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Derivation and Use of Simple Relationships between Aerodynamic and Optical Particle Measurements

Kori D. Moore¹; Randal S. Martin²; William J. Bradford³; Christian C. Marchant⁴; Derek S. Jones⁵; Michael D. Wojcik⁶; Richard L. Pfeiffer⁷; John H. Prueger⁸; and Jerry L. Hatfield⁹

Abstract: A simple relationship, referred to as a mass conversion factor (MCF), is presented to convert optically based particle measurements to mass concentration. It is calculated from filter-based samples and optical particle counter (OPC) data on a daily or sample period basis. The MCF allows for greater temporal and spatial mass concentration information than typical filter-based measurements. Results of MCF calculations from several field studies are summarized. Pairwise comparisons from a collocated study with multiple OPCs and mass samplers suggest the minimum variability of the MCF is 5–10%. The variability of the MCF within a sample period during a field study with distributed samplers averaged 17–21%. In addition, the precision of the Airmetrics MiniVol Portable Air Sampler for particulate matter (PM) was typically ≤10%. Comparisons with federal reference method (FRM) samplers showed that MiniVols yield PM2.5 concentrations essentially equivalent to FRMs with slightly greater deviations from the FRM for PM10 under tested ambient conditions. DOI: 10.1061/(ASCE)EE.1943-7870.00000893. © 2014 American Society of Civil Engineers.

Author keywords: Air pollution; Particles; Monitoring; Instrumentation; Calibration; Remote sensing.

Introduction

Many different properties can be used to describe a single particle. These include shape, chemical speciation, density, index of refraction, aerodynamic diameter, optical diameter, and so on. Numerous measurement techniques have been developed to quantify various properties, although most are capable of measuring only one or two properties. Comparisons between simultaneous measurements of an aerosol mixture made using different techniques may provide valuable information about relationships between the measurement methodologies and the measured properties, as well as additional information not measured.

Estimating specific particle properties even from a combination of measurement techniques may be challenging both theoretically and in practice. For example, Schmid et al. (2007) provides a detailed explanation of mathematical relationships between density, shape, effective density, and various equivalent diameters for spherical and nonspherical particles. Deriving a property from such methods requires significant investment in equipment, as well as knowledge or assumptions of other pertinent particle properties. However, comparisons between two or more measurement techniques may be made in order to derive an empirical relationship that incorporates all applicable properties into a more simple expression. While this method does not provide insight into the values of specific properties, it can be very useful in calibrating the output of a sensor to provide information not directly measured, such as the calibration of an optical particle counter (OPC) to provide particulate matter (PM) mass concentration. A significant advantage of an OPC over typical filter-based mass samplers is that the OPC can provide a much more temporally resolved dataset and may yield valuable information about changes in concentration.

Binnig et al. (2007) describes the calibration of an OPC to yield concentrations of PM with an aerodynamic diameter \(d_{a} \leq 2.5 \mu m (PM_{2.5})\) for a well-defined aerosol utilizing known particle density and assuming uniform composition across the size range. This procedure, however, should not be applied in situations with significant fractions of particles that are not well-defined, as is often the case in ambient measurements. Instead, researchers tend to rely on historical data to develop these empirical relationships for converting optical measurements to PM mass concentrations (Grimm and Eatough 2009). Several commercially available ambient PM...
monitors currently utilize mass conversion relationships based on historical data to report PM concentrations from optical systems, such as the Aerosol Spectrometer series by GRIMM Technologies (Ainring, Germany), the TSI DusTrak series (Shoreview, Minnesota), and the Palas Fidas System (Karlsruhe, Germany).

The accuracy of PM concentrations, calculated from optical data and converted using relationships based on historical data, is strongly influenced by how closely the properties of the monitored aerosol match the properties of the historical dataset. For instance, errors in PM estimates at a clean background site, rural site, or a site heavily impacted by a single source could be significant if the employed PM calibration was created from measurements in an urban area, all of which have different aerosol sources and thus optical properties. Estimating this relationship based on measurements of the aerosol of interest through an in situ calibration, referred to by the writers as the mass conversion factor (MCF), can decrease the error due to dissimilar aerosols. This method may also be used to provide a sample period PM calibration for instruments that do not have a historical dataset. Zavyalov et al. (2009) touched very briefly on how the MCF is calculated and potential uses. In this paper more details are provided on calculating the MCF, data col-

**Methodology**

**Instrumentation and Analysis**

The PM mass concentration data were collected using filter-based MiniVol portable air samplers from Airmetrics (Eugene, Oregon). These are portable, battery-operated instruments with program-
mable sample times. Air is pulled into the sample head at a nominal flow rate of 5.0 L min\(^{-1}\) where size separation occurs based on particle inertia through the use of a removable impactor plate assembly. This inertial particle separation method is the same principle as that used in FRM samplers for PM with \(d_{sp} \leq 10 \mu m\) (PM\(_{10}\)) and PM\(_{2.5}\), although the design is different and the collection efficiency curve of the MiniVol assembly is not as steep as that of the FRM samplers (Hill et al. 1999). The MiniVol can sample PM\(_{10}\), PM\(_{2.5}\), or PM with \(d_{sp} \leq 1 \mu m\) (PM\(_{1}\)), depending on the impactor assembly used; total suspended particulate (TSP) matter may be collected if the impactor assembly is not used. Impaction plates were coated with a thin layer of high vacuum silicone grease to prevent particles removed from the airstream from being reentrained in the sample flow. A filter holder is located downstream of the size separator to collect particles remaining in the airstream.

Sample flow is not actively maintained at 5.0 L min\(^{-1}\) by the MiniVol. Instead, it is set using a calibrated rotameter before each run and verified during sample retrieval. Flow calibrations were conducted yearly and prior to deployment for each instrument used. The calibration equations and estimated sample period average pressure and ambient temperature \((T_{amb})\) were used to calculate the sample period specific rotameter settings necessary to achieve a sample flow of 5.0 L min\(^{-1}\). Occasional sampling or handling irregularities occurred with MiniVol samples, all of which were noted. Any sample with a noted issue was excluded from further calculations.

Teflon filters 47 mm in diameter were used to collect all samples herein reported. Filters were preconditioned according to the protocols outlined in Title 40, Part 50, Appendix J of the U.S. Code of Federal Regulations (i.e., 40 CFR 50 Appendix J). Final average filter weights for both pretest and posttest were calculated from three stable weights within ±5 µg determined using a micro-

Aerosol Profilers, Model No. 9722 (Met One Instruments, Grants Pass, Oregon) were used to measure the optical diameter \((d_{op})\) of individual particles. These OPCs measure the amount of light scattered by a particle and compare that quantity to light scattered by calibration particles of various sizes to determine the particle \(d_{op}\). Measured \(d_{op}\) are grouped into eight bins with the following size ranges: (1) 0.3–0.5 µm, (2) 0.5–0.6 µm, (3) 0.6–1.0 µm, (4) 1.0–2.0 µm, (5) 2.0–2.5 µm, (6) 2.5–5.0 µm, (7) 5.0–10.0 µm, and (8) >10.0 µm. The OPC produces total particle counts per size bin over the sample period of duration \(t\), ranging from 2 to 60 s. The PM mass concentration calibrations based on historical data have not been developed for these OPCs. The OPC flow measurements, usually made before and after experiments using a soap bubble displacement system (Gilian Gilibrator2 Calibration System, Sensidyne, Clearwater, Florida), reported that average flow rates \((q)\) ranged from 0.8–1.2 L min\(^{-1}\) between OPCs but that the \(q\) for a given OPC was very stable. Sampled aerosol was not preconditioned to control temperature or relative humidity (RH) in measurements reported in this paper as they were made in dry climates. However, preconditioning is suggested as high RH may have substantial effects on particle properties and measurements, particularly for hygroscopic particles.

For a specific OPC \((j)\), number concentration \(N_{ij}\) per bin \((i)\) is a function of raw particle counts \((p_{ij})\), the measured average flow rate \((q_{j})\), and the sample time \((t)\)

\[
N_{ij} = \frac{p_{ij}}{q_{j}t}
\]

The units for \(N\) are no. cm\(^{-3}\), \(p\) is number, \(q\) are cm\(^3\) min\(^{-1}\), and \(t\) is min.

Intercalibration of OPC particle counts was performed in post-
analysis to ensure comparability between deployment sites. The intercalibration equations, referred to by the authors as counting correction factors (CCFs), were calculated based on data collected either as a collocated group before or after an experiment or, if a collocated dataset did not exist, from multiple periods over the deployment during which the source under study was not active and OPCs were measuring a consistent, uniform background aerosol. As instrument response for each upper bin limit in each OPC must be factory calibrated individually, so too the CCFs must be calculated for each bin of each OPC. A CCF \(_{ij}\) is estimated through comparison of the average particle number concentration \(\bar{N}_{ij}\) over the identified period with the average particle number concentration across all OPCs \(\bar{N}_{i}\). The CCFs were applied to all \(N_{ij}\) prior to further analysis.

Both scalar and linear function \((y = mx + b)\) CCFs greatly decrease interinstrument variability. As an example, the variability between \(\bar{N}_{ij}\) prior to CCF application to a collocated dataset was 18.0%, calculated as the relative standard deviation (RSD). Application of scalar CCF \(_{ij}\) values reduced the RSD to 6.8% and application of linear function CCFs yielded a RSD of 6.5%. Other types of CCF equations may be used as deemed appropriate.

The volume concentration \(V\) of sampled particles based on \(N\) may be calculated based on the following simplifying assumptions:
(1) the particles are spheres, and (2) the maximum measured \(d_{op}\) is 20 \(\mu\)m. The assumption of a maximum measured \(d_{op}\) provides an upper bound for the largest-sized channel. The geometric mean \(d_{GMD}\) per bin (GMD.) was selected as the representative diameter of the particles in a given bin \(i\) with the assumption of a log-normal distribution of particle counts. The cumulative \(V(V_k)\) up to a particle diameter \(k(d_k)\) may be calculated

\[
V_k = \frac{\pi}{6} \int_0^{d_k} n(d) d^3 \, dd
\]

where \(n(d) = \text{number concentration at diameter} \, d\). For application to the collected OPC data, Eq. (2) is discretized and expressed in the subsequent terms that have been previously defined

\[
V_k = \frac{\pi}{6} \sum_{i=1}^{GMD \leq d_k} \text{GMD}_i^3 \, N_i
\]

where the units are GMD (\(\mu\)m); \(N_i\) (no. cm\(^{-3}\)); and \(V_k\) (\(\mu\)m\(^3\) cm\(^{-3}\)). In this case, the \(V_k\) definition is similar to PM \(i\) concentrations; the total volume of particles whose \(d_{op}\) is \(\leq k = 1 \, \mu\)m, 2.5 \(\mu\)m, 10 \(\mu\)m, and \(\infty\) for TSP.

**Mass Conversion Factor Calculations**

The MCF is calculated from optical and aerodynamic particle measurements. The \(V_k\) data, as calculated in Eq. (3), are averaged over the corresponding MiniVol sample time. The MCF, with units of density (grams per cubic centimeter), for each PM size fraction \(k\) is calculated

\[
\text{MCF}_k = \frac{\text{PM}_k}{V_k}
\]

The MCF is typically averaged across sample locations. This MCF is different from the MCF described by Binnig et al. (2007), which includes particle shape factor and density, information that must be supplied by the user. However, this MCF incorporates the many properties from the particles, the environment, and the measurement techniques that influence the reported PM \(i\) and \(V_k\) values without requiring explicit consideration. Including these factors in the MCF may lead to significantly different values and larger variability in MCF \(k\) across sample periods and instrumentation than other conversion factors (or mean density correction methods) report.

Properties of particles that may influence optical and aerodynamic measurements include but are not limited to chemical composition, effective density, shape, and index of refraction, which are interdependent to varying degrees. Chemical composition affects both the index of refraction and effective density. As OPC measurements are dependent to varying degrees. Chemical composition affects both the measurements include but are not limited to chemical composition, other conversion factors (or mean density correction methods) report.

One factor affecting mass measurement systems is the effectiveness of the size selection mechanism. The FRM PM \(_{10}\) and PM \(_{2.5}\) size segregation sample heads have been designed to mimic the particle removal efficiency of the human respiratory system, with most utilizing a particle’s inertia for separation if it is above the designed \(d_c\) cut point. The removal efficiencies can be represented by an s-shaped curve with some particles smaller than the targeted cut point being removed, half the particles at the cut point being removed, and some particles larger than the cut point passing through the removal mechanism. The MiniVol impactor removal efficiency is designed to be similar to FRMs, although the slope is not as steep (Hill et al. 1999). Significant particle loading on the MiniVol impactor plate may lead to particles impacting the surface and returning to the airstream for collection on the filter. This is known as particle bounce and may result in higher PM \(i\) being reported than is actually present. The manufacturer suggests the use of a thin grease film on the impactor plate as a preventative measure, with a cleaning and film renewal cycle based on sampling frequency and sampled concentrations. If cleaning and renewal cycles are too infrequent, particle buildup may occur and result in particle bounce (Tropp et al. 1998).

The MCF values have been calculated from data collected during six field studies conducted in the San Joaquin Valley (SVJ) of California, in the Cache Valley along the border between Utah and Idaho, and on the Colorado Plateau in eastern Utah. Measurements were taken during summer and fall seasons between the years 2007 and 2012, under the meteorological and potential PM source conditions listed (Table 1). Field study average \(T_{amb}\) were above 20\(^\circ\)C during all but one, and average RH values were in the 30–40\% range. Maximum RH values were between 60 and 80\%, and
occurred for short periods of time in early morning when $T_{\text{amb}}$ was lowest. Typical point sensor deployment on these field studies consisted of collocating an OPC with one to four MiniVol samplers. Sampler inlets were arranged at approximately the same elevation and maintained data were plotted in the graph inset [Fig. 1(b)]. The linear fit is significantly more representative (Marchant et al. 2011).

The MiniVol Accuracy and Precision Tests

Several collocated ambient tests were conducted in which multiple MiniVol samplers and FRMs were deployed to determine the precision and accuracy of the MiniVols. The FRM instruments used were Anderson regulated air sampler (RAS) units operated by the writers for PM$_{10}$, a Partisol Plus Model 2025 sequential air sampler operated by the State of Utah Division of Air Quality (UDAQ) for PM$_{2.5}$, and a Partisol FRM Model 2000 air sampler operated by UDAQ for PM$_{10}$, all of which were manufactured by Rupprecht and Patashnick (now Thermo Fisher Scientific, Waltham, Massachusetts). All filter samples collected by the writers were conditioned and weighed as previously discussed. Filter treatment by UDAQ were in accordance with established U.S. National Ambient Air Quality Standards (NAAQSs) monitoring protocols. Samples were collected over 23 or 24-h sample periods, with samplers arrayed to minimize horizontal and vertical spread while maintaining a minimum of 0.5-m distance between samplers.

A PM$_{2.5}$ comparison test was conducted in early March 2004 utilizing 15 MiniVol samplers and UDAQ’s PM$_{2.5}$ FRM over 4 days. A PM$_{10}$ comparison test was then conducted in late March 2004 over four sample periods with six MiniVols and the Anderson RAS PM$_{10}$ FRM. Samples were collected every 2 or 3 days to allow for filter deployment and collection. Another comparison study was carried out in July 2007 over 5 consecutive days. In this test, 20 MiniVol samplers were arranged adjacent to the UDAQ PM$_{2.5}$ and PM$_{10}$ FRMs. Three MiniVols sampled PM$_{1}$, seven sampled PM$_{2.5}$, seven sampled PM$_{10}$, and three sampled TSP. The UDAQ FRMs had multiple filter cassettes with automated switching, allowing them to run nearly continuously. The MiniVols, however, required manual filter swapping between each sample. Therefore, the MiniVols sampled from 0:30 to 23:30, with the 1-h break to allow time to switch sample heads, record elapsed sample run time, and adjust sampler flows. Verified PM$_{2.5}$ and PM$_{10}$ values were obtained from UDAQ for all sample dates.

The accuracy and precision tests were carried out in the Cache Valley. Silva et al. (2007) showed that periods of elevated PM$_{2.5}$ in Cache Valley in early 2004 were dominated by secondary particles, mostly NH$_4$NO$_3$, (NH$_4$)$_2$SO$_4$, and organic carbon (OC), with 90% of the mass present in the submicron range. Cache Valley and other nearby mountain valleys experience episodic events of air pollution levels above NAAQS limits during winter due to a combination of topographical, meteorological, and source characteristics (Malem et al. 2006; Silva et al. 2007; Silcox et al. 2012; Lareau et al. 2013). Summertime elevated PM has typically occurred due to impacts from wildfire and windblown dust events.

Results and Discussion

Field Study MCF Results

Six field deployments have resulted in a total of 95 samples for comparison between reported OPC and MiniVol values for PM$_{1}$, 380 for PM$_{2.5}$, 394 for PM$_{10}$, and 208 for TSP. Fig. 1 presents scatter plots of all the data, separated into the four size fractions. The PM$_{1}$ was almost always greater than V$_{3}$ as few points are below the one-to-one line. Linear trends were evident in the $k = 1 \mu m$, 10 $\mu m$, and TSP graphs, with slopes between 1.2 and 1.6 and 0.78 $< R^2 < 0.82$. The linear fit to $k = 2.5 \mu m$ data had a slope of 1.4 but did not represent the data well ($R^2 = 0.06$) due to a collection of low V$_{2.5}$ values ($<10 \mu m^3 cm^{-3}$) paired with high PM$_{2.5}$ concentrations ($>100 \mu m^3 cm^{-3}$). The majority of the high PM$_{2.5}$/low V$_{2.5}$ pairings come from a single field study. The cause of these unusual values and their grouping is discussed at the end of this subsection. The $k = 2.5 \mu m$ values from the field study with multiple high PM$_{2.5}$/low V$_{2.5}$ pairings were removed and the remaining data were plotted in the graph inset [Fig. 1(b)]. The linear fit is significantly more representative ($R^2 = 0.66$) with a slope of 2.4 ($n = 279$).

Chemical composition analyses were performed on select PM$_{2.5}$ samples from two of the six datasets and on select PM$_{2.5}$, PM$_{10}$, and TSP filters from one dataset, all collected in the SJV. Water-soluble ions were quantified for all samples, while OC and elemental carbon (EC) were quantified in PM$_{2.5}$ samples only based on the assumption that the majority of OC and EC were

Table 1. Conditions during Each Field Campaign with the Mass Conversion Factor Calculated and Included in This Paper

<table>
<thead>
<tr>
<th>Location</th>
<th>Month(s)</th>
<th>Sample periods</th>
<th>Average±SD</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Potential PM sources</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cache Valley, UT</td>
<td>July 2007</td>
<td>5</td>
<td>$T_{\text{amb}}$ (°C) $25 \pm 7$</td>
<td>11</td>
<td>36</td>
<td>Combustion, small industrial processes, agriculture, construction, and mobile</td>
<td>—</td>
</tr>
<tr>
<td>Colorado Plateau, UT</td>
<td>October 2009</td>
<td>4</td>
<td>$T_{\text{amb}}$ (°C) $9 \pm 5$</td>
<td>-4</td>
<td>18</td>
<td>Long-range transport (Malm et al. 2004), windblown dust, mobile, and unpaved roads</td>
<td>—</td>
</tr>
<tr>
<td>San Joaquin Valley, CA</td>
<td>October 2007</td>
<td>7</td>
<td>$T_{\text{amb}}$ (°C) $23 \pm 4$</td>
<td>14</td>
<td>30</td>
<td>Samples collected around agricultural operations. Other sources include i.e., combustion, industrial processes, construction, mobile, and others</td>
<td>Moore et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>May and June 2008</td>
<td>13</td>
<td>$T_{\text{amb}}$ (°C) $30 \pm 4$</td>
<td>18</td>
<td>37</td>
<td>(Held et al. 2004)</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>August 2012</td>
<td>5</td>
<td>$T_{\text{amb}}$ (°C) $28 \pm 7$</td>
<td>15</td>
<td>39</td>
<td></td>
<td>—</td>
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Meteorological conditions

<table>
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$^a$Meteorological values are those recorded during sample periods only.
present in the PM_{2.5} fraction. The results showed that most of the mass in analyzed samples (50–85%) was composed of elements/compounds not in the list of analytes. Malm and Hand (2007) used six particle composition classes to represent PM_{2.5} dry mass based on the Interagency Monitoring of Protected Visual Environments (IMPROVE) protocols; NH_4NO_3, (NH_4)_2SO_4, OC, EC, crustal, and sea salt. As NH_4NO_3, (NH_4)_2SO_4, and sea salt were quantified in the water-soluble ion test, the majority of PM during the research reported in this paper in the SJV was therefore assumed to be associated with crustal material. Particle chemical composition for the remaining three field studies is unknown.

A statistical summary of sample period average MCF_k values for all periods with more than two collocated comparisons is presented as a box and whisker plot (Fig. 2). As points of reference, the average density of soil is 2.65 g cm^{-3}, the density of mercury is 13.5 g cm^{-3}, and Peters (2006) provided several ambient PM density values derived from field studies that range from 1.77 to 2.64 g cm^{-3} (USDA 2007). The y-axis in Fig. 2 has been limited in order to show details at the lower values; one sample period had an average MCF_{2.5} of 23.5 g cm^{-3}. Outliers are shown as plus signs and calculated as greater than (less than) the 75th (25th) percentile value plus (minus) 1.5× the interquartile range (IQR). The IQR is calculated as the difference between the 25th and 75th percentiles, which are shown by the top and bottom lines of the boxes. The whiskers extend to the most distant data values from the box edges within 1.5× the IQR. The MCF_{10} and MCF_{TSP} values were more tightly grouped than the MCF_{1} and MCF_{2.5} values, as indicated by the smaller IQRs. This is also supported by the locations of the mean values for MCF_{10} and MCF_{TSP}, shown by the dots within circles, being much closer to the median, shown by the center line in the boxes. The overall mean ± one SD and the median of the period average values, respectively, were as follows: (1) MCF_{1} = 4.3 ± 2.2 and 3.2 g cm^{-3} (n = 5), (2) MCF_{2.5} = 5.0 ± 1.1 and 3.2 g cm^{-3} (n = 36), (3) MCF_{10} = 1.6 ± 0.3 and 1.5 g cm^{-3} (n = 38), and (4) MCF_{TSP} = 1.6 ± 0.4 and 1.3 g cm^{-3} (n = 33). The absence of outliers for MCF_{1} is likely due the calculations being based on just five data points from a single field deployment.

The RSD between MCF values from different sample locations within a sample period averaged between 17 and 21% for MCF_{2.5}, MCF_{10}, and MCF_{TSP}, with maximum and minimum values for each size around 60 and 5%, respectively. Samplers were spread around various facilities/operations for five studies. The sixth study was conducted as a part of the MiniVol precision and accuracy test in July 2007, and had lower variability than the others. Seven OPCs were deployed with 20 MiniVols, providing multiple pairwise collocated comparisons to determine the minimum variability of the calculated MCFs. The RSD averages were 10% for MCF_{1}, 8% for MCF_{2.5}, and 5% for both MCF_{10} and MCF_{TSP} with maximum values of 17, 11, 8, and 6% for MCF_{1}, MCF_{2.5}, MCF_{10}, and MCF_{TSP}, respectively. The data from all deployments show that calculated MCF values can be expected to have a minimum RSD of 5–10%, an average RSD ≤ 25%, and maximum RSDs can be >50%. High RSDs were found across the range of average MCF values and the amount of variability was different across size fractions within a sample period.

High individual MCF values were calculated during multiple field studies but were usually limited to the MCF_{2.5}. Some factors potentially contributing to variations in MCF were discussed previously, including the properties of the particles, past and present environmental conditions, and sampling methodologies. Sample period average MCF_k values were graphically compared (not shown) with sample period average T_{amb}, RH, wind speed, and percent of OC, EC, ionic, and unknown chemical composition. Trends were not evident in any of these plots.

Sampling errors or irregularities may also influence the MCF. The majority of MCF_{2.5} values above 5 g cm^{-3}, including the maximum of 66.1 g cm^{-3}, were from the field study referenced previously with the high PM_{2.5}/low V_{2.5} pairs. The cause of this grouping of high MCF_{2.5} values is unclear, although sampling irregularities are suspected. Meteorological conditions were hot and dry throughout, minimizing potential effects of water absorption by hygroscopic particles. There was not a significant PM_{2.5} composition difference between periods with higher and lower MCFs within this field study. MCF_{10} and MCF_{TSP} patterns tended to be in accordance with MCF_{2.5}, having correlation coefficients (R) of 0.64 and 0.84, respectively, but with much smaller changes in amplitude. Comparing MCF values with sample duration produced good negative correlations (−0.69 ≤ R ≤ −0.64) for all MCF_k, which means that MCF_{1} tended to increase as sample duration decreased. Contamination during filter handling and storage is a possible cause, one to which samples with smaller mass catch, i.e., samplers with PM_{2.5} impactor configurations and/or shorter sample times, would be more sensitive. Field and lab blanks, unfortunately, were not taken to monitor for and quantify contamination. Contamination mitigation and monitoring strategies have since been developed and successfully implemented.
that a poor quality PM$_{10}$ dataset resulted in the unusually high MCF$_{2.5}$ values for a portion of this individual study.

The MCF method should be applied carefully and the quality of the data used in its calculation should be verified, as shown in the example discussed previously. In cases with poor quality data, the writers have occasionally chosen not to use the calculated MCF and instead used density values for the dominant particulate chemical component. In the example discussed previously, the average density of soil (2.65 g cm$^{-3}$; USDA 2007) replaced the calculated MCF$_{2.5}$ values as measurements were being made of agricultural tillage plumes. If all the MCF$_{i}$ values for this field study were removed, the mean ± one SD and median values become 3.2 ± 0.6 and 2.7 g cm$^{-3}$ for MCF$_{2.5}$ ($n$ = 27), 1.4 ± 0.3 and 1.3 g cm$^{-3}$ for MCF$_{10}$ ($n$ = 28), and 1.1 ± 0.2 and 1.1 g cm$^{-3}$ for MCF$_{FSP}$ ($n$ = 21). The MCF$_{i}$ statistics do not change as PM$_{1}$ measurements were not made during that individual study.

**Application of the MCF**

Calculated MCF$_{k}$ values have been used to convert $V_k$ data collected by multiple optical instruments into PM$_{k}$. The MCFs were applied to OPC data, allowing the examination of temporal changes in mass loadings unresolved by filter-based MiniVols. For example, PM$_{10}$ concentrations measured by a collocated MiniVol and OPC downwind of a commercial dairy over 2 days are shown (Fig. 3). The MiniVol collected integrated samples from 00:30 to 23:30 hrs. each day, yielding a single average concentration per sample period. The OPC provided a data point every 20 s, which have been have averaged up to 5 min and 23 h, corresponding to the MiniVol sample time, and multiplied by the average MCF$_{10}$ for both days of 1.3 g cm$^{-3}$. The diurnal PM$_{10}$ patterns easily shown by the 5-min averaged OPC data are not evident in the 23-h average data that span the same time period. However, the influence of the evening peak is included in the 23-h average concentrations as they are higher than the OPC 5-min average levels throughout most of the sample period. Applying the MCF in this case allows for the analysis of PM$_{10}$ at much smaller temporal scales, which may help to explain emissions patterns and lead to more effective and efficient mitigation strategies.

A main objective of most of the field deployments was to estimate PM emissions from a source. In all such cases, an emissions estimation methodology was employed that used the difference between downwind and upwind MiniVol concentrations. The OPC data may also be used for this after the conversion to mass concentration and on a finer temporal scale. For instance, Moore et al. (2011) estimated emissions during a wind erosion event based on OPC PM$_{10}$.

Another optical instrument to which the MCF has been applied is the Agtile elastic light detection and ranging (lidar) system, as described by Marchant et al. (2009). The Agtile lidar is a three wavelength system capable of scanning in both horizontal and vertical directions that measures laser pulse returns from particles in the atmosphere. The lidar data analysis algorithm, described by Zavyalov et al. (2009), utilizes OPC data collected during the lidar operation to calibrate the lidar return signal, with the final product being an estimate of $V_k$ in each lidar bin. The MCF$_{k}$ values are then used to convert lidar $V_k$ to PM$_{k}$ (Fig. 4).

Comparisons between MiniVol PM$_{k}$ measurements and lidar and OPC data converted to PM$_{k}$ with the MCF$_{k}$ have been made in most of the field campaigns involving the lidar (Bingham et al. 2009; Zavyalov et al. 2009; Marchant et al. 2011; Moore et al. 2013). In summary, the results have shown good agreement between the three at upwind locations with more variability between the lidar and the other two point measurements downwind of sources, particularly nonstationary sources such as agricultural tillage operations. A large factor contributing to the observed differences is that the lidar is normally operated in a scanning mode and thereby collects coincident data at the downwind OPC and MiniVol location for only 5–10% of a given time period. The OPC PM$_{10}$ values have usually been closer to MiniVol measurements due to collocation throughout the measurement period. For instance, the OPC 5-min average data (Fig. 3) were averaged over the 23-h MiniVol sample periods and plotted. The 23-h average OPC PM$_{10}$ values are indistinguishable from the MiniVol reported concentrations, being only 2% higher. Refer to Moore et al. (2013) for more explanation of possible reasons for differences between the three measurements.

The SD of PM$_{k}$ derived from MCF$_{k}$ is calculated per Berthouex and Brown (2002)

$$\frac{SD_{PM_k}^2}{PM_k^2} = \frac{SD_{MCF_k}^2}{MCF_k^2} + \frac{SD_{V_k}^2}{V_k^2} \quad \text{or} \quad (RSD_{PM_k})^2 = (RSD_{MCF_k})^2 + (RSD_{V_k})^2 \quad (5)$$

![Fig. 3](image1.png) **Fig. 3.** Time series of PM$_{10}$ concentrations measured immediately downwind of a dairy farm over 2 days as measured by a collocated MiniVol and OPC

![Fig. 4](image2.png) **Fig. 4.** (Color) Example of PM$_{10}$ concentrations calculated from a single lidar scan through the use of the MCF; this vertical scan was taken along the downwind edge of an agricultural field being tilled
In the case of the MCF datasets presented in this paper, the RSD$_{PM4}$ for the sample period average minimum RSD$_{MCF4}$(5%), RSD$_{MCF10}$ for an array deployment (20%), and maximum RSD$_{MCF10}$(50%) were calculated as 21, 28, and 54%, respectively, assuming a RSD$_{VL}$ value of 20%. If a RSD$_{VL}$ value of 10% is used, the RSD$_{PM4}$ values drop to 11, 22, and 51%, respectively.

Mass-calibrated lidar data have also been used to estimate source emissions through the application of a mass balance. Bingham et al. (2009) provide a description of the sampling and analysis methodology utilized to perform the mass-balance emission calculations. Several papers have estimated emissions based on this technique (Bingham et al. 2009; Marchant et al. 2011; Moore et al. 2011, 2013). A scanning, mass-calibrated lidar system such as this can provide PM concentration and emissions data over a large area in time steps on the order of seconds or minutes, allowing the identification of spatial inhomogeneity and temporal fluctuations and patterns, on horizontal and vertical extents not achievable through point measurements.

If researchers desire to use this MCF technique to provide a mass concentration calibration for optical systems, it is recommended that the reliability and reproducibility of the particle measurement systems be sufficiently characterized, particularly the optical systems. The writers use calibrations in concert with collocated tests in typical deployment conditions to accomplish this objective. The development and use of the CCF$_ij$ has proven key in normalizing OPC count data to RSD values of ≤10%; the variability in counts between the OPCs employed by the writers during a collocated test challenges the confidence in any one of them to provide the true absolute particle count. While this reduces the confidence in calculated $V$ and $V_k$, the MCF provides a stable point of reference for PM$_{ij}$. Additionally, the MCF should be applied with care as described previously.

**MiniVol Precision and Accuracy Test Results**

Collocated comparison tests between filter-based PM sensors were conducted in three separate studies, each with replicate MiniVol samplers over four to five sample periods. The PM$_{2.5}$ concentrations measured by the FRM units ranged from 7.4 to 53.4 µg m$^{-3}$, while PM$_{10}$ levels ranged from 4.0 to 40.7 µg m$^{-3}$. The maximum and minimum PM$_{10}$ concentrations being lower than the PM$_{2.5}$ values are not of concern; all but one of the PM$_{10}$ comparison tests were conducted on separate days from the PM$_{2.5}$ tests and, in the case of the coincident test, the reported PM$_{10}$ level was higher than the PM$_{2.5}$ level. All data were screened for noted sample handling and collection errors.

Fig. 5 presents both PM$_{2.5}$ and PM$_{10}$ comparisons with the MiniVol data along the x-axis and the FRM data along the y-axis. Most of the MiniVol data are fairly well clustered, with most cluster cores within ±10% of the one-to-one line across the range of observed values (Fig. 5). However, there are several points significantly outside of the clusters. The extreme value test was used to determine if these points were statistical outliers. Nineteen points were statistical outliers and have been marked on Fig. 5 by a dot inside the marker. All but two of the outliers were found in the PM$_{2.5}$ dataset, and 12 of those were in the PM$_{2.5}$ comparison test carried out in March 2004. Out of the four sample periods in this single collocated test, one sampler contributed four statistical outliers, a second contributed three outliers, and a third contributed two outliers. Multiple outliers resulting from a single sampler is suggestive of sampler operational issues. Therefore, all data from these samplers were removed from further analysis and the outlier analysis for this PM$_{2.5}$ dataset was performed again, resulting in only three identified as statistical outliers for a total of 10 from all datasets. All other samplers with outlier data points had just one each. The subsequent linear regression equations were developed based on the remaining points; FRM = 0.99 × MiniVol + 0.31, $R^2 = 0.962$, for PM$_{2.5}$; and FRM = 0.83 × MiniVol + 3.90, $R^2 = 0.918$, for PM$_{10}$.

Potential causes of variability and outliers between the MiniVol samples may include, but not limited to, the following: (1) recording errors during weighing or operation logging, (2) improper setting of the sample flow, (3) sample contamination, (4) improper assembly of the sampler head, (5) nonuniform PM levels across the inlets, and (6) random variability in sampler operation and mass catch determination. Preventative measures were taken to decrease the likelihood of the first five listed causes. Personnel were trained on proper instrument assembly, instrument operation, sample handling, filter weighing, and data logging procedures to minimize human error. Filter exposure during handling and transport was minimized to prevent contamination. Samplers were deployed close together, in the ambient air, and within areas of uniform surface and source conditions to maximize uniformity in average PM concentrations. Random variability in sampler operation would likely result in relatively small variations in reported concentrations, not the large differences seen in the case of some outliers. The outliers seen in the research reported in this paper and not removed due to sampler operational issues, as previously discussed, are likely the result of a combination of human error, instrument operation anomalies, or random variations in PM concentration, although the exact cause(s) were not identifiable. Unless otherwise noted, these data were not excluded from further calculations due to the lack of an identified cause.

Table 2 lists various statistical measures of the variability between the MiniVol samplers for each size fraction in each study. The variability of reported PM concentrations between the MiniVols within a sample period, expressed as the RSD, ranged from 1 to 27%. The variability between MiniVols was generally smaller across all size ranges during the year 2007 study compared to the year 2004 studies with all average RSDs below 10%. The bias of the MiniVols was calculated by subtracting the sample period FRM concentration from the average MiniVol concentration and averaging across the sample periods within each study. The average PM$_{2.5}$ biases were less than ±1 µg m$^{-3}$, but the PM$_{10}$ biases averaged −1.9 µg m$^{-3}$ during the March 2004 study.
and +4.9 μg m⁻³ for the single PM₁₀ sample period in the July 2007 study with a corresponding FRM sample.

The results of the FRM and MiniVol comparison from these collocated sample periods are presented in Table 2 as a ratio. An FRM/MiniVol ratio of 1.0 shows the MiniVol reported the same PM concentration as the FRM, while a ratio greater than 1.0 results from lower MiniVol concentrations and vice versa for ratios less than 1.0. The average ratios from the two PM₂.₅ tests ± the 95% confidence interval (CI) were 1.03 ± 0.04 and 0.96 ± 0.04 for the year 2004 and 2007 studies, respectively. These show the MiniVols were, on average, in very good agreement with the PM₂.₅ FRM under these conditions, even that the 95% CIs bound the value 1.00 in both cases. The PM₁₀ ratios showed a higher deviation from 1.00, with average ratios of 1.08 ± 0.04 and 1.06 ± 0.04 for the two studies, although the average values are still within 15% of 1.00.

Several previous MiniVol precision and accuracy studies have been reported in multiple PM sampling configurations. Heal et al. (2000), Baldauf et al. (2001), and Chen et al. (2007) reported very good MiniVol precision. Baldauf et al. (2001), Chow et al. (2002), and Chen et al. (2011) found the MiniVols yielded PM levels very similar to the comparison sampling systems. Hill et al. (1999) found that the PM₂.₅ MiniVol was statistically equivalent to an FRM only when results were field blank corrected. Chow et al. (2006) found differences between PM₂.₅ MiniVols and FRMs at multiple sites ranging from 1.23 to 1.41 and had an overall average of 1.32. Heal et al. (2000) reported the MiniVol correlated very well with a FRM PM₁₀ sampler in indoor environments with PM₁₀ levels ~10 μg m⁻³, but on average reported mass concentrations 23% greater. Salter and Parsons (1999) found a MiniVol did not correlate well in comparisons with a tapered element oscillating microbalance (TEOM; Rupprecht and Patashnick, now Thermo Fisher Scientific, Waltham, Massachusetts) and a Partisol. Kingham et al. (2006) found weak PM₁₀ correlations with data from both a TEOM and a DustTrak during one series of measurements and good correlations during a second series of measurements.

Insights gained through these tests and analyses with respect to obtaining accurate and precise PM measurements using MiniVols (or any other PM system) should be noted. First, proper maintenance and regular inspection of the MiniVol is required, with particular focus on flow calibration and the impactor assembly. Second, occasional collocated tests are suggested for comparisons between multiple MiniVols and, if possible, an FRM to monitor for operational issues. If possible, these tests should be carried out under conditions typical of deployments. Third, proper personnel training is key to reducing human error.

### Summary and Conclusions

Currently available PM monitoring systems based on optical measurements generally use calibration factors calculated from historical data to estimate PM concentrations. However, the applicability of these calibrations may be questionable when properties of the measured aerosol are different from properties of the aerosols used to estimate the calibration factor. In this paper a simple, onsite procedure to determine the MCF₁ was presented that may be adapted to convert data from an optical instrument into PM levels based on the actual measurement conditions. This procedure may also be used with an optical system for which a PM calibration has not been developed. Data from field measurements have been presented to demonstrate typical MCF₁ values for k = 1 μm, 2.5 μm, 10 μm, and TSP. The MCF₁ and MCF₂ values tend to be higher than MCF₁₀ and MCF₁₀ within a sample period. The average RSDs were about 20% for arrayed measurements made during multiple field studies and <10% for collocated measurements. The MCF₁ has been key in converting optical instrument data to mass concentration, which has allowed for examination of concentrations and emissions data on much smaller time scales and, in the case of a sampling lidar, over much greater spatial scales.

Results from studies examining the precision and accuracy of the MiniVol PM sampler are given. The sample period RSDs were usually <10% for PM₁, PM₂.₅, PM₁₀, and TSP size fractions. Comparisons at the PM₂.₅ size fraction between MiniVols and FRMs showed excellent agreement with average FRM/MM ratios ±95% CI of 1.03 ± 0.04 and 0.96 ± 0.04 and average biases ≤1 μg m⁻³. Results of the PM₁₀ comparisons were not as strong with average ratios of 1.15 ± 0.14 and 0.88 ± 0.01, and biases of −1.9 μg m⁻³ and +4.9 μg m⁻³. In conclusion, the MiniVols yielded PM₂.₅ values that were essentially equivalent to PM₂.₅ concentrations reported by FRM samplers under these test conditions and PM₁₀ values were in good agreement with PM₁₀ FRM measurements.

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References


