# Addressing New Technologies and Data in Transportation Conformity: Pilot Study

MEMORANDUM

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Texas A&M Transportation Institute

# TECHNICAL MEMORANDUM

## Interagency Contract No: 21853

## Sub-Task 2.1 - TWG Technical Issues Analysis

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# 1. INTRODUCTION

This report summarizes a case study analysis for a Texas non-attainment area, conducted as part of the TTI-TxDOT Air Quality and Conformity Interagency Contract (IAC). This is the second part of a two-part task, which is aimed at providing a forward-looking assessment of how transportation conformity analyses can potentially incorporate new and innovative data and methods, or address trends such as electric vehicle adoption, to advance the state-of-practice in Texas. The findings of the overview and assessment conducted as the first part of the task are summarized in a separate technical memorandum. This report describes a pilot study to demonstrate how new data or assumptions can be incorporated into a regional emission inventory.

The pilot study focuses on electric vehicles (EVs), as an example of how a disruptive technology can be incorporated into a regional emissions inventory. This is a hypothetical example that does not currently have direct applicability to current, established procedures. However, it is aimed at providing an understanding of how such an analysis may be approached in the future, and possible implications to consider in terms of computations as well as in terms of results.

Specifically, the pilot study analyzes the impact of light-duty battery electric vehicles (BEVs) on regional emission inventories, using the emission inventories conducted by TTI for conformity analysis within Texas. The analysis uses an existing emission inventory generated by TTI as input, and re-estimates emissions after explicitly incorporating BEVs. In this case study, a recently-completed analysis for the El Paso nonattainment region was used as the baseline. Major objectives of this pilot analysis included:

- Develop a streamlined approach to quantify the critical pollutants generated by EVs within the current TTI conformity analysis framework
- Support scenario analysis regarding different EV adoption rates and EV fleet compositions
- Provide initial insight into potential changes in total emission inventories in non-attainment areas within Texas

The remainder of this report covers the methodology of calculating emissions from BEVs and the linkage between EV emission analysis and conformity results. Then, potential BEV adoption scenarios are proposed, and these are applied to the analysis, and the results then discussed. The impact of BEV adoption on emission inventories are discussed for different scenarios, emission processes, and pollutants.

# 2. METHODOLOGY

This section describes the methodology of developing a streamlined BEV emission calculation process (in the form of a streamlined tool), to demonstrate a technical approach to include a new source of data into the conformity process workflow. It is designed to be compatible with current conformity analysis procedures in Texas. With appropriate changes, this tool and approach is also transferrable to other regions or states as the work flow mainly follows the current conformity guidance (*2*, *3*).

## 2.1 METHODOLOGY OVERVIEW

Based on US EPA requirement and current practices in Texas, the regional emission inventories includes the following processes, consistent with the Motor Vehicle Emissions Budget (MVEB) from the State Implementation Plan (SIP) developed by the Texas Commission on Environmental Quality (TCEQ) (*4*) :

1. Running emission, including running exhaust for all pollutants and brake wear and tire wear for PM only
2. Evaporative emissions, including evaporative emissions from vehicle operation and vehicle parking
3. Start exhaust
4. Truck hoteling emissions

The methodology of incorporating BEV emissions is developed for the above emission sources. In addition, in some regions, the PM emissions from re-entrained road dust (also known as 'resuspension emissions') needs to be quantified using US EPA's 2011 AP-42 methodology. This is specifically applicabile in $PM_{10}$ nonattainment and maintenance areas and any PM2.5 nonattainment and maintenance areas if certain conditions apply (*5*). In Texas, as El Paso County is designated $PM_{10}$ non-attainment area, the resuspension emission inventory is considered in this pilot study as well.

Finally, the electricity consumed by BEVs are supplied by power plants and can contribute to stationary sources of emissions as well (*6*, *7*). Those upstream emissions from power plants are not currently included in mobile source emissions inventories and are not discussed in this work. However, it is important to consider those emissions in any assessment of total emissions in a region.

In this study, the emission adjustment methods to address BEVs are included for running exhaust, evaporative emission (running and parked vehicles), start exhaust, truck hoteling and resuspension emissions respectively, based on information from published literature. This methodology of preparing BEV emission rates is discussed in the next section.

## 2.2 Emission Rate Development

The current US EPA MOVES model allows users to define BEVs in the alternative fuel and powertrain input for light-duty vehicles (*8*). However, based on preliminary testing performed by TTI, the MOVES model does not provide BEV emission rates for certain pollutants (such as VOC and $PM_{10}$ running exhaust). In addition, emission rates of brake wear and tire wear are essentially the same as conventional vehicles, which contradict findings from other research. In this case, this pilot study adopts assumptions regarding BEV emission rates from existing studies to achieve a more representative assessment.

A BEV has a battery instead of a gasoline tank, and an electric motor instead of an internal combustion engine (*9*). As no fuel is used and no combustion involved, BEVs generate zero exhaust emissions at the point of use (*10*). Therefore, the running exhaust, evaporative emissions and start exhaust emission rates are all zero for BEVs. While MOVES assumes same levels of brake and tire wear emissions as conventional vehicles, studies indicate that this is not the case. For example, studies indicate potential disbenefits related to PM (*11*, *12*). This is because non-exhaust PM emissions, such as resuspension emissions and tire wear, could be higher for BEVs as they are heavier than their conventional counterparts. Brake wear emissions of BEVs tends to be nearly zero due to the application of regenerative braking technology (*13*). Friction brakes are only required for severe braking which can be avoided in most cases.

Finally, given the very limited proliferation of EVs in the medium- and heavy-duty truck market (*14*), this study only assesses the impacts of light-duty BEVs. Therefore, truck hoteling emissions remain unchanged in the pilot assessment.

Based on these findings, the following assumptions are used to represent BEV emissions in a regional emissions inventory:

- **Running emissions**
    - Use 0 gram/mile running exhaust for all pollutants
    - Use 0 gram/mile brake wear for $PM_{10}$ emissions

    - The BEV tire wear emission rates for $PM_{10}$ is 18% higher than their conventional counterparts (*12*)
- **Evaporative emissions**
    - Use 0 gram/mile for evaporative emissions during operation for all pollutants
    - Use 0 gram/source hour parked for evaporative emissions during parking for all pollutants
- **Start exhaust**
    - Use 0 gram/engine start for start exhaust for all pollutants
- **Truck hoteling emissions**
    - No adjustment (not applicable)

The resuspension emission factors used in current conformity analysis are derived from an empirical equation in USEPA AP-42 guidance (*15*). The resuspension emission factors depend on particle size, road surface silt loading and vehicle weight (*15)*, which are different from MOVES emission rates. In this case, instead of identifying resuspension emission factors from literature, the vehicle weight distribution of BEVs were adopted as input to generate the resuspension emission factors following the AP-42 guidance, as discussed in the next section.

The final emission adjustment methods by emission sources is summarized in Table 1. The emission adjustment discussed in this section is applied to the existing conformity analysis tools, resulting in a streamlined BEV emissions calculator as discussed in the next section.

## 2.3 Incorporating BEV Emissions into Current Analyses

As discussed in the introductory report, utilities and procedures developed in-house by TTI are used for developing emissions inventories for conformity purposes (*16*), using a streamlined automated tool. This is with the exception of the resuspension $PM_{10}$ emissions, which are computed using a separate spreadsheet-based tool to estimate these emissions for El Paso, TX (the only $PM_{10}$ non-attainment area within Texas). The details about the TTI emission inventory tool can be found in previous reports (*4*, *17*).

In this study, the EV emission analysis is performed for direct vehicle emissions as well as resuspension emission respectively. The BEV emission calculator uses the EV market penetration and vehicle type composition as inputs and generates adjusted regional emission inventories as outputs for the combination of BEVs and conventional vehicles. The BEV activity is split from total vehicle activity based on the market penetration level[1]. The BEV emissions will then be estimated as the product of BEV activities and emission rates based on assumptions discussed previously.

The structure of this calculator follows the current emission modeling structure as much as possible in order to achieve comparable results. It is designed per the following criteria to be consistent with the current emission modeling approach:

1. The emissions will be estimated with current emission inventories as inputs, with adjustments made to incorporate BEVs.
2. The emissions will be estimated for all the emission processes included in current emission inventories (running exhaust, start exhaust, etc.), without eliminating or adding emission processes.
3. The emission outputs will be aggregated at the same aggregation levels as current emission inventories.
4. The estimation of emissions does not require additional conventional vehicle fleet mix or vehicle activities to be collected or used.
5. The estimation of emissions does not require any modifications on the methodology of current emission inventories from conventional vehicles (in other words, the current TTI utility tool does not need to be re-run for this analysis).

In this analysis, an EV emission calculator is developed to post-process the emission inventory generated from recent conformity analysis and adjust the emission inventory based on pre-defined EV adoption scenarios. The calculations were performed using different methods as summarized in Table 1, to obtain the adjusted emission inventory with a fraction of BEVs presented in the fleet. The calculations and direction of changes in emission results vary by emission process. The direct vehicle emissions are computed using a Python script with conformity analysis results and EV-related specifications serving as major inputs. The resuspension emission were computed using the spreadsheet tool TTI developed using AP-42 methodology, with adjustments made to accommodate EVs in the fleet.

[1] In real-world condition, BEVs might have different operation patterns compare to its ICEV counterparts, such as their route choice and driving range. However, as the TDM used in conformity analysis does not provide individual trip-level information and there were no readily-available in-use BEV data, a simple assumption is adopted. Further adjustments can be made in the future as more data are available.

## Table 1. Summary of Emission Calculation Method

| Emission process | Component | Impacted by EVs? | Direction of changes | Emission adjustment | Time resolution in Analysis | Emission aggregation level |
|---|---|---|---|---|---|---|
| Running | Running exhaust + crankcase running exhaust | Yes | Zero pollutants | Only include emissions from non-BEV part of fleet | By hour | By vehicle type, road type |
| Brake wear | Brake wear | Yes | Zero $PM_{10}$ | Only include emissions from non-BEV part of fleet | By hour | By vehicle type, road type |
| Tire wear | Tire wear | Yes | Increased $PM_{10}$ | Scale up BEV portion with adjustment factors from previous study (*12*) | By hour | By vehicle type, road type |
| Start | Start exhaust + crankcase start exhaust | Yes | Zero pollutants | Only include emissions from non-BEV part of fleet | By hour | By vehicle type |
| Evaporative - parking | Permeation, fuel leak, tank vapor venting | Yes | Zero pollutants | Only include emissions from non-BEV part of fleet | By hour | SHP: by vehicle type |
| Evaporative - operation | Permeation, fuel leak, tank vapor venting | Yes | Zero pollutants | Only include emissions from non-BEV part of fleet | By hour | SHO: by vehicle type, road type |
| Hoteling | Extended idling emission, auxiliary power unit (APU) emission, crankcase extended idling emission | No | N/A | No adjustment | - | - |
| Resuspension | Resuspension emission | Yes | Increased $PM_{10}$ | Adjust vehicle weight distribution to reflect heavier BEVs | Whole day | By road type |

# 3. BEV ADOPTION SCENARIO DEVELOPMENT

## 3.1 Current Market Penetration in Texas

In 2019, only 0.12% registered vehicles in Texas were BEVs, based on a report from the Texas DMV (*1*). This suggests a negligible emission impact of BEVs in current analysis years. TTI recently acquired registration data collected by a private company named IHS-Markit (formerly R. L. Polk & Company) to support current conformity analysis work. The registration data contains vehicle registered in Texas as of late 2019 and is aggregated by county, fuel type, model year and vehicle registration class. Based on the Polk registration data, the current light-duty vehicle (LDV) count (Class 1 and 2) by fuel type is provided in Table 2:

**Table 2. Light-duty Vehicle Count by Fuel Type in 2019 Polk Registration Data**

| Fuel | Count | Percent |
|---|---|---|
| Compressed natural gas | 1129 | 0.01% |
| Convertible | 1448 | 0.01% |
| Diesel | 705526 | 4.44% |
| **Electric** | **5401** | **0.03%** |
| **Electric and gas hybrid** | **47987** | **0.30%** |
| Flexible | 2180292 | 13.73% |
| Gas | 12939521 | 81.48% |
| Hydrogen fuel cell | 1 | 0.00% |
| Propane | 1 | 0.00% |
| Unknown | 51 | 0.00% |
| **Total** | **15881357** | **100%** |

The 2019 Polk data indicates only 0.03% of the registered LDV fleet are BEVs, with 5401 BEVs registered in total. Even considering the broad categories of EVs (BEVs and hybrid), they make up only 0.33% of LDV fleet in Texas. However, the EV market is rapidly growing in Texas. Based on the vehicle count by model year from the Polk dataset (shown in Figure 1), EVs purchases have grown in recent years. If this trend continues, a higher penetration of EVs is forseeable in the future, making it important to evaluate the impact of EVs on various aspects of transportation, including on emissions.

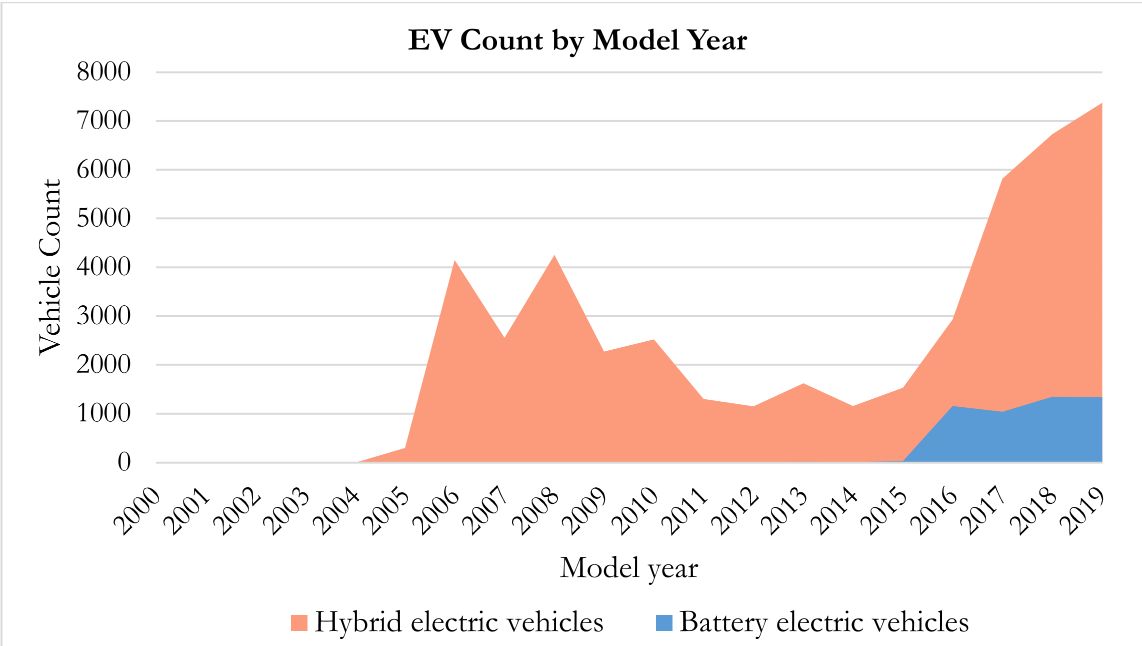


**Figure 1. EV Count by Model Year**

## 3.2 Assumptions in this Analysis

In this analysis, the emission inventories are estimated for the future analytical year results, with likely emission impact contributed by a higher share of BEVs in the fleet. So far, the future of EV market penetration is largely uncertain and the market share variability is dependent on several key factors such as price sensitivities, energy cost, range limitation, and charging availability (*18*). Although the emission rates in current MOVES model may contain a small portion of alternative fuel and powertrain vehicles in the total fleet (to meet more stringent emission standards by year), it doesn't account for a substantial amount of EVs in the fleet above and beyond minimum levels. Further, differences in brakewear, tirewear, and resuspended dust emissions are not not currently reflected in MOVES and in existing procedures.

This analysis approach can therefore model a range of EV adoption and fleet turnover scenarios. The BEV emission calculator allows replacing a pre-defined fraction of conventional vehicles with EVs that share the similar vehicle types. In this case, the tool can be used to answer 'what-if' questions under different BEV adoption scenarios.

Regarding future BEV penetration level, The Electric Reliability Council of Texas (ERCOT) recently forecasted 3 million BEVs in Texas by 2033 (*19*), which is roughly 10% of total vehicles in Texas[2]. Based on this, the analysis assumes a 10% EV penetration level in 2030 for passenger cars in this study. Other assumptions regarding different market penetration levels can be made in this tool easily by updating the input BEV market penetrations.

The BEV fleet was modeled using existing BEV models that are available on the market now. The market share of BEVs are collected using EV sales data from 2011 to 2019 (*20*), and BEV sales were aggregated into three types (100-mile, 200-mile and 300-mile ranges) based on the electric range of vehicles. For each type of BEV, the BEV model with highest market share is chosen to represent this type, and the specifications of the three representative models were used for emission modeling in this analysis. In this study, the Nissan Leaf is selected to represent 100-mile BEVs, the 2016 Chevrolet Bolt represents 200-mile BEVs and 2016 Tesla Model S is selected to represent 300-mile BEVs. The vehicle specifications, such as battery capacity and vehicle weight, were retrieved from a full-system vehicle simulator called the Future Automotive Systems Technology Simulator, or FASTSim (*21*). The vehicle specifications in Table 3 were used to estimate average vehicle weight in resuspension emission calculation.

**Table 3. Summary of BEV Specifications**

| BEV Type | Representative Model | Battery Capacity (kWh) | Vehicle weight (lbs) | Market Share |
|---|---|---|---|---|
| 100-mile BEV | 2016 Nissan Leaf | 30.4 | 3657.5 | 25% |
| 200-mile BEV | 2017 Chevrolet Bolt | 60.0 | 3875.2 | 13% |
| 300-mile BEV | 2016 Tesla Model S | 101.2 | 5004.5 | 52% |

In this pilot study, the conformity analysis result from El Paso, TX is selected to demonstrate the impact of explicitly including BEVs in regional emission inventories.

[2] The total number of light-duty vehicles in Texas is about 22.8 million in 2019 (https://autoalliance.org/in-your-state/TX?export), and growing at 2% rate based on historic vehicle registration data from TxDMV (https://www.txdmv.gov/txdmv-forms/cat_view/13-publications/25-reports-data/65-vehicle-titles-registration/229-registration-data/274-vehicles-registered-by-registration-class). In this case, the estimated total number of LDVs in 2033 is about 30 million.

The primary reason for choosing El Paso is because of its non-attainment designation -- El Paso County is currently a PM-10 nonattainment area and Carbon Monoxide (CO) maintenance area. The Sunland Park City near El Paso is an Ozone Nonattainment Area. Due to this, the regional emission inventory of El Paso contains several criteria pollutants, including NOx, VOC, CO, and $PM_{10}$. In addition, as road dust is identified as a major contributor of $PM_{10}$ emission, the resuspension emissions are also needed for El Paso. Finally, TTI has performed the conformity analysis for El Paso MPO recently with the latest data sources and methodology available (*22*). Therefore, using recent emission inventories from El Paso as a case study enabled an assessment of more pollutants, including resuspension emissions, using recent data.

# 4. RESULTS AND ANALYSIS

In this analysis, the emission inventories from winter 2030, El Paso County are selected as the model input. To incorporate BEVs, the analysis assumed 10% of passenger cars (MOVES source type = 21) are replaced with BEVs. Emissions calculations were performed using the methodology in Section 2 and parameters and assumptions outlined in Section 3. The emission results from direct vehicle use and resuspension emission are presented in the remainder of this section. The intention of this study is not to provide an assessment of real world impacts or implications for an actual conformity determination. Rather, it is meant to demonstrate impacts for a simple hypothetical scenario.

## 4.1 Emissions from Vehicle Use

The total emissions per day from direct vehicle use are listed in

Table 4 . As seen in the results, the direct vehicle $PM_{10}$ emissions (running, start, brake and tire wear, etc.) were reduced by 3.7%, due to there being no tailpipe emissions from BEVs during operation. Similarly, the VOC, CO and $NO_X$ emissions per day were reduced by 5.5%, 5.7% and 1.8%. However, the statistical significance of these emission reduction estimates cannot be computed, as it depends on the uncertainty of underlying emission rates, which are not provided in the current MOVES output. Thus, the statistical significance of the results are not discussed.

**Table 4. El Paso 2030 Winter Emissions from Direct Vehicle Use**

| Scenario | VMT | Speed (mph) | $PM_{10}$ (US ton) | VOC (lbs) | CO (lbs) | NOx (lbs) |
|---|---|---|---|---|---|---|
| Baseline (No EV) | 22,708,611.79 | 35.17 | 1.39 | 10,020.26 | 102,717.16 | 19,502.32 |
| 10% PC to EV | 22,708,611.79 | 35.17 | 1.34 | 9,467.72 | 96,856.09 | 19,149.36 |
| **Difference** | **0%** | **0%** | **-3.7%** | **-5.5%** | **-5.7%** | **-1.8%** |

Finally, the direct vehicle emissions disaggregated by emissions process for each pollutant are provided in Figure 2. In terms of $PM_{10}$, the emission reduction is mostly contributed by brake wear reduction. The increment of tire wear emissions is relatively small compared to the emission reduction benefits from other sources. For CO and NOx, the major emission reduction comes from start emissions and running emissions. Finally, the emission reductions of VOC are mostly contributed by the reduction in the start and evaporative emissions, not so much reduction gained from running exhaust. This shows that while BEVs reduce direct emissions of all pollutants in the study, the contributing factor to the reduction (in terms of the most-affected process) differs by pollutant.

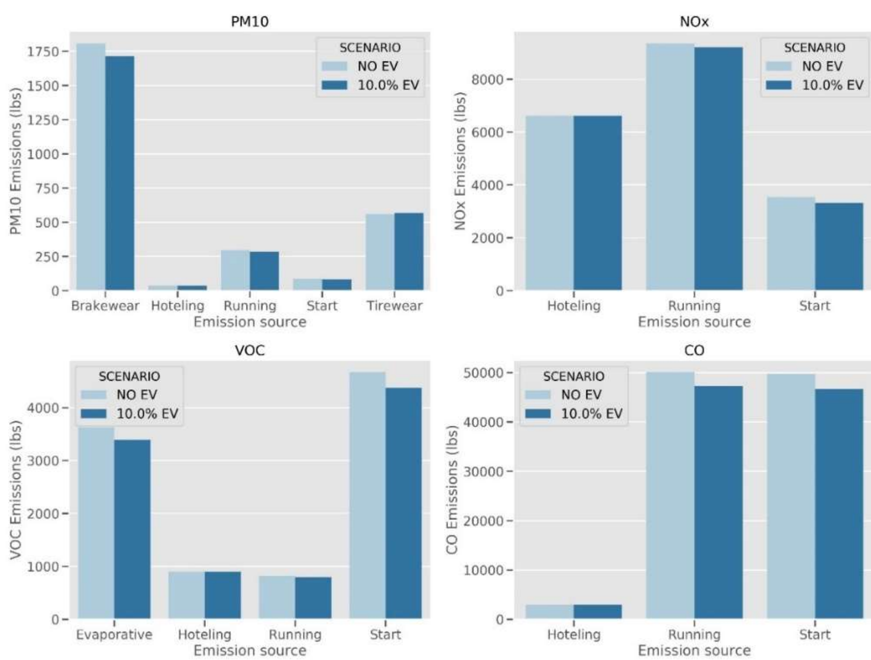


**Figure 2. Emission Inventory Results by Emission Process**

## 4.2 Results for Resuspension Emissions

As described in previous sections, the resuspension $PM_{10}$ emissions were estimated using the US EPA AP-42 method and updated passenger car weight. As BEVs are heavier than their conventional counterparts, the average vehicle weight of passenger cars with 10% BEVs included increases from 3000 lbs. to 3152 lbs., which causes an increase of 1.4% in resuspended road dust based on the AP-42 method (0.11 tons of $PM_{10}$ increment). As with the direct emissions, the statistical significance of this result cannot be fully established, due to the underlying uncertainty associated with emission factors adopted in the calculation, especially the uncertainty of resuspended emissions.

The uncertainty of resuspended emission will affect the direction of changes as it currently dominates the $PM_{10}$ emission inventory. Based on the EPA documentation of resuspended emission factors (*23*), the confidence interval of estimated coefficients (the exponential terms of silt loading and vehicle weight) are large. It is expected that 95% of future data would fall within equations with exponents of 0.677 and 1.14 for the silt term and 0.852 and 1.19 for the weight term (in TTI's analysis, coefficient of silt term is 0.91 and coefficient of weight term is 1.02). In this case, the upper and lower bound of the emissions is also provided in Table 5 below as an indicator of the uncertainty in results. The actual emission increment estimated is much smaller than the range of uncertainty, and the emission difference is likely not statistically significant. Again, the results provided here demonstrate the effectiveness of this emission calculation tool and showcase the output of the process of incorporating BEVs.

**Table 5. El Paso 2030 Winter Emissions from Resuspension Emission**

| **Scenario** | **VMT** | **Speed (mph)** | **Resuspension $PM_{10}$ emission (US ton)**<br>(95% CI estimation provided in parenthesis) |
|---|---|---|---|
| no EV | 22,708,611.79 | 35.17 | 6.49 (3.1– 15.0) |
| 10% PC to EV | 22,708,611.79 | 35.17 | 6.58 (3.1 – 15.2) |
| Difference | 0% | 0% | **1.4%** |

# 5. CONCLUDING REMARKS

In this report, a streamlined EV emission modeling approach is proposed to demonstrate how EVs can be incorporated into current emissions inventory processes, and investigate the impact of EVs on a representative emission inventory. A case study for El Paso, Texas is performed to demonstrate the effectiveness of the method and provide insights of EVs' impact on regional emission inventories. This work was performed within the current conformity analysis framework, building on existing TTI utilities and procedures. The EV analysis was appended as a post-processor to the current process, without the need to perform additional calculations.

The emission results suggested that incorporating a 10% share of EVs into the Texas (El Paso) fleet may reduce direct vehicle emissions (exhaust, brake wear, crankcase, vehicle starts etc.) by between 2 to 6 percent, depending on types of pollutant being investigated. Reduction in $PM_{10}$ emissions may be offset by a slight increase in resuspension emissions caused by typically heavier EVs compared to conventional vehicles. However, this analysis was for a hypothetical scenario. Refined activity data and fleet penetration data are desirable for more representative assessments.

In conclusion, the sketch analysis performed in this study provided an example of potential adjustments to current conformity procedures to include disruptive technologies such as EVs. It also indicated the potential for changes in emissions with increased market shares of EVs. However, as discussed in the report summarizing the first part of this task, making changes to conformity analysis procedures to incorporate new data and technologies is a more complicated, longer-term process. It requires coordination and discussion among stakeholders, and consistency with the State Implementation Plan development process. However, as demonstrated with this work, such analyses are feasible and can be considered to improve the state-of-practice in the future.

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