280	1.206
wgtclass 3 vs 4	0.700	0.289	1.697

Table LRBC20-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.1703
WgtClass=1 vs WgtClass=3	0.2999
WgtClass=2 vs WgtClass=3	0.2327
WgtClass 1, 2, 3	0.2189

Table LRBC20-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-15.

TPP-25

We now show results for TPP-25 for which the criterion for a peak is that it exceed the mean plus twenty-five standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRBC25-1 present the overall significance of the relationship of TPP-25 probability of occurrence and Weight Class. The p-value is greater than our criterion for statistical significance ($p<0.05$) indicting that there is not an association between Weight Class and TPP-25 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP25 event increases steadily with Weight Class, as we shall see. Further, the small number of TPP25 events substantially diminishes the statistical power to assess this effect.

We report the same Tables for TPP20 and TPP25 here for completeness, but the reduction in sample size for TPP20 (N=160) and TPP25(N=107) makes it difficult for any statistically valid modeling results of this type to be undertaken.

Analysis of Effects	
Effect	**p-Value**
wgtclass	0.7293

Table LRBC25-1. The overall statistical significance of a the model relating TPP-10 at Weight Class.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.070	0.390	2.933
wgtclass 2 vs 4	0.829	0.287	2.395
wgtclass 3 vs 4	0.862	0.243	3.061

Table LRBC25-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.9070
WgtClass=1 vs WgtClass=3	0.9402
WgtClass=2 vs WgtClass=3	0.7601
WgtClass 1, 2, 3	0.8643

Table LRBC25-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-25.

Summary of Data Analytic Results for Black Carbon

The remaining air pollution data gathered were through real-time particle analyzers collectively referred to as Black Carbon microAeth data. This report focuses on those data. Particulate measurements are taken on a minute-by-minute basis at four locations on the airport grounds. Analysis of these data indicates the presence of basic background particulate levels punctuated by peak concentrations lasting several minutes at levels as much as 100 times higher than background. These high concentrations advect and disperse back to background in time frames of a few minutes. Our goal in this phase of the investigation was to correlate air pollution measurements, as indicated by these peaks in concentration-referred to as an “Transient Particle Peak” or TPP, with aircraft operation and identify, if possible, associations between these TPPs and aircraft maximum takeoff weight (MTOW).

Two algorithms were developed to assess these correlations, based upon the identification of a time-specified TPP and the presence of an aircraft in the vicinity, as indicated by transponder signal from stationary and mobile noise monitor data. The first, referred to as a Heuristic Approach relied on assessing whether a larger percentage of aircraft in heavier weight classes produced a disproportionate fraction of TPPs when compared to the fraction of aircraft of that type using the airport during the time frame of interest. The second algorithm relied on a statistical approach using logistic regression and performed a statistically rigorous assessment of the probability of an aircraft falling into a range of MTOW producing an TPP. We performed analysis at eight different TPP levels to assess not only the effect of MTOW on BC production but also to evaluate whther this impact was different for larger magnitude TPP events.

The results of the Heuristic Approach suggested that larger aircraft were more likely to results in BC TPP events than those of smaller aircraft. Quantitatively, such aircraft produced about twice the number of TPP5 events, for example, events than might be expected given their contribution based on the fleet mix at PDK. But the approach was heuristic and, while appealing, would be difficult to defend from both a scientific and statistical point of view as it depends on a subjective view of the results with little quantitative support.

The lack of a firm basis for the Heuristic Approach led us to pursue logistic regression as powerful statistical tool to evaluate the impact of aircraft MTOW on particulate air pollution levels. We performed logistic regression using the same eight levels of TPP in an effort to explain effects. For the lowest level, we showed a strong dependence on MTOW. However, this was a very weak measure of effect that was barely measurable, yet was still evident from this type of statistical analysis. Using a more reasonable level from TPP, namely TPP3 gave results that showed no difference among the various Weight Classes and no predictive power by introducing Weight Class as a variable. Using a more stringent criterion for the presence of a TPP gave an unusual result in that, overall, there was an association between Weight Class and the probability of the TPP but that the effect was not increasing with MTOW but rather was significant because Weight Class 2 and Weigh Class 3 differed from one another, but not from the others. These varying results suggest that any statistically significant difference is likely to be in the lower magnitude peaks and may reflect different ages of aircraft in the Different Weight Classes. Higher levels of TPP, e.g., TPP10, TPP15, TPP20, and TPP25 were suggestive of an MTOW dependence, but suffered from small sample size as the number of such events diminished rapidly with increasing TPP. In summary, the effect of MTOW on BC TPP events was not strongly established by this analsysi The Heuristic Analysis was suggestive of such an effect and the low and intermediate levels of TPPP were suggestive as well bu inconsistent results do not offer strong support to inferences regarding an association between MTOW and BC TPP events.

Data Analysis- Condensation Particle Counter (Total Particles < 2.5 µm) Data

Heuristic Analysis

We note here that we have 34,403 15-minute Time Segments in our study BC study. Inspection of Table CPC-1 indicates that no aircraft is present during 9,962 or approximates 28.96% of the Time Segments. This reflects reduced frequency of airport operations during, for example, night hours. We further note that smaller aircraft (<25,000 lbs MTOW) and UNKNOWN aircraft (Weight Classes 1) are operational during the largest fraction of Time Segments. Weight Class 1 Aircraft in 70.23% of the total number of Time Segments and 98.86% of the Time Segments for which an aircraft is present. The other Weight Classes follow on. We note that larger aircraft, Weight Classes 3 and 4 are present in smaller fractions of Time Segments. By way of explanation, the total number of Time Segments parsed by Weight Class exceeds the total number of Time Segments overall as multiple aircraft can be present in the same Time Segment.

Weight Class	Time Segments with Aircraft in Class	Percent of Total Time Segments	Percent of Time Segments with Aircraft Present
No Aircraft	**9,962**	**28.96**	**-**
Weight Class 1	**24,162**	**70.23**	**98.86**
Weight Class 2	**7,386**	**21.47**	**30.22**
Weight Class 3	**1,657**	**4.82**	**6.78**
Weight Class 4	**894**	**2.60**	**3.66**

Table HCPC-1- Time Segments with Aircraft with Specific Weight Class present. Black Carbon.

During the Black CPC monitoring period, there were 34,403 15-minute Time Segments monitored. During this period 24,441 of the Time Segments had one or more aircraft present, 9,962 Time Segments had no aircraft present.

For CPC, TPP events do not occur in every Time Segment. Most Time segments are characterized by urban background levels with no transient peaks noted anywhere on the airport grounds. Using the loose criterion of a transient excursion of one standard deviation from the background (TPP1), only 35.19% of the Time Increments show any excursion. As we look at exclusions of larger magnitude (TPP3, TPP5, TPP15), the percentage of Time Segments where such excursion occur diminish to less than 20%, less than 10%, and about 1% respectively; these events are unusual. Transient events occur approximately 39.72% of the time when aircraft are present.

Transient Level	Number	Percent
TPP1	**8,600**	**35.19**
TPP3	**4,214**	**17.24**
TPP4	**3,170**	**12.97**
TPP 5	**2,441**	**9.99**
TPP 10	**750**	**3.07**
TPP 15	**297**	**1.22**
TPP 20	**161**	**0.25**
TPP 25	**110**	**0.45**

Table HCPC-2- Number of Transient CPC Particle Events occurring when Aircraft is Present. There are 24,441 Time Segments with aircraft present out of total of 34,403 time segments. The total number of Time Segments with TPP events with aircraft- perhaps from more than one Weight Class present- is 8,660 or 35.19%.

We now examine the association of transient events with the weight class of the aircraft present during such an event. Tables BC-5a and BC-5b present these results. Note that the numbers on the Total row of BC-5a do not quite match the ones due to the presence of multiple aircraft of a given classification in the same Time Segment. The data are presented in numbers of such events in BC-5a and in percentage in BC-5b.

Weight Class	Aircraft	TPP1	TPP3	TPP4	TPP5	TPP10	TPP15	TPP20	TPP25
WC1	63.17%	74.39%	76.22%	76.30%	76.66%	78.41%	78.61%	77.72%	75.00%
WC2	26.65%	19.22%	17.76%	17.66%	17.54%	17.88%	17.22%	18.65%	19.70%
WC3	6.43%	3.96%	3.65%	3.61%	3.36%	2.07%	1.94%	1.55%	2.27%
WC4	3.75%	2.44%	2.38%	2.43%	2.44%	1.64%	2.22%	2.07%	3.03%

Table HCPC-3- A Comparison of the fraction of aircraft by Weight Class contributing to Transient Particle Peaks at various levels for CPC data.

A number of features stand out in this analysis. First, going across the columns in Table CPC-3, we note that the percent, the fraction of all TPP for a given Weight Class does not vary greatly. Further, Weight Class 1 (<25,000 lbs and UNKNOWN) dominate the various TPP values. Larger aircraft, Weight Classes 2, 3, and 4 make up smaller percentages of the TPP values. However, one does note that the fraction of aircraft in Weight Class 1 is consistently higher for the various TPP levels when compared to the number of aircraft of that type observed. For example, 74.39%% of TPP1 events are associated with Weight Class 1 while only 63.17% of the aircraft observed are in this category. The opposite is true of the other; a smaller percentage of all TPP level events are associated with these aircraft when compared with the fraction of aircraft in the fleet mix during this monitoring period.

A graphical depiction of these data can be found in Figure CPC-1. Visually we not the same trends, and note that they are more clearly represented in this visual display. WE note here that it is clearly evident that it is clearly evident that Weight Class 1 aircraft or overrepresented in TPP events for all categories relative to their presence in the mix of aircraft present overall (Note the hoeght of the Blue coponets of the bars on the TPP bars relative to the Aircraft bar. While there may be a downward trend n this observation for higher TPP categories, these categories are less stable as the number of events decreases substantially above TPP10.

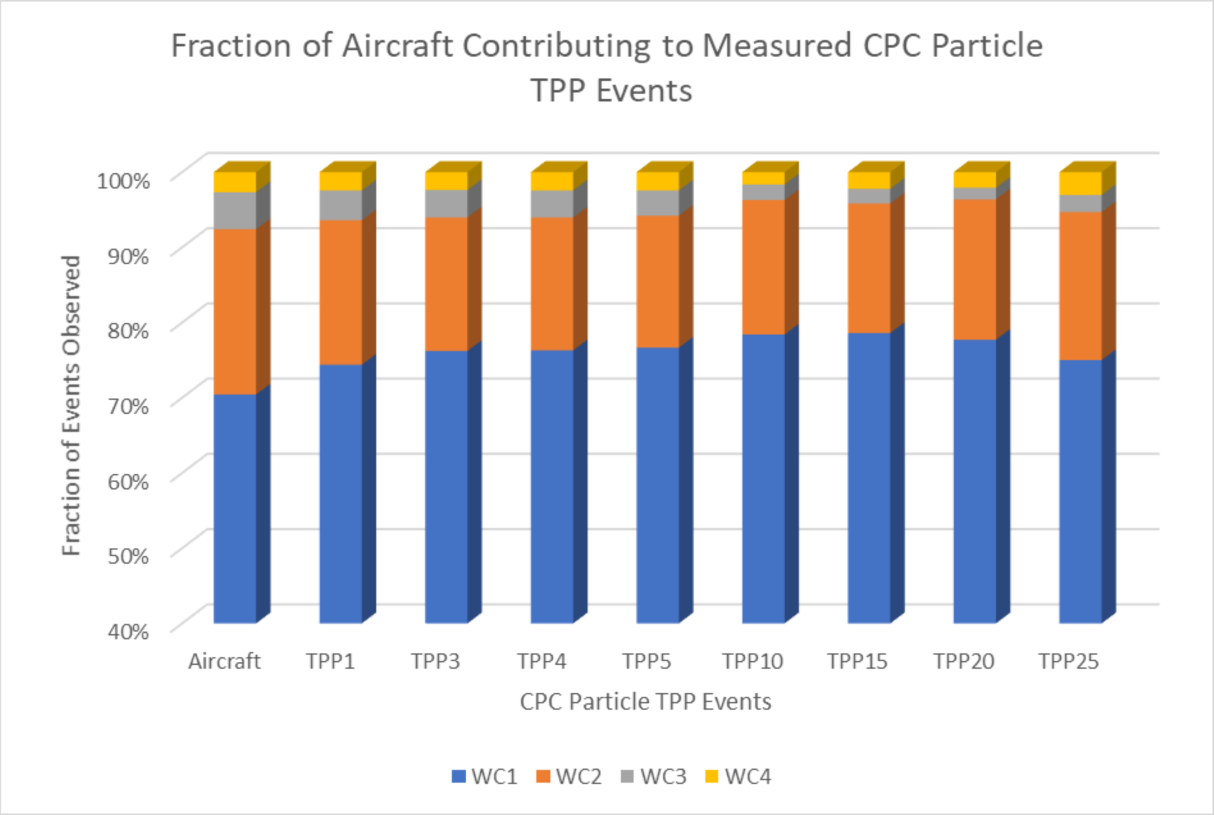


Figure HCPC-1- A comparison of the fraction of each Weight Class associated with CPC TPP events.

The results of Heuristic Analysis of CPC TPP events is compelling. In each case, there is a suggestion that smaller aircraft may be producing a disproportionate fraction of TPP events, and again by analogy, air pollution on the airport grounds. This suggest the need for more sophisticated and detailed analysis.

Logistic Regression Analysis

Table LGCPC1-1 presents the overall statistical significance of the model. We ask the statistical question: "What is the probability that we would have achieved a results such as the one we saw had there been, in truth, no effect associated with Weight Class We use the common statistical criterion that the probability, listed as p-Value, must be less than 0.05 in order to interpret the results as statistically significant ad not due to random chance. In this case, we see that there is less than 0.01 chance that we would have seen an effect relating Weight Class to the presence of a TPP at the TPP-1 level had there been no such relationship. Since our observed value is less than 5%, we deem this a statistically significant effect; Weight Class is associated with TPP-1.

TPP1

Analysis of Effects	
Effect	**p-Value**
wgtclass	**<.0001**

Table LRCPC1-1. The overall statistical significance of a the model relating TPP-1 at Weight Class.

This is an important result, but one that should be viewed with some caution. Recall that the criterion for TPP1 is that a peak is defined as being present if the CPC mean concentration exceeds the mean by one standard deviation. This is a very loose criterion as 16% of the time such a peak would occur just due to normal statistical fluctuation of the background levels. However, CPC data are very noisy when compared to Black Carbon data resulting in a larger standard deviation. Nevertheless, such a result is suggestive of moving forward with the analysis, so we continue onward.

The next analysis we present is to compare the probability ratios between each of the Weight Classes with the highest Weight Class. Here we are looking at the probability of a TPP1 level peak occurring with air craft in, say, Weight Class 1 (MTOW < 25,000 or UNKNOWN) with the probability of a TPP1 event occurring with aircraft in Weight Class 4- (MTOW > 75,000 lbs). The "Point Estimate" is the best statistical "guess" for this ratio. A value of 1.000 would imply that there is equal probability of noting a TPP-1 event in Weight Class 0 and in Weight Class 4. This is a null result; there is no difference. What we note in this table is that all of the Point Estimates are less than 1.000 indicating that it is less likely to see a TPP-1 event in Wight Class 0 than in Weight Class 4. But this is the "average" result. In looking at all of the data for the two weight classes, we can make further statements. This is expressed in the "95% Confidence Limits." The data we have collected allow us to say with 85% confidence (we would be wrong 5% of the time) that the true ratio lies between the two values. For the comparison of Weight Class 0 with Weight Class 4, we are 95% confidence that the true ratio lies between 1.675 and 2.352. It is important that this 95% confidence limit covers the null value of 1.00 as this implies that this, too, is a statistically significant result and adds credence to the overall significance displayed in Table LRCPC1-1.

Examining the rest of Table LRCPC1-2, we note that two of the four comparisons indicate differences between the lower Weight Classes and Weight Class 4, i.e., in particular, Weight Class 4 is less likely to give rise to a TPP1 event than Weight Class 0, as we have said, but also Weight Class 1. On the other hand, from a statistical point of view, we cannot say that Weight Class 2 or Weight Class 3 differs from Weight Class 4.

Odds Ratio Estimates

Effect	**Point Estimate**	**95% Wald Confidence Limits**	
wgtclass 1 vs 4	1.474	1.273	1.707
wgtclass 2 vs 4	0.970	0.833	1.130
wgtclass 3 vs 4	0.825	0.688	0.989

Table LRCPC1-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

At this point, we have established that Weight Class 4 is less likely to give rise to a TPP1 event than Weight Class 1 but more likely to give rise to TPP1 event than Weight Class 3 as in both cases, the 85% confidence limites do not span 1.000. We would like to compare all of the weight classes to each other, and group them in an appropriate way. We do this by "contrasting" the Weight Classes and determining whether they differ from one another. These data are presented in Table LRCPC1-3. We note that for the pairwise comparisons, only Weight Class 1 and 2 differ from one another in a statistical sense. Using these data and the data from Table LRCPC1-2, we can establish a hierarchy of pairs. While Weight Class 1 is most likely, relative to the number of aircraft in this category, to produce a TPP1 event, Weight Class 3, with Weight Classes 2 and 4 is resulting in approximately the same likelihood of producing a TPP1 event.

But this simply says they are different; it does not give an ordering. Combining data from the two tables allows us to infer that in terms of probability of a TPP-1 event occurring, we rank the weight Classes as Weight Class 1 > Weight Class 3 > Weight Class 2 ~ Weight Class 4. This behavior may be due to differences of the fleet mix between Weight Class in terms of aircraft age, etc., but also may be due, at least in part, to the loose criterion associated with TPP1 as we will discuss presently.

Contrast Test Results

Contrast	**P_Value**
WgtClass=1 vs WgtClass=2	0.0167
WgtClass=1 vs WgtClass=3	0.2154
WgtClass=2 vs WgtClass=3	0.1600
WgtClass 1, 2, 3	0.4713

Table LRCPC1-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios.

TPP3

As mentioned above, TPP1 is a very loose criterion for the establishment of a true peak. Because of this, we repeated analyses for other criteria, particularly defining a peak only if it exceeded three standard deviations from the mean (TPP3), and four standard deviations from the mean (TPP4), etc. We have more confidence that these criteria would result in more meaningful associations as they provide a definition of a “peak” that is larger in magnitude and more likely to be impactful on the larger community. We first examine TPP3, i.e., using a definition of a “peak” that requires a deviation from the mean of three standard deviations.

Analysis of Effects	
Effect	**p-Value**
wgtclass	<0.0001

Table LRCPC3-1. The overall statistical significance of a the model relating TPP3 at Weight Class.

Table LRCPC3-1 presents the overall results for the associations of Weight Class with TPP-3. As in the case for TPP1, we immediately we note the p-Value exceeds is well below the cut off for statistical significance (0.05). This tells us that there is a statistically significant difference in TPP3 probability associated with Weight Class. For this case we note that Weight Class 1 has a higher probability of producing as TPP-3 than Weight Class 4 , while the other Weight Classes show a non-significant effect in that the confidence limits displayed in Table LRCPC3-2 span the null values of 1.000. The differences noted between Weight Class 4 and Weight Classes 1 is sufficient to results in the highly significant value for the entire model.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.515	1.249	1.838
wgtclass 2 vs 4	0.930	0.760	1.138
wgtclass 3 vs 4	0.790	0.618	1.009

Table LRCPC3-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

The results given in Table LRCPC3-2 are borne out by the Contrasts displayed in Table LRCPC3-3. We note that, despite the strong statistical significance of the model overall, we see no statistically significant differences in the contrasts. The difference between Weight Class 1 and Weight Class 2 does approach statistical significance.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.0826
WgtClass=1 vs WgtClass=3	0.3912
WgtClass=2 vs WgtClass=3	0.1451
WgtClass 1, 2, 3	0.7243

Table LRCPC3-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-3.

TPP4

We now examine TPP4, i.e., using a definition of a “peak” that requires a deviation from the mean of four standard deviations. Table LRCPC4-1 indicates a strong statistical association for the model.

Analysis of Effects

Effect	DF	p-Value
wgtclass	3	<.0001

Table LRCPC4-1. The overall statistical significance of a the model relating TPP3 at Weight Class.

This results is borne out bey the point estimate evident for the difference in TPPP4 likelihood between Weight Class 1 and Weight Class 4 presented in Table LRCPC4-2. Note that this relations is statistically significant- the confidence limits do not span 1.000 and that we observe the consistent result that Weight Class 1 has a larger likelihood of producing a TPP1 event.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.453	1.170	1.803
wgtclass 2 vs 4	0.906	0.722	1.137
wgtclass 3 vs 4	0.774	0.587	1.020

Table LRCPC4-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Looking at the remining contrasts in Table LRCPC4-3, we note that none have a statically significant result suggesting that the difference between Weight CAlss 1 and Weight class 4 is the driving force for the significance of the model.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.2137
WgtClass=1 vs WgtClass=3	0.6182
WgtClass=2 vs WgtClass=3	0.1361
WgtClass 1, 2, 3	0.9556

Table LRCPC3-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP4.

TPP5

We now show results for TPP-5 for which the criterion for a peak is that it exceed the mean plus five standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRCPC5-1 present the overall significance of the relationship of TPP-5 probability of occurrence and Weight Class. The p-value is less than our criterion for statistical significance (p<0.05) indicating that there is an association between Weight Class and TPP5 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP5 event increases steadily with Weight Class.

Analysis of Effects

Effect	p-Value
wgtclass	<0.0001

Table LRCPC5-1. The overall statistical significance of a the model relating TPP5 at Weight Class.

In Table LRCPC5-2, we report the comparisons of lower Weight Class probabilities and those of Weight Class 4. We notice a steadily decreasing point estimate that suggest that the probability of observing a TPP5 event in a given Weight Class, *relative to Weight Class 4*, decreases. This implies that Weight Class 1 has a higher probability of producing a TPP5 than Weight Class 2, Weight Class 2 has a higher probability then Weight Class 3, etc., which may seem counterintuitive. However, we note that, as for TPP1 and TPP3, these estimates have 95% confidence limits that cross the null value of 1.00. We cannot say with confidence that any of these values are different from Weight Class 4.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.447	1.135	1.845
wgtclass 2 vs 4	0.896	0.695	1.157
wgtclass 3 vs 4	0.704	0.513	0.966

Table LRCPC5-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.2952
WgtClass=1 vs WgtClass=3	0.9435
WgtClass=2 vs WgtClass=3	0.0876
WgtClass 1, 2, 3	0.8135

Table LRCPC5-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-5.

Looking at the remaining contrasts in Table LRCPC5-3, we note that none have a statically significant result suggesting that the difference between Weight Class 1 and Weight Class 4 is the driving force for the significance of the model.

TPP10

We now show results for TPP-10 for which the criterion for a peak is that it exceed the mean plus ten standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP.

Table LRCPC10-1 present the overall significance of the relationship of TPP10 probability of occurrence and Weight Class. The p-value is less than our criterion for statistical significance (p<0.05) indicating that there is an association between Weight Class and TPP10 probability. However, we must keep in mind that this does not give us information on the shape of that curve. It does not, for example, suggest that the probability of observing a TPP5 event increases steadily with Weight Class.

Type 3 Analysis of Effects

Effect	DF	p-Value
wgtclass	3	<.0001

Table LRCPC10-1. The overall statistical significance of a the model relating TPP5 at Weight Class.

In Table LRCPC10-2, we report the comparisons of lower Weight Class probabilities and those of Weight Class 4. We notice a steadily decreasing point estimate that suggest that the probability of observing a TPP5 event in a given Weight Class, *relative to Weight Class 4*, decreases. This implies that Weight Class 1 has a higher probability of producing a TPP5 than Weight Class 2, Weight Class 2 has a higher probability then Weight Class 3, etc., which may seem counterintuitive. However, we note that, as for the lower TPP levels, these estimates have 95% confidence limits that cross the null value of 1.00 for Weight Classes 2 and 3. We cannot say with confidence that any of these values are different from Weight Class 4. However, for Weight Class 1 we see a larger point estimate indicating a larger difference between Wight Class 1 and weight Class 4 than for lower TPP levels. Further, the confidence interval, which is beginning to expand as sample size is reduced, does not span the null value of 1.000. We are quite confident that Weight Class 1 does differ from Weight Class 4.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	2.215	1.321	3.716
wgtclass 2 vs 4	1.427	0.836	2.436
wgtclass 3 vs 4	0.640	0.318	1.288

Table LRCPC10-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Looking at the remaining contrasts in Table LRCPC10-3, we note that none have a statically significant result suggesting that the difference between Weight Class 1 and Weight class 4 is the driving force for the significance of the model.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.0295
WgtClass=1 vs WgtClass=3	0.5444
WgtClass=2 vs WgtClass=3	0.8764
WgtClass 1, 2, 3	0.3919

Table LRCPC15-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP15.

TPP15

We now show results for TPP15 for which the criterion for a peak is that it exceed the mean plus fifteen standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP. We note that the significant levels has increased to 0.0001 from <0.0001. While still highly significant, we begin to see the effects of reduced sample size on the statistical significance of results.

Type 3 Analysis of Effects

Effect	DF	p-Value
wgtclass	3	0.0001

Table LRCPC15-1. The overall statistical significance of a the model relating TPP5 at Weight Class.

In Table LRCPC15-2, we report the comparisons of lower Weight Class probabilities and those of Weight Class 4. We notice a steadily decreasing point estimate that suggest that the probability of observing a TPP5 event in a given Weight Class, *relative to Weight Class 4*, decreases. This implies that Weight Class 1 has a higher probability of producing a TPP5 than Weight Class 2, Weight Class 2 has a higher probability then Weight Class 3, etc., which may seem counterintuitive. However, we note that, as for the lower TPP levels, these estimates have 95% confidence limits that cross the null value of 1.00 for all compariosns. We cannot say with confidence that any of these values are different from Weight Class 4. However, for Weight Class 1 we see a larger point estimate indicating a larger difference between Wight Class 1 and weight Class 4 than for lower TPP levels.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.629	0.802	3.308
wgtclass 2 vs 4	1.011	0.482	2.123
wgtclass 3 vs 4	0.424	0.147	1.226

Table LRCPC15-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Looking at the remaining contrasts in Table LRCPC10-3, we note that none has a statically significant result. While not statistically significant for any one point estimate, the monotonically decreasing values in the point estimates given in Table LRCPC15-1 apparently are the driving force for the significance of the model.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.4914
WgtClass=1 vs WgtClass=3	0.6527
WgtClass=2 vs WgtClass=3	0.3077
WgtClass 1, 2, 3	0.7552

Table LRCPC15-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP-15.

TPP20

We now show results for TPP20 for which the criterion for a peak is that it exceed the mean plus twenty standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP. We note that the significant levels has increased to 0.0177. While still highly significant, we continue to see the effects of reduced sample size on the statistical significance of results.

Type 3 Analysis of Effects	
Effect	**p-Value**
wgtclass	0.0177

Table LRCPC20-1. The overall statistical significance of a the model relating TPP5 at Weight Class.

In Table LRCPC20-2, we report the comparisons of lower Weight Class probabilities and those of Weight Class 4. We notice a steadily decreasing point estimate that suggest that the probability of observing a TPP5 event in a given Weight Class, *relative to Weight Class 4*, decreases. This implies that Weight Class 1 has a higher probability of producing a TPP5 than Weight Class 2, Weight Class 2 has a higher probability then Weight Class 3, etc., which may seem counterintuitive. However, we note that, as for the lower TPP levels, these estimates have 95% confidence limits that cross the null value of 1.00 for all comparisons. We cannot say with confidence that any of these values are different from Weight Class 4. However, for Weight Class 1 we see a larger point estimate indicating a larger difference between Wight Class 1 and weight Class 4 than for lower TPP levels.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.741	0.642	4.726
wgtclass 2 vs 4	1.166	0.413	3.295
wgtclass 3 vs 4	0.425	0.095	1.904

Table LRCPC20-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Looking at the remaining contrasts in Table LRCPC20-3, we note that none has a statically significant result. While not statistically significant for any one point estimate, the monotonically decreasing values in the point estimates given in Table LRCPC20-1 apparently are the driving force for the significance of the model. We further note the mitigation of the p-Values due to reduced sample size.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.4878
WgtClass=1 vs WgtClass=3	0.7955
WgtClass=2 vs WgtClass=3	0.5487
WgtClass 1, 2, 3	0.9279

Table LRCPC20-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP20.

TPP25

We now show results for TPP25 for which the criterion for a peak is that it exceed the mean plus twenty-five standard deviations. Such peaks would almost never occur purely by chance and one is safe in assuming that such an event is a real example of a TPP. We note that the significant levels has increased to 0.2199. This level is no longer statistically significant according to our criterion. This is a manifestation of the effects of reduced sample size on the statistical significance of results.

Type 3 Analysis of Effects

Effect	DF	p-Value
wgtclass	3	0.2199

Table LRCPC15-1. The overall statistical significance of a the model relating TPP5 at Weight Class.

In Table LRCPC25-2, we report the comparisons of lower Weight Class probabilities and those of Weight Class 4. Despite tehlack of statistical significance for the overall model, or the lack of statsitcal significance for the compariososn displayed in Table LRCPC25-2, we still note a steadily decreasing point estimate that suggest that the probability of observing a TPP5 event in a given Weight Class, *relative to Weight Class 4*, decreases. This implies that Weight Class 1 has a higher probability of producing a TPP5 than Weight Class 2, Weight Class 2 has a higher probability then Weight Class 3, etc. However, we note that, as for the lower TPP levels, these estimates have 95% confidence limits that cross the null value of 1.00 for all comparisons. We cannot say with confidence that any of these values are different from Weight Class 4. However, for Weight Class 1 we see a larger point estimate indicating a larger difference between Wight Class 1 and Weight Class 4 than for lower TPP levels, yet the pattern remains.

Odds Ratio Estimates

Effect	Point Estimate	95% Confidence Limits	
wgtclass 1 vs 4	1.143	0.418	3.129
wgtclass 2 vs 4	0.822	0.285	2.375
wgtclass 3 vs 4	0.425	0.095	1.905

Table LRCPC20-2. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

Looking at the remaining contrasts in Table LRCPC25-3, we note that none has a statically significant result.

Contrast Test Results

Contrast	p-Value
WgtClass=1 vs WgtClass=2	0.9518
WgtClass=1 vs WgtClass=3	0.5351
WgtClass=2 vs WgtClass=3	0.3712
WgtClass 1, 2, 3	0.5732

Table LRCPC25-3. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios for TPP20.

Summary of Data Analytic Results for Condensation Particle Concentrations

The remaining air pollution data gathered were through real-time particle analyzers collectively referred to as CPC/microAeth data. This report focuses on those data. Particulate measurements are taken on a minute-by-minute basis at four locations on the airport grounds. Analysis of these data indicates the presence of basic background particulate levels punctuated by peak concentrations lasting several minutes at levels as much as 100 times higher than background. These high concentrations advect and disperse back to background in periods of a few minutes. Our goal in this phase of the investigation was to correlate air pollution measurements, as indicated by these peaks in concentration- referred to as an "Transient Particle Peak" or TPP, with aircraft operation and identify, if possible, associations between these TPPs and aircraft maximum takeoff weight (MTOW).

Two algorithms were developed to assess these correlations, based upon the identification of a time-specified TPP and the presence of an aircraft in the vicinity, as indicated by transponder signal from stationary and mobile noise monitor data. The first, referred to as a Heuristic Approach relied on assessing whether a larger percentage of aircraft in heavier weight classes produced a disproportionate fraction of TPPs when compared to the fraction of aircraft of that type using the airport during the time frame of interest. The second algorithm relied on a statistical approach using logistic regression and performed a statistically rigorous assessment of the probability of an aircraft falling into a range of MTOW producing a TPP.

The results of the Heuristic Approach suggested that larger aircraft were more likely to results in TPP events than those of smaller aircraft. Quantitatively, such aircraft produced about twice the number of TPP events than might be expected given their contribution based on the fleet mix at PDK. But the approach was heuristic and, while appealing, would be difficult to defend from both a scientific and statistical point of view as it depends on a subjective view of the results with little quantitative support.

The lack of a firm basis for the Heuristic Approach led us to pursue logistic regression as powerful statistical tool to evaluate the impact of aircraft MTOW on particulate air pollution levels. We performed logistic regression analysis using three levels of TPP in an effort to explain effects. The results of the statistically powerful logistic regression analysis in many ways contradicts the details of the Heuristic approach, but does conclude that there is an effect of MTOW on the production of TPP events. In particular, the Logistic Regression approach suggest that the smaller aircraft, particularly those with UNKNOWN MTOW or MTOW < 25,000 lbs, are more likely t produce TPP events than larter aircraft. Th Heuristic Approach suggested the opposite focusing attention on the larger aircraft. While there does seem to be a contradiction, the Logistic Regression Approach is far more powerful and is not subject to unconscious biases that may be event in the Heuristic approach. Further, the differences seen in the Heuristic Approach were small and relied on a comparison of the fraction of aircraft in a particular Weight Class as the primary measurement. In this sense, it was a low-level analysis. More sophisticated analysis suggest that smaller aircraft, and those without identified MTOW are more likely to produce a TPP even, at all levels, i.e., TPP1, TPP3, and TPP5, than are larger aircraft.

Summary of Data Analytic Results for Black Carbon and CPC Data as a Whole

The remaining air pollution data gathered were through real-time particle analyzers collectively referred to as CPC/microAeth data. This report focuses on those data. Particulate measurements are taken on a minute-by-minute basis at four locations on the airport grounds. Analysis of these data indicates the presence of basic background particulate levels punctuated by peak concentrations lasting several minutes at levels as much as 100 times higher than background. These high concentrations advect and disperse back to background in time frames of a few minutes. Our goal in this phase of the investigation was to correlate air pollution measurements, as indicated by these peaks in concentration- referred to as an “Transient Particle Peak” or TPP, with aircraft operation and identify, if possible, associations between these TPPs and aircraft maximum takeoff weight (MTOW).

Two algorithms were developed to assess these correlations, based upon the identification of a time-specified TPP and the presence of an aircraft in the vicinity, as indicated by transponder signal from stationary and mobile noise monitor data. The first, referred to as a Heuristic Approach relied on assessing whether a larger percentage of aircraft in heavier weight classes produced a disproportionate fraction of TPPs when compared to the fraction of aircraft of that type using the airport during the time frame of interest. The second algorithm relied on a statistical approach using logistic regression and performed a statistically rigorous assessment of the probability of an aircraft falling into a range of MTOW producing an TPP.

The results of the Heuristic Approach suggested that larger aircraft were more likely to results in BC TPP events than those of smaller aircraft while the converse was true for CPC TPP events. Quantitatively, such aircraft produced about twice the number of TPP events than might be expected given their contribution based on the fleet mix at PDK. But the approach was heuristic and, while appealing, would be difficult to defend from both a scientific and statistical point of view as it depends on a subjective view of the results with little quantitative support.

The lack of a firm basis for the Heuristic Approach led us to pursue logistic regression as powerful statistical tool to evaluate the impact of aircraft MTOW on particulate air pollution levels. We performed logistic regression using three levels of TPP in an effort to explain effects. For the lowest level, we showed a strong dependence on MTOW. However, this was a very weak measure of effect that was barely measurable, yet was still evident from this type of statistical analysis. Using a more reasonable level from TPP, namely TPP-3 gave results that showed no difference among the various Weight Classes and no predictive power by introducing Weight Class as a variable. Using a more stringent criterion for the presence of a TPP gave an unusual result in that, overall, there was an association between Weight Class and the probability of the TPP but that the effect was not increasing with MTOW but rather was significant because Weight Class 2 and Weigh Class 3 differed from one another, ut not from the others. These varying results suggest that any statistically significant difference is likely to be in the lower magnitude peaks and may reflect different ages of aircraft in the Different Weight Classes.

Noise Monitoring

Data Analysis

Preliminary Analysis of Fixed-Site Monitoring Data

The surrounding community considers airport-related noise to be one of the major problems associated with DeKalb Peachtree Airport (PDK). As part of their investigations, Open DeKalb, a citizen's action group, has requested information regarding the association of noise with larger aircraft. Earlier work on this study (*Study of Air Pollution and Noise Impact on the Community Surrounding DeKalb Peachtree Airport, Chamblee Georgia.* P. Barry Ryan October 2015) focused on data collected at fixed sight monitors calibrated to indicate Noise Events in which the noise level exceeded either 90 dBA (at site NMS2, NSM3, and NSM4) or 93 dBA at NSM1. Table S-1 repeats the results of those analyses here.

Maximum Takeoff Weight	Percent of Airport Operations	Percent of Noise Events
<25,000 lbs	86.45	74.03
25,000 – 66,000 lbs	9.03	12.12
66,000 – 75,000 lbs	3.47	12.55
>75,000 lbs[1]	1.04	1.30

1. Only 50 aircraft operations and 3 complaints noted.

Table S-1. Comparison of aircraft fleet mix at PDK Airport and percentage of Noise Violations above from Fixed Site Monitors. Noise threshold violations occur when one or more fixed-site noise monitors measure more than 90 dBA. Total number of unique aircraft identified: 4783 unique identified aircraft. Total number of noise threshold violations: 231.

In this Table, we present information on airport operations involving aircraft of different Maximum Takeoff Weights (MTOW). The first column classifies these weights into four categories The second column identifies the percentage of airport operations in each of these categories, while the third column identifies the percentage of Noise Events associated with each weight class. If there were no association of MTOW with Noise Events, then one would expect the percentage of Airport Operations and Noise Events to be the same. We note, however, that the percentage of Noise Events is lower than the percentage of Airport operations for the lowest MOTW weigh class The percentage of Noise Events for the higher weight classes, in particular those with MTOW greater than 66,000 lbs, suggest an increased likelihood of producing a "Noise Event" defined as an exceedance of the cutoff threshold defined above. We note that very few events were associated with the highest weight class (>75,000 lbs) so those data should be viewed cautiously. On the other hand, there were numerous Noise Events associated with the 66,000 – 75,000 lbs class and the percentage of Noise Events exceeds the value expected given the fraction of Airport Operations in the weight class by a factor of nearly four. These results suggest a positive association of Noise Events with MTOW

Open DeKalb was interested in these results, but was surprised by the small number of Noise Events identified. Discussion with PDK staff indicated that many more data were available for Noise Events at lower levels ranging as low as 60 dBA. They requested that further analysis look into differing thresholds for Noise Events. Emory researchers agreed to do so. The analysis is presented below

Full Analysis of Fixed-Site Monitoring Data

In March 2016, we were supplied with a much richer dataset on Noise Events by staff at PDK comprised of all recorded data commencing on October 1, 2013 and continuing through September 30, 2014. As was the case with the preliminary dataset, our analysis begins with the notion of categorizing an Noise Events of varying intensity with MTOW of aircraft. Table N1 defines the Weight Classes used in these analyses. These Weight Classes were selected based on both FAA classification and the requirements of the Contract to understand the impact of classes of MTOW on noise levels. The weight classes are the same as those used in the previous analysis discussed above. Finer graduation analysis is possible but Open DeKalb expressed primary interest on the larger MTOW weight classes.

We investigated all events recorded by fixed site noise monitors around the airport grounds during the monitoring period. There were 58,722 recorded noise events during this time. Of these 20,366 (38.39%) were General Aviation aircraft without transponders, precluding specific identification of the aircraft type. However, it should be noted that that aircraft not equipped with transponders are usually privately owned, smaller aircraft with MTOW typically under 10,000 lbs and often under 3,000 lbs MTOW. The remaining 32,121 Noise Events with identifiable aircraft included 6,462 were unique (different aircraft) with differing tail numbers. In this analysis, and subsequent analysis, we have combined all aircraft with identified MTOW < 25,000 lbs and those categorized as UNKNOWN, into a single weight class, Weight Class = 1 (See Table N1 below.) Additionally, we have categorized aircraft into three additional Weight Classes with associated MTOW identified in N1.

Weight Class	MTOW (lbs)
1	<25,000 + UNKNOWN
2	25,001 – 66,000
3	66,001 – 75,000
4	>75,000

Table N1- Weight Classifications for Aircraft Maximum Takeoff Weight

In Table N2, we display a categorization of all noise events parsed by Weight Class. In excess of 89% of the noise events are associated with aircraft in Weight Class 1, consistent with the fraction of total Flight Events at PDK for this Weight Class. Further, we note the small percentage of Noise Events associated with the larger aircraft, but further note that there are still significant number of such events occurring for Weight Class 3, about three per day, and Weight Class 4, approximately two per day on average. The aircraft percentages for each weight class are consistent with he observed airport operations data.

Weight Class	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	52487	89.38	52487	89.38
2	4537	7.73	57024	97.11
3	1084	1.85	58108	98.95
4	614	1.05	58722	100.00

Table N2. Noise Event frequency by MOTW Weight Class for the 58,722 identified events the monitoring period.

The primary focus of this analysis is to identify whether there is an association between Noise Events, defined as an exceedance of some threshold noise level, with MTOW of aircraft. We have selected six Noise Event categories for analysis. These were selected based upon inspection of the new data supplied to us in March 2016 by PDK staff. The levels are presented in Table N3. The lowest level defined for Noise Events, < 70 dBA, represent a noise level that would be unlikely to interfere with any activities. Typical conversation is at about 60-65 dBA, for example. We then chose 5 dBA increments as these increments represent a noticeably different level of noise. We grouped all reported values above 90 dBA in one category at the top end for two reasons. First, any value in this range would results in disruption in enjoyment of the surroundings. Secondly, we wanted to ensure that there were sufficient numbers of Noise Events to allow assessment of associations as there are relatively few such events at these levels. AS an aside, it is important to note that the typical duration of these Noise Events at any particular location centers on 10-20 seconds.

In an effort to understand the data we have presented the overall noise categorization both in tabular from (See Table N4) and in graphical form, Figure N5.   It is evident from both the Table and the figure, that Events in Category 6 (>90 dBA) are unusual, yet they occur on average once per day. The mode is in Category 2, which are events in the 70-74.9 dBA range. There are significant numbers of events in Categories 3 and 4, spanning the range of 75-85 dBA.

Noise Event Category	Noise Event Level
1	<70 dBA
2	70 – 74.9 dBA
3	75 – 79.9 dBA
4	80 – 84.9 dBA
5	85-89.9 dBA
6	≥ 90 dBA

Table N3- Noise Event Level Classifications

Noise Event Category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
< 70 dBA	13307	22.66	13307	22.66
70 – 74.9 dBA	20564	35.02	33871	57.68
75 – 79.9 dBA	10218	17.40	44089	75.08
80 – 84.9 dBA	11308	19.26	55397	94.34
85-89.9 dBA	2948	5.02	58345	99.36
≥ 90 dBA	377	0.64	58722	100.00

Table N4- **Tabular depiction of Noise Events by Noise Category**

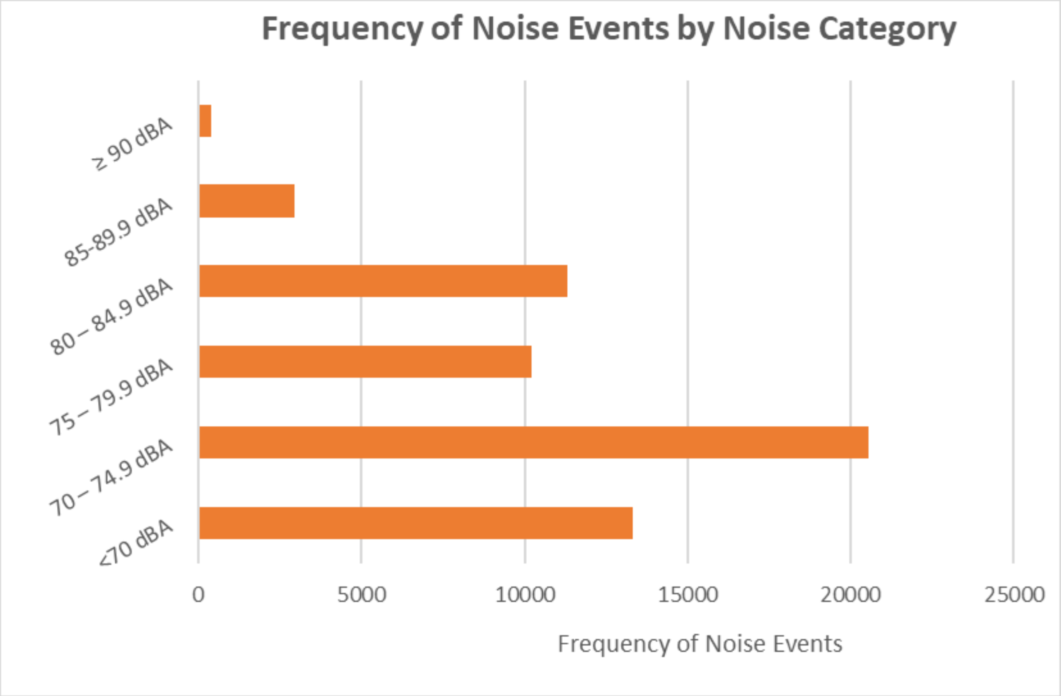


Figure N1- **Graphical depiction of Frequency of Noise Events by Noise Category**.

Heuristic Analysis

Table N2 presents the frequency of Noise Events associated with each weight class. We note that nearly 90% of aircraft operations during the monitoring period were attributable to Weight Class 1 aircraft (those with MTOW < 25,000 lbs or with UNKNOWN characteristics) while approximately 2.9% (162 events) are associated with the largest aircraft, i.e., those over 75,000 lbs MTOW. Two-hundred sixty (6.24%) Noise Events were associated with larger aircraft, i.e., >66,000 lbs. As pointed out in the discussion of previous work, If Noise Events occurred randomly and were not associated with the size of the aircraft, one would expect to note approximately the same fraction of aircraft in the larger weight classes to be associated with each noise class.

Tables N4 a-f present such analysis of such data. In these tables, data are presented for each individual Noise Event Category for each weight class. Table 4a present data for Noise Category 1, Table 4b for Noise Category 2, and so on.

Table N4a presents the MTOW breakdown for the lowest category of Noise Event, those registering < 70 dBA on the monitors. The 13,307 such events represent approximately 22.7% of the total number of Noise Events recorded in during the monitoring period. Of these 13,307 events, 226 (1.70%) are from the larger aircraft, Weight Classes 3 and 4, somewhat below the expected 2.90% of aircraft associated with all Noise Events noted in Table XXX2.

Noise Category=1				
WgtClass	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
1	**12433**	**93.43**	**12433**	**93.43**
2	**648**	**4.87**	**13081**	**98.30**
3	**170**	**1.28**	**13251**	**99.58**
4	**56**	**0.42**	**13307**	**100.00**

Table N4a- Data presented for Noise Category 1, < 70 dBA

Table N4b presents the MTOW breakdown for the second category of Noise Event, those registering 70 - 75 dBA on the monitors. The 20,564 such events represent approximately 35.0% of the total number of Noise Events recorded during the monitoring period; this Noise Category has the largest fraction of Noise Events during this period. Of these 20,564 events, 254 (1.24%) are from the larger aircraft, Weight Classes 3 and 4, below the expected 2.90% of aircraft associated with all Noise Events noted in Table N2.

Noise Category=2				
WgtClass	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
1	**19429**	**94.48**	**19429**	**94.48**
2	**881**	**4.28**	**20310**	**98.76**
3	**175**	**0.85**	**20485**	**99.62**
4	**79**	**0.38**	**20564**	**100.00**

Table N4b- Data presented for Noise Category 2, 70-75 dBA

Table N4c presents the MTOW breakdown for the third category of Noise Event, those registering 75 - 80 dBA on the monitors. The 10,218 such events represent approximately 17.0% of the total number of

Noise Events recorded during the monitoring period. Of these 10,218 events, 315 (3.08%) are from the larger aircraft, Weight Classes 3 and 4, similar to expected 2.90% of aircraft associated with all Noise Events noted in Table N2.

Noise Category=3				
WgtClass	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
1	**8985**	**87.93**	**8985**	**87.93**
2	**918**	**8.98**	**9903**	**96.92**
3	**174**	**1.70**	**10077**	**98.62**
4	**141**	**1.38**	**10218**	**100.00**

Table N4c- Data presented for Noise Category 3, 75 – 80 dBA

Table 4d presents the MTOW breakdown for the fourth category of Noise Event, those registering 80 - 85 dBA on the monitors. The 11,308 such events represent approximately 19.3% of the total number of Noise Events recorded during the monitoring period. Of these 11,308 events, 739 (6.54%) are from the larger aircraft, well above the expected 2.90% value given in Table N2.

Noise Category=4				
WgtClass	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
1	**8950**	**79.15**	**8950**	**79.15**
2	**1619**	**14.32**	**10569**	**93.46**
3	**447**	**3.95**	**11016**	**97.42**
4	**292**	**2.58**	**11308**	**100.00**

Table N4d- Data presented for Noise Category 4, 80-85 dBA

Table 4e presents the MTOW breakdown for the fourth category of Noise Event, those registering 85 - 90 dBA on the monitors. The 2,948 such events represent approximately 5.0% of the total number of Noise Events recorded during the monitoring period. Of these 2,948 events, 139 (4.72%) are from the larger aircraft, somewhat more than the expected 2.90% value given in Table N2.

Noise Category=5				
WgtClass	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
1	**2413**	**81.85**	**2413**	**81.85**
2	**396**	**13.43**	**2809**	**95.28**
3	**97**	**3.29**	**2906**	**98.58**
4	**42**	**1.42**	**2948**	**100.00**

Table N4e- Data presented for Noise Category 5, 85-90 dBA

Table 4f presents the MTOW breakdown for the sixth category of Noise Event, those registering >90 dBA on the monitors. The 377 such events represent approximately <1% of the total number of Noise Events recorded during the monitoring period. Of these 377 events, 25 (6.63%) are from the larger aircraft, a value larger than the expected 2.90% value given in Table N2.

are from the larger aircraft. However, the number of Noise events of this type, i.e., >90 dBA, is comparable with the multi-month analysis presented in the October 2015 Report (*Study of Air Pollution and Noise Impact on the Community Surrounding DeKalb Peachtree Airport, Chamblee Georgia.* P. Barry Ryan October 2015), which covered an 18-month period.

Figure N2 is a bar chart displaying the same data that was present in Table N2 and Tables N4a-f and is a graphical presentation of the same data is given in Figure N2. The first bar on the left of the Figure N2 is the fraction of aircraft in each Weight Class noted in the Noise Monitoring data. The remaining six bars represent the fraction of observations for each of the Noise Categories labeled at the bottom. In each of the seven bars, the component of the bar representing Weight Class -1 has been truncated so that differences in the bars is more easily seen. Our Heuristic Analysis claims that, if there were no effect of MTOW on the likelihood of experiencing a Noise Event, then the bars, which are the fraction of aircraft of that Weight Class that were noted, should match the fraction of aircraft in that Weight Category. For example, if 15% of the aircraft were of Weight Class 3 and Weight Class was not predictive of Nosie Events, then 15% of Noise Events would be associated with Weight Class 3. A larger or smaller than expected value, would indicate an effect of Weight Class.

Noise Category=6

WgtClass	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	**277**	**73.47**	**277**	**73.47**
2	**75**	**19.89**	**352**	**93.37**
3	**21**	**5.57**	**373**	**98.94**
4	**4**	**1.06**	**377**	**100.00**

Table N4f- Data presented for Noise Category 6, >90 dBA

The trends is more easily seen in this graphical representation. In the lower Weight Classes, the fraction of aircraft in Weight Class 1 that contribute to the Noise Category is higher than expected, while the fraction from the higher Weight Classes is less than expected. In the upper Noise Category ranges, the fraction of aircraft from Weight Class 1 contributing to the Noise Category diminishes, while those of higher Weight Classes increases. This is particularly noteworthy for Weight Class 2 as one sees clearly that component of the stacked bar chart becomes larger as the categories increase in noise level. While somewhat less clearly depicted, but still evident, Weight Class 3 also displays the same behavior. There is a sense from this presentation that a similar trend may be evident for Weight Class 4, but the data are subject to more variability as the number of aircraft from Weight Class 4 is quite small in the higher Noise Categories.

In summary, our Heuristic Analysis suggests that the likelihood of experiencing a Noise Event at a higher level increases with the MTOW of the aircraft and that smaller aircraft are associated with Noise Events at lower levels. Further, the data indicate that moderate Noise Events, those below 80 dBA are about three times more prevalent than those above that level (See Table N4 and Figure N1.)

The result of this investigation contrast somewhat with those of the first investigation. However, they are not directly comparable, except for, perhaps Noise Category 6. This is because the Noise Events themselves are not the same. In the initial analysis, data were only available for the high-level Noise Events. This work looked at a number of different levels, which we now discuss.

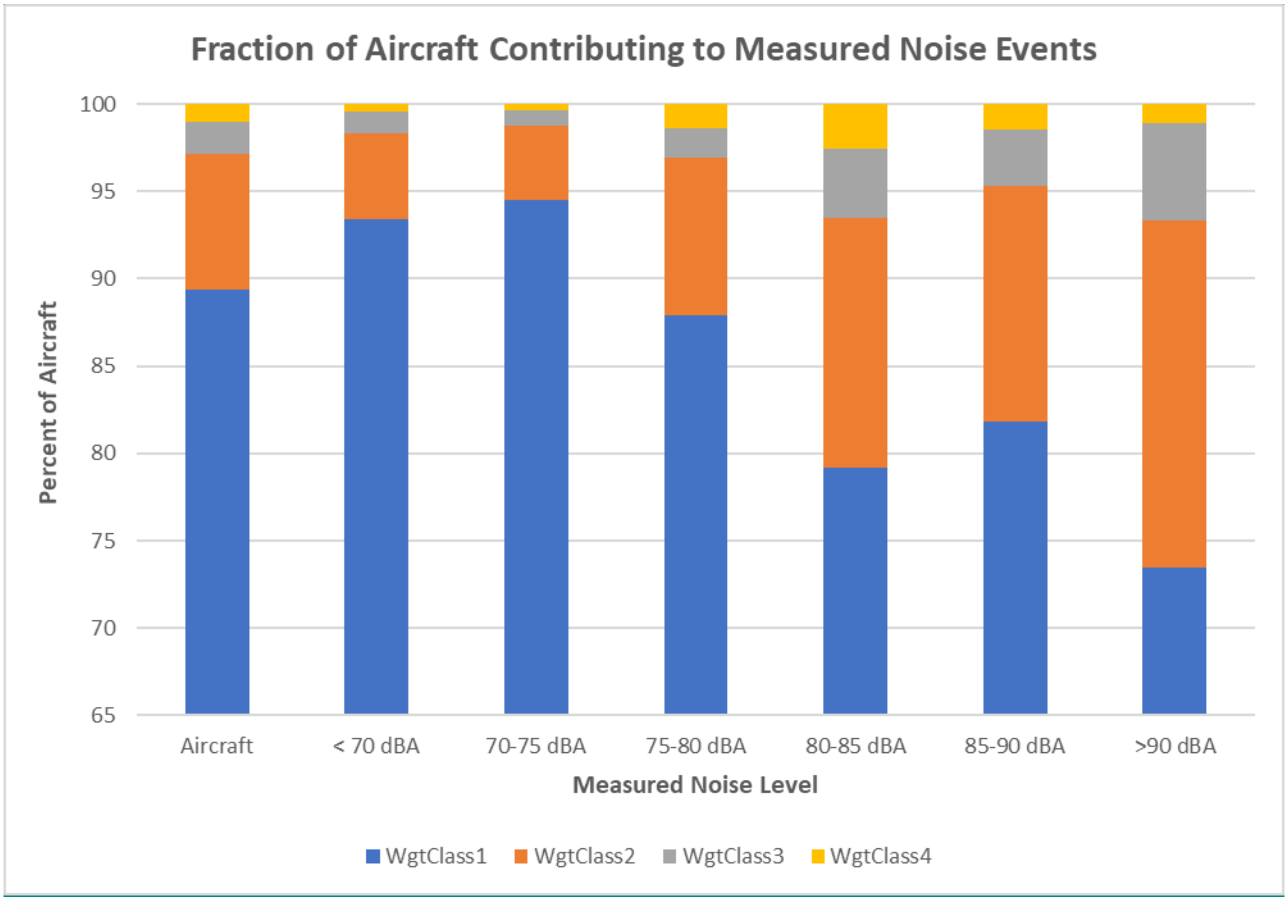


Figure N2. - **Graphical depiction of Frequency of Noise Events by Noise Category**.

Logistic Regression Analysis

Logistic regression is a statistical method that puts what we have done in the Heuristic Approach on a firm statistical footing. The methods asks the question: is the outcome of interest more likely to occur in one class of a variable than in another? In this analysis, the outcome of interest is the occurrence of a Noise Event. The class of variables in our analysis is the Weight Class of the aircraft. We ask a series of questions, again similar to what we did in the Heuristic Approach: Is there any difference among the Weight Classes with respect to the probability of seeing a Noise Event? Is the probability of experiencing a Noise Event (of any particular magnitude) different if a Weight Class 1 aircraft is present from, say, a Weight Class 2 aircraft being present? In particular, we are interested in the relationship between Weight Classes 3 and 4, and the other classes, as these are the Weight Classes containing the higher MTOW aircraft. We explore all of the possible interactions. Further, we explore them for Noise Category 1, Noise Category 2, etc., to evaluate whether there is a trend associated with aircraft MTOW and the magnitude of the Noise Event., and i.e., are there differences for higher noise levels that might not be present for lower noise levels. Evidence from our Heuristic Analysis suggests that there might be significant trends of this type.

The results will be presented separately for the six Noise Categories. We will present this in a series of tables showing the statistical results., which will be explain in detail for the first set describing the outcome of analysis for Noise Category 1. In all of these analyses, the outcome variable is the probability that a Noise Event occurs given knowledge of the Weight Class.

Analysis for Noise Category 1

To begin this analysis, through inspection of Figure N1, our Heuristic Analysis suggests that the fraction of aircraft associated with Category 1 Noise Events is higher than expected for Weight Class 1 aircraft and, perhaps lower, for the other Noise Categories. However, the logistic modeling system used evaluates all of the Weight Classes and determines whether any of the Weight Classes is different from the others. If this were the case, then the model would be “significant” as there would be a measurable improvement in prediction of a Noise Event by knowing the Weight Class of the aircraft.

To begin this analysis, through inspection of Figure N1, our Heuristic Analysis suggests that the fraction of aircraft associated with Category 1 Noise Events is higher than expected for Weight Class 1 aircraft and, perhaps lower, for the other Noise Categories.

Table N5 presents the overall model result for Category 1 Noise Events. In this case, we see that the probability of seeing an effect as large as the one we say when there was no effect is very small, less than 1 in 10,000. Hence, we would accept the alternative hypothesis that there is a difference in the probability of a Noise Event at the Noise Category 1 level associated with MTOW. We now want to establish the direction of this effect: are higher MTOW aircraft more likely to see such a Noise Event?

Analysis of Effects	
Effect	**p-Value**
WgtClass	<.0001

The next analysis we present is to compare the probability ratios between each of the Weight Classes with the highest Weight Class (See Table N6.) Here we are looking at the probability of a Category 1 Noise Event occurring with aircraft in, say, Weight Class 1 with the probability of a Category 1 Noise Event occurring with aircraft in Weight Class 4. The “Point Estimate” is the best “guess” for this ratio. A value of 1.000 would imply that there is equal probability of noting a Category 1 Noise Event in Weight Class 1 and in Weight Class 4. We note that the Pont Estimate is 3.092 indicating that it is more than three times more likely that a Category 1 Noise Event would occur for Weight Class 1 aircraft than for Weight Class 4 Aircraft. However, this is the “average” result. In looking at all of the data for the two weight classes, we can make further statements. This is expressed in the “95% Confidence Limits.” The data we have collected allow us to say with 95% confidence (we would be wrong 5% of the time) that the true ratio lies between the two values. For the comparison of Weight Class 1 with Weight Class 4, we are 95% confidence that the true ratio lies between 2.347 and 4.072. It is important that this 95% confidence limit does not cover the null value of 1.00 as this implies that this, too, is a statistically significant result and adds credence to the overall significance displayed in Table XXX2 and Figure .

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Confidence Limits**	
WgtClass 1 vs 4	3.092	2.347	4.072
WgtClass 2 vs 4	1.660	1.246	2.211
WgtClass 3 vs 4	1.853	1.346	2.551

Table N6. A Comparison of Odds Ratios between each Weight Class with the Referent Weight Class, Weight Class 4.

At this point, we have established that Weight Class 1 is more likely to give rise to a Category 1 Noise Event than some of the other classes. We would like to compare all of the Weight Classes to one another, and group them in an appropriate way. We do this by “contrasting” the Weight Classes and determining whether they differ from one another. These data are presented in Table Table N7.

We note that for the pairwise comparisons, all pairs differ. But this simply says they are different; it does not give an ordering. Combining data from Table N6 and Table N7 and Figure N2 allows us to infer that Weight Class 1 is more likely than expected to produce a Noise Category 1 Noise Event than all other Weight Classes, but that all other Weight Classes are less likely than expected to produce a Category 1 Noise Event. It is important to note that Category 1 Noise Events are at the low end of the noise scale producing noise levels that are only slightly above normal conversation levels.

Contrast Test Results	
Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	<.0001
WgtClass=1 vs WgtClass=3	<.0001
WgtClass=2 vs WgtClass=3	0.0001
WgtClass 1, 2, 3	<.0001

Table N7. A Comparison of paired and grouped analyses of Weight Classes Odds Ratios.

Analysis for Noise Category 2

Noise Category 2 (75-80 dBA), displays many of the characteristics of the analysis done on Noise Category 1. Weight Class 1 is more likely to produce a a Category 2 Noise Event than the other Noise Categories while each of the other Noise Categories is less likely to produce a Noise Event at this level than would be expected if there were no effect of MTOW on the presence of a Noise Event. Results of the analyses on Noise Category 2 events is displayed in the tables labeled Table N8. The interpretation of all components is the same as was discussed under Analysis for Noise Category 1.

Analysis of Effects	
Effect	**p-Value**
WgtClass	<.0001

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Confidence Limits**	
WgtClass 1 vs 4	3.979	3.139	5.042
WgtClass 2 vs 4	1.631	1.274	2.089
WgtClass 3 vs 4	1.303	0.979	1.735

Contrast Test Results	
Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	<.0001
WgtClass=1 vs WgtClass=3	<.0001
WgtClass=2 vs WgtClass=3	0.0034
WgtClass 1, 2, 3	<.0001

Table N8. Logistic regression analysis results for Category 2 Noise Events with Weight Class.

Analysis for Noise Category 3

Noise Category 3 includes measurements of noise levels between 75 and 80 dBA. At this level, noise would start to become bothersome and, perhaps, interfere with conversation and enjoyment of outdoor activities if it were to be continuous. Table N9 presents the results of the logistic analysis for this Noise Category. We note that the overall model is, itself, statistically significant indicating that there is an effect of Weight Class and, hence MTOW, on the likelihood of observing a noise event in this category. The Odds Ratio Estimates suggests that, unlike Noise Categories 1 and 2, for this Noise Category, Weight Class 1 aircraft are less likely to produce a noise event at this level than might be expected by the fraction of aircraft this Weight Class represents. Further, Weight Class 4 is more likely to produce such Noise Event that all other weight classes, although the comparison with Weight Class 2 does not reach statistical significance as the 95% confidence limit does span 1.000. The Contrast Test Results indicate that all classes are different from one another with respect to the relationship between observed and expected likelihood of a Noise Event of Category 3 occurring. Coupling this with the results presented in Figure N2 we can infer that all aircraft of Weight Class 2 and higher produce a higher than expected probability of association with this Noise Category.

Analysis of Effects	
Effect	**p-Value**
WgtClass	<.0001

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Confidence Limits**	
WgtClass 1 vs 4	0.693	0.573	0.837
WgtClass 2 vs 4	0.851	0.695	1.041
WgtClass 3 vs 4	0.641	0.500	0.822

Contrast Test Results	
Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	0.0069
WgtClass=1 vs WgtClass=3	0.0001
WgtClass=2 vs WgtClass=3	0.0043
WgtClass 1, 2, 3	0.0013

Table N9. Logistic regression analysis results for Category 3 Noise Events with Weight Class.

Analysis for Noise Category 4

Noise Category 4 includes measurements of noise levels between 80 and 85 dBA. At this level, noise would likely be bothersome and, perhaps, interfere with conversation and enjoyment of outdoor activities if it were to be continuous. Table N10 presents the results of the logistic analysis for this Noise Category. We note that the overall model is, itself, statistically significant indicating that there is an effect of Weight Class and, hence MTOW, on the likelihood of observing a noise event in this category. The Odds Ratio Estimates, as was the case for Noise Category 3, Weight Class 1 aircraft are less likely to produce a noise event at this level than might be expected by the fraction of aircraft this Weight Class represents. Further, and similar to the Noise Category 3 analysis, Weight Class 4 is more likely to produce such Noise Event that all other weight classes and that this effect is more marked and is statistically significant for all Weight Classes comparisons with Weight Class 4. Weight Class 4 aircraft are significantly more likely to be associated with a Noise Category 4 event than all other classes of aircraft. The Contrast Test Results indicate that all classes are different from one another with respect to the relationship between observed and expected likelihood of a Noise Event of Category 4 occurring. Coupling this with the results presented in Figure N2 we can infer that all aircraft of Weight Class 2 and higher produce a higher than expected probability of association with this Noise Category and that this effect is stronger than was present for Noise Category 3 aircraft.

Analysis of Effects	
Effect	**p-Value**
WgtClass	<.0001

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Confidence Limits**	
WgtClass 1 vs 4	0.227	0.193	0.266
WgtClass 2 vs 4	0.612	0.516	0.725
WgtClass 3 vs 4	0.774	0.634	0.944

Contrast Test Results	
Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	<.0001
WgtClass=1 vs WgtClass=3	<.0001
WgtClass=2 vs WgtClass=3	<.0001
WgtClass 1, 2, 3	<.0001

Table N10. Logistic regression analysis results for Category 4 Noise Events with Weight Class.

Analysis of Noise Category 5

Noise Category 5 includes measurements of noise levels between 85 and 90 dBA. At this level, noise would be bothersome and interfere with conversation and enjoyment of outdoor activities if it were to be continuous. Table N11 presents the results of the logistic analysis for this Noise Category. We note that the overall model is, itself, statistically significant indicating that there is an effect of Weight Class and, hence MTOW, on the likelihood of observing a noise event in this category. The Odds Ratio Estimates indicate that Weight Classes 1 and 4 differ from one another in their likelihood of producing a Noose Event at this level, but that other comparison with the highest Weight Class are not statistically significant. Similarly, the Contrast Test values do not indicate differences among Weight Classes 2 and higher. Coupling this with the results presented in Figure N2 and Table N4 suggest a potential problem. Noise Category 5 events are less prevalent than Noise Events from lower Noise Categories representing only about 5% of all Noise Events. The loss of statistical power results in larger expected variability in any of these estimates. Combining our analyses together, there is still a sense that higher MTOW aircraft are more likely to produce Noise Events and this level, particularly with respect to Weight Class 1 aircraft, but the variability intrinsic to these measurements precludes giving an ordering beyond Weight Class 1 being less likely than Weight Class 4 to produce such an event.

Analysis of Effects	
Effect	**p-Value**
WgtClass	<.0001

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Confidence Limits**	
WgtClass 1 vs 4	0.656	0.478	0.900
WgtClass 2 vs 4	1.302	0.937	1.811
WgtClass 3 vs 4	1.339	0.919	1.950

Contrast Test Results	
Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	0.6289
WgtClass=1 vs WgtClass=3	0.7012
WgtClass=2 vs WgtClass=3	0.1031
WgtClass 1, 2, 3	0.7853

Table N11. Logistic regression analysis results for Category 5 Noise Events with Weight Class.

Noise Category 6

Noise Category 5 includes measurements of noise levels between > 90 dBA. At this level, noise would certainly be bothersome and interfere with conversation and enjoyment of outdoor activities for the duration of the Noise Event. Table N12 presents the results of the logistic analysis for this Noise Category. In this analysis, we note that the overall model is statistically significant due to the significant difference between Weight Class 3 and Weight Class 4 and Weight Class 2 and 3. Figure N2 suggest that Weight Classes 2 and 3 are over-represented in the Noise Category, while Weight Class 1 is underrepresented. We note that Weight Class 4 is at about the expected level.

All of these observations must be tempered by the small number of Noise Events (377, See Table XXX4) occurring in this Noise Category. The wide confidence limits in the Odds Ratio Estimates reflect this small number. In all of these analyses, we count on the large number of observations to reduce the effect of statistical variability. For this Noise Category, we do not have that luxury. Any results obtained for this Category should be viewed cautiously.

Analysis of Effects	
Effect	**p-Value**
WgtClass	<.0001

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Confidence Limits**	
WgtClass 1 vs 4	0.809	0.301	2.178
WgtClass 2 vs 4	2.563	0.934	7.034
WgtClass 3 vs 4	3.015	1.030	8.823

Contrast Test Results	
Contrast	**p-Value**
WgtClass=1 vs WgtClass=2	0.4709
WgtClass=1 vs WgtClass=3	0.3862
WgtClass=2 vs WgtClass=3	0.0479
WgtClass 1, 2, 3	0.2298

Table N12. Logistic regression analysis results for Category 6 Noise Events with Weight Class.

Supplemental Analysis of Noise Data on a Monthly Basis

Noise events were also analyzed on a monthly basis. Results of the Monthly analysis are summarized in Figure N-1. Note, there was an average of 4898 Noise Events measure each month. However, there was substantial varaibiity as measured by the standard deviation in this number (599 or 12.2%)

Analysis of these data showed no statistically significant differences in the fraction of aircraft in the various MTOW classifications with respect to their contribution to noise events (analysis not shown.) The data are presented in Appendix 6- Analysis of Noise Data by Month

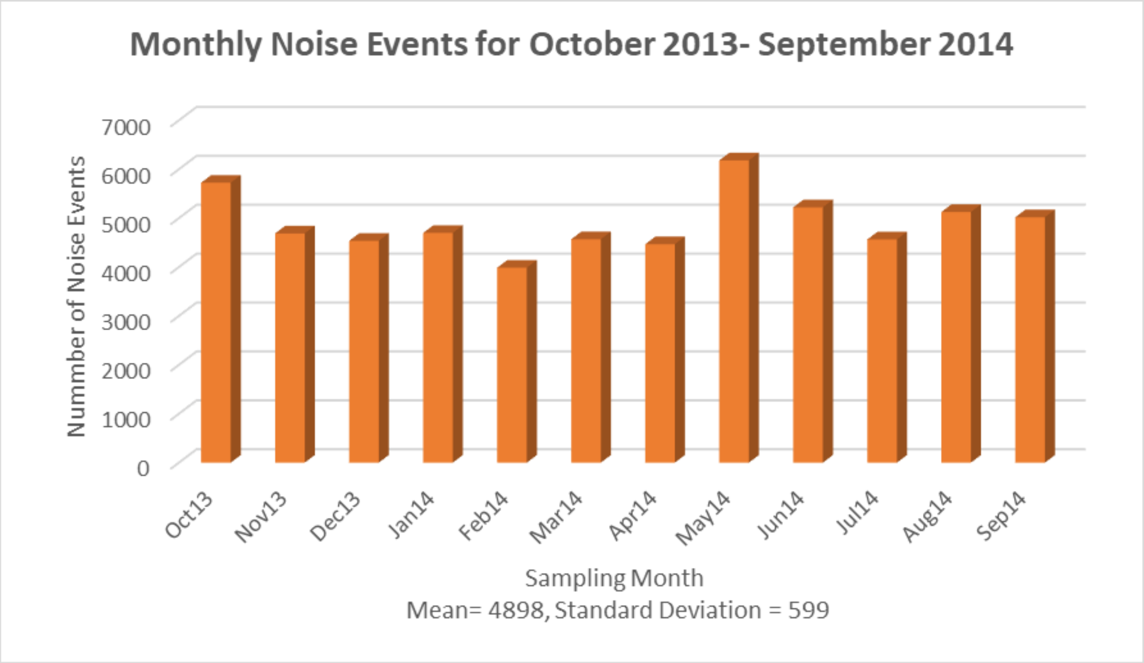


Figure N-1- A comparison of Monthly Noise Events during Sampling Period.

Summary of Data Analytic Results for of Fixed-Site Monitoring Data Noise Events

We developed two algorithms were developed to assess these correlations between MTOW and Noise Events, based upon the identification of individual aircraft and specific measured and categorized noise levels. The first, referred to as a Heuristic Approach relied on assessing whether a larger percentage of aircraft in heavier weight classes produced a disproportionate fraction of Noise Events of various magnitudes when compared to the fraction of aircraft of that type using the airport during the timeframe of interest. The second algorithm relied on a statistical approach using logistic regression and performed a statistically rigorous assessment of the probability of an aircraft falling into a range of MTOW producing a Noise Event in a specific Noise Category.

The results of the Heuristic Approach suggested that smaller aircraft were more likely to produce Noise Events in Noise Categories of lower magnitude, while larger aircraft produced Noise Events in higher magnitude Noise Categories. However, the approach was heuristic and, while appealing, would be difficult to defend from both a scientific and statistical point of view as it depends on a subjective view of the results with little quantitative support.

The lack of a firm basis for the Heuristic Approach led us to pursue logistic regression as powerful statistical tool to evaluate the impact of aircraft MTOW on Noise Levels. We performed logistic regression on six Noise Categories in an effort to explain effects. For the lowest noise-level categories, logistic regression indicated that smaller aircraft- those with MTOW < 25,000 lbs and those with UNKNOWN characteristics, are over-represented, while larger aircraft are under-represented. As the noise level measured, and consequently the Noise Category, increase, this observation reversed with small aircraft now under-represented and larger aircraft more abundant. From the point of view of the community, the larger aircraft- those with MTOW > 25,000 lbs, and for some Noise Categories, MTOW > 66,000 lbs, are more likely to produce Noise Events of concern. This is particularly the case for Noise Categories with noise levels exceeding 80 dBA (Noise Categories ≥ 3.)

The results we present in this discussion stand in contrast to results from preliminary analyses that suggested that there was no effect on the likelihood of observing a Noise Event associated with MTOW of aircraft. These disparate results can be explained by the reversal in trends as we go from lower Noise Categories to higher Noise Categories. Lumping all Noise Categories together into a single Noise Event would give results that for some measurements Weight Class 4 occurred less frequently than expected and for other measurements, the opposite was true. Overall, the effect would be non-significant. Only by observing the Noise Categories separately, is this be observable.

Community Measurements

During the approximately 14 months that the portable noise monitor was placed within the community, we noted 10,983 noise exceedance events. It should be noted that during our monitoring period, months, May 2014 through September 2014, the portable noise monitor was recalibrated to threshold level of 135 dBA threshold. Not surprisingly, the 135 dBA threshold, equivalent to a jet engine at 20 meters, was never exceeded.

Of the nearly 11,000 recorded events by the mobile monitor, 8,394 or approximately 76%, were from a single site, a church located approximately 500 meters south of the southern end of the principal runway. Additionally, sites near the Airport accounted for 10-15% of the total, with the balance scattered around the community. Our background site, located about 8 km south of the Airport (near the VA Hospital on Clairmont Road) recorded 6 threshold exceedances during the monitoring period. It should be noted as well, that 5,780, or more than 50% could not be associated with any aircraft in the area. Events such as lawn mower use, a noisy car, even children playing may have triggered these events. Percentages for these unknown events mirrored those from known events; 75% were at the single site mentioned above, with the remainder mimicking percentages for the total set of monitor locations

Comparison with Other Studies Conducted in and around Similar Airports

Goal 5 focuses on comparisons between air pollution and noise data from PDK and similar airports. Studies of this type on similar airports are few and data are sparse. Ryan, and co-workers, performed a long-term (29 year) study of nitrogen dioxide concentrations in and around Boston’s Logan International

Airport, similar to the passive nitrogen dioxide investigation around PDK discussed above. This airport is much larger than PDK and may be expected to have a much larger impact on local air pollution levels. However, their results showed a downward trend in the measured concentration of this contaminant on the airport grounds and in the surrounding community commensurate with the reduction of nitrogen dioxide emissions from both automobiles and aircraft. Levels noted in Boston in the community are approximately equivalent to those noted in this study. As of 2012, concentrations in the community surrounding Logan ranged from about 6 ppb to about 15 ppb, down from levels of around 35-40 ppb in the early- and mid-1980s. Nitrogen dioxide concentrations are somewhat higher on average in Atlanta than in Boston due to larger amounts of vehicular traffic in Atlanta. A more complete investigation focusing on air toxics, but including BTEX, was carried out at this location in 2007-2009. BTEX levels reported in the Boston study were quite similar to those reported in the PDK study with the exception of benzene concentrations in this study, which were much lower, an observations consistent with reduced benzene concentrations in gasoline and related fuels over the time period. It must be emphasized, however, that Logan is a much larger facility than PDK so direct comparisons may not be warranted. Nevertheless, these results suggest that levels noted in the PDK study are consistent with other urban areas.

Several studies have been performed at Teterboro Airport (TEB) in Bergen County, New Jersey. TEB is similar in size to PDK with approximately 150,000 airport operations in 2010, but its fleet mix had significantly less general aviation aircraft. The studies performed include a screening study done over a few days in 2001, a modeling study done in 2002, and a year-long monitoring study conducted by ENIVIRON, in 2006. The TEB monitoring study done in 2006 was both similar and different from the PDK study. Data collected at TEB were primarily from the airport grounds, rather than a mix of airport monitoring and community-based monitoring. The results from this study suggest that VOC concentrations on the airport grounds are higher than we see in the community surround PDK by a factor of 3 to 5. This is consistent with dispersion of contaminants as they move away from the source. Further, results from surrounding communities taken from New Jersey Department of Environmental Protection are similar to our community-based results. Black carbon and particle counts on the airport ground at TEB are consistent with our Airport-based results as well. Particle mass concentration at TEB is similar to PDK, with values ranging from 15-20 µg/m^3 on the TEB airport grounds. TEB is located in a more congested area with regard to vehicular traffic than PDK, which may account for some of the more elevated values for both VOCs and particle measures there, although the values the levels differ by only 20% or so. It should be noted that the preponderance of jet aircraft as opposed to General Aviation aircraft at TEB when compared to PDK makes comparison difficult.

Appendix 1. List of Aircraft with Multiple Noise Level Exceedances above 90 dBA.

Mobile Noise Monitoring and Aircraft Identification

While the stationary monitors were calibrated to a threshold of 90 or 93 dBA, the mobile noise monitor placed out in the community was calibrated to record noise events that exceeded 65 dBA as FAA deems that a relevant value in a community setting. As noted previously, the level of 65 dBA is roughly equivalent to general conversation levels in indoor environments. While this level of noise may modestly interfere with the conduct of such activities, it is of little relevance to health outcomes, and may just reach the nuisance level.

Tail Number or Identifier	Number of Threshold Violations	Maximum Takeoff Weight (pounds)	Aircraft Type
N773RC	10	11,550	Piaggo P180
N900JB	7	38,801	1982 DASSAULT-BREGUET FALCON 50
N30WR	6	69,700	1981 Gulfstream Aerospace G-1159A
N330WR	5	69,700	1981 Gulfstream American Corp G-1159A
N200EA	4	12,500	Beechcraft Super King Air 200
CNS130	3	10,450	Pilatus PC-12
CNS35	3	10,450	Pilatus PC-12
N400DW	3	15,780	Beechcraft Beechjet
N442GJ	3	16,100	Beechcraft Beechjet
N522DJ	3	9,920	Pilatus PC-12
N65RA	3	15,780	BEECH 400
N690XL	3	20,000	Cessna Citation 560XL
N8834M	3	3,300	Beechcraft 35 Bonanza
N96757	3	69,700	Gulfstream Aerospace Gulfstream 3

Table S-2. Identified aircraft with 3 or more unique noise threshold violations during the monitoring period. Noise threshold violations occur when one or more fixed-site noise monitors measure more than 85 dBA.

Appendix 2- Data Processing of Real-Time Particle Measures- A Detailed Description of the Algorithm Used with Illustrative Example.

We begin our analysis of air pollution data by identifying the total number of airport operations by during our monitoring period for each of the weight classes of interest to us. In Table AP-1, we present information on the airport operations. The first column denotes the Weight Class categorization, while the second column specifies the MTOW for these six categories. The second column identifies the percentage of airport operations in each of these categories. These categories reflect both FAA classifications and classifications of interest to PDK senior staff and Open DeKalb. Note that Weoght Class = -1 will be dropped from further analysis.

Weight Class	Criteria	Number of Events	Percent	Cumulative Frequency
-1*	Non-Fixed Wing	137	0.13	137
0	UNKNOWN	37,447	36.62	37,584
1	<25,000 lbs	52,302	51.14	89,886
2	25,000 – 66,000 lbs	9,645	9.43	99,531
3	66,000 – 75,000 lbs	1,786	1.75	101,317
4	>75,000 lbs	948	0.93	102,265

***Not included in further analysis**

Table AP-1- Summary of Airport Operations during the monitoring period commencing on October 10, 2013 and continuing through October 120, 2014.

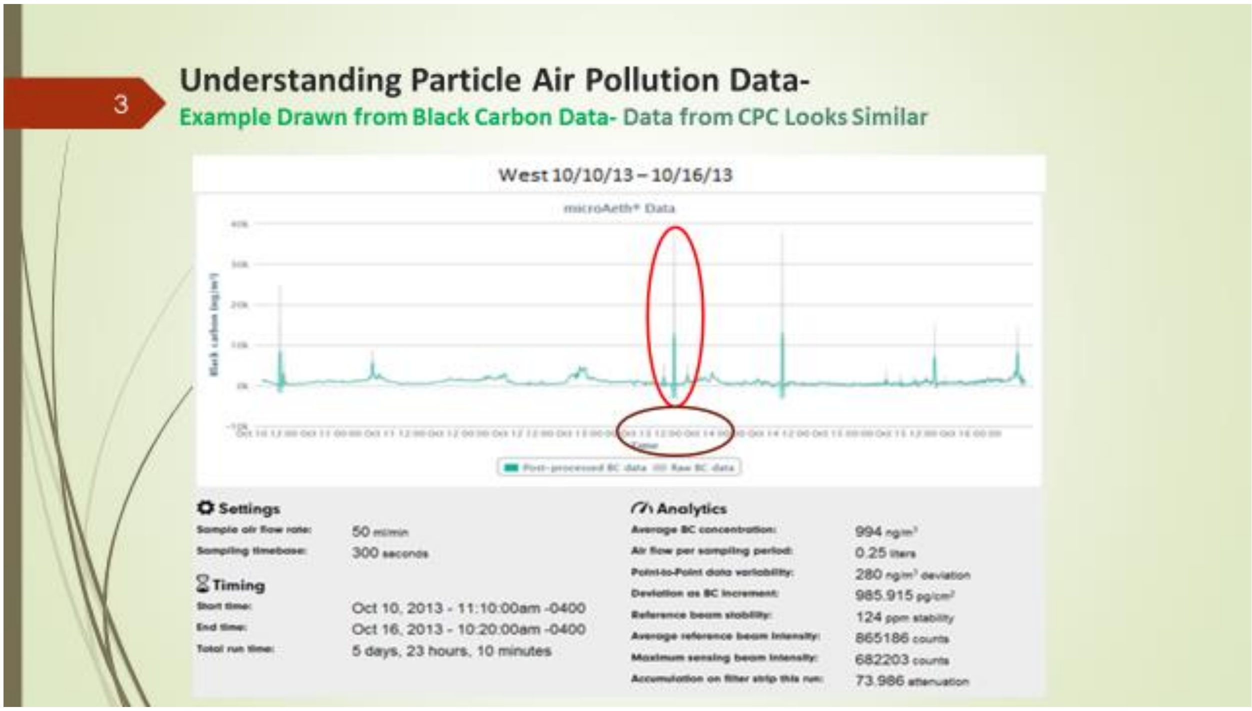
In the data collected at PDK Airport we used two different real-time monitors that measured particulate matter in the air. The first of these, the Condensation Particle Counter (CPC) measured particles in the respirable (<2.5 µm in diameter) range. It is particles of this size that are of importance in human health effects. The second of these, the Black Carbon Aethelomoter sold under the name micrAeth ® (we refer to these data as Black Carbon or BC) also measured these fine particles, but focused on the component of these fine particles that are made up of finely divided , primarily unburned, carbon, which is a material consisting of very fine particles, general < 1.0 µm in diameter. Further, these particles are typically associated with diesel exhaust, and exhaust from the burning of kerosene and similar compounds, associated with jet fuel. The physics of how these instruments work is covered in some detail in the report above.

I present the particulars of the measurement process, focusing on the real-time aspects of the data collection and the averaging time over which the measurements as implemented were carried out. For Both the BC and the CPC data were collected essentially second-by-second, then averaged over varying time periods. During preliminary testing. We initially selected 300-second (five-minute) averages as this time scale gives us stable measurements, but afforded understanding of transient peaks in the concentrations that could be associated with individual aircraft. Later, we reduced the time averaging to 60-second, but consolidated measurements over 15-minute increments for comparison in order to afford adequate time for diffusion of air pollutants emitted during airport operations to the various pollutant monitors.

Figure AP-1 depicts a trace of typical data collected in our investigations. This particular trace is from the Black Carbon data; the CPC data looks similar but this presentation, which is from the manufacturer's software, shows the trace better and offers a graphical depiction directly from the software. The data presented here cover approximately six days of sampling starting at the beginning of our study. First we examine the entire trace to get sense of what the data the data presentation. Note that data collection begins at about 12:00 on October 10, 2013, and continues through about 10:30 on October 16, 2013. The first thing we note are that the values are relatively low and constant for much of the time. However, we do see a trace that varies somewhat but is punctuated by transient, short-term events lasting a only a few minutes, before dissipating then returning to the slowly varying and modestly fluctuating, background levels. We refer to these as punctuating excursions as Transient Particle Peaks (TPP).

Note that there are a number of these transients throughout the particle data. On this trace, covering about six days of sampling we can identify at least four relatively large peaks and a number of smaller ones. Since our database extends over an entire year for each of eight instruments- four CPC (All particles) and four microAeth (Black Carbon particles) monitors, we conducted a search for TPP events aided by a computer. The background level of particulate matter varies over time as particulate levels in an urban area are influenced by numerous sources and local meteorological conditions such as wind speed and wind direction. Our goal is to identify air pollution events associated with aircraft operations. Hence, the identification of air pollution events such as TPP events and the association of such events with aircraft operations can give us insight as to the impact of aircraft on such events.

Because of the large number of data gathered, we use a statistical determination of a TPP using the definitions on the left of the figure. In our analysis, we identify a TPP as a change from the average CPC or Black Carbon that is "significant" in some sense. The instruments used are "counting instruments" in that the count the number of particles procedure (CPC) or the attenuation of a light beam associated with the presence of colored particle (BC). Background, urban air pollution results in a variable single for these instruments. This signal, on average, varies slowly with time, but displays very short term variability that is statistical in nature. We can see this by examining the trace of particle counts (for CPC) or concentrations (for BC). Note the BC trace in Figure X-1 focusing on the data between 12:00 on Oct 14 and 12:00 on Oct 15. The data show variability, but in a relatively confined magnitude range of perhaps a couple of hundred ng/m^3. TPPs are observed, then, reflect a sudden change in BC levels increasing 10- or even 100-fold above the background level. These changes are transient, they last for only a very short period of time, generally less than five minutes. The key is identifying such peaks in the large amount of data available thereby addressing the question: How do we distinguish events from naturally occurring background variability. Let us examine a particular TPP to illustrate the process. We choose the peak highlighted with the red oval that centers on October 13, 2013, at 14:25.The selection of this peak is arbitrary. We are just using as an illustration of the process.



Understanding Particle Air Pollution Data-

Example Drawn from Black Carbon Data- Data from CPC Looks Similar

Settings

Sample air flow rate: 50 ml/min
Sampling timebase: 300 seconds

Timing

Start time: Oct 10, 2013 - 11:10:00am -0400
End time: Oct 16, 2013 - 10:20:00am -0400
Total run time: 5 days, 23 hours, 10 minutes

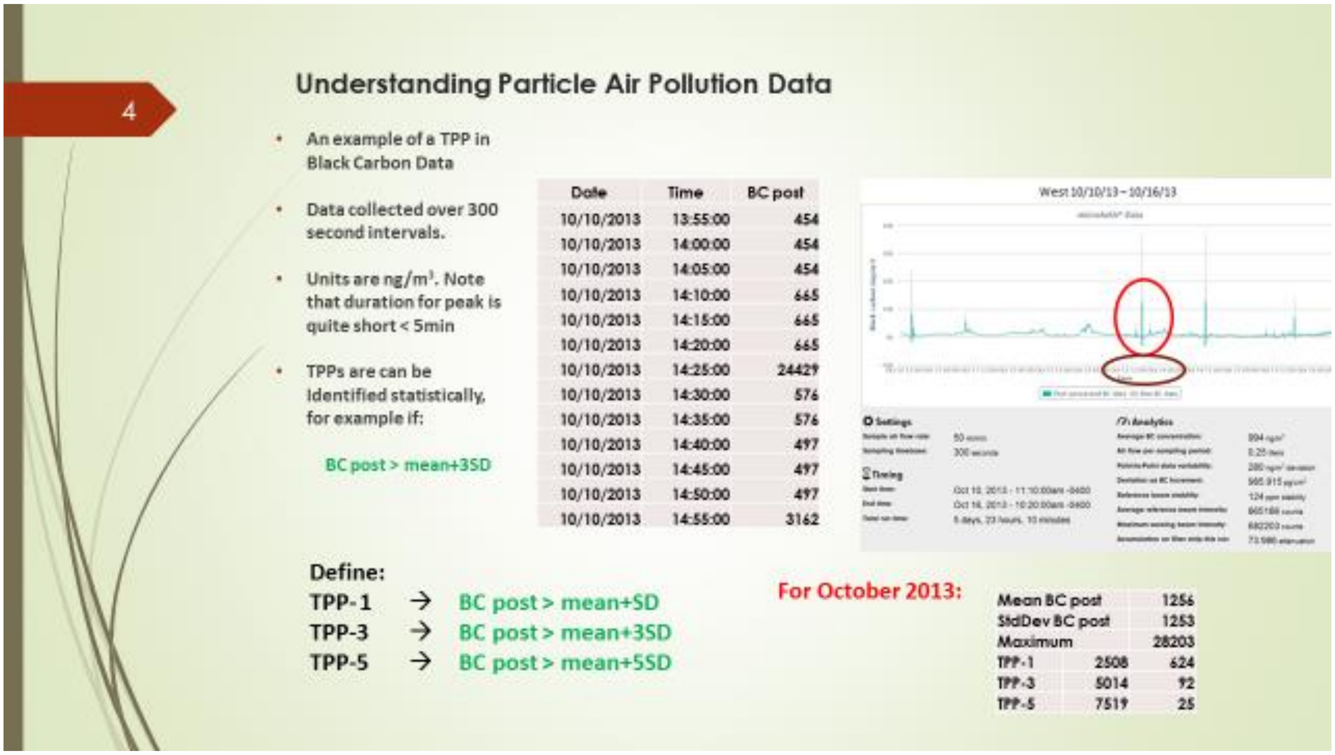
Analytics

Average BC concentration: 994 ng/m³
Air flow per sampling period: 0.25 liters
Point-to-Point data variability: 280 ng/m³ deviation
Deviation as BC increment: 985.915 pg/cm²
Reference beam stability: 124 ppm stability
Average reference beam intensity: 865186 counts
Maximum sensing beam intensity: 682203 counts
Accumulation on filter strip this run: 73.986 attenuation

Figure AP-1. Screen Capture of processed Black Carbon (Aethelometer) Data for October 10-October 16, 2013.

Figure AP-2 displays the same trace from the BC data, but also includes additional information. Since this is a complicated presentation, I will spend some time discussing the components. On the right is the trace from the instrument software seen in the Figure AP-1. In the middle of the figure, we present the data from time shortly before and after this TPP in tabular form. Note the progression of values. The concentrations are low <700 ng/m^3 from the beginning of this record through 14:20. We then see a marked increase, a TPP, at 14:25 that quickly dissipates back to background by 14:30. The concentration remains low and relatively constant through 14:50. At 14:55, we note another TPP, albeit substantially lower than the earlier one. These features are reflected in the trace encircled in red in this figure as well as in the previous one.

We now invoke a statistical definition of a TPP. A TPP-1 transient means that the value recorded exceed the average level measured by one standard deviation. TPP-3 implies a changes of three standard deviations from the average. TPP-5, five standard deviations. The greater the standard deviations, the greater the likelihood that this is significantly beyond the likelihood of occurring randomly or naturally. Further, one may infer that the higher peaks- the ones with larger deviation from the mean value, are larger in magnitude; there is a greater concentration of particulate matter for larger peaks. In statistical parlance, the greater the variance from the mean, the greater the likelihood that this is significantly beyond the likelihood of occurring randomly or naturally. From practical point of view, the greater the variance from the mean, the larger the magnitude of the local source of particle pollution. One may infer that the higher peaks- the ones with larger standard deviation from the mean value, are larger in magnitude; there is a greater concentration of particulate matter for larger peaks. One may infer that the higher peaks- the ones with larger standard deviation from the mean value, are larger in magnitude; there is a greater concentration of particulate matter for larger peaks.



Understanding Particle Air Pollution Data

- An example of a TPP in Black Carbon Data
- Data collected over 300 second intervals.
- Units are ng/m^3. Note that duration for peak is quite short < 5min
- TPPs are can be identified statistically, for example if:

BC post > mean+3SD

Date	Time	BC post
10/10/2013	13:55:00	454
10/10/2013	14:00:00	454
10/10/2013	14:05:00	454
10/10/2013	14:10:00	665
10/10/2013	14:15:00	665
10/10/2013	14:20:00	665
10/10/2013	14:25:00	24429
10/10/2013	14:30:00	576
10/10/2013	14:35:00	576
10/10/2013	14:40:00	497
10/10/2013	14:45:00	497
10/10/2013	14:50:00	497
10/10/2013	14:55:00	3162

West 10/10/13 – 10/16/13
Settings
50
300 seconds
Timing
Oct 10, 2013 - 11:10:00am -0400
Oct 16, 2013 - 10:20:00am -0400
5 days, 23 hours, 10 minutes
Analytics

Define:
TPP-1 → BC post > mean+SD
TPP-3 → BC post > mean+3SD
TPP-5 → BC post > mean+5SD

For October 2013:

Mean BC post		1256
StdDev BC post		1253
Maximum		28203
TPP-1	2508	624
TPP-3	5014	92
TPP-5	7519	25

Figure AP-2. Examination of Black Carbon Data for one Transient Particle Peak (TPP). Peak is centered o 14:25 10 October 2013.

In October, 2013, the mean Black Carbon concentration observed at this monitor was 1256 ng/m^3 as indicated in the table at the lower right. The standard deviation- a measure of the natural variability for this measure was 1253 ng/m^3, the fact that these numbers are close to one another is coincidental; they are not always of the same magnitude. According to statistics, a difference as large as TPP-1 might be expected to occur about 16% of the time, just by random chance. A value at the TPP-1 level might well be due to nothing mare than normal background variability. A value at TPP-3 would only occur randomly less than 1% of the time. We would be quite confident that we are measuring an important "Statistically Significant" transient event when a TPP-3 event was noted. Finally, a TPP-5 event would occur randomly with a frequency of < 0.01% of the time. Any event at the TPP-5 level would have almost no likelihood of occurring randomly- these events are real.

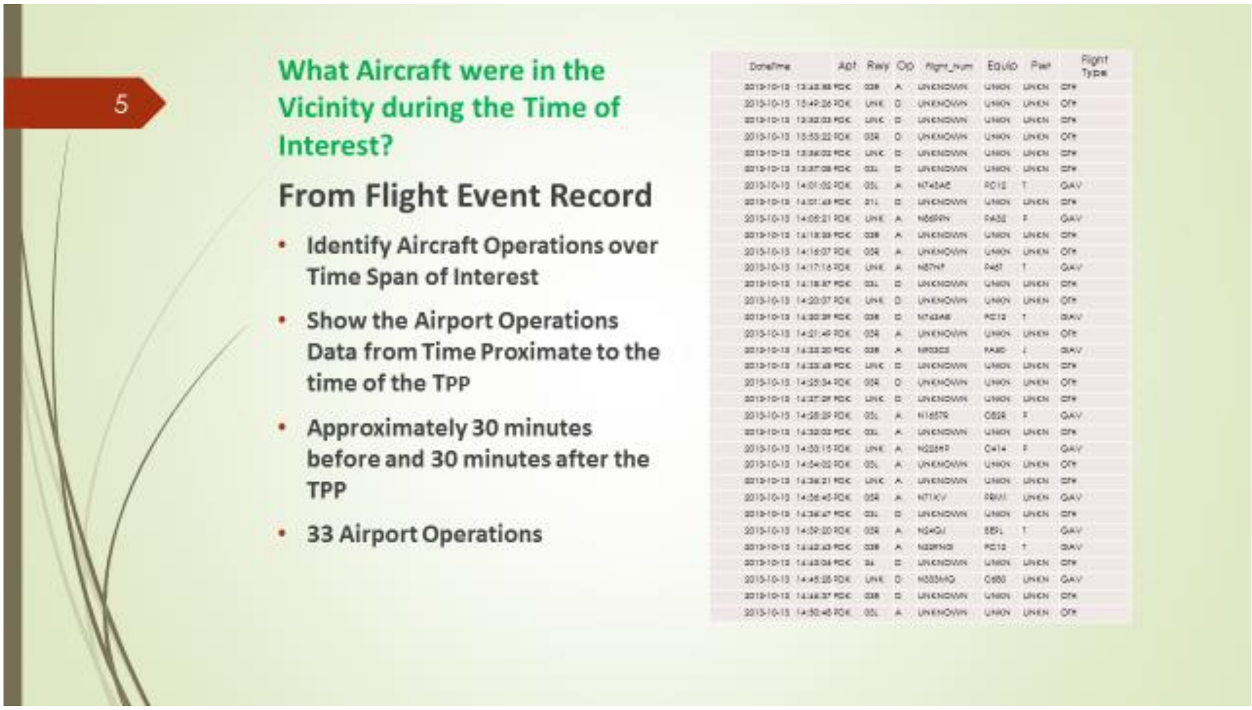
Performing the calculations using the mean and standard deviation for the month of October 2013, indicated that the TPP-1 level was 2508 ng/m^3 we observed 624 such events during the monitoring period commencing October 10, 2013, and concluding on October 31, 2013, given a total of approximately 2000 measurements. Ninety-two such measurements were noted at the TPP-3 level; 25 at the TPP-5 level.

At this point, we have identified a TPP and an associated time for that event across our analysis period. Given the data on aircraft operations supplied to us in January, we can now more precisely link takeoffs and landings, referred to as airport operations with individual aircraft and clarify whether or not the aircraft actually landed or took off from PDK.

To show how the analysis proceeds, we present data in Figure AP-3 identifying aircraft operations for approximately 30 minutes before and 30 minutes after the TPP of interest, which occurred on October 13, 2013, at 14:25. As we have noted that the TPP events dissipate rapidly,- within about five minutes-examining airport operations in this 30 minute window affords us the opportunity to assess which aircraft performed an operation dung the time period the instruments were reporting a TPP event. According to the Flight Event Records (FER), there were 33 airport operations during this time. The FER displays information including the Date and Time of the operation, the Airport identifier, the Runway for the operation, the Flight Number, which enables identification of the aircraft through the Tail Number, the Type of Equipment, if known, how the Aircraft was powered, and information on the Flight Type.

Many of these data are unnecessary for our purposes or do not supply information in sufficient detail to enable identification of the aircraft. Therefore, they are not used in our analysis. We have cleaned the dataset so that only essential information is maintained. Twenty-two of these aircraft are identified with Flight_Num UNKNOWN, meaning that there is no corresponding transponder signal affording identification of the Unique Tail Number associated with the aircraft. The Tail Number affords identification of the aircraft with respect to Maximum Take-Off With (MTOW), the essential variable of interest in this investigation. However, these aircraft are typically smaller, General Aviation, aircraft with MTOW < 10,000 lbs. Overall, we have found that about 36% of aircraft operations at PDK were in this category. In our analyses, these UNKNOWN aircraft are lumped to gather into a single Weight Class (WgtClass=0) for classification purposes (See below). Eliminating those aircraft the number during this examination time period, reduces the number of Operations from 33 to 11. We present these aircraft and information about them in Figure AP-4.

In this example presentation, we are focused only on the TPP that occurred on October 13, 2013, at 14:25. It is clear that operations that took place after 14:25 on that date cannot influence the measurement, so we eliminate those from consideration. Further, we have made the assumption that and TPP-like event occurring more than 15 minutes prior to our measurement would have dissipated to background. This assumption can be visually validated by noting that the TP events themselves seldom span more than one five-minute increment.


5

What Aircraft were in the Vicinity during the Time of Interest?

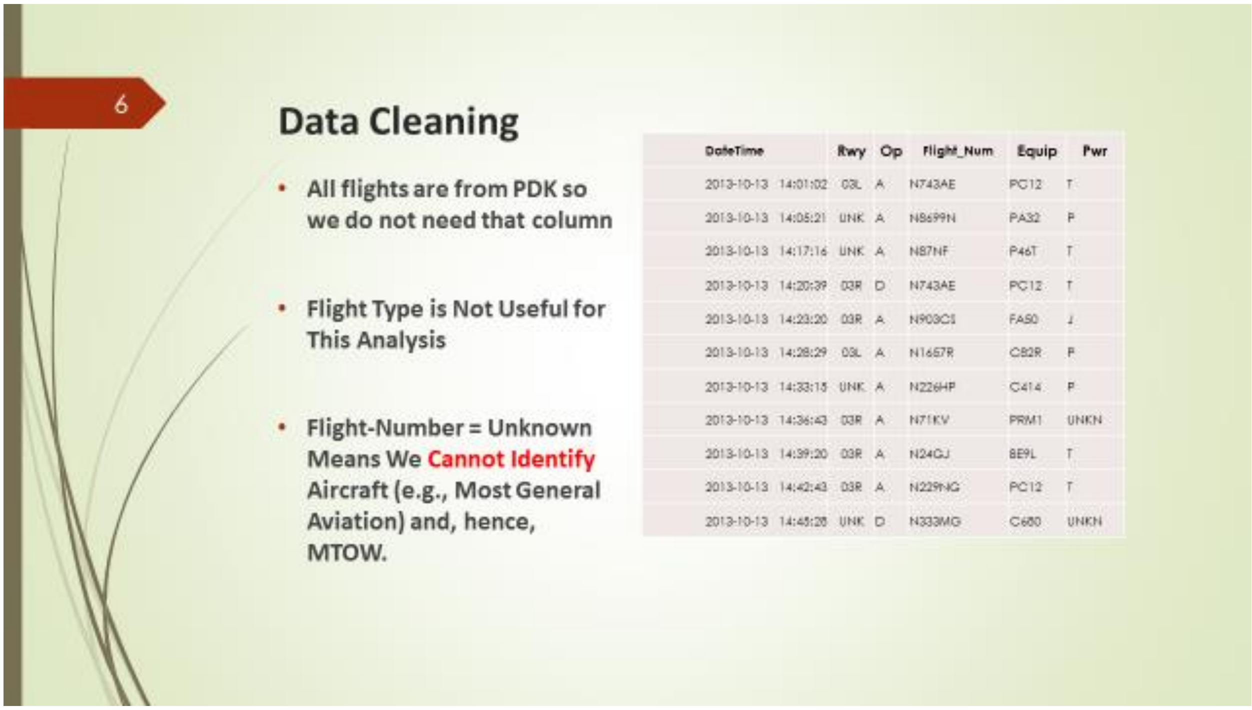
From Flight Event Record

- Identify Aircraft Operations over Time Span of Interest
- Show the Airport Operations Data from Time Proximate to the time of the TPP
- Approximately 30 minutes before and 30 minutes after the TPP
- 33 Airport Operations

Figure AP-3. Observed Flight Events at approximately the same time as the TPP noted in the previous figures.

For the event under current study, that leaves us with only four aircraft that could have influenced the event. They are identified in this Figure X-5. The four aircraft have MTOWs as listed. We now draw upon our data relating tail numbers to aircraft type. The column Labeled Equip does this as well, but our analysis makes use of a “Dictionary” that we have developed mapping some 8,037 unique tail numbers that have PDK Airport Operations during our monitoring period, to a specific aircraft, affording a better and more accurate determination of MTOW. We note that, in addition to the UNKNOWN aircraft defined above, three of the aircraft have MTOW < 25,000 lbs, which is our lowest category. One aircraft, the Falcon Air 50, has a MTOW of 39,700 lbs, placing this aircraft in Category 2 with 25,000 lbs < MTOW < 66,000 lbs. Category 3 is 66,000 lbs < MTOW < <75000 lbs. Category 4 is MTOW > 75,000 lbs.

Note that these aircraft, in addition to the UNKNOWN aircraft, are mapped to a specific Time Segment of 15 minutes. There are 96 such time segments during each 24-hr period and 365 24-hour periods during our monitoring year, for a total of approximately 35,000 analyses similar to this one that are performed for each of the four sites on the airport grounds and for each of the two monitoring instrument types.



6

Data Cleaning

- All flights are from PDK so we do not need that column
- Flight Type is Not Useful for This Analysis
- Flight-Number = Unknown Means We Cannot Identify Aircraft (e.g., Most General Aviation) and, hence, MTOW.

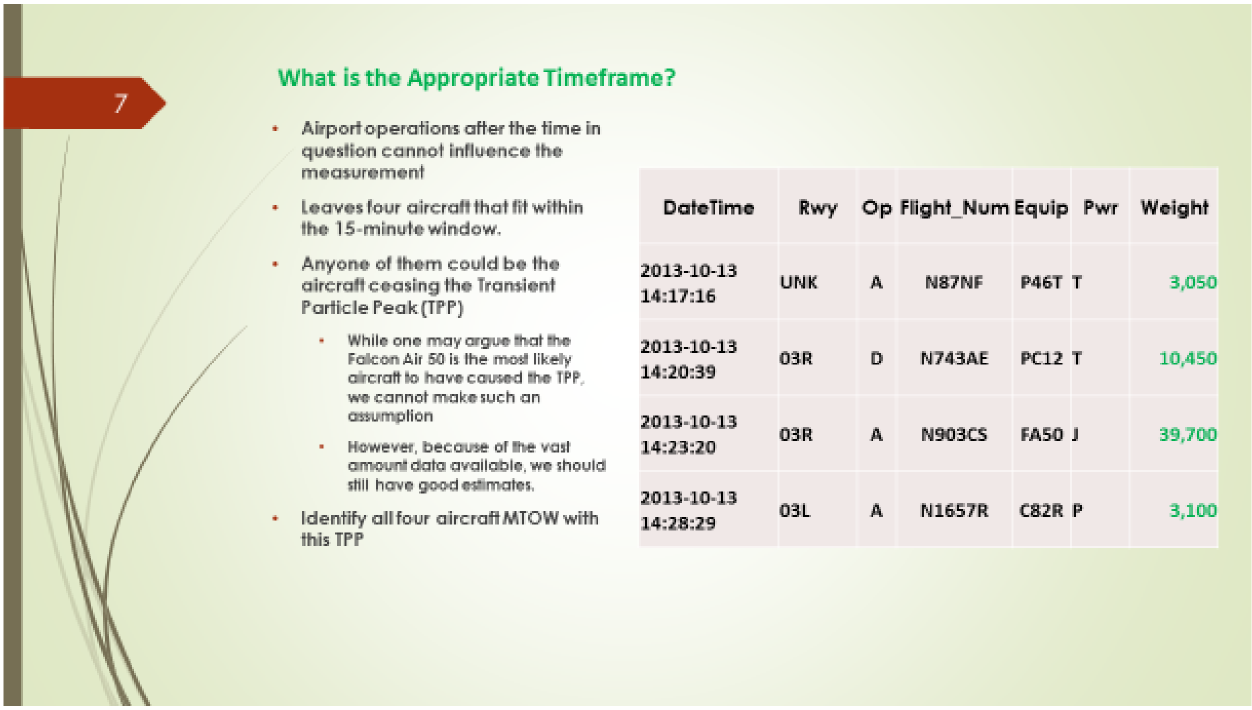
DateTime	Rwy	Op	Flight_Num	Equip	Pwr
2013-10-13 14:01:02	03L	A	N743AE	PC12	T
2013-10-13 14:05:21	UNK	A	N8699N	PA32	P
2013-10-13 14:17:16	UNK	A	N87NF	P46T	T
2013-10-13 14:20:39	03R	D	N743AE	PC12	T
2013-10-13 14:23:20	03R	A	N903CS	FA50	J
2013-10-13 14:28:29	03L	A	N1657R	C82R	P
2013-10-13 14:33:15	UNK	A	N226HP	C414	P
2013-10-13 14:36:43	03R	A	N71KV	PRM1	UNKN
2013-10-13 14:39:20	03R	A	N24GJ	BE9L	T
2013-10-13 14:42:43	03R	A	N229NG	PC12	T
2013-10-13 14:45:28	UNK	D	N333MG	C680	UNKN

Figure AP-4- Table showing non-UNKNOWN aircraft.

Categories according to the scheme discussed with the previous slide: Category 1 MTOW < 25,000, Category 2 25,000 lbs < MTOW < 66,000 lbs. Category 3 66,000 lbs < MTOW < <75000 lbs. Category 4 MTOW > 75,000 lbs.

After collecting the data over the entire monitoring period, we perform two types of analyses to assess the relationship between TPP events and MTOW of aircraft. These are the Heuristic procedures in which we evaluate heuristically if the number of such fraction of such TPP events attributable to each Weight Class is similar to the fraction of aircraft operations for that Weight Class. If the fractions are similar, then there is no association between TPP events and MTOW. WE follow this with a more rigours statistical procedure invoking Logistic Regression. In this analysis. We assess the relative likelihood of an event TPP event occurring in association with an aircraft in a particular Weight Class relative to other Weight Classes. Logistic regression is a statistical method that has long been used to identify associations between the probability of a "binary" or "Yes/No" event occurs based on hypothesized factors. Here our binary event is the presence of a TPP. The factors on the Weight Classes. We ask, is the appearance of a TPP more like to occur when the Flight Event involves a heavier weight class, than a lighter (or UNKNOWN) weight class. In particular, we look to compare the results for the heaviest MTOW Categories 3 and 4, with the smaller-aircraft Categories.

We have given but one example of the analysis here. There are, for example, typically about 125 TPP-3 events during the typical month or about 1,500 over the course of the monitoring period for each monitor. So, we now have a clean dataset that we can use for the analysis intended.



What is the Appropriate Timeframe?

- Airport operations after the time in question cannot influence the measurement
- Leaves four aircraft that fit within the 15-minute window.
- Anyone of them could be the aircraft ceasing the Transient Particle Peak (TPP)
  - While one may argue that the Falcon Air 50 is the most likely aircraft to have caused the TPP, we cannot make such an assumption
  - However, because of the vast amount data available, we should still have good estimates.
- Identify all four aircraft MTOW with this TPP

DateTime	Rwy	Op	Flight_Num	Equip	Pwr	Weight
2013-10-13 14:17:16	UNK	A	N87NF	P46T	T	3,050
2013-10-13 14:20:39	03R	D	N743AE	PC12	T	10,450
2013-10-13 14:23:20	03R	A	N903CS	FA50	J	39,700
2013-10-13 14:28:29	03L	A	N1657R	C82R	P	3,100

Figure AP-5.- Identification of Aircraft that could be influencing the TPP at 14:25 on 13 October 2013.

The final step in this analysis is to gather all data together. We associate each specific TPP with the aircraft that could have influenced it. Each aircraft is associated with a MTOW and assigned MTOW

In Figure AP-6, we present ae schematic of the data analysis approach. Using the Black Carbon and CPC data, we identify a Transient Particle Peak (TPP). For the CPC data, the TPP is particle number count which is statistically different from the average value, while for the microAeth apparatus it is a concentration of Black Carbon, in ng/m^3 that is statistically different from the average value. We choose three different levels for this analysis in order to assess the variability of this statistical measure and include an assessment of the magnitude of the transient particle peak, assuming larger peaks have larger impact on the community.

Once the peak is identified, we determine the time window in which that peak falls. We put these in 15-minute segments to allow time for diffusion particles to the monitor.

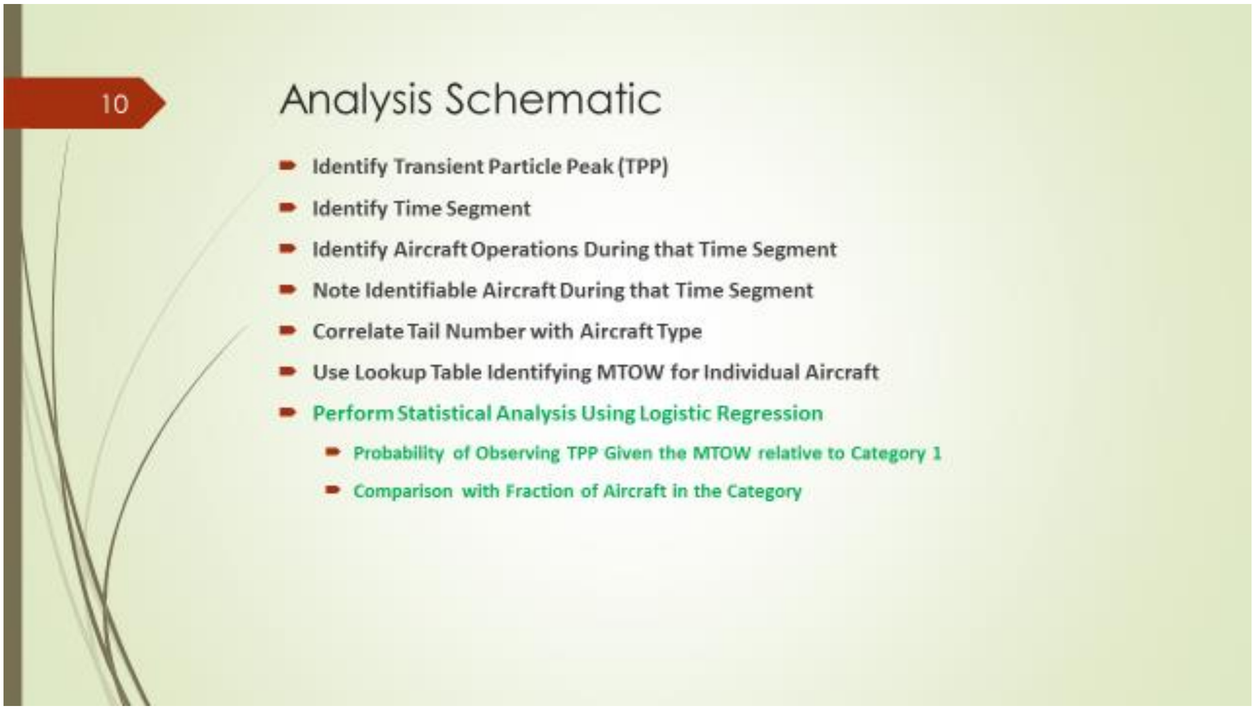
Using the Flight Event Data, we identity aircraft operations in the 15-minutes prior to that time window. These operations identify the aircraft by Tail number for those aircraft where such identification is possible.

Using the Tail Number of those Aircraft, we identify the aircraft type.

Using a lookup table we have developed we identify aircraft type with MTOW.

At this point, we have identified all aircraft that could have produced the TPP and an associated MTOW.

Using logistic regression, we determine whether there is a relationship between MTOW and the presence of a TPP.



Analysis Schematic

- Identify Transient Particle Peak (TPP)
- Identify Time Segment
- Identify Aircraft Operations During that Time Segment
- Note Identifiable Aircraft During that Time Segment
- Correlate Tail Number with Aircraft Type
- Use Lookup Table Identifying MTOW for Individual Aircraft
- Perform Statistical Analysis Using Logistic Regression
    - Probability of Observing TPP Given the MTOW relative to Category 1
    - Comparison with Fraction of Aircraft in the Category

Figure X-5.- Analytical schematic for particulate air pollution analysis.

<u>To clarify the algorithm:</u>

1) For each of the monitors on the airport ground (generally four) note the mean number of particles per cubic centimeter (#/cm^3) for that day and the standard deviation of #/cm^3 over the 1440 measurements of particle concentrations for the day. **Example-** For one of the monitors we note that the mean concentration seen is 5,000 particles/cm^3 and that the standard deviation is 2,000 particles/cm^3.
2) Calculate a value that is the mean #/cm^3 plus three times the standard deviation of #/cm^3 over the day. **Example-** From the above, that number would be: 5000 particles/cm^3 + 3 x 2000 particles/cm^3 = **11,000 particles/cm$^{3.}$**
3) If that number is exceeded for that minute, a Peak is noted.
4) Aggregate the 1440 daily measurements for each monitor into 96 15-minute increments.
5) If a Peak is noted for any time increment during that 15-minute time period, note a Peak for the 15-minute period for that monitor.
6) If a Peak is noted in any of the monitors on the airport grounds, note a Peak for the airport during that 15-minute period.

At the end of this portion of the analysis, we have 96 values for each day- one for each 15-minute time increment- that indicates whether an TPP took place at any monitor on the airport grounds during that a given 15-minute period on that day. This is repeated for all days during the evaluation period giving nominal total of 35,040 increments for each of the monitors in our study. Actual numbers are somewhat less given downtime for instruments. However, we identify and air pollution event- a TPP- if any of the monitors of a given type reveals an event. We are now ready to assess the impact of aircraft MTOW on air pollution events. While this method is crude and does come up with false positives, as we shall see, the large size of the dataset of air pollution data allows us to use statistical analysis of the data to assess this impact.

Appendix 3- SAS Code for the Analysis of Black Carbon Data

```
/****************************************************************************
************

SAS Code to produce analysis of PDK Blac Carbon Data. This uses previously
developed
dataset:

      1. analysis.Flight_Events_Weights
            Data for all FLight Events from early October 2013 to mid-October
2014.

*****************************************************************************
************/
libname analysis 'C:\Working Files\Research\PDK Airport\Analysis 2018\Flight
Event Data';

/* Now Construct MTOW WgtClass */
data analysis.Flight_Events_Weights;
  set analysis.Flight_Events_Weights;
  WgtClass=-1;
  /* If wgt < 0 it is because the aircraft type is UNKNOWN. This represents
slightly less than 37% of the
    Flight Events. This will be included in as a separate WgtClas and
Analyzed as such.

  Modified after 28 June 2018 Meeting to combine UNKNOWN aircraft with Weight
Class=1 aircraft to produce
  new  Weight Class=1 making up approxomately 89% of all airport operations.
  */

  if wgt=-999 then WgtClass=0;
  if wgt > 0 and wgt <= 25000 then WgtClass = 1;
  if wgt > 25000 and wgt <= 66000 then WgtClass = 2;
  if wgt > 66000 and wgt <= 75000 then WgtClass = 3;
  if wgt > 75000 then WgtClass = 4;
  /*  Reassign UNKNONW Classification to WgtClass 1*/
  if WgtClass=0 then WgtClass=1;

/* Creat a new more fonely divided weight class designation in cae Open
DeKalb requests further analysis.  */

  WCF=-1;
  if wgt=-999 then WCF=0;
  if wgt > 0 and wgt <= 2500 then WCF = 1;
  if wgt > 2500 and wgt <= 5000 then WCF = 2;
  if wgt > 5000 and wgt <= 10000 then WCF = 3;
  if wgt > 10000 and wgt <= 20000 then WCF = 4;
  if wgt > 20000 and wgt <= 40000 then WCF = 5;
  if wgt > 40000 and wgt <= 66000 then WCF = 6;
  if wgt > 66000 and wgt <= 75000 then WCF = 7;
  if wgt > 75000 then WCF = 8;
  run;
```

```
/* Output of PROC CONTENTS for analysis.Flight_Events_Weights

Alphabetic List of Variables and Attributes
# Variable Type Len Format Informat Label
5 Equip Char 4 $4. $4. Equip
4 Flight_Num Char 7 $7. $7. Flight_Num
3 Op Char 1 $1. $1. Op
6 Pwr Char 4 $4. $4. Pwr
2 Rwy Char 3 $3. $3. Rwy
1 Time_Segment Num 8 BEST.   Time Segment
10 WC0 Num 8
11 WC1 Num 8
12 WC2 Num 8
13 WC3 Num 8
14 WC4 Num 8
9 WCF Num 8
7 Wgt Num 8 BEST.   Wgt
8 WgtClass Num 8


proc contents data=analysis.Flight_Events_Weights;
  run;
  */

/* Macros to Read in Black Carbon Data and create Peak information and
various levesl of Transient Particle Pekas (TPP)*/

/* Ancillary macros. */

  /* time_segments macro
   Takes as input the file infilename, creates Time_Segements based on
Adjusted-Date and Adjusted Time
   and outputs that information to the file outfilename. This is a general
macro that can be called inside another macro,
   e.g., any of the Read_BC macros. */

%macro time_segments(infilename,outfilename);
/*  Macro to construct 15-minute Time Segments starting at the begining of
the study 10 October 2013. Ther are approaximately
      35,000 15-minute time increments in the one-year monitoring period.*/
  data &outfilename;
    set &infilename;
    dt1=(Adjusted_Date-19641);
    dt2=Adjusted_Time/86400;
    dt3=(dt1+dt2)*96;
    Time_Segment=int(dt3);
    keep Adjusted_Date Adjusted_Time BC_Post Time_Segment;
    run;
  %mend;
/* Macro to test the integrity of the Excel Files with respect to
Adjusted_Date and Adjusted_Time */
%macro test_data(filename);
proc sort data=&filename;
  by Adjusted_Date Adjusted_Time;
  run;
%mend test_data;
```

```
/* Macro to determine TPP Values for a given Month contained in filename */
%macro TPP(filename);
  /* Get mean and standard deveiation for the BC Post Processed Data and
output to filename.

  Mean Value --> BC_Mean
  StDev Value --> BC_Std
  In macro, would use NOTABLE */
proc means data=&filename NOPRINT;
  var BC_Post;
  output out=Means Mean=BC_Mean Std=BC_Std;
  run;
/* Use SAS trick to allow means and standard deveiations to apply to every
observation. */
data Means;
    set Means;
      mrger=1;
      run;
data &filename;
  set &filename;
  mrger=1;
  run;
proc sort Data=Means;
  by mrger;
  run;
proc sort data=&filename;
  by mrger;
  run;
data &filename;
  merge &filename Means;
  by mrger;
  run;
/* Construct TPP values in SAS to compare with Excel */
data &filename;
  set &filename;
  TPP1=0;
  TPP3=0;
  TPP4=0;
  TPP5=0;
  TPP10=0;
  TPP15=0;
  TPP20=0;
  TPP25=0;
  if BC_post>=BC_Mean+1*BC_Std then TPP1=1;
  if BC_post>=BC_Mean+3*BC_Std then TPP3=1;
  if BC_post>=BC_Mean+4*BC_Std then TPP4=1;
  if BC_post>=BC_Mean+5*BC_Std then TPP5=1;
  if BC_post>=BC_Mean+10*BC_Std then TPP10=1;
  if BC_post>=BC_Mean+15*BC_Std then TPP15=1;
  if BC_post>=BC_Mean+20*BC_Std then TPP20=1;
  if BC_post>=BC_Mean+25*BC_Std then TPP25=1;
  run;
%mend TPP;
%macro findpeaks(infile);
  /* Within each Increment of 15 minutes, we sum the peak indicators. If the
sum witin a Increment is greater than or equal to
```

```
   one, we identify the Increment as having a peak. */

/* Sum TPP indicator across time_segments. Initialize TPP indicator to zero.
If there is a TPP indicator anywhere in that time_segement,
   then set ispeak to 1 meaning there has been a peak identified. this is
saved in peakfile along with the time_segement. Should store
   month and site with this file as well.*/


proc sort data=&infile;
  by time_segment;
  run;
proc means data=&infile NOPRINT;
  output out=peakfile SUM=;
  var TPP1 TPP3 TPP4 TPP5 TPP10 TPP15 TPP20 TPP25;
  by time_segment;
  run;
data peakfile;
  set peakfile;
  ispeak_1=0;
  if TPP1 > 0 then ispeak_1=1;
  ispeak_3=0;
  if TPP3 > 0 then ispeak_3=1;
  ispeak_4=0;
  if TPP4 > 0 then ispeak_4=1;
  ispeak_5=0;
  if TPP5 > 0 then ispeak_5=1;
  ispeak_10=0;
  if TPP10 > 0 then ispeak_10=1;
  ispeak_15=0;
  if TPP15 > 0 then ispeak_15=1;
  ispeak_20=0;
  if TPP20 > 0 then ispeak_20=1;
  ispeak_25=0;
  if TPP25 > 0 then ispeak_25=1;
  keep time_segment ispeak_1 ispeak_3 ispeak_4 ispeak_5 ispeak_10 ispeak_15
ispeak_20 ispeak_25;
  run;
proc sort data=&infile;
  by time_segment;
  run;
proc sort data=peakfile;
  by time_segment;
  run;
data &infile;
  merge &infile peakfile;
  by time_segment;
  run;
%mend findpeaks;

/* This macro takes data from  the file input, which is the output of other
macros and determines whether a given time segment
   has a TPP of a specific type. The file produced goes into putfile and
contains only the time segment identifier and
   an indicator of whether a peak of the specific type has occurred in this
time segment. This file will be merged with a
```

```
   similar file indicating whether aircraft of a specific weight class had an
operation during this time segment.

   This macro is redundant with findpeaks is the intermediate file is stored.
*/

%macro putpeaks(infile,putfile);
  /* Within each Increment of 15 minutes, we sum the peak indicators. If the
sum within an Increment is greater than or equal to
   one, we identify the Increment as having a peak. */
proc sort data=&infile;
  by time_segment;
  run;
proc means data=&infile NOPRINT;
  output out=peakfile SUM=;
  var ispeak_1 ispeak_3 ispeak_4 ispeak_5 ispeak_10 ispeak_15 ispeak_20
ispeak_25;
  by time_segment;
  run;
data peakfile;
  set peakfile;
  ispeak1=0;
  if ispeak_1 > 0 then ispeak1=1;
  ispeak3=0;
  if ispeak_3 > 0 then ispeak3=1;
  ispeak4=0;
  if ispeak_4 > 0 then ispeak4=1;
  ispeak5=0;
  if ispeak_5 > 0 then ispeak5=1;
  ispeak10=0;
  if ispeak_10 > 0 then ispeak10=1;
  ispeak15=0;
  if ispeak_15 > 0 then ispeak15=1;
  ispeak20=0;
  if ispeak_20 > 0 then ispeak20=1;
  ispeak25=0;
  if ispeak_25 > 0 then ispeak25=1;
  keep time_segment ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15
ispeak20 ispeak25;
  run;
data &putfile;
  set peakfile;
  run;
%mend putpeaks;

/* The macro below reads in data files from specific excel Files To be
generalized */


/* New Generalized Macro to Read all Datasets */

%macro read_dataset(dataset,location,time);
proc import datafile=&dataset
       out=analysis.BC_&location&time DBMS=xlsx REPLACE;
/* Make range long enough to ensure all data are read. */
   range="&time$a1:b100000,k1:k100000";
   getnames=yes;
   run;
/* Call the time_segments macro to calculate the time segements and append
infromation to file. */
/*%time_segments(analysis.BC_south_553_&time,analysis.BC_south_553_&time);

%test_data(analysis.BC_south_553_&time);
%TPP(analysis.BC_south_553_&time);
%findpeaks(analysis.BC_south_553_&time);*/
%time_segments(analysis.BC_&location&time,analysis.BC_&location&time);

%test_data(analysis.BC_&location&time);
%TPP(analysis.BC_&location&time);
%findpeaks(analysis.BC_&location&time);
data analysis.BC_&location&time;
  set analysis.BC_&location&time;
  Month="&time";
  run;

%let peaks=_peaks;
%putpeaks(analysis.BC_&location&time,analysis.BC_&location&time&peaks);
data analysis.BC_&location&time&peaks;
  set analysis.BC_&location&time&peaks;
  Month="&time";
  Site="&location";
  run;
/*proc print data=analysis.BC_&location&time&peaks (OBS=1);
  run;
proc freq data=analysis.BC_&location&time&peaks;
  table ispeak1 ispeak3 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;*/
%mend read_dataset;

/*    Using the Main meacro read_dataset and the various Ancillary Macros, we
proceed through the the months of the study
      and teh four data locations. South, East, North, and West. */

/* Need to pass these two arguments to read_dataset macro, namely, the name
and location of the dataset and the nemae and identifier
      of the sampler location.*/

/* South */
%let dataset="C:\Working Files\Research\PDK Airport\Analysis 2018\Flight
Event Data\South 553.xlsx";
%let location_monitor=South_553_;

/* Call to read_dataset */
%read_dataset(&dataset,&location_monitor,October13);
%read_dataset(&dataset,&location_monitor,November13);
%read_dataset(&dataset,&location_monitor,December13);
%read_dataset(&dataset,&location_monitor,January14);
%read_dataset(&dataset,&location_monitor,February14);
%read_dataset(&dataset,&location_monitor,March14);
%read_dataset(&dataset,&location_monitor,April14);
%read_dataset(&dataset,&location_monitor,May14);
%read_dataset(&dataset,&location_monitor,June14);
```

```
/*%read_dataset(&dataset,&location_monitor,July14);
%read_dataset(&dataset,&location_monitor,August14);
%read_dataset(&dataset,&location_monitor,September4);
%read_dataset(&dataset,&location_monitor,October14);*/

/* East */
%let dataset="C:\Working Files\Research\PDK Airport\Analysis 2018\Flight
Event Data\East 559.xlsx";
%let location_monitor=East_559_;

/* Call to read_dataset */
%read_dataset(&dataset,&location_monitor,October13);
%read_dataset(&dataset,&location_monitor,November13);
%read_dataset(&dataset,&location_monitor,December13);
%read_dataset(&dataset,&location_monitor,January14);
%read_dataset(&dataset,&location_monitor,February14);
%read_dataset(&dataset,&location_monitor,March14);
%read_dataset(&dataset,&location_monitor,April14);
%read_dataset(&dataset,&location_monitor,May14);
%read_dataset(&dataset,&location_monitor,June14);
%read_dataset(&dataset,&location_monitor,July14);
%read_dataset(&dataset,&location_monitor,August14);
%read_dataset(&dataset,&location_monitor,September14);
%read_dataset(&dataset,&location_monitor,October14);

/* North */
%let dataset="C:\Working Files\Research\PDK Airport\Analysis 2018\Flight
Event Data\North 560.xlsx";
%let location_monitor=North_560_;

/* Call to read_dataset */
/* %read_dataset(&dataset,&location_monitor,October13);
%read_dataset(&dataset,&location_monitor,November13);*/
%read_dataset(&dataset,&location_monitor,December13);
%read_dataset(&dataset,&location_monitor,January14);
%read_dataset(&dataset,&location_monitor,February14);
%read_dataset(&dataset,&location_monitor,March14);
%read_dataset(&dataset,&location_monitor,April14);
%read_dataset(&dataset,&location_monitor,May14);
%read_dataset(&dataset,&location_monitor,June14);
%read_dataset(&dataset,&location_monitor,July14);
%read_dataset(&dataset,&location_monitor,August14);
%read_dataset(&dataset,&location_monitor,September14);
%read_dataset(&dataset,&location_monitor,October14);

/* West */
%let dataset="C:\Working Files\Research\PDK Airport\Analysis 2018\Flight
Event Data\West 546.xlsx";
%let location_monitor=West_546_;

/* Call to read_dataset */
%read_dataset(&dataset,&location_monitor,October13);
%read_dataset(&dataset,&location_monitor,November13);
%read_dataset(&dataset,&location_monitor,December13);
%read_dataset(&dataset,&location_monitor,January14);
%read_dataset(&dataset,&location_monitor,February14);
```

```
%read_dataset(&dataset,&location_monitor,March14);
%read_dataset(&dataset,&location_monitor,April14);
%read_dataset(&dataset,&location_monitor,May14);
%read_dataset(&dataset,&location_monitor,June14);
%read_dataset(&dataset,&location_monitor,July14);
%read_dataset(&dataset,&location_monitor,August14);
%read_dataset(&dataset,&location_monitor,September14);
%read_dataset(&dataset,&location_monitor,October14);

/*    Attemps to write a general macro to combine the varaious monthly
datasets into a single yearly dataset are stymied
      by the differing months available for each site. Hwoever, the general
strucure is the same. Hence, we produce multiple macros
      that are called for the approapriate sites. */

/* East and West Monitors contain data for all months. */

%macro combine_monthsEW(location);
data analysis.BC_&location;
  set analysis.BC_&location&October13 analysis.BC_&location&November13
analysis.BC_&location&December13 analysis.BC_&location&January14
      analysis.BC_&location&February14 analysis.BC_&location&March14
analysis.BC_&location&April14 analysis.BC_&location&May14
      analysis.BC_&location&June14 analysis.BC_&location&July14
analysis.BC_&location&August14 analysis.BC_&location&September14
        analysis.BC_&location&October14;
        Site_ID="&location";
        run;
/*proc contents data=analysis.BC_&location;
  run;
proc print data=analysis.BC_&location (OBS=10);
  run;*/
%mend combine_monthsEW;

/* South Monitor is missing data from July-October 2014 */
%macro combine_monthsS(location);
data analysis.BC_&location;
  set analysis.BC_&location&October13 analysis.BC_&location&November13
analysis.BC_&location&December13 analysis.BC_&location&January14
      analysis.BC_&location&February14 analysis.BC_&location&March14
analysis.BC_&location&April14 analysis.BC_&location&May14
      analysis.BC_&location&June14;
        Site_ID="&location";
        run;
/*proc contents data=analysis.BC_&location;
  run;
proc print data=analysis.BC_&location (OBS=10);
  run; */
%mend combine_monthsS;

/* North Monitor is missing data from October-November 2013 */
%macro combine_monthsN(location);
data analysis.BC_&location;
  set analysis.BC_&location&December13 analysis.BC_&location&January14
      analysis.BC_&location&February14 analysis.BC_&location&March14
analysis.BC_&location&April14 analysis.BC_&location&May14
```

```
      analysis.BC_&location&June14 analysis.BC_&location&July14
analysis.BC_&location&August14 analysis.BC_&location&September14
        analysis.BC_&location&October14;
        Site_ID="&location";
        run;
/*proc contents data=analysis.BC_&location;
  run;
proc print data=analysis.BC_&location (OBS=10);
  run;*/
%mend combine_monthsN;

/* These Macros combines Peak Files to produce a single file */

/* East and West Monitors have data for all months.*/
%macro combine_monthsEW_peaks(location);
%let peaks=_peaks;
data analysis.BC_&location&peaks;
  set analysis.BC_&location&October13&peaks
analysis.BC_&location&November13&peaks
      analysis.BC_&location&December13&peaks
analysis.BC_&location&January14&peaks
      analysis.BC_&location&February14&peaks
analysis.BC_&location&March14&peaks analysis.BC_&location&April14&peaks
analysis.BC_&location&May14&peaks
      analysis.BC_&location&June14&peaks analysis.BC_&location&July14&peaks
analysis.BC_&location&August14&peaks analysis.BC_&location&September14&peaks
        analysis.BC_&location&October14&peaks;
        Site_ID="&location";
        run;
/*proc contents data=analysis.BC_&location&peaks;
  run;
proc print data=analysis.BC_&location&peaks (OBS=10);
  run;*/
%mend combine_monthsEW_peaks;

/* South Monitor is missing data from July-October 2014 */
%macro combine_monthsS_peaks(location);
%let peaks=_peaks;
data analysis.BC_&location&peaks;
  set analysis.BC_&location&October13&peaks
analysis.BC_&location&November13&peaks
      analysis.BC_&location&December13&peaks
analysis.BC_&location&January14&peaks
      analysis.BC_&location&February14&peaks
analysis.BC_&location&March14&peaks analysis.BC_&location&April14&peaks
analysis.BC_&location&May14&peaks
      analysis.BC_&location&June14&peaks;
        Site_ID="&location";
        run;
/*proc contents data=analysis.BC_&location&peaks;
  run;
proc print data=analysis.BC_&location&peaks (OBS=10);
  run;*/
%mend combine_monthsS_peaks;

/* North Monitor is missing data from October-November 2013 */
```

```
%macro combine_monthsN_peaks(location);
%let peaks=_peaks;
data analysis.BC_&location&peaks;
  set analysis.BC_&location&December13&peaks
analysis.BC_&location&January14&peaks
      analysis.BC_&location&February14&peaks
analysis.BC_&location&March14&peaks analysis.BC_&location&April14&peaks
analysis.BC_&location&May14&peaks
      analysis.BC_&location&June14&peaks analysis.BC_&location&July14&peaks
analysis.BC_&location&August14&peaks analysis.BC_&location&September14&peaks
        analysis.BC_&location&October14&peaks;
        Site_ID="&location";
        run;
/* proc contents data=analysis.BC_&location&peaks;
  run;
proc print data=analysis.BC_&location&peaks (OBS=10);
  run;*/
%mend combine_monthsN_peaks;

/*    Define Names of Months to be used in FIle Names, etc.*/

%let October13=October13;
%let November13=November13;
%let December13=December13;
%let January14=January14;
%let February14=February14;
%let March14=March14;
%let April14=April14;
%let May14=May14;
%let June14=June14;
%let July14=July14;
%let August14=August14;
%let September14=September14;
%let October14=October14;

/*    Run Macros to Produce Yearly Dataset */
%combine_monthsS(South_553_);
%combine_monthsEW(East_559_);
%combine_monthsN(North_560_);
%combine_monthsEW(West_546_);

/*    Run Macros to Produce Yearly Dataset for Peaks */
%combine_monthsS_peaks(South_553_);
%combine_monthsEW_peaks(East_559_);
%combine_monthsN_peaks(North_560_);
%combine_monthsEW_peaks(West_546_);

/*    Calculate Peak Frequencies. */

proc freq data=analysis.bc_south_553__peaks;
  title "Black Carbon Peak Frequencies for South 553";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

proc freq data=analysis.bc_east_559__peaks;
  title "Black Carbon Peak Frequencies for East 559";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

proc freq data=analysis.bc_north_560__peaks;
  title "Black Carbon Peak Frequencies for North 560";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

proc freq data=analysis.bc_west_546__peaks;
  title "Black Carbon Peak Frequencies for West 546";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

/*    Combine sites into a single Peak dataset */
data analysis.BC__peaks;
 set analysis.BC_South_553__peaks analysis.BC_East_559__peaks
analysis.BC_North_560__peaks analysis.BC_West_546__peaks ;
 drop Site_ID;
 run;

/*    Calculate all-site freqencies. Then repeat site-specifc frqunceis fro
large dataset for consistency */
proc freq data=analysis.BC__peaks;
  title "All Sites";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;
proc sort data=analysis.BC__peaks;
  by site;
   run;
proc freq data=analysis.BC__peaks;
/*    Peak Frequncies by site. */
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by site;
  run;


  /**** Flight Event Data ***/

/*    Construct WCX Variables and count the number of each Weight Class. Note
that WgtClass=0 should not exist at this point
      so that WC0=0 for all observations.*/

data analysis.Flight_Events_Weights;
  set analysis.Flight_Events_Weights;
  WC0=0;
  WC1=0;
  WC2=0;
  WC3=0;
  WC4=0;
  if WgtClass=0 then WC0=WC0+1;
  if WgtClass=1 then WC1=WC1+1;
  if WgtClass=2 then WC2=WC2+1;
  if WgtClass=3 then WC3=WC3+1;
  if WgtClass=4 then WC4=WC4+1;
  run;
```

```
proc freq data=analysis.Flight_Events_Weights;;
  table WC0 WC1 WC2 WC3 WC4 WCF;
  run;
/*    We begin the development of variables indicating that an aircraft in a
specific wieght class was present in
      each time segment. We sort by time segment in order to generate the
approiraite varibes, i.e., the total number of aircraft
      identified in each time segment. There may be multiple aircraft of any
given weight class or multiple aircraft of various
      weight classes in a given time segment. Our goal is to identify whether
any aircraft of a given weight class was was noted
      in a time segment. Proc Means does this noting that we output the sums
in weightclass to a dataset named sumwc. The output
      the time segement and the sum of the number of all indetified aircraft
in each time segement. The file is further modified
      to indicate only whther any aircraft of theat weight class was present
in the time segment.*/
proc sort data=analysis.Flight_Events_Weights;
  by Time_Segment;
  run;
proc means data= analysis.Flight_Events_Weights NOPRINT;
  output out=sumwc SUM=;
  var WC1 WC2 WC3 WC4;
  by time_segment;
  run;
data sumwc;
  set sumwc;
  if WC0 > 0 then WC0=1;
  if WC1 > 0 then WC1=1;
  if WC2 > 0 then WC2=1;
  if WC3 > 0 then WC3=1;
  if WC4 > 0 then WC4=1;
  run;
data analysis.sumwc;
  set sumwc;
  run;
proc freq data=analysis.sumwc;
  table WC0 WC1 WC2 WC3 WC4;
  run;
/*    We are now ready to merge this data file with the Peak file.*/


/***************************************************************************
*******************************************
/* Merge Weigh Class Data and Peak Data. Data contained in newfile

  Merged datasets too soon here. Must aggregate over time segments for both
files then merge dta/


****************************************************************************
******************************************  */

  /* Sum ISPEAKx values found in each time_segment*/
proc sort data=analysis.BC__peaks;
  by time_segment;
  run;
proc means data=analysis.BC__peaks noprint;
  output out=sumpeaks sum=;
  var ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by time_segment;
  run;

/****************************************************************************
*************

  Stopped describing code here 5 July 2018


*****************************************************************************
************/

/* Merge Peak Data with Weight Class Data. Clean up by deleting data prior to
time segement 43 and Weight Class =0 */

proc sort data=sumpeaks;
  by time_segment;
  run;
proc sort data=analysis.BC__peaks;
  by time_segment;
  run;

data newfile;
  merge sumpeaks sumwc;
  by time_segment;
  if time_segment < 43 then delete;
  drop wc0;
  run;

proc freq data=newfile;
  title "Merged BC__Peaks and Summed WC Data.";
  table WC1 WC2 WC3 WC4;
  run;

/*    Identify presence of any identifiable aricraft- including UNKNOWN under
WC1. WCX varaibles are
      now indicator varaibels for the presence of that weight aircraft. Work
only with aircraft_present =1
      data.*/

data sumnf;
  set newfile;
  aircraft_present=1;
  if WC1 =. then aircraft_present=0;
  if WC1 > 0 then WC1=1;
  if WC2 > 0 then WC2=1;
  if WC3 > 0 then WC3=1;
  if WC4 > 0 then WC4=1;
  run;
proc freq data=sumnf;
  table aircraft_present;
  run;
```

```
proc sort data=sumnf;
  by time_segment;
  run;
data analysis.BC_Analysis;
  set sumnf;
  run;
proc print data=analysis.BC_Analysis(OBS=30);
  title "BC_Analysis Permanent Dataset";
  run;

/*    The analysis indicated below matches the analysis done for BC.
Reproduce Tables for CPC Data in Report.

      The dataset doanal sums peaks and identifieis Weight Classes. This will
be used in both Heiristic and Logistic Analysis */
data doanal;
  set analysis.BC_Analysis;
  if WC1=1 then wgtclass=1;
  if WC2=1 then wgtclass=2;
  if WC3=1 then wgtclass=3;
  if WC4=1 then wgtclass=4;
  if wgtclass=. then delete;
  if ispeak1=. then delete;
  if ispeak1 > 1 then ispeak1=1;
  if ispeak3 > 1 then ispeak3=1;
  if ispeak4 > 1 then ispeak4=1;
  if ispeak5 > 1 then ispeak5=1;
  if ispeak10 > 1 then ispeak10=1;
  if ispeak15 > 1 then ispeak15=1;
  if ispeak20 > 1 then ispeak20=1;
  if ispeak25 > 1 then ispeak25=1;
  where aircraft_present=1;
  run;

  /*  Determine overall frequencies of peaks over time segments.*/

proc freq data=doanal;
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

  /*  Determine overall frequencies of peaks over time segments for each
Weight Class.*/
proc sort data=doanal;
  by wgtclass;
  run;
proc freq data=doanal;
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by wgtclass;
  run;

/*
         Heuristic Analysis

*/
proc freq data=doanal;
```

```
  title "Overall Aircraft";
  table wc1 wc2 wc3 wc4;
  run;

proc freq data=doanal;
  title "ISPEAK1";
  table wc1 wc2 wc3 wc4;
  where ispeak1=1;
  run;

proc freq data=doanal;
  title "ISPEAK3";
  table wc1 wc2 wc3 wc4;
  where ispeak3=1;
  run;

proc freq data=doanal;
  title "ISPEAK4";
  table wc1 wc2 wc3 wc4;
  where ispeak4=1;
  run;

proc freq data=doanal;
  title "ISPEAK5";
  table wc1 wc2 wc3 wc4;
  where ispeak5=1;
  run;

proc freq data=doanal;
  title "ISPEAK10";
  table wc1 wc2 wc3 wc4;
  where ispeak10=1;
  run;

proc freq data=doanal;
  title "ISPEAK15";
  table wc1 wc2 wc3 wc4;
  where ispeak15=1;
  run;

proc freq data=doanal;
  title "ISPEAK20";
  table wc1 wc2 wc3 wc4;
  where ispeak20=1;
  run;

proc freq data=doanal;
  title "ISPEAK25";
  table wc1 wc2 wc3 wc4;
  where ispeak25=1;
  run;

/*

  Logistic Regression Analysis
  */
proc logistic data=doanal;
  title "ISPEAK1";
  class wgtclass / param=ref;
  model ispeak1 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK3";
  class wgtclass / param=ref;
  model ispeak3 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK4";
  class wgtclass / param=ref;
  model ispeak4 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK5";
  class wgtclass / param=ref;
  model ispeak5 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK10";
  class wgtclass / param=ref;
  model ispeak10 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK15";
  class wgtclass / param=ref;
  model ispeak15 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
```

```
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK20";
  class wgtclass / param=ref;
  model ispeak20 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "ISPEAK25";
  class wgtclass / param=ref;
  model ispeak25 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;
```

Appendix 4- SAS Code for the Analysis of CPC Data

```
/*****************************************************************************
************

SAS Code to produce analysis of PDK CPC Data. This uses previously developed
dataset:

      1. analysis.Flight_Events_Weights
            Data for all FLight Events from early October 2013 to mid-October
2014.

*****************************************************************************
************/


/* Set libname for CPC Data Files'*/

libname CPCSAS 'C:\Working Files\Research\PDK Airport\CPC Data\SAS Files';
libname analysis 'C:\Working Files\Research\PDK Airport\Analysis 2018';



/* Macro to Read Multiple Data files */

/* Ancillary macros. */

  /* time_segments macro
   Takes as input the file infilename, creates Time_Segments based on
Adjusted-Date and Adjusted Time
   and outputs that information to the file outfilename. This is a general
macro that can be called inside another macro,
   e.g., any of the Read_BC macros. */

%macro time_segments(infilename,outfilename);
data &outfilename;
  set &infilename;

  /*  infilename is the name of the nput file contiang the monthly data
            outfilename is the file to receive the modified data.  */

  /*  Perform a series of maniulations to determine whether daylight savings
time corrections must be made.

            EST was in effect from 3 November 2013 to 9 March 2014. The
transition days were those two dates. During
            that time period the times as recorded were accurate. For other
periods, DST was in effect resulting
            in timing being off by one hour. In particular, midnight was
recorded as 1:00:00, 11PM recorded as 23:00:00
            and teh last minute of the day recorded as 0:00:59.*/

  /*  datetime contains the number of days since 1 Jan 1960 with the
fractional part representing the fraction
            of a day associated witht he specific time the sample was taken.
For example, datetime=19654.00069444
            represents 0:01:00 (12:01 AM) on November 2, 2013.
            I have not been able to find a "fractional part" funcsion in SAS
so I just constructed one.*/

    frc_dt=datetime-int(datetime);

/*          This DO group resets the times for the DST time period. */

      if datetime < mdy(11,4,2013) or datetime > mdy(3,9,2014) then do;
        if frc_dt > 1/24 then frc_dt=frc_dt-1/24;

        else if frc_dt <= 1/24 then frc_dt=frc_dt+23/24;

        datetime=int(datetime)+frc_dt;
        end;
/*          The following do conversions to afford assessment of the correct
dates and time. They can be
            removed, but I have elected to leave them in. They are not used
further. */

      yr=year(datetime);
      mnth=month(datetime);
      dy=day(datetime);

      hr=int(frc_dt*24);
      min=int(60*(frc_dt*24-int(frc_dt*24))+0.5);

/*          Correct datetime to begin on midnitht of day 1 of our sampling
(10 Oct 2013.) */
    dt1=(datetime-19641);

/*          Ther are 96 15 minute increments in each day. Calulate which time
segment we are in.
            this allows keying to aircraft operations. */

      dt3=(dt1)*96;
    Time_Segment=int(dt3);

      /* Keep only necessary data but keep a copy of all the other material
handy.
      keep datetime yr mnth dy hr min frc_dt CPCConc Time_Segment; */

      keep datetime CPCConc Time_Segment;
    run;
  %mend;

/* Macro to test the integrity of the Excel Files with respect to
Adjusted_Date and Adjusted_Time */

/*%macro test_data(filename);
proc sort data=&filename;
  by Adjusted_Date Adjusted_Time;
  run;
%mend test_data;*/

/* Macro to determine TPP Values for a given Month contained in filename */
```

```
%macro TPP(filename);
  /* Get mean and standard deveiation for the BC Post Processed Data and
output to filename.

  Mean Value --> CPCConc_Mean
  StDev Value --> CPCConc_Std
  In macro, would use NOTABLE */
proc means data=&filename NOPRINT;
  var CPCConc;
  output out=Means Mean=CPCConc_Mean Std=CPCConc_Std;
  run;
/* Use SAS trick to allow means and standard deveiations to apply to every
observation. */
data Means;
    set Means;
      mrger=1;
      run;
data &filename;
  set &filename;
  mrger=1;
  run;
proc sort Data=Means;
  by mrger;
  run;
proc sort data=&filename;
  by mrger;
  run;
data &filename;
  merge &filename Means;
  by mrger;
  run;
/* Construct TPP values in SAS*/
data &filename;
  set &filename;
  TPP1=0;
  TPP3=0;
  TPP4=0;
  TPP5=0;
  TPP10=0;
  TPP15=0;
  TPP20=0;
  TPP25=0;
  if CPCConc>=CPCConc_Mean+1*CPCConc_Std then TPP1=1;
  if CPCConc>=CPCConc_Mean+3*CPCConc_Std then TPP3=1;
  if CPCConc>=CPCConc_Mean+4*CPCConc_Std then TPP4=1;
  if CPCConc>=CPCConc_Mean+5*CPCConc_Std then TPP5=1;
  if CPCConc>=CPCConc_Mean+10*CPCConc_Std then TPP10=1;
  if CPCConc>=CPCConc_Mean+15*CPCConc_Std then TPP15=1;
  if CPCConc>=CPCConc_Mean+20*CPCConc_Std then TPP20=1;
  if CPCConc>=CPCConc_Mean+25*CPCConc_Std then TPP25=1;
  run;
%mend TPP;

%macro findpeaks(infile);
```

```
  /* Within each Increment of 15 minutes, we sum the peak indicators. If the
sum witin a Increment is greater than or equal to
   one, we identify the Increment as having a peak. */

/* Sum TPP indicator across time_segments. Initialize TPP indicator to zero.
If there is a TPP indicator anywhere in that time_segement,
   then set ispeak to 1 meaning there has been a peak identified. this is
saved in peakfile along with the time_segement. Should store
   month and site with this file as well.*/


proc sort data=&infile;
  by time_segment;
  run;
proc means data=&infile NOPRINT;
  output out=peakfile SUM=;
  var TPP1 TPP3 TPP4 TPP5 TPP10 TPP15 TPP20 TPP25;
  by time_segment;
  run;
data peakfile;
  set peakfile;
  ispeak_1=0;
  if TPP1 > 0 then ispeak_1=1;
  ispeak_3=0;
  if TPP3 > 0 then ispeak_3=1;
  ispeak_4=0;
  if TPP4 > 0 then ispeak_4=1;
  ispeak_5=0;
  if TPP5 > 0 then ispeak_5=1;
  ispeak_10=0;
  if TPP10 > 0 then ispeak_10=1;
  ispeak_15=0;
  if TPP15 > 0 then ispeak_15=1;
  ispeak_20=0;
  if TPP20 > 0 then ispeak_20=1;
  ispeak_25=0;
  if TPP25 > 0 then ispeak_25=1;
  keep time_segment ispeak_1 ispeak_3 ispeak_4 ispeak_5 ispeak_10 ispeak_15
ispeak_20 ispeak_25;
  run;
proc sort data=&infile;
  by time_segment;
  run;
proc sort data=peakfile;
  by time_segment;
  run;
data &infile;
  merge &infile peakfile;
  by time_segment;
  run;
%mend findpeaks;

/* This macro takes data from  the file input, which is the output of other
macros and determines whether a given time segment
   has a TPP of a specific type. The file produced goes into putfile and
contains only the time segment identifier and
```

```
   an indicator of whether a peak of the specific type has occurred in this
time segment. This file will be merged with a
   similar file indicating whether aircraft of a specific weight class had an
operation during this time segment.

   This macro is redundant with findpeaks is the intermediate file is stored.
*/

%macro putpeaks(infile,putfile);
  /* Within each Increment of 15 minutes, we sum the peak indicators. If the
sum witin an Increment is greater than or equal to
   one, we identify the Increment as having a peak. */
proc sort data=&infile;
  by time_segment;
  run;
proc means data=&infile NOPRINT;
  output out=peakfile SUM=;
  var ispeak_1 ispeak_3 ispeak_4 ispeak_5 ispeak_10 ispeak_15 ispeak_20
ispeak_25;
  by time_segment;
  run;
data peakfile;
  set peakfile;
  ispeak1=0;
  if ispeak_1 > 0 then ispeak1=1;
  ispeak3=0;
  if ispeak_3 > 0 then ispeak3=1;
  ispeak4=0;
  if ispeak_4 > 0 then ispeak4=1;
  ispeak5=0;
  if ispeak_5 > 0 then ispeak5=1;
  ispeak10=0;
  if ispeak_10 > 0 then ispeak10=1;
  ispeak15=0;
  if ispeak_15 > 0 then ispeak15=1;
  ispeak20=0;
  if ispeak_20 > 0 then ispeak20=1;
  ispeak25=0;
  if ispeak_25 > 0 then ispeak25=1;

keep time_segment ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20
ispeak25;
  run;
data &putfile;
  set peakfile;
  run;
%mend putpeaks;


/* The macro below reads in data files from specific excel Files To be
generalized */


/* New Generalized Macro to Read all Datasets */
```

```
/*proc print data=CPCSAS.cpc_south_699_October13 (OBS=10);
  run;

proc print data=CPCSAS.october13_east_901 (OBS=10);
  run;*/

%macro read_dataset(location,time);

%time_segments(CPCSAS.cpc_&location&time,CPCSAS.cpc_&location&time);

/*%test_data(CPCSAS.cpc_&location&time);*/
%TPP(CPCSAS.cpc_&location&time);
%findpeaks(CPCSAS.cpc_&location&time);
data CPCSAS.cpc_&location&time;
  set CPCSAS.cpc_&location&time;
  Month="&time";
  run;

%let peaks=_peaks;
%putpeaks(CPCSAS.CPC_&location&time,CPCSAS.CPC_&location&time);
data CPCSAS.CPC_&location&time;
  set CPCSAS.CPC_&location&time;
  Month="&time";
  Site="&location";
  run;
/*proc print data=CPCSAS.CPC_&location&time (OBS=1);
  run;
proc freq data=CPCSAS.CPC_&location&time;
  table ispeak1 ispeak3 ispeak5;
  run;*/
%mend read_dataset;

/* Need to pass these two arguments to read_dataset macro */

/*     Call to read_dataset. In order for this to run propoerly, the datasets
in:
       C:\Working Files\Research\PDK Airport\CPC Data\SAS Files\Full Monthly
Data for Each Sitefor All Sites
       must be used. the datasets in the main CPCSAS directory have been
moified to remove extranous variables btu
       do not contain the varaibles needed to make the finalized dataset.  PBR
9 Jul 2018*/

/* South */

%let location_monitor=South_699_;

%read_dataset(&location_monitor,October13);
%read_dataset(&location_monitor,November13);
%read_dataset(&location_monitor,December13);
%read_dataset(&location_monitor,January14);
%read_dataset(&location_monitor,February14);
%read_dataset(&location_monitor,March14);
%read_dataset(&location_monitor,April14);
%read_dataset(&location_monitor,May14);
%read_dataset(&location_monitor,June14);
```

```
%read_dataset(&location_monitor,July14);
%read_dataset(&location_monitor,August14);
%read_dataset(&location_monitor,September14);
%read_dataset(&location_monitor,October14);


/* East */

%let location_monitor=East_901_;

/* Call to read_dataset */
%read_dataset(&location_monitor,October13);
%read_dataset(&location_monitor,November13);
%read_dataset(&location_monitor,December13);
%read_dataset(&location_monitor,January14);
%read_dataset(&location_monitor,February14);
%read_dataset(&location_monitor,March14);
%read_dataset(&location_monitor,April14);
/*%read_dataset(&location_monitor,May14);*/
%read_dataset(&location_monitor,June14);
%read_dataset(&location_monitor,July14);
%read_dataset(&location_monitor,August14);
%read_dataset(&location_monitor,September14);
%read_dataset(&location_monitor,October14);

/* North */

%let location_monitor=North_499_;

/* Call to read_dataset */
%read_dataset(&location_monitor,October13);
%read_dataset(&location_monitor,November13);
%read_dataset(&location_monitor,December13);
%read_dataset(&location_monitor,January14);
%read_dataset(&location_monitor,February14);
/*%read_dataset(&location_monitor,March14);*/
%read_dataset(&location_monitor,April14);
%read_dataset(&location_monitor,May14);
%read_dataset(&location_monitor,June14);
/*%read_dataset(&location_monitor,July14);*/
%read_dataset(&location_monitor,August14);
%read_dataset(&location_monitor,September14);
%read_dataset(&location_monitor,October14);


/* West */

%let location_monitor=West_698_;

/* Call to read_dataset */
%read_dataset(&location_monitor,October13);
%read_dataset(&location_monitor,November13);
%read_dataset(&location_monitor,December13);
%read_dataset(&location_monitor,January14);
%read_dataset(&location_monitor,February14);
%read_dataset(&location_monitor,March14);
```

```
%read_dataset(&location_monitor,April14);
%read_dataset(&location_monitor,May14);
%read_dataset(&location_monitor,June14);
%read_dataset(&location_monitor,July14);
%read_dataset(&location_monitor,August14);
%read_dataset(&location_monitor,September14);
%read_dataset(&location_monitor,October14);




/* Macro to combine all months into one site-specific permanent Sas Data
set.*/

%let October13=October13;
%let November13=November13;
%let December13=December13;
%let January14=January14;
%let February14=February14;
%let March14=March14;
%let April14=April14;
%let May14=May14;
%let June14=June14;
%let July14=July14;
%let August14=August14;
%let September14=September14;
%let October14=October14;

/*          Because each site is different with respect to number of months
of data available,
            and the macro is alread written to comnbine months, repeat teh
macro at each location */

/*          All months are available for South 699  */

%macro combine_months(location);
data cpcsas.cpc_&location;
  set cpcsas.cpc_&location&October13 cpcsas.cpc_&location&November13
cpcsas.cpc_&location&December13 cpcsas.cpc_&location&January14
      cpcsas.cpc_&location&February14 cpcsas.cpc_&location&March14
cpcsas.cpc_&location&April14 cpcsas.cpc_&location&May14
      cpcsas.cpc_&location&June14 cpcsas.cpc_&location&July14
cpcsas.cpc_&location&August14 cpcsas.cpc_&location&September14
        cpcsas.cpc_&location&October14
        ;

        run;
/*proc contents data=cpcsas.cpc_&location;
  run;
proc print data=cpcsas.cpc_&location (OBS=10);
  run;*/
%mend combine_months;


%combine_months(South_699_);
```

```
/*          East 901 has no data for May 2014 */

%macro combine_months(location);
data cpcsas.cpc_&location;
  set cpcsas.cpc_&location&October13 cpcsas.cpc_&location&November13
cpcsas.cpc_&location&December13 cpcsas.cpc_&location&January14
      cpcsas.cpc_&location&February14 cpcsas.cpc_&location&March14
cpcsas.cpc_&location&April14 /*cpcsas.cpc_&location&May14 */
      cpcsas.cpc_&location&June14 cpcsas.cpc_&location&July14
cpcsas.cpc_&location&August14 cpcsas.cpc_&location&September14
        cpcsas.cpc_&location&October14
        ;

        run;
/*proc contents data=cpcsas.cpc_&location;
  run;
proc print data=cpcsas.cpc_&location (OBS=10);
  run;*/
%mend combine_months;

%combine_months(East_901_);


/*          North 499 has no data for March 2014 and July 2014*/

%macro combine_months(location);
data cpcsas.cpc_&location;
  set cpcsas.cpc_&location&October13 cpcsas.cpc_&location&November13
cpcsas.cpc_&location&December13 cpcsas.cpc_&location&January14
      cpcsas.cpc_&location&February14 /*cpcsas.cpc_&location&March14*/
cpcsas.cpc_&location&April14 cpcsas.cpc_&location&May14
      cpcsas.cpc_&location&June14 /*cpcsas.cpc_&location&July14*/
cpcsas.cpc_&location&August14 cpcsas.cpc_&location&September14
        cpcsas.cpc_&location&October14
        ;

        run;
/*proc contents data=cpcsas.cpc_&location;
  run;
proc print data=cpcsas.cpc_&location (OBS=10);
  run;*/
%mend combine_months;

%combine_months(North_499_);


/*          All months are available for West 698  */

%macro combine_months(location);
data cpcsas.cpc_&location;
  set cpcsas.cpc_&location&October13 cpcsas.cpc_&location&November13
cpcsas.cpc_&location&December13 cpcsas.cpc_&location&January14
      cpcsas.cpc_&location&February14 cpcsas.cpc_&location&March14
cpcsas.cpc_&location&April14 cpcsas.cpc_&location&May14
```

```
      cpcsas.cpc_&location&June14 cpcsas.cpc_&location&July14
cpcsas.cpc_&location&August14 cpcsas.cpc_&location&September14
        cpcsas.cpc_&location&October14
        ;

        run;
/*proc contents data=cpcsas.cpc_&location;
  run;
proc print data=cpcsas.cpc_&location (OBS=10);
  run;*/
%mend combine_months;

%combine_months(West_698_);




%macro peakfreq(location);
proc sort data=CPCSAS.cpc_&location;
  by month;
  run;
proc freq data=CPCSAS.cpc_&location;
  title "Peak Frequencies by Month and Location S, E, N, W";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by month;
  run;
%mend peakfreq;

%peakfreq(South_699_);
%peakfreq(East_901_);
%peakfreq(North_499_);
%peakfreq(West_698_);

/* Combine to form one Dataset */
data CPCSAS.CPC_peaks;
  set CPCSAS.CPC_South_699_ CPCSAS.CPC_East_901_ CPCSAS.CPC_North_499_
CPCSAS.CPC_West_698_;
  /*  Remove test data at the beginning of ocotber 2013 and extra data as
sites were decommisioned in OCtober 2014*/
  if time_segment < 1 or time_segment > 35040 then delete;
  run;

/*    Calculate Peak frequencies over all sites. */
proc freq data=CPCSAS.CPC_peaks ;
  title "All Sites";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

  /*proc means data=CPCSAS.CPC_peaks;
  var time_segment;
  run;

data CPCSAS.CPC_peaks;
  set CPCSAS.CPC_peaks;
  if time_segment < 1 or time_segment > 35040 then delete;
  run;
```

```
proc print data=CPCSAS.CPC_peaks (OBS=10);
  run;
proc means data=CPCSAS.CPC_peaks;
  var time_segment;
  run;*/


/*    Calculate Peak frequencies for each site. */
proc sort data=CPCSAS.CPC_peaks;
  by site;
   run;
proc freq data=CPCSAS.CPC_peaks;
  title "Peak Frequencies by Site";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by site;
  run;

  /* Accumulate across all sites for each Time_Segement. */
proc sort data=cpcsas.cpc_peaks;
  by time_segment;
  run;

  proc means data=cpcsas.cpc_peaks NOPRINT;
  output out=sumcpc_peaks SUM=;
  var ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by time_segment;
  run;

  proc sort data=sumcpc_peaks;
    by time_segment;
      run;

proc freq data=sumcpc_peaks;
  title "Summed Peak Frequencies";
    table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20
ispeak25;
      run;

/*    Now we note if there is a peak at only of the locations. If we note a
peak in one or more locations,
      we set the indicator varible. ispeak=1 mens that there is a peak of
this magnitude somewhere on the
      airport grounds. For this analysis we do not care where. Put this in:
CPCSAS.sumcpc_peaks
      */

 data CPCSAS.sumcpc_peaks;
   set sumcpc_peaks;
   if ispeak1 >=1 then ispeak1=1;
   if ispeak3 >=1 then ispeak3=1;
   if ispeak4 >=1 then ispeak4=1;
   if ispeak5 >=1 then ispeak5=1;
   if ispeak10 >=1 then ispeak10=1;
   if ispeak15 >=1 then ispeak15=1;
   if ispeak20 >=1 then ispeak20=1;
   if ispeak25 >=1 then ispeak25=1;
   if time_segment <43 or time_segment > 35040 then delete;
   run;

/* Produce a table indicating presence of a peak in each time segment.*/

proc freq data=CPCSAS.sumcpc_peaks;
  title 'CPCSAS.sumcpc_peaks';
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;
/*proc print data=CPCSAS.sumcpc_peaks (OBS=30);
  run;*/

/*****************************************************************************
*******************

      Begin combining datesets for Weight Classes, determined previously and
stored in libname
      analysis = 'C:\Working Files\Research\PDK Airport\Analysis 2018'

******************************************************************************
*******************/

 /* Sum ISPEAKx values found in each time_segment*/

proc means data=CPCSAS.sumcpc_peaks noprint;
  output out=sumpeaks sum=;
  var ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by time_segment;
  run;

/* Merge Peak Data with Weight Class Data. Clean up by deleting data prior to
time segement 43 and Weight Class =0 */

libname analysis 'C:\Working Files\Research\PDK Airport\Analysis 2018\Flight
Event Data';

data sumwc;
  set analysis.sumwc;
  run;
proc freq data=sumwc;
  table WC0 WC1 WC2 WC3 WC4;
  run;

proc sort data=sumwc;
  by time_segment;
  run;

  proc sort data=sumpeaks;
  by time_segment;
  run;

data newfile;
  merge sumpeaks sumwc;
  by time_segment;
  if time_segment < 43 then delete;
  drop wc0;
  run;

proc freq data=newfile;
  title "Merged CPC Peaks and Summed WC Data.";
  table WC1 WC2 WC3 WC4;
  run;

/*    Identify presence of any identifiable aricraft- including UNKNOWN under
WC1. WCX varaibles are
      now indicator varaibels for the presence of that weight aircraft. Work
only with aircraft_present =1
      data.*/

data sumnf;
  set newfile;
  aircraft_present=1;
  if WC1 =. then aircraft_present=0;
  if WC1 > 0 then WC1=1;
  if WC2 > 0 then WC2=1;
  if WC3 > 0 then WC3=1;
  if WC4 > 0 then WC4=1;
  run;
proc freq data=sumnf;
  title "Aircraft Present=1 Not Present=0";
  table aircraft_present;
  run;

proc sort data=sumnf;
  by time_segment;
  run;
data CPCSAS.CPC_Analysis;
  set sumnf;
  run;
/*proc print data=CPCSAS.CPC_Analysis(OBS=30);
  title "CPC Analysis Permanent Dataset";
  run;/*

/*    The analysis indicated below matches the analysis done for BC.
Reproduce Tables for CPC Data in Report.

      The dataset doanal sums peaks and identifieis Weight Classes. This will
be used in both Heiristic and Logistic Analysis */
data doanal;
  set CPCSAS.CPC_Analysis;
  if WC1=1 then wgtclass=1;
  if WC2=1 then wgtclass=2;
  if WC3=1 then wgtclass=3;
  if WC4=1 then wgtclass=4;
  if wgtclass=. then delete;
  if ispeak1=. then delete;
  if ispeak1 > 1 then ispeak1=1;
  if ispeak3 > 1 then ispeak3=1;
  if ispeak4 > 1 then ispeak4=1;
  if ispeak5 > 1 then ispeak5=1;
  if ispeak10 > 1 then ispeak10=1;
  if ispeak15 > 1 then ispeak15=1;
  if ispeak20 > 1 then ispeak20=1;
  if ispeak25 > 1 then ispeak25=1;
  where aircraft_present=1;
  run;

  /*  Determine overall frequencies of peaks over time segments.*/

proc freq data=doanal;
  title "Peak Frequencies All Time Segments";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  run;

  /*  Determine overall frequencies of peaks over time segments for each
Weight Class.*/
proc sort data=doanal;
  by wgtclass;
  run;
proc freq data=doanal;
  title "Peak Frequencies by Weight Class";
  table ispeak1 ispeak3 ispeak4 ispeak5 ispeak10 ispeak15 ispeak20 ispeak25;
  by wgtclass;
  run;

/*
         Heuristic Analysis

*/
proc freq data=doanal;
  title "Heuristic Analysis- Overall Aircraft";
  table wc1 wc2 wc3 wc4;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK1";
  table wc1 wc2 wc3 wc4;
  where ispeak1=1;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK3";
  table wc1 wc2 wc3 wc4;
  where ispeak3=1;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK4";
  table wc1 wc2 wc3 wc4;
  where ispeak4=1;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK5";
  table wc1 wc2 wc3 wc4;
  where ispeak5=1;
  run;
```

```
proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK10";
  table wc1 wc2 wc3 wc4;
  where ispeak10=1;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK15";
  table wc1 wc2 wc3 wc4;
  where ispeak15=1;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK20";
  table wc1 wc2 wc3 wc4;
  where ispeak20=1;
  run;

proc freq data=doanal;
  title "Heuristic Analysis- ISPEAK25";
  table wc1 wc2 wc3 wc4;
  where ispeak25=1;
  run;

/*

  Logistic Regression Analysis

  */
proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK1";
  class wgtclass / param=ref;
  model ispeak1 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK3";
  class wgtclass / param=ref;
  model ispeak3 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK4";
  class wgtclass / param=ref;
  model ispeak4 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK5";
  class wgtclass / param=ref;
  model ispeak5 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK10";
  class wgtclass / param=ref;
  model ispeak10 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK15";
  class wgtclass / param=ref;
  model ispeak15 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK20";
  class wgtclass / param=ref;
  model ispeak20 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Logistic Analysis- ISPEAK25";
  class wgtclass / param=ref;
  model ispeak25 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;
```

Appendix 5- SAS Code for the Analysis of Noise Data

```
/***************************************************************************
****

      Analysis of All Noise Data July 2018

***************************************************************************
***/

/*    All work for Noise analysis will be done using the noise libname*/
libname noise "C:\Working Files\Research\PDK Airport\Noise Work\SAS Files";


/*    Read in the Noise Data from Single File defined as dataset. The file
ddataset is an MSExcel file containg all
      relevnat data as obtianed from PDK airport staff. Monthly data have
been placed in separate worksheets in the
      singel file dataset*/

%let dataset="C:\Working Files\Research\PDK Airport\Noise Work\SAS Files\Full
Study Noise Data.xlsx";


/*    Thisis a simple macro to read each month;s data in. Note that the
maximum number of observations in a
      given month is 5826 in September 2014. The read allows up tp 6000 (See
"range" below. This will need to be increased
      if more data are evident in any month.

      The month name is passed in as an argument and is appended to the
dataset as "Monitoring Month. Will consider
      changing this from Oct13 to 1310, 1311, 1312, 1401, 1402, etc. to get
proper ordering. DONE

      Output file is noise.&month, e.g, noise.Oct13  */
%macro read_month(month,yearmonth);
proc import datafile=&dataset
       out=noise.&month DBMS=xlsx REPLACE;
/* Make range long enough to ensure all data are read. */
      range="&month$a1:j6500";
   getnames=Yes;
   run;
data noise.&month;
  set noise.&month;
  Month_Ind=&yearmonth;
  run;
%mend read_month;

/*    Read each month*/
%read_month(Oct13,1310);
%read_month(Nov13,1311);
%read_month(Dec13,1312);
%read_month(Jan14,1401);
%read_month(Feb14,1402);
```

```
%read_month(Mar14,1403);
%read_month(Apr14,1404);
%read_month(May14,1405);
%read_month(Jun14,1406);
%read_month(Jul14,1407)
%read_month(Aug14,1408);
%read_month(Sep14,1409);
/*%read_month(Oct14,1410);*/

/*    Combine all months to produce a single dataset. noise.alldata */
data noise.alldata;
  set       noise.Oct13 noise.Nov13 noise.Dec13 noise.Jan14 noise.Feb14
noise.Mar14
            noise.Apr14 noise.May14 noise.Jun14 noise.Jul14 noise.Aug14
noise.Sep14
            /*noise.Oct14*/;
  run;

/*    Using the value LMAX, contruct noise categories for all events using
the following table of values:

      if LMAX > 90 then noise_category=6;
      else if LMAX > 85 and < 90 then noise_category=5;
      else if LMAX > 80 and < 85 then noise_category=4;
      else if LMAX > 75 and < 80 then noise_category=3;
      else if LMAX > 70 and < 75 then noise_category=2;
      else noise_category=1;*/
data noise.alldata;
  set noise.alldata;
  noise_category=-1;
  if LMAX > 90 then noise_category=6;
  else if LMAX > 85 then noise_category=5;
  else if LMAX > 80 then noise_category=4;
  else if LMAX > 75 then noise_category=3;
  else if LMAX > 70 then noise_category=2;
  else noise_category=1;
  run;

proc freq data=noise.alldata;
  table noise_category;
  run;

proc sort data=noise.alldata;
  by month_ind;
  run;
proc freq data=noise.alldata;
  table noise_category;
  by month_ind;
  run;

/*    Task is now to identify unique Equipment Types. This allows merger of
Weights*/


/*    Note that date___time has three underscore lines between the words.
      Sort by date and time. This will be used to calcualte segments later.*/
```

```
proc sort data=noise.alldata;
  by date___time;
  run;

/*    Look at varous cuts on the data. "look" files are intemediare and will
be converted to permanet files as needed.

      This code will be used to eliminate multiple noise monitors picking up
the same aircraft.*/
data look;
  set noise.alldata;
  same_aircraft=0;
  if Flight_Num=lag(Flight_Num) then same_aircraft=1;
  run;
proc freq data=look;
  table same_aircraft;
  run;



/*    Now look for unique aircraft equipment types. There are a realtively
small number of them ~300- that are then converted
      to MTOW and identified with specific Tail Numbers.

      First, determine the unique equipment types in the noise data.



/*    Now look for unique aircraft equipment types. There are a realtively
small number of them ~300- that are then converted
      to MTOW and identified with specific Tail Numbers.

      First, determine the unique equipment types in the noise data.

  */

proc sort data=noise.alldata;
  by equip;
  run;
data noise_unique_equip;
  set noise.alldata;
  if lag(equip)=equip then delete;
  keep equip;
  run;
proc print data=noise_unique_equip (OBS=30);
  run;

/*    The permanent file analysis.flight_event_weights has the most complete
listing of eqipment types and weights. Use it to
      Use it to detemine weights of aircraft.*/

libname analysis 'C:\Working Files\Research\PDK Airport\Analysis 2018';

data best_equip_wgt;
  set analysis.Flight_event_Weights;
  keep equip wgt;
  run;
proc sort data=best_equip_wgt;
  by equip;
  run;
data best_equip_wgt;
  set best_equip_wgt;
  if lag(equip)=equip then delete;
  run;
proc print data=best_equip_wgt (OBS=30);
  run;

/*    Sort and merge these two files together*/

proc sort data=noise_unique_equip;
  by equip;
  run;
proc sort data=best_equip_wgt;
  by equip;
  run;
data noise_equip_wgt;
  merge noise_unique_equip best_equip_wgt;
  by equip;
  run;

/*    There are wo equipment types found in the noise data for which there is
no MTOW data. These are:
                  N187MG      C25 10,700 lb from existing information on
N187MG
                  N7ZD  C400 3,400 lb from existing information on N7ZD

      */

/*    Merge the noise_equip_wgt database with the noaise_alldata database and
store as a permanent dataset. */
proc sort data=noise.alldata;
  by equip;
  run;
proc sort data=noise_equip_wgt;
  by equip;
  run;
data noise_equip_wgt_alldata;
  merge noise.alldata noise_equip_wgt;
  by equip;
/*    Fix two Missing Weights in Database. */
  if Flight_Num=Flight_Num='N7ZD' then wgt=3400;
  if Flight_Num=Flight_Num='N187MG' then wgt=1070;
  run;

/*    Clean up observations for no equipment, helicopters, and blimps.*/
data noise_equip_wgt_alldata;
  set noise_equip_wgt_alldata;
  if wgt = -998 or wgt = -997  then delete;
/* Some equipment types were not found in the noise data. If they are not in
the data they can be deleted.*/
  if Month_Ind=. then delete;
  run;
/*    Seem to have lost information on two aricraft with undefined equipment
types. Must find.  FOUND*/

proc sort data=noise_equip_wgt_alldata;
  by date___time;
  run;


/*    Reset weights for UNKNOWN to zero. They wil be modified later. */
data noise_equip_wgt_alldata;
  set noise_equip_wgt_alldata;
  if Flight_Num='UNKNOWN' then wgt=2500;
  run;

/*    All noise events have been identified and the MTOW of the aircraft
involved has been specified. Note that that UNKNOWN aircraft have been
      arbtratily assigned a weight of 2500*/
proc means data=noise_equip_wgt_alldata;
  var wgt;
  where Flight_Num='UNKNOWN';
  run;

data noise_equip_wgt_alldata;
  set noise_equip_wgt_alldata;
  if wgt >= 0 and wgt <= 25000 then WgtClass = 1;
  if wgt > 25000 and wgt <= 66000 then WgtClass = 2;
  if wgt > 66000 and wgt <= 75000 then WgtClass = 3;
  if wgt > 75000 then WgtClass = 4;

/* Create a new more finely divided weight class designation in cae Open
DeKalb requests further analysis.  */

  WCF=-1;
  if wgt=-999 then WCF=0;
  if wgt > 0 and wgt <= 2500 then WCF = 1;
  if wgt > 2500 and wgt <= 5000 then WCF = 2;
  if wgt > 5000 and wgt <= 10000 then WCF = 3;
  if wgt > 10000 and wgt <= 20000 then WCF = 4;
  if wgt > 20000 and wgt <= 40000 then WCF = 5;
  if wgt > 40000 and wgt <= 66000 then WCF = 6;
  if wgt > 66000 and wgt <= 75000 then WCF = 7;
  if wgt > 75000 then WCF = 8;
  NC1=0;
  NC2=0;
  NC3=0;
  NC4=0;
  NC5=0;
  NC6=0;
  if noise_category=1 then nc1=1;
  if noise_category=2 then nc2=1;
  if noise_category=3 then nc3=1;
  if noise_category=4 then nc4=1;
  if noise_category=5 then nc5=1;
  if noise_category=6 then nc6=1;
  run;
```

```
/*    Keep as permanent dataset */
data noise.noise_wgt;
  set noise_equip_wgt_alldata;
  run;
proc contents data=noise.noise_wgt;
  run;

/*    Commence Analysis of Noise Events by Wgt Class and Noise Category.

      Get local copy of Noise Events by Wgt Class and Noise Category. */

data doanal;
  set noise.noise_wgt;
  run;

/*    Heuristic Analysis*/

proc freq data=doanal;
  title 'Frequency of Noise Events by Weight Class';
  table WgtClass;
  run;
proc freq data=doanal;
    title 'Frequency of Noise Category';
  table noise_category;
  run;
proc sort data=doanal;
  by noise_category;
  run;
proc freq data=doanal;
  title 'Frequency of Noise Events by Noise Category';
  table WgtClass;
  by noise_category;
  run;

/*

  Logistic Regression Analysis

  */

proc logistic data=doanal;
  title "Noise Category 1";
  class wgtclass nc1/ param=ref;
  model nc1 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Noise Category 2";
  class wgtclass nc2/ param=ref;
  model nc2 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
```

```
        contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
        contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
        contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
           run;

proc logistic data=doanal;
  title "Noise Category 3";
  class wgtclass nc3/ param=ref;
  model nc3 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Noise Category 4";
  class wgtclass nc4/ param=ref;
  model nc4 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Noise Category 5";
  class wgtclass nc5/ param=ref;
  model nc5 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc logistic data=doanal;
  title "Noise Category 6";
  class wgtclass nc6/ param=ref;
  model nc6 (descending)=wgtclass;
    contrast 'WgtClass=1 vs WgtClass=2' wgtclass 1 1 0;
      contrast 'WgtClass=1 vs WgtClass=3' wgtclass 1 0 1;
      contrast 'WgtClass=2 vs WgtClass=3' wgtclass  0 1 1;
      contrast "WgtClass  1, 2, 3" wgtclass 1 1 1 ;
         run;

proc export data=doanal
  outfile="C:\Working Files\Research\PDK Airport\Noise Work\SAS
Files\doanal.csv"
  DBMS=csv
  REPLACE;
  run;
```

Appendix 6- Analysis of Noise Data by Month

October 2113

The FREQ Procedure
Month_Ind=1310

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1354	23.65	1354	23.65
2	1989	34.75	3343	58.40
3	1001	17.49	4344	75.89
4	1073	18.75	5417	94.64
5	275	4.80	5692	99.44
6	32	0.56	5724	100.00

November 2013 6

The FREQ Procedure
Month_Ind=1311

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1125	24.00	1125	24.00
2	1658	35.37	2783	59.36
3	852	18.17	3635	77.54
4	794	16.94	4429	94.48
5	227	4.84	4656	99.32
6	32	0.68	4688	100.00

December 2013 6

The FREQ Procedure
Month_Ind=1312

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1030	22.71	1030	22.71
2	1485	32.74	2515	55.45
3	854	18.83	3369	74.27
4	865	19.07	4234	93.34
5	261	5.75	4495	99.10
6	41	0.90	4536	100.00

January 2014

The FREQ Procedure
Month_Ind=1401

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	971	20.67	971	20.67
2	1667	35.48	2638	56.15
3	910	19.37	3548	75.52
4	848	18.05	4396	93.57
5	276	5.87	4672	99.45
6	26	0.55	4698	100.00

February 2014

The FREQ Procedure
Month_Ind=1402

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	839	21.04	839	21.04
2	1548	38.83	2387	59.87
3	759	19.04	3146	78.91
4	628	15.75	3774	94.66
5	190	4.77	3964	99.42
6	23	0.58	3987	100.00

March 2014

The FREQ Procedure
Month_Ind=1403

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	986	21.58	986	21.58
2	1724	37.74	2710	59.33
3	876	19.18	3586	78.50
4	728	15.94	4314	94.44
5	223	4.88	4537	99.32
6	31	0.68	4568	100.00

April 2014

The FREQ Procedure
Month_Ind=1404

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	935	20.93	935	20.93
2	1269	28.41	2204	49.34
3	596	13.34	2800	62.68
4	1496	33.49	4296	96.17
5	147	3.29	4443	99.46
6	24	0.54	4467	100.00

May 2014

The FREQ Procedure
Month_Ind=1405

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1362	22.04	1362	22.04
2	2305	37.29	3667	59.33
3	1019	16.49	4686	75.81
4	1145	18.52	5831	94.34
5	305	4.93	6136	99.27
6	45	0.73	6181	100.00

June 2014

The FREQ Procedure
Month_Ind=1406

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1199	22.96	1199	22.96
2	1852	35.47	3051	58.43
3	897	17.18	3948	75.60
4	982	18.81	4930	94.41
5	267	5.11	5197	99.52
6	25	0.48	5222	100.00

July 2014

The FREQ Procedure
Month_Ind=1407

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	916	20.07	916	20.07
2	1594	34.93	2510	55.00
3	803	17.59	3313	72.59
4	954	20.90	4267	93.49
5	265	5.81	4532	99.30
6	32	0.70	4564	100.00

August 2014

The FREQ Procedure
Month_Ind=1408

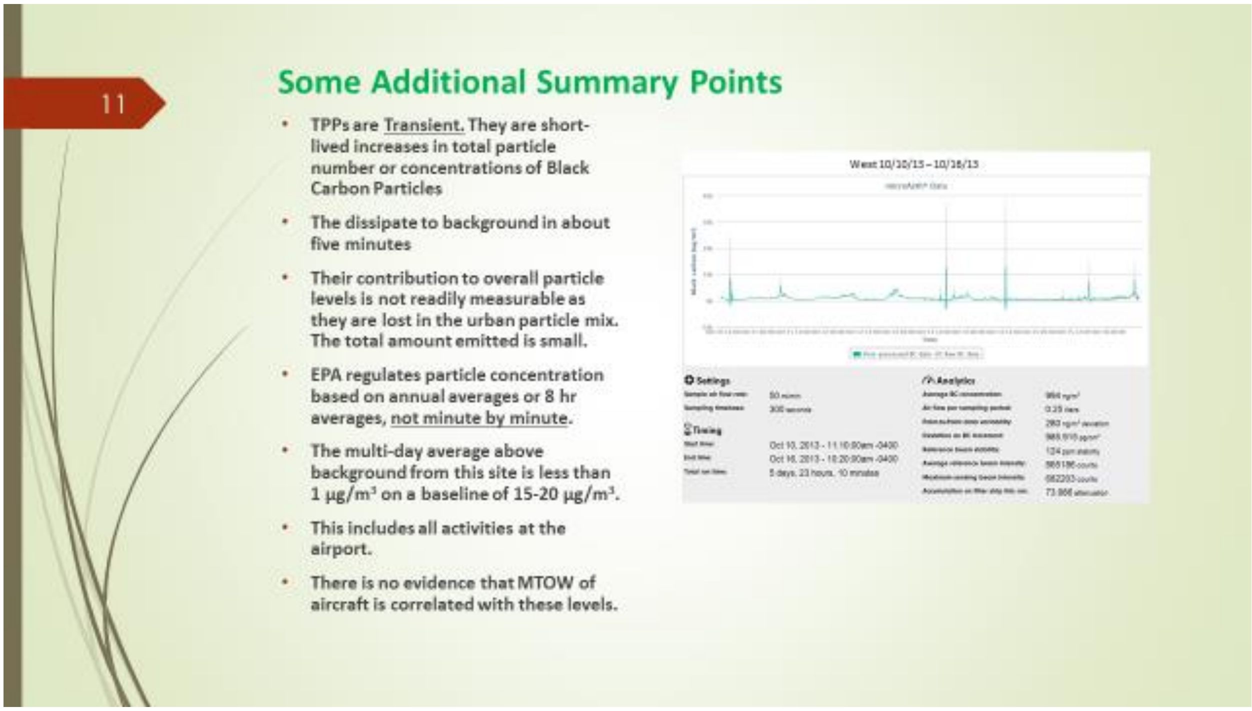
noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1337	26.09	1337	26.09
2	1753	34.20	3090	60.29
3	800	15.61	3890	75.90
4	933	18.20	4823	94.11
5	263	5.13	5086	99.24
6	39	0.76	5125	100.00

September 2014

The FREQ Procedure
Month_Ind=1409

noise_category	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1281	25.52	1281	25.52
2	1737	34.61	3018	60.13
3	854	17.02	3872	77.15
4	869	17.31	4741	94.46
5	250	4.98	4991	99.44
6	28	0.56	5019	100.00

Appendix 7 – Supplemental Information



Some Additional Summary Points

- TPPs are Transient. They are short-lived increases in total particle number or concentrations of Black Carbon Particles
- The dissipate to background in about five minutes
- Their contribution to overall particle levels is not readily measurable as they are lost in the urban particle mix. The total amount emitted is small.
- EPA regulates particle concentration based on annual averages or 8 hr averages, not minute by minute.
- The multi-day average above background from this site is less than 1 µg/m³ on a baseline of 15-20 µg/m³.
- This includes all activities at the airport.
- There is no evidence that MTOW of aircraft is correlated with these levels.

West 10/10/13 – 10/16/13
Settings
50 ml/min
300 seconds
Timing
Oct 10, 2013 - 11:10:00am -0400
Oct 16, 2013 - 10:20:00am -0400
5 days, 23 hours, 10 minutes
Analytics

- The TPPs, themselves, are transient. The peaks are sharp, and short in duration, lasting no more than about five minutes before values return to background level. The overall contribution to particles in the air is not readily measurable as they are soon lost as part of the full urban mix of air contaminants.
- The transient nature of these peaks is not reflected in regulatory strategies. EPA regulates particulate matter based on annual averages or, at very high levels, eight-hour averages. Transients contribute to the long-term averages, but only in a marginal way.
- The multiday average above suggests that the total Black Carbon measured amounts to about 1 µg/m^3 over the time period indicated. This is typical of urban areas overall. Averages at the airport are no higher than averages across the city.

Weight Class Identifier	Description (MTOW)	N	Fraction of Total
-1	Non-Fixed Wing	137	0.13%
0	Unknown*	37,447	35.62%
1	MTOW < 25,000 lbs	52,302	52.14%
2	25,000 lb < MTOW < 66,000 lbs	9,645	9.43%
3	66,000 lbs < MTOW < 75,000 lbs	1,786	1.75%
4	MTOW > 75,000 lbs	948	0.93%

*Analysis requested by Open DeKalb

Table APP-1. Weigh Classifications for 102,265 Flight Events

Site Identifier	Number of Observations	Fraction of Observations
West_546	728,542	28.3%
South_553	408,553	15.9%
East_559	680,061	26.4%
North_560	756,675	39.4%
Total Black Carbon	**2,574,235**	

Table APP-2. Black Carbon data. Data collected in six-day cycles. Compiled by Month of 13 months (October 2013 – October 2014, October 2013 and October 2014 are partial months.)

Site Identifier	Number of Observations	Fraction of Observations
West_698	433,559	26.7%
South_699	404,773	24.9%
East_901	447,640	27.5%
North_499	339,943	20.9%
Total Black Carbon	**1,634,915**	

Table APP-3. Condensation Particle Counter (CPC) data. Data collected in one-day cycles. Compiled by Month of 13 months (October 2013 – October 2014, October 2013 and October 2014 are partial months.)