Using MAC Readers for Real-Time Arterial Emissions Estimates

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ABSTRACT
This paper demonstrates the use of matched-vehicle travel times generated from MAC readers for emissions estimates on urban arterials. A conceptual model is described for applying MAC data for real-time arterial emissions estimates. The core of the estimation method is then applied to a case study using a small set of probe vehicle trajectories with simulated MAC detectors and the MOVES 2010 emissions model. Results show that the accuracy of the MAC-based emissions estimates – as compared to more detailed emissions estimates using second-by-second speed profiles – varies greatly by vehicle and pollutant. MAC reader spacing does not have a large impact on the accuracy of emissions estimates, either in terms of changing corridor lengths or changing detector spacing over a fixed corridor length. Similarly, average travel speed does not affect the accuracy of MAC-based emissions estimates. The key issue for accuracy here is that MAC-based emissions estimates rely on the real-world relevance of a library of drive schedules to be matched to the measured travel speeds. The research results suggest that a simple factor adjustment to the emissions estimates from default drive schedules can improve MAC-based emissions estimates with only a few probe vehicle runs. Although this study is based on a small number of probe runs at one location, it provides insights into the potential for applying MAC address readings for arterial emissions estimates.

INTRODUCTION
The lack of data for arterial roadways is an increasingly recognized gap in our understanding of system performance (1). With travel times and speeds not widely and accurately measured, secondary estimates of emissions and fuel consumption are challenging and highly uncertain. Yet urban arterials are not only a major locality for motor vehicle emissions, as activity centers they are also the setting for high human exposure to traffic-related pollution. Urban arterial emissions estimates are important performance metrics for public health, ecology, and climate change concerns.

Media Access Control (MAC) address readers are an emerging tool for directly collecting roadway travel time data (2-5). MAC addresses are unique identifiers broadcast over a limited spatial range, most commonly encoded in Bluetooth™-enabled wireless devices. Detection and matching of a MAC address at two locations in the roadway network allows calculation of the intervening travel time for the wireless device – which is assumed to be accompanied by a traveler. Travel times from MAC address readings can be used to calculate various arterial performance measures. One such application is emissions estimates based on real-time, real-world travel speed data – something rarely undertaken in the past but with potential uses in road-user information services and pollution-responsive dynamic traffic management systems.

This research addresses the use of matched-vehicle travel times generated from MAC readers for emissions estimates on urban arterials. Included in this paper are a discussion of applying MAC travel time information for real-time emissions estimates and a case study using probe vehicle trajectories on an urban arterial in Portland, Oregon with the MOVES 2010 mobile-source emissions model. The objectives of this study are 1) to illustrate the use of MAC-based travel times for arterial emissions estimates and quantify the accuracy of such an approach, and 2) to identify the impacts of MAC reader spacing on the accuracy of arterial emissions estimates. The rest of the paper is organized as follows: background information, a description of the conceptual model for real-time arterial emissions estimates, case study methodology and results, and conclusions.

BACKGROUND
MAC address readings are an emerging transportation data source enabled by field-ready technology and undergoing operational tests in various locations (2-5). While the MAC address detection technology is readily accessible, the accurate estimation of travel times from MAC readings requires algorithms for matching and filtering that are still being researched. Beyond travel times, MAC address readers are also being deployed to collect data on network routing and origin-destination pairings. Several ongoing
challenges of applying MAC readers for travel information exist, including privacy concerns, discerning
the mode of travel, demographic bias, and siting and spacing issues for the devices themselves.

Three classes of MAC readers with varying powers and operating ranges are available. Class I
radios can detect Bluetooth\textsuperscript{tm}-enabled devices up to 100 m away (2). The ability and accuracy of MAC
readers to detect devices depends on power and line of sight. Typical capture rates of the MAC readers lie
between 0.5 – 6\% of average daily traffic (2-5). These previous studies have shown that the travel time
estimates from MAC Readers are comparable to the estimates obtained via other methods such as floating
car studies, automatic license plate recognition, etc. Thus, MAC address matching using Bluetooth
technology represents a cost effective and reliable technique to capture travel times. With accurate
knowledge of the roadway distance between MAC readers, these travel time measurements can also
generate average travel speeds.

Accurate emissions and fuel consumption estimates require some knowledge or assumptions
about the operating speeds of vehicles in a traffic stream. Microscopic emissions estimates employ
detailed second-by-second vehicle speed profiles for activity data on each vehicle (see, for example U.C.
Riverside’s CMEM model (6)). When detailed vehicle activity data are not available, average travel
speeds (estimated or measured) can be used for emissions estimates using macroscopic models. Rather
than assuming a constant speed, macroscopic emissions models typically use average travel speed to
select an appropriate speed profile (speed time-series) from archived drive schedules (also known as drive
cycles); see, for example, the MOVES 2010 model from the U.S. Environmental Protection Agency
(EPA) (7), which has both microscopic and macroscopic applications. Drive schedules are archetypal
driving patterns for different combinations of facility type, vehicle type, and average speed. The accuracy
of such an approach (as compared to a microscopic model) depends on the relevance of the drive schedule
to local, real-world driving behavior and the accuracy of the travel speed input data (8-13).

Due to the lack of arterial travel time data, most macroscopic emissions modeling currently uses
average travel speed estimates based on measured or modeled traffic flows and relationships between
flow and speed – e.g. (14-16). The resulting emissions estimates vary greatly depending on the travel
speed estimation method (17,18). Another option is the generation of speed profiles from traffic
microsimulation, though that approach has not been well validated for emissions estimates because of key
differences from real-world driving in vehicle accelerations and unsteady cruise speeds (19-21).
Alternatively, MAC address readers provide the opportunity for real-time arterial emissions estimates
based on directly measured travel times and speeds. Given the importance to emissions estimates of
having accurate travel speeds, the proposed approach is an advance over current macroscopic approaches
because it makes it possible (a) to provide real-time or offline corridor-level emissions estimates using
measured speeds and (b) to utilize a single factor to adjust default drive schedules to actual corridor traffic
conditions. Additionally, the proposed approach is not as onerous in terms of calibration or estimation
time as microsimulation models because it allows the efficient utilization of drive schedule libraries.
Although MAC travel times are still a macroscopic data source, they offer potential improvements over
current methods of arterial emissions estimation.

CONCEPTUAL MODEL FOR APPLYING MAC-ADDRESS TRAVEL TIMES FOR ARTERIAL
EMISSIONS ESTIMATES
In this section we propose a conceptual model for real-time arterial emissions estimates based on MAC
matched-vehicle travel times. The general strategy is to use MAC-detected average travel speeds with
other local data (stored or measured) and an emissions model to generate arterial emissions estimates.
Figure 1 illustrates the proposed data sources, models, and estimation steps. Emissions estimates can be
made for road sections down to the spatial resolution of the MAC readers. Most of this approach is
essentially the same as other macroscopic emissions estimates, with the key difference of incorporating
real-time, real-world travel speed information. Detailed steps are described below, along with a discussion
of emissions modeling and accuracy issues.
Data Sources

Applying MAC-based travel times for arterial emissions estimates requires a mix of data sources. Ideally, input data for an emissions model are directly measured in real time, though that is infeasible for several classes of data (fuel formulations, for example). Alternatively, appropriate average data can be applied from local databases, as in (14,22,23). In the approach described here, travel speeds and traffic counts are measured in real-time from the roadway and other inputs come from archived data.
Estimation Steps (See Figure 1)

1. For each vehicle (a) traveling between MAC reader 1 and MAC reader 2, the time difference between detections is used (with appropriate filtering) to calculate the travel time (as in (2,4)). The vehicle’s travel time is combined with the roadway distance between MAC readers to calculate its average travel speed (5). Additionally, inductive loop detectors or traffic cameras at signalized intersections provide counts of vehicles on the corridor (24). As an unrestricted facility with entering and exiting vehicles, traffic counts at multiple detection locations between MAC readers are combined for average traffic flow rate on the corridor. The result is real-time measurements of average travel speeds (b) and traffic flows (c) on the road section between two MAC readers.

   Each measured travel speed is then used to mine an appropriate drive schedule from a drive schedule library (d) by matching the average speed of the drive schedule to the travel speed – or by selecting the two drive schedules with the closest average speeds to the measured travel speed and interpolating the final emissions rate estimates between them (the internal approach of the MOVES 2010 emissions model (7)). In addition to average speed, drive schedules are selected by relevant facility type and vehicle type. Since vehicle types are not associated with the measured travel speeds, drive schedules are selected at (d) using the measured vehicle speed and the relevant facility type with all on-road vehicle types, and a marginal emissions rate is computed for each speed-facility-vehicle type combination (in steps d-h). The final marginal emissions rate for each vehicle (a) is then computed as the weighted average of these emissions rates, weighted by the on-road vehicle type distribution. This parallels the macroscopic approach of MOVES 2010 and other average-speed models, where composite emissions rates are weighted averages from on-road vehicle type distributions.

   The selected drive schedules (d) are one type of input to the emissions model (e), required to determine the activity (operating mode) distribution of the modeled vehicles. Some of the other emissions model inputs are mined as average values from a local database (f), including fuel formulation, vehicle age distributions, and inspection and maintenance (I/M) programs (as in (22,23)). Other inputs can be measured and input real-time if the system architecture permits (e.g. vehicle type distributions from length-based vehicle class detectors, or temperature and humidity from a nearby meteorological station) – or can be based on local averages as well (g). The use of license plate recognition cameras tied to a vehicle registration database would allow even more detailed real-time vehicle fleet data – including vehicle ages and fuel types (gasoline, diesel, etc.).

   The output (h) from the emissions model is marginal emissions rates (in mass emissions per vehicle-mile) for each measured vehicle (a). The final marginal rates are computed by interpolating between drive schedules (if neighboring drive schedules are used), and taking the average of vehicle-type rates weighted by the on-road vehicle type distribution (either directly measured or from a local average (g)). In the final step, all computed marginal emissions rates in a time interval are averaged and multiplied by the measured traffic flow (c) to generate a roadway emissions rate estimate in mass per mile of roadway, per hour (i). The averaging of measured-vehicle emissions rates for application to all vehicles in a time interval relies on unbiased MAC reader travel time measurements – or algorithms to compensate for MAC bias.

Emissions Model

The emissions model (e) using drive schedules as input is a microscopic model, such as CMEM (6), MOVES 2010 project-level (7), VERSIT (25), or others. Alternatively, a macroscopic, average-speed emissions model can be applied that takes the average measured travel speed (b) as input and uses an internal drive schedule library (essentially, (d) is embedded in (e) – as in MOVES 2010 regional estimates). The breadth and depth of accompanying input data demands in (f) and (g) depend on the emissions model selected. Since emissions models are often computationally expensive, the emissions estimation can be executed and the outputs tabulated for each potential drive schedule using a range of local scenarios for other input data (steps d-h). Then, the tabulated marginal emissions rates can be quickly mined based on real-time measured speed data to allow faster execution and more feasible application in a real-time estimation environment (similar to (26)).
Accuracy Issues

The essential point to the accuracy of this approach (as in all average-speed emissions modeling) is the representativeness of the drive schedules for the real-world driving activity of on-road vehicles. Depending on the microscopic emissions model methodology, the drive schedules are used to distribute the vehicle’s activity into operating modes of some type (for example by speed bins, a combined speed and acceleration matrix, or engine loads/vehicle specific power – see (27)). Error is introduced when the operating mode distribution of the drive schedule doesn’t match the real-world distribution (8). Further error can be introduced by the drive pattern for models (such as CMEM) that use a time-based approach to estimation (meaning the model has memory of preceding operating modes, unlike MOVES 2010, which distributes activity by operating mode without accounting for sequence). Research is underway to improve estimates of vehicle specific power distributions based on facility-specific average speeds (27), which would reduce the error of apportioning operating mode distributions in average-speed approaches such as this.

A particular problem for MAC-based travel times is that the measured travel speeds are not associated with specific vehicle types (though this problem is shared by other macroscopic emissions estimation approaches). As such, the above method does not account for average-speed bias by vehicle class – although it does account for speed profile differences by using vehicle class-specific drive schedules. Research is needed to determine if facility-specific average-speed correction factors can be applied to adjust for average-speed vehicle class bias in MAC travel time readings.

CASE STUDY METHODOLOGY

This case study is designed to assess the accuracy of MAC-based arterial emissions estimates. Probe vehicle data are used to generate ground-truth emissions estimates and to simulate MAC readings for average-speed emissions estimates. The key questions are how do MAC-based estimates compare to estimates using detailed vehicle trajectory data, and what are the impacts of varying MAC reader spacing.

Real-world second-by-second speed profiles from probe vehicles on an urban arterial are used to estimate “ground truth” emissions rates (as in (28)). MAC-based travel times are then simulated from the trajectory data at a range of detector spacings, and emissions estimates made using the average travel speed approach illustrated in Figure 1. Comparisons between ground-truth emissions and MAC-based emissions assess the accuracy of MAC-based estimates as compared to estimates using idealized vehicle activity data – not compared to directly measured emissions. Also, simulating MAC readings from the probe vehicle data assumes accurate MAC address travel time calculations. The post-processing of MAC address readings for accurate travel time estimates is outside the scope of this paper, while recognizing that emissions estimates are subject to the same ongoing issues as travel time applications (filtering stopovers, multiple readings from single vehicles, demographic bias, etc.).

Study Location

The study location is SE Powell Boulevard (U.S. 26 – an urban arterial in Portland, Oregon) between 12th and 82nd avenues. This 6 km corridor is a four lane undivided arterial with two lanes in each direction, with left turn bays present at intersections. There are eleven signalized intersections along the study corridor (at SE 21st, SE 26th, SE 33rd, SE 39th, SE 50th, SE 52nd, SE 65th, SE 69th, SE 71st, SE 72nd and SE 82nd avenues). The corridor is heavily traveled and serves approximately 37,750 vehicles per day. Since the corridor connects downtown Portland to the eastside suburbs, the westbound (WB) direction experiences heavy traffic in the morning peak period and similarly the eastbound (EB) direction has heavier traffic in PM peak period.

For this study 17 probe vehicle runs were collected during the AM and PM peak periods using passenger cars traveling in both directions (with and against peak flows). The trajectory data were gathered using in-vehicle GPS devices collecting location information and differentiating for speed at 1 second intervals. Probe vehicles followed an “average car” data collection approach, wherein the test vehicles traveled at the average speed of the traffic stream. Travel lanes were not specified, with the drivers being allowed to use their own judgment for lane changing maneuvers.
Figure 2 shows a map of the study corridor on the left side (west is up) with a sample WB peak-direction probe vehicle run where each point is a one-second speed reading; green dots are higher speeds and red dots are lower. The right side of Figure 2 shows the same sample probe vehicle trajectory on the space-time plane, where instantaneous speed is the slope of the trajectory line. Four simulated MAC readers are also illustrated in Figure 2, with equal spacing of 2 km. Each simulated MAC reader is assumed to detect the probe vehicle as it passes by, and travel times are calculated by the time elapsed between successive MAC readings (illustrated here between readers #2 and #3). Combined with the distance between detectors, the measured travel times provide an average speed estimate between simulated detectors (which is then used as (b) in the emissions estimation process shown in Figure 1).

Figure 2. Map of study corridor with sample WB (peak direction) probe vehicle run from 4:30pm on 6/10/2010 (speeds as colored dots, where red is slow and green is fast), with simulated MAC readers and the same probe vehicle trajectory on the space-time plane (map source: Google Earth)
Emissions Model

For consistency, all emissions modeling in this study (both microscopic and macroscopic) uses the MOVES 2010 mobile-source emissions model from the EPA (7). MOVES allows for microscopic emissions estimates using the project-level analysis with custom drive schedule inputs (second-by-second speeds from trajectory data) – see MOVES documentation for details (29). These “ground-truth” microscopic emissions estimates are made using full run trajectories and using trajectories broken into shorter segments of approximately 600 meters (with each run broken into 10 run-segments) – for a total of 170 run-segments.

In addition to the drive schedules, required MOVES inputs include fuel formulation, I/M program, and meteorology (all taken from Multnomah County defaults for January 2010), and vehicle age distribution by class (assumed using national average projections from the MOBILE 6.2 emissions model, EPA’s predecessor to MOVES). Emissions rate estimates are performed for 7 pollutants: CO$_2$e (greenhouse gases in carbon dioxide equivalent units), CO (carbon monoxide), HC (gaseous hydrocarbons), PM$_{2.5}$ (particulate matter smaller than 2.5 microns), benzene, and NO$_x$ (nitrogen oxides). Each pollutant is modeled for 4 vehicle types common on urban arterials: gasoline passenger car (PassCar_gas), gasoline passenger truck (PassTruck_gas), diesel passenger truck (PassTruck_diesel), and diesel light-duty commercial vehicle (LtCommTrk_diesel). The modeled emissions are for January 2010, on an urban unrestricted roadway facility at 0% grade. Running, evaporative, and brake/tire emissions are included, but start, refueling, and extended idle emissions processes are not.

MAC-based (average-speed) emissions estimates are made in MOVES using project-level analysis with average “link” speeds, which MOVES uses to cull relevant drive schedules from its internal library. Other than the substitution of average speeds for custom drive schedules, all other model inputs are the same. In this way we can isolate the emissions estimation differences due to different levels of vehicle activity data (detailed trajectories versus run-segment average travel speed). As stated above, the average speeds are calculated from the trajectory data by assuming MAC detection as the probe vehicle passes the simulated MAC reader locations. The MAC-based emissions estimates then connect steps (b) and (h) in Figure 1 above.

As with the trajectory-based estimates, the average-speed emissions rate estimates are performed for full probe runs (2 simulated MAC readers 6 km apart – 1 at each end of the corridor) and for run-segments of 600 meters (11 simulated MAC readers – at equally-spaced locations delineating 10 segments per probe run). Additionally, in order to investigate MAC-reader spacing effects, average-speed emissions estimates are performed for a range of run-segment lengths (detector spacings) from 200 to 3,000 meters (up to 30 segments per probe run). The MAC-based emissions rate estimates (h) are then compared with the ground-truth emissions rates estimates to generate the results presented in the following section.

RESULTS

Figure 3 shows the variability of ground-truth CO$_2$e emissions rates from PassCar_gas over the course of each run, separated by direction. The vertical axis units are percent difference in a run-segment’s emissions rate from the run’s average emissions rate. The box-plot for each run shows the spread of emissions rates over 10 run-segments of 600m each, caused by different speed profile characteristics on each run-segment. Overall, the run-segment emissions rate variability was greater in the peak flow direction, which involved more stops due to congestion. This variability is important when considering local pollution hotspots – either related to traffic characteristics or sensitive populations. Emissions rate variability for other pollutant-vehicle combinations is similar, and excluded for space economy.
Figure 3. Variability in ground-truth PassCar_gas CO$_2$e emissions rates over 10 run-segments of 600m each for 8 runs in peak flow direction and 9 runs in off-peak direction (with departure times)

Figure 4. Percent error in total corridor emissions from MAC-based estimates at a range of detector spacings (run-segment lengths); each line is a probe run
Figure 4 shows the percent error in total run emissions rates for MAC-based estimates using detector spacings from 200 to 6,000 meters, with one line for each probe run. A selection of vehicle-pollutant combinations is presented, though the results from other combinations were consistent with these. There is a slight decrease in MAC-based emissions rates at spacings shorter than 1km, but the detector spacing does not have a large effect on the total corridor error. This suggests that errors in the MAC-based emissions estimates are not due to the spatial resolution of the average-speed activity data.

Figure 5 compares the emissions rate versus average speed relationships of average-speed modeled (lines) and full-corridor ground-truth (points) emissions estimates. The probe run average speeds over the full corridor range from 15 to 30 mph. Throughout this range the ground-truth estimates and the average-speed estimates both follow the same curve shape, though with a slight offset. This pattern is consistent across pollutants and vehicle types, though the offset size and direction fluctuates. Since MAC-based emissions estimates are computed using the average-speed methodology, this result suggests that in addition to not being affected by detector spacing (Figure 4), the MAC-based emissions error is not skewed by congestion level (as indicated by average speed or delay).

**Figure 5. Emissions rate vs. average speed curves; lines are average-speed modeled and points are full-corridor trajectory-based estimates**

A similar situation is seen in Figure 6, which shows the average-speed modeled emissions rate vs. speed curves for PassCar_gas only (line), along with ground-truth emissions rates from 600m run-segments on all runs (points). Although there is more spread with more data points, the ground-truth data still match the shape of the average-speed modeled line, and over a wider range of speeds. The ground-truth data do not trend away from the MAC estimated rates at high or low speeds, indicating again that congestion level does not have a major impact on the accuracy of the method. The average-speed
approach, though it does produce error, is not noticeably poorer at estimating a slow run-segment with stop-and-go conditions than a free-flowing run-segment with average travel speed over 35 mph.

Figure 6. Emissions rate vs. average-speed curves
lines are average-speed modeled and points are 600m run-segment trajectory-based estimates

The varying error bias of the MAC-based estimates over all vehicle-pollutant combinations is shown as mean percent error (MPE) in Figure 7. The MPE is calculated by comparing MAC-based and ground-truth emissions rates over the full 6km corridor (Total_MPE) and over 600m run-segments (Segment_MPE). There is a great deal of variability across vehicle-pollutant combinations, though in general the MAC-based approach overestimates emissions rates on this corridor. The highest percentage errors are for pollutants with very low emissions rates (PM$_{2.5}$ and NO$_x$ from gasoline vehicles). The MAC method is generally more accurate for diesel vehicles than gasoline. The corridor and run-segment MPE is similar for all vehicle-pollutant combinations. Although the segment-level emissions can vary greatly (see Figure 3), the average-speed approach to estimation is similar in accuracy for 600 and 6,000 meter road sections.
Figure 7. Mean percent error (MPE) of all runs over the 6km corridor and over 600m run-segments, for all vehicle-pollutant combinations

The errors described here arise from speed profile differences between the measured probe trajectories and the drive schedules mined from the MOVES database. Speed profile/drive schedule differences lead to operating mode distributions within the emissions model that do not reflect the true operating mode distribution of the probe vehicles. In order to look in more detail at the sources of error in these estimates, we can mine the EPA drive schedules for a range of speeds, facilities, and vehicle classes from the MOVES 2010 MySQL database. Figure 8 presents drive schedule comparisons using Gaussian kernel density plots of the speed distributions of all probe runs combined (a) and for 3 individual probe runs with different average speeds (b - d) along with the MOVES drive schedules for passenger cars on urban arterials having the closest average speeds. In (a-c) the probe vehicle runs have more distinct bimodal distributions around free-flow speeds and stops, while the MOVES distributions are more spread. Both the probe run and MOVES schedule in (d) had more moderate and low speeds than the other speed profiles – reflective of more congested driving at the lower average speed.

The speed profile differences reflected in this Figure lead to the emissions rate differences shown in Figures 4 through 7. While the drive schedule average speed might match closely for a given run, the
distribution of speeds can be markedly different (e.g. Figure 8c). As we see in Figure 7, those speed profile differences affect different vehicle types and pollutants in different ways.

Comparing the speed distributions of the MOVES drive schedules with the probe vehicle data reveals unique local driving characteristics, as could be expected of any one locality (13,30). The more spread nature of the MOVES schedules in Figure 8 reflects the fact that they are archetypal driving patterns designed to represent a wide variety of urban arterial roads and drivers for aggregate emissions estimates throughout the U.S. For average-speed arterial emissions estimates, the database of drive schedules would ideally be collected locally on the arterial of interest, to be more representative. But recording a unique set of drive schedules at the full range of average speeds and vehicle types for every arterial in a city would be a time and cost intensive process. If not collected on the exact roadway, a compromise effort would be a database of drive schedules collected on other regional arterials with similar characteristics (lane configuration, intersection density, commercial activity, etc.) — though this could still be a costly undertaking.

As an alternative approach, we propose a simple method to partially localize the emissions estimates using a small amount of probe vehicle data. From the results above, the error across runs for each vehicle-pollutant combination tended to have a consistent bias unaffected by detector spacing or average speed (Figures 4 through 7). Thus, the proposed method applies a correction factor that is simply the mean ratio of ground-truth to average-speed total run emissions rates for each vehicle-pollutant combination.
combination. This correction can be calculated with only a handful of probe runs on each arterial, and
need not span all congestion levels.

As an illustration, we perform a random draw of 8 probe runs from the 17 of this study to
calculate a correction factor, then apply that correction factor to the MAC-based emissions rates of the
other 9 runs. The resulting MPE and mean absolute percent error (MAPE) are computed with respect to
ground-truth rates for the adjusted subset of 9 runs. This process was repeated with 100 random draws to
generate the full-corridor and 600m run-segment percent errors shown in Figure 9 (averaged across all
pollutants and vehicles). The corrections greatly reduce error for these data, with similar results across
vehicle-pollutant combinations. Correction factors were consistently in the range of 0.5 to 1.1, and mostly
around 0.8 as implied Figure 7. Although this method still requires some probe vehicle runs, it is less
costly than developing a full set of custom drive schedules and improves the accuracy of MAC-based
emissions rate estimates. The correction method works here on a small set of probe runs collected over a
short time range with only two different drivers. Further validation is required to see if the relationships
hold under more varying traffic and driver conditions.

![MPE and MAPE for adjusted MAC-based emissions rates, averaged across all pollutants and vehicles; spread is from 100 random draws to calculate adjustment factors](image)

**CONCLUSIONS**

This paper demonstrates the use of matched-vehicle travel times generated from MAC readers for
emissions estimates on urban arterials. A conceptual model is described for applying MAC readers for
real-time arterial emissions estimates. The core of the estimation method is then applied to a case study
using a small set of probe vehicle trajectories with simulated MAC detectors and the MOVES 2010
emissions model. Results show that the accuracy of the MAC-based emissions estimates – as compared to
more detailed emissions estimates using second-by-second speed profiles – varies greatly by vehicle and
pollutant.

MAC reader spacing does not have a large impact on the accuracy of emissions estimates, either
in terms of changing corridor lengths or changing detector spacing over a fixed corridor length. There are,
however, other potential benefits of increased detector density such as improved capture and match rates,
and more localized emissions estimates (which can vary greatly over a corridor). Similar to detector
spacing, average travel speed does not affect the accuracy of MAC-based emissions estimates. For the
probe runs of this study, the accuracy of MAC-based emissions estimates was better for diesel vehicles
than for gasoline.

The key issue for accuracy here is that MAC-based emissions estimates rely on the real-world
relevance of a library of drive schedules to be matched to the measured travel speeds. As shown in these
results, national default drive schedules (such as contained in the MOVES model) will not always apply
for an individual arterial of interest. While a complete set of locally-collected drive schedules for all
travel speeds and vehicle types would be ideal, these research results suggest that a simple factor 
adjustment to the emissions estimates from default drive schedules can improve MAC-based emissions 
estimates with only a few probe vehicle runs. 
Although this study is based on a small number of probe runs at one location, it provides insights 
into the potential for applying MAC address readings for arterial emissions estimates. Next steps include 
validation of these results with a broader set of probe vehicle data, establishment of a data structure for 
compiling a regional database of locally-collected speed profiles/drive schedules, and integration of real-
time arterial emissions estimates into the PORTAL transportation data archive at Portland State 
University (portal2.its.pdx.edu), which is currently in the process of incorporating MAC reader data from 
SE Powell Blvd.

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