



Article

EV Adoption Influence on Air Quality and Associated Infrastructure Costs

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Abstract: Exploring the system-level interactions within the modern urban transportation system, factors such as human health, vehicle exhaust pollution, air quality, emerging personal transportation technologies, and local weather events, are increasingly expedient considering the growth of human population centers projected in the 21st century. Pollutants often accumulate to unhealthy concentrations during winter inversion events such as those that commonly occur in Utah's Salt Lake valley and other mountainous regions. This work examines the degree to which replacing conventionally powered vehicles with electric vehicles (EV) could reduce the near-road accumulation of criteria pollutants under various degrees of inversion depth and wind speed. Vehicle emissions data are combined with inversion and wind factors to determine changes in the Air Quality Index, and a first-order estimate of the cost required to build an EV charging infrastructure to support a given EV adoption scenario is also derived. Results are presented in the form of multiple Pareto frontiers and a simplified cost-benefit formula that inform potential public and private EV charging infrastructure investments to drive the EV adoption that would result in optimal air quality improvements during average weather and winter inversion events.



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Keywords: environmental impact; electric vehicles; air quality; criteria pollution; modeling and simulation

1. Introduction

The smolderings of an electric vehicle (EV) revolution evident in the early 2000s have, in recent years, grown into a fast pace roll-out of dozens of new EV models sporting increasingly longer range batteries, class-leading performance statistics, and state-of-the-art technologies that promise a future of fully autonomous vehicles and emissions-free transportation. One of the strongest arguments in favor of pursuing accelerated EV adoption is the reality that they produce zero tail-pipe emissions. Transportation accounts for approximately 30% of greenhouse gas emissions in the US and anywhere between a few percent and 55% of criteria pollution [1,2]. In the state of Utah, for example, transportation is responsible for 12% of PM_{2.5} emissions [3].

Criteria pollution concentrated near human populations is responsible for a variety of pulmonary health problems, including acute bronchitis, pneumonia, and early onset asthma [4,5]. These effects are primarily seen in individuals exposed to bad air over a long period of time or in at risk groups such as children and the elderly [6,7]. There are however, two exceptions to these trends: individuals that are exposed to exceptionally high particulate matter buildup over shorter periods of time [8,9] and individuals that live in areas with high vehicle traffic [5,9,10].

Criteria pollutants are particularly concerning in Utah and other regions that experience severe winter inversion events. In and of themselves, the inversions are not particularly dangerous to humans—they only involve a layer of cool air close to the ground being overlaid by a layer of warm air higher in the troposphere. However, these phenomena tend to trap pollution near the ground in the mountain valleys in which the majority of

Utah's population lives [11]. Depending on the length of the inversion, criteria pollutant accumulation can become dangerous. During a severe inversion, for example, PM_{2.5} levels can exceed 150 on the air quality index (AQI) [12]. An AQI of between zero and 50 is considered "good", an AQI between 50 and 150 indicates that the air may be unhealthy for various sensitive or at-risk groups of people, and an AQI of above 150 is considered to be unhealthy for all groups [8]. Such high levels of pollution accumulation during inversion events put local populations at risk of both long-term and acute negative health effects.

Among criteria pollutant sources in Utah, on-road internal combustion engine (ICE) vehicles account for 12% of total PM_{2.5} emissions and between 1% and 38% of other criteria pollutant emissions [3]. Though those statistics are reduced from similar ones from the 1980s and 1990s, vehicle emissions still account for hundreds of thousands of pounds of criteria air pollution every year in the state [13].

Unlike ICE vehicles, electric vehicles (EVs) produce zero tailpipe emissions. Consequently, EVs have been presented as part of a broader solution to poor air quality around the world [14–16]. This study examines hypothetical situations in which EVs compose different percentages of the total vehicle population and the resulting impact that those EV adoptions could have on air quality. Additionally, it examines the financial costs associated with purchasing and installing the physical charging infrastructure required to support each hypothetical EV population. The resulting model employs traffic throughput data; US Department of Energy (DOE) predictions for EV infrastructure costs; and over 161,000 unique combinations of light duty vehicle (LDV), light duty truck (LDT), and heavy duty vehicle (HDV) electrification, inversion events, and wind conditions to predict air quality improvement and the financial costs associated with supporting that improvement.

The traffic along a 32 km stretch of I-15 (Utah's most heavily traveled interstate freeway) in Salt Lake County is used as a model test case. Results from the test indicate generally that, though environmental factors such as wind and inversion are massively influential in determining local air quality, widespread vehicle electrification can be a significant factor in improving air quality. During typical winter and summer weather, with minimal inversion and average winds of five and seven miles per hour, respectively, electrification scenarios in which at least one vehicle class has between 75% and 100% EV adoption can yield an air quality improvement of between six and nine AQI points. This is a respectable and valuable improvement. Furthermore, during a strong inversion event and when winds are below three miles per hour, similar electrification scenarios could result in improvements of between 30 and 50 AQI points. Such a significant improvement in air quality could dramatically reduce the risk to human health associated with poor local air quality, especially to at-risk populations. The cost associated with building a charging infrastructure capable of supporting the EV population needed to drive such air quality and human health improvements varies between USD 100 to USD 320 million dollars, depending on the specific EV adoption strategy.

This work's scope is confined to vehicle tailpipe emissions, and does not examine life-cycle ICE vehicle or EV pollution (e.g., pollution from vehicle and battery manufacture, energy production, fuel refinement, battery disposal) or non-fuel-related pollution (e.g., tire and road wear), though those factors are important and are well considered in the larger conversation regarding EV adoption strategies. Its purpose is not to directly promote EV adoption or argue against the continuation of ICE production. Rather, it constitutes a systems-level examination of the relationship between traffic along major transportation corridors, environmental factors, vehicle-generated tailpipe pollution, air quality, human health, and infrastructure requirements.

The value presented by this work is the examination of multiple factors that influence public health, spending, and opinion—few other analyses simultaneously consider the synergies between technological, social, and environmental issues. The issues examined in this work comprise the urban ecosystem in which most of Utah's, and the world's, population lives. As the human population within the system grows, vehicle traffic increases, and the negative impact of vehicle emissions on human health must be understood and alleviated.

Local weather patterns can aggravate those health impacts. Emerging personal transportation options such as the proliferation of EV technology should be examined as possible methods for pollution mitigation, especially in the context of pollution-aggravating local weather patterns.

1.1. Background

Since the early 1990s, research has shown that vehicle pollution emissions have a negative effect on human health [4–6,10,17,18]. Additionally, publications about EV technology and its effect on human-generated pollution have increased in number since the early 2000s [13,19–21]. Some of these studies are briefly presented below to establish the context and background information for this work.

1.1.1. Negative Physical and Social Health Effects of Criteria Pollution

The negative effects of criteria pollutants on human health are well documented. Researchers and government organizations classify criteria pollutants as contributors to the development of common pulmonary and cardiovascular sicknesses [18,22]. Multiple studies have found evidence linking an increase in adolescent asthma cases to increased criteria air pollutant concentrations in urban settings [10]. Analysis of criteria air pollutant emissions and the health risks they present to on- and near-road populations is also extensive [5]. Beyond localized communities, the negative health effects associated with prolonged exposure to particulate matter have been observed across multiple geographic regions [9]. All of these studies should cause concern among policy makers and local stakeholders as increasing numbers of vehicles traverse roadways and urbanization continues near and around major transportation thoroughfares.

The negative health effects associated with criteria pollution have also been observed as being disproportionately present in certain low income and underrepresented populations [23,24]. Other studies have found correlations between the locations of these at-risk populations and major highways [25,26]. The resulting correlation seems to indicate that vehicle-sourced pollution may have a disproportionately large effect on populations that have less opportunity than others to change their situation. Consequently, it is likely that improving air quality near major roadways may also help to address the issues of social inequality that plague modern urban areas.

1.1.2. Pollutant Emission, Accumulation, and Dispersion Models

Models that determine the type and rate of vehicle emissions range from simplistic to incredibly complex. The national and industry standard is the US EPA MOVES model [27]. However, to the authors' knowledge, MOVES does not provide the flexibility required to explore different EV adoption strategies as per this work's objective. Consequently, it was used primarily as a reference point to validate the method used herein, i.e., to use vehicle miles traveled data, vehicle age and class distributions, and government emissions standards to estimate the volume of pollution produced in a certain area over a certain time.

Pollution accumulation and dispersion modeling is a well-developed field within environmental health research. Some models, such as the QUIC-URB model developed at Los Alamos National Laboratory, examine the effect of building height and spacing as well as street-level wind patterns on urban pollution dispersion [28–30]. Others focus on larger urban areas and pollution/particle movement within the lower atmosphere [31,32]. Of particular interest to this study are models that specifically target near-road, vehicle-emitted pollution [33]. The EPA has also developed and published a set of guidelines for forecasting air quality [34].

1.1.3. Weather Pattern Analysis

Winter weather patterns in Utah are of particular interest to this work because of the effect that inversion events have on pollutant accumulation. Multiple studies have been conducted examining wintertime air movement in the Salt Lake Valley [35,36]. Additionally,

studies on deep inversion events in Utah's Cache Valley were beneficial in determining the extreme extent to which pollution can accumulate during inversions [12]. The general principles of inversion development presented by Neuberger were also useful [37].

1.1.4. Environmental Benefits of EVs over ICE Vehicles

Because EVs are largely viewed as an alternative to traditional ICE vehicles, the two are commonly compared to determine the extent to which they impact pollution emissions [20,38,39]. The conclusion of life-cycle studies, including a recent study on urban air pollution in Mexico City, that include analysis of tailpipe, energy production and refinement, and manufacturing-related pollution is that impact largely depends on the type of fuel source used for electricity generation (i.e., well-to-tank emissions) [40,41]. However, the reduction in tailpipe emissions, and thus the impact on air quality in densely populated regions, related to EVs is undeniable [19,42]. It has been shown that, in countries with high vehicle sales (e.g., the United States), replacement of ICE vehicles with EVs reduces greenhouse gas emissions [43]. It follows that criteria pollutant emissions could be similarly reduced, in particular via aggressive EV adoption strategies. Other studies indicate that, while ICE vehicles do produce more source (i.e., tailpipe) emissions than EVs, those emissions have been in continuous decline since the turn of the century [13], insinuating that they may become less problematic in the future, depending on federal and state regulations.

1.2. Summary

While each of these studies provides excellent insight into various aspects of the overall system, and some do cross over into the other subsystems to varying degrees, seldom do they simultaneously consider the systems-level relationships between human, vehicle, economic, and environmental factors. This work's contribution is filling that space by providing an interdisciplinary, techno-socio-economic analysis of the impact that increasing EV populations could have on tailpipe emissions, the costs associated with that increase, pollution accumulation during typical local weather patterns, and human health. While the model presented in the following sections employs a lower level of fidelity than that found in other subsystem models, its synthesis of critical information from technological, social, environmental, and economic disciplines allows for a holistic analysis of the multifaceted, complex human–transportation–environment ecosystem.

The work's purpose is to allow stakeholders in the human–transportation–environment ecosystem to explore trade offs between EV infrastructure investment and local air quality improvements resultant from the increased EV adoption supported by that infrastructure investment. In continuation, this article develops the data gathering and modeling methods used to synthesize data from each of the areas of study discussed above into a high-level systems model for the entire ecosystem. Figure 1 provides an outline for the structure of the rest of this document.

- Section 2 discusses the methods for creating the Compiled Data repository and Design of Experiments (DOE), Cost Model, and AQI Model sub-models.
- Section 3 discusses the results from each sub-model and details the creation of the Decision-Making Surrogate Model based on the results of those analyses.
- Section 4 provides conclusions drawn from each of the sub-model analyses and the decision-making model, a discussion of their merit and utility, and a brief outline of work that may be pursued to improve upon the work presented herein.

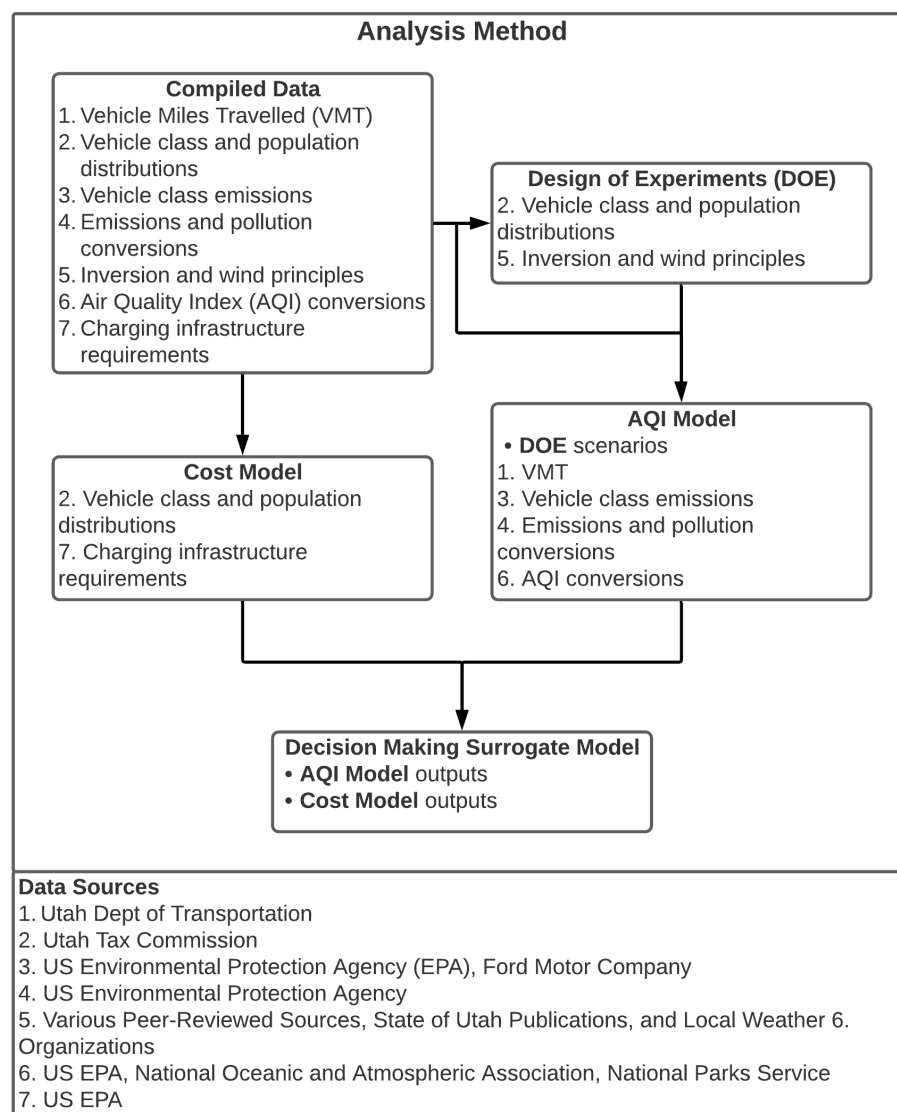


Figure 1. The structure and method of analysis developed in this work. Citations for each data source are provided in context in the article’s main body.

2. Methods

This section describes the data collection and analysis, assumptions, and mathematical models used in the model’s development. It first describes the data and assumptions used to inform the model. The second section describes the individual components of the model and their coordinating relationships. The mathematical models were all developed in MATLAB and the SAS-developed dynamic statistical analysis software JMP was used to post-process and interpret the results data.

2.1. Data Analysis and Assumptions

In order to achieve the project’s goal of modeling the effect of EV populations on air quality improvement near major highways and the costs associated with supporting those EV populations, data were acquired from repositories created or sponsored by the Utah Department of Transportation (UDOT), the Utah State Tax Commission [44], the United States Environmental Protection Agency (EPA) [45], the United States Department of Energy (DOE) [46,47], the Ford Motor Company [48], and from various academic and database sources [36,49,50]. The following sections summarize the various data gathered, the sources for each data set, and the assumptions made by the model regarding unknown or unquantifiable data properties.

2.1.1. Vehicle Miles Traveled

Traffic data for the test case area (Salt Lake County, UT, USA) were compiled in the form of vehicle miles traveled (VMT) data from the UDOT Performance Measurement System (PeMS) [51]. The PeMS database monitors over 1500 traffic measurement stations along Utah's highways. For the test case, only the north-bound section of I-15 between mile markers 290 and 310 (approximately the section that transects Salt Lake City) was considered. However, the same analysis could be performed on other highway sections.

The PeMS system intakes traffic flow data from radar sensors and aggregates this into VMT, flow, and density data sets. For this study, the model samples VMT data from approximately every tenth of one mile at one hour intervals. The data used for computations in the test case are from the first week of August 2017. Traffic from that week closely matches the average weekly VMT for the entire year and thus is used to represent year-round traffic in this work.

2.1.2. Vehicle Categories

The vehicle population within the model is divided into three general categories: light duty vehicles (LDV), light duty trucks (LDT), and heavy duty vehicles (HDV). The LDV category consists of street-legal, four-wheeled vehicles that are not considered to be trucks (e.g., passenger cars) and must have a gross vehicle weight rating (GVWR) of less than 8500 lbs. LDT vehicles abide by the same weight constraints as LDVs, but differ in body type and emissions regulation. Examples of LDTs are pickup trucks, SUVs, and crossovers. The HDV category consists of all trucks or passenger vehicles with a GVWR greater than 8500 lbs. Semi tractor trailers, city buses, snow plows, and garbage collection vehicles are examples of HDVs. Medium duty passenger vehicles (MDPV) such as large vans are included in the HDV class, as they have similar GVWRs and emissions standards and represent a tiny portion of the total vehicle population in Utah. Several categories of vehicles were not included in this study because their total emissions in Salt Lake County can be considered negligible when compared to those of vehicles in the classes described above, either because the vehicles do not frequently drive on major roadways (e.g., agricultural and mining vehicles) or because their emissions are so low that their replacement with electric equivalents would not significantly change air quality (e.g., motorcycles). Information regarding vehicle classifications can be found on the EPA website [52].

The number of vehicles used in the study is the number of vehicles from each class registered in Salt Lake County in 2018, as per the Utah Tax Commission [44]. Figure 2 shows the distribution of vehicle registrations from 1902 to the present, with the vast majority of registered vehicles being produced after 1985. As of the end 2018, there are 509,154 LDVs, 347,332 LDTs, and 29,006 HDVs registered in Salt Lake County.

2.1.3. Vehicle Emissions Standards

The model operates under the assumption that the vehicles produced in any given year adhere to the EPA-defined emissions standards for that year. The emissions standards specify that, for a given vehicle type and bin number (a subcategory of vehicle type used interchangeably with vehicle emission category), a vehicle can only produce up to a specified mass of a given pollutant per mile traveled. Emission standards are assigned to vehicles in two primary groups, each corresponding to the weight classifications identified by the EPA [52]. LDVs and LDTs are divided into three groups: Tier 1, Tier 2, and Tier 3 vehicles and HDVs are presented in one group.

LDV and LDT Group

In this work, the three LDV and LDT emissions standards are assigned to vehicles as follows: vehicles produced before 2004 follow Tier 1 standards, vehicles produced between 2004 and 2016 follow Tier 2 standards, and vehicles produced after 2016 follow Tier 3 standards. All emissions standards used by the model for LDVs and LDTs are listed in

Table 1. Though the Tier 1, Tier 2, and Tier 3 EPA standards officially took effect in 1994, 2004–2008, and 2012, respectively, their implementation by automobile manufacturers was only slowly phased in. For example, though Tier 3 standards were published in 2012, the first Ford vehicles that adhered to those standards were not sold until 2016 [48]. Additionally, the Tier 1 vehicle emission standard is applied to all vehicles produced before 2004 because the Tier 1 standard is the first widely applied vehicle emissions standard. The model assumes that all vehicles produced before the Tier 1 standard’s publication would emit at least at the levels it specifies.

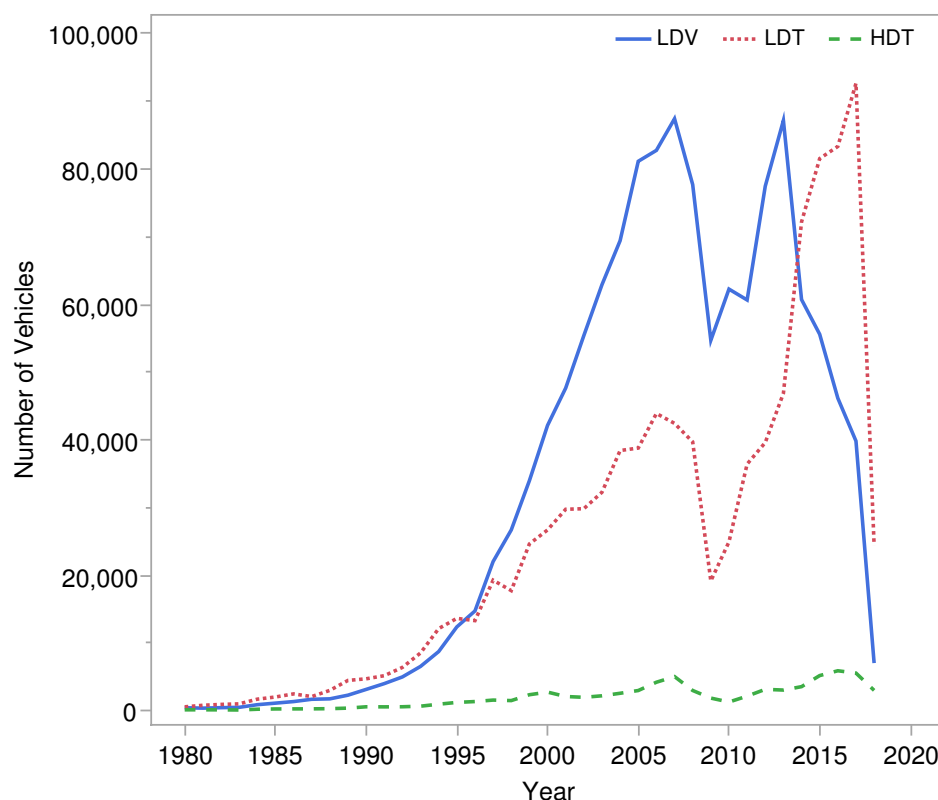


Figure 2. Number of registered LDVs, LDTs, and HDVs by production year in Salt Lake County in 2018 [44].

Table 1. LDV and LDT emissions standards for all tiers and bin numbers, as presented by the model (note that some bin numbers have been changed from those assigned by the EPA for modeling simplicity and that the PM column includes aggregated data for all measured particulate matter, including PM2.5 and PM10) [53]. Units shown are g/mi.

Year	Tier	Bin #	NOx	CO	PM	HCHO
2004	Tier 1	1	0.91	4.2	0.01	0.8
2016	Tier 2	1	0	0	0	0
		2	0.03	2.1	0.01	0.004
		3	0.085	2.1	0.01	0.011
		4	0.11	2.1	0.01	0.011
		5	0.16	4.2	0.01	0.018
		6	0.19	4.2	0.01	0.018
		7	0.24	4.2	0.02	0.018
		8	0.325	4.2	0.02	0.018
		9	0.39	4.2	0.06	0.018
		10	0.756	4.2	0.08	0.018
		11	1.18	7.3	0.12	0.032

Table 1. *Cont.*

Year	Tier	Bin #	NOx	CO	PM	HCHO
2018	Tier 3	1	0	0	0	0
		2	0.02	1.0	0.01	0.004
		3	0.03	1.0	0.01	0.004
		4	0.05	1.7	0.01	0.004
		5	0.07	1.7	0.01	0.004
		6	0.125	2.1	0.01	0.004
		7	0.160	4.2	0.01	0.004
		8	0.150	1.5	0.06	0.006
		9	0.170	1.5	0.06	0.006
		10	0.200	2.6	0.06	0.006
		11	0.250	2.6	0.06	0.006
		12	0.340	3.2	0.06	0.006
		13	0.395	6.4	0.12	0.006

HDV Group

The other group comprises all HDV emissions standards published by the EPA between 1988 and the present. Published standards exist from as early as 1974, but they are the same as the 1988 standards. Consequently, it is assumed that all HDVs built before 1988 emit at or above the levels specified by that year's standards. The EPA gives the emissions standards for HDVs in units of grams per bhp-hour (g/bhp-hr), a measure of engine horsepower before losses to mechanical inefficiencies. To convert this measure into grams per mile (g/mi), as emissions are measured for LDVs and LDTs, the following equations presented by the EPA in [54] are used.

$$\gamma_{con} = \frac{\rho}{BSFC \times MPG} \quad (1)$$

where γ_{con} is the conversion factor in units of bhp-hr/mi, ρ is the density of fuel in units of lb/gal, BSFC is the brake-specific fuel economy (estimated at 0.4 for buses and trucks that use diesel fuel [54]), and MPG is the vehicle fuel efficiency in mi/gal of an average diesel truck or bus (population average estimated at 5 MPG [55]). Hourly emissions for HDVs are calculated as follows.

$$E_{g/mi} = \gamma_{con} E_{g/bhp-hr} \quad (2)$$

where $E_{g/mi}$ and $E_{g/bhp-hr}$ are the emissions of pollutant per mile and per bhp-hour, respectively, of a given vehicle, and γ_{con} is derived in Equation (1). The HDV standards are shown in Table 2.

Table 2. EPA emissions standards for compression-engine (i.e., diesel-powered) HDVs built between 1988 and 2018. Units shown are g/mi (g/(bhp-hp)).

Year	NOx	CO	PM	HCHO
1988	14.6 (6.0)	37.8 (15.5)	1.46 (0.60)	3.17 (1.3)
1991	12.2 (5.0)	37.8 (15.5)	0.42 (0.17)	3.17 (1.3)
1994	12.2 (5.0)	37.8 (15.5)	0.21 (0.09)	3.17 (1.3)
1998	9.74 (4.0)	37.8 (15.5)	0.17 (0.07)	3.17 (1.3)
2004	5.85 (2.4)	37.8 (15.5)	0.17 (0.07)	3.17 (1.3)
2007	5.85 (2.4)	37.8 (15.5)	0.02 (0.01)	3.17 (1.3)

2.1.4. Vehicle Bin Distributions

In order to take advantage of the bin-level fidelity of the EPA emissions standards, it is necessary to identify how many LDVs and LDTs in Salt Lake County fall into each emissions standards bin. Because the Utah Tax Commission data are only defined in terms of vehicle type and does not provide any information regarding vehicle pollution categories

(i.e., bin numbers), it is appropriate to find these data for a sufficiently large sample of the population.

The major automotive OEMs report vehicle compliance with EPA emissions standards, and are consequently an excellent source for vehicle pollution bin data. Among the big three US automobile manufactures (Ford, GM, Fiat-Chrysler), Ford's vehicles represent 14.5% of total light duty vehicles and trucks sold in Utah during 2017. Consequently, this work assumes that Ford vehicles are adequately representative of the Utah and Salt Lake County vehicle populations [56]. The Ford Fleet Emissions Guide is a comprehensive database of all Ford-built vehicles from 2004 to the present [48]. In addition to vehicle category (e.g., LDV, HDV), it indicates the EPA-assigned vehicle pollution category, or bin number, for each vehicle in the Ford fleet.

The emissions bin data for all available years are processed to model the number of vehicles in each EPA emissions bin in Salt Lake County as follows. For every year, the number of vehicles in each bin is recorded and, because of the progressive nature of vehicle emissions regulations over time, the vehicles are divided into the three tier categories explained in Section 2.1.3. Then, a probability mass distribution (PMD) and corresponding probability mass function (PMF) are created by dividing each category by the total number of Ford vehicles in each tier. Equation (3) shows how the PMF is created.

$$\epsilon(i) = \frac{N_i}{\sum_{j=1}^k N_j} \quad (3)$$

where $\epsilon(i)$ is the PMF of the percentage of vehicles in the i th emissions bin, N_i is the number of vehicles in the i th emissions bin, k is the total number of bins, and N_j is the number of vehicles in the j th bin. The PMF can then be multiplied by the number of vehicles in Salt Lake County to determine the number of vehicles in each emissions tier and bin in Salt Lake County.

2.1.5. Environmental Factors

The process for determining criteria pollutant emissions' impact on air quality is extraordinarily complex. In the case of $PM_{2.5}$, it involves not only the primary pollutant form that is directly output in engine exhaust, but also the volatile organic and inorganic aerosols that react with each other and other airborne criteria pollutants such as nitrogen and sulfur oxides to form secondary particulates. In some cases, these secondary particulates constitute more than half of the total $PM_{2.5}$ pollution present in urban areas [57]. This model does not consider these secondary pollutants, as it considers them life-cycle vehicle emissions rather than primary tailpipe emissions. Thus the results for total pollution accumulation provided by the model only consider tailpipe emissions. Measuring primary emissions alone still provides a clear, if conservative, estimate of the impact of electric vehicle adoption on air quality.

Atmospheric and weather conditions can have an impact on the accumulation of primary and secondary particulate pollution. Among the most influential factors in the transport, distribution, and accumulation of particulate air pollution are wind and atmospheric conditions (e.g., inversions, which concentrate pollutants at low altitudes) [58]. Consequently, this work considers wind speed and inversion magnitude, or depth, as the primary environmental factors that impact pollutant accumulation. In the model, the two are compiled into a general accumulation coefficient that is used to determine the percentage of tailpipe-emitted pollution that accumulates from hour to hour.

The general accumulation coefficient is generated using Equations (4)–(7).

$$\alpha = I - W \quad (4)$$

where α is the dimensionless accumulation coefficient, I is the dimensionless inversion factor, and W is the dimensionless wind factor.

It is difficult to measure the depth of an inversion quantitatively in terms of pollution accumulation, other than by recording its duration and effect on the AQI during its occurrence. This presents a problem because, in this study, the AQI is the model's objective function and cannot be used to compute itself. Additionally, the duration of the inversion is an unknown factor and must therefore be assumed. Though very few deep inversion events last longer than one to three days, winter weather and surface temperature conditions in mountain valleys can cause multiple, near-simultaneous inversion events over longer periods of time [11,35]. Because the instantaneous inversion depth could range from mild to severe at any time during a one-week period with several near-simultaneous inversion events, a qualitative, average inversion factor is assumed and used in the model. Consequently, this work assumes an average inversion effect over a week-long period with an initial condition of zero accumulated pollution.

The inversion factor occurs in two cases. In the general case, it is an assigned value on the continuous scale between zero and 0.9, with zero signifying that there is no significant inversion affect and 0.9 signifying a deep inversion that can dramatically increase local pollution accumulation. The mathematical definition of the general inversion factor (I_{gen}) can be seen in Equation (5).

$$I_{gen} = \begin{cases} 0 & \text{no influence on accumulation} \\ \dots & \\ 0.9 & \text{heavy influence on accumulation} \end{cases} \quad (5)$$

The general inversion coefficient is sometimes insufficient because the affects of an inversion can be aggravated by calm winds [11]. Consequently, when wind speeds are below four miles per hour, Equation (6) describes the inversion factor.

$$I_{calm} = I_{gen} + \delta - W \quad (6)$$

where I_{calm} is the calm wind inversion factor, I_{gen} is the general inversion factor, δ is an offset representing the aggravation of an inversion by calm winds, and W is the wind factor. The aggravation offset δ is set to 0.5, which allows for an increase in the inversion factor at a wind factor of between 0.0 and 0.4 (corresponding to zero and four mph, respectively) but still allows winds speeds at the higher end of that range to affect the accumulation of pollutants, as described below. Note that for any value of I_{calm} greater than 0.9, the value is adjusted to 0.9 in the model.

The wind factor serves as a qualitative counterbalance to the inversion factor. It is calculated based solely on wind speed, and not wind direction. A study in Kuwait City has shown wind speed to be a significant factor in the development or dispersal of inversions. Though wind direction can be a major influencing factor on inversion development in the mountain valleys where inversions commonly occur, this work is only focused on the air immediately surrounding a roadway, and wind direction will not likely affect the immediately local air quality as much as wind speed. Though some wind speeds can promote the occurrence of inversion events, as discussed above, wind generally tends to disperse accumulated pollutants [59]. Consequently, it serves to decrease the accumulation coefficient, as shown in Equation (4). Equation (7) shows the calculations for wind factor.

$$W = \begin{cases} 0 & v = 0 \text{ mph } (v = 0 \text{ k/h}) \\ \frac{v}{10} & 0 < v < 9 \text{ mph } (0 < v < 14.5 \text{ k/h}) \\ 0.9 & 9 \leq v \text{ mph } (14.5 \leq v \text{ k/h}) \end{cases} \quad (7)$$

where W is the wind factor and v is the wind speed in miles per hour. Note that for wind speeds greater than 9 mph, it is assumed that the wind has a similarly high effect on dispersing air pollution in the form of vehicle exhaust emissions.

2.1.6. Air Quality Index

The Air Quality Index (AQI) is a public service project sponsored by the EPA, National Oceanic and Atmospheric Association, National Parks Service, and multiple state and local governments in the United States. Its primary goal is to translate air quality information into visual information accessible to the public [8]. The data are represented on a color scale in Table 3. Table 4 represents the correlation between small particulate matter (PM_{2.5}) pollution concentration and AQI. The AQI can also be measured in terms of carbon monoxide and sulfur dioxide. However, because particulate matter concentrations are a commonly, if not the most commonly, used metric for air quality, this model only considers them in terms of vehicle pollutant output. In the model, exact values for pollutant concentration and AQI level are computed using linear interpolation between the provided values.

Table 3. Color Scale for the AQI system with corresponding AQI ranges and air quality condition classifications.


Air Quality Index (AQI) Range		Colors	Air Quality Conditions
0–50		Green	Good
51–100		Yellow	Moderate
101–150		Orange	Unhealthy for Sensitive Groups
151–200		Red	Unhealthy
201–300		Purple	Very Unhealthy
301–500		Maroon	Hazardous

Table 4. Interpolation constants for PM_{2.5} AQI [60].

Concentration (ρ) in $\mu\text{g}/\text{m}^3$			
ρ_{low}	ρ_{high}	χ_{low}	χ_{high}
0	12.0	0	50
12.1	35.4	51	100
35.5	55.4	101	150
55.5	150.4	151	200
150.5	250.4	201	300
250.5	350.4	301	400
350.5	500.4	401	500

2.1.7. Charging Infrastructure

In order to calculate the costs associated with building the public and private charging infrastructure needed to support an EV population, the type of charging stations needed must be considered. In order to accomplish this, the model employs the Electric Vehicle Infrastructure Projection Tool (EVI-Pro), a charging-infrastructure calculator created and operated by the Alternative Fuels Data Center in the US EPA [47]. The EVI-Pro tool projects the number of workplace level 2, public level 2, and public level 3 DC fast charging plugs needed to support a given EV population. Its calculations are based on the state or metropolitan area in which the EVs will be driven, how much of the vehicle population is composed of different types of electric vehicles, and the level of support that the infrastructure must provide to the vehicle population. This work does not account for the costs associated with upgrading the electrical grid infrastructure needed to support the designed charging infrastructures.

Using the EVI-Pro tool to manually calculate the number of charging plugs needed for every scenario in a DOE with thousands of entries is not practical. Instead, a range of vehicle population inputs from the Utah State Tax Commission [44] were provided to the EVI-Pro tool and the tool's outputs were used to generate first and third-order linear regression equations that predict the number of chargers needed for any rate of EV adoption input into the model. Thus, the cost models discussed in continuation are

validated based on their derivation from a pre-validated EPA tool and their source data's origination in a responsible government institution.

The third-order equations are given in Equation (8), and, with R-values of 0.999, very closely follow the data points available from the EVI-Pro tool.

$$\begin{aligned}\eta_{L2w} &= 0.015n - (1.23 \times 10^{-8})n^2 + (3.24 \times 10^{-14})n^3 \\ \eta_{L2p} &= 0.007n - (1.01 \times 10^{-8})n^2 + (1.40 \times 10^{-14})n^3 \\ \eta_{L3p} &= 0.009n - (2.25 \times 10^{-8})n^2 + (2.95 \times 10^{-14})n^3\end{aligned}\quad (8)$$

where η_{L2w} is the number of workplace level 2 chargers, η_{L2p} is the number of public level 2 chargers, η_{L3p} is the number of public level 3 DC fast chargers, and n is the number of EVs (LDVs, LDTs, and HDVs combined) in the vehicle population.

Unfortunately, however, the EVI-Pro tool only supports charging infrastructure estimations for between one and ten percent of the total vehicle population of an area. For EV adoption rates greater than ten percent, then, a certain degree of extrapolation is required. The third-order equations are inappropriate for use in extrapolation because, at high EV adoption rates, the number of charging plugs they predict is quite unreasonable. Consequently, the simple first-order regression model, given in Equation (9), is used in the model. With R-values of between 0.98 and 0.99, the three equations in the model still provide an accurate prediction for data points within the EVI-Pro range and represent a more conservative model from which to extrapolate the infrastructure needs for higher EV adoption rate scenarios. In any case, however, it must be acknowledged that cost predictions where EV adoption rates are above ten percent are speculative and intended only as ball-park estimates.

$$\begin{aligned}\eta_{L2w} &= 0.010n \\ \eta_{L2p} &= 0.006n \\ \eta_{L3p} &= 0.005n\end{aligned}\quad (9)$$

where the variables are as in Equation (8).

2.2. Mathematical Model

The primary mathematical model used in this analysis was created in MATLAB and incorporates probabilistic methods for determining the impact that a given EV adoption strategy could have in improving air quality around major roadways. The primary inputs are as follows: (1) percentage of LDVs to be replaced by EVs, (2) percentage of LDTs to be replaced by EVs, (3) percentage of HDVs to be replaced by EVs, (4) inversion factor, and (5) wind speed. Additionally, and as discussed in Section 2.1, the model also requires information about VMT, vehicle population numbers and distributions, existing vehicle emissions standards, and environmental factors.

As primary outputs, the model provides the amount by which air quality is improved in terms of reduction in AQI (e.g., holding the weather patterns constant, one candidate design might reduce AQI by eight points versus the AQI associated with the same scenario without EV adoption) and the costs associated with building, but not maintaining, the charging infrastructure needed to support the EV adoption present in each design run.

2.2.1. Design of Experiments

The first step of the mathematical model is to generate an appropriate sampling of the design space represented by EV adoption within the LDV, LDT, and HDV vehicle populations and the weather patterns associated with inversions and wind factors. For this study, EV adoption ranged between zero and 100 percent (0.0–1.0), the inversion factor between zero and 0.9, and the wind speeds between 0 and 10 mph. For the Salt Lake County test case discussed in Section 3, a full factorial DOE was created to test 161,051 unique candidate scenarios. A small sample of the design of experiments is provided in Table 5.

Table 5. Sample of the design of experiments with several test case model inputs. Units for the three vehicle-type (LDV, LDT, HDV) EV adoption columns are percent (i.e., 0.8 = 80%), Inv stands for inversion and is a dimensionless factor, and wind is in mph (k/h).

% LDV	% LDT	% HDV	Inv	Wind
0.8	0.6	1	0.4	2 (3.2)
0.7	0.9	0.5	0.6	6 (9.7)
0.3	0.9	0.3	0.5	6 (9.7)
0.8	0.8	0	0.9	2 (3.2)
0.9	0.6	0.2	0	2 (3.2)
0.7	0.6	0.7	0.5	2 (3.2)
0.4	0.4	0.6	0.8	0 (0)
0.7	0.7	0.6	0.2	9 (14.5)
0.9	0.2	0.4	0.1	8 (12.9)
0.4	0.4	0.2	0.6	10 (16.1)

2.2.2. AQI Calculations for Candidate EV Adoption Scenarios

For each candidate EV adoption scenario in the DOE, the air quality (given in AQI) is calculated for both the designed EV adoption scenario and the current vehicle population. There are many paths by which the air quality impact of EV adoption could be estimated, ranging from a simple emission coefficient multiplied by average speed to stochastic methods based on Markov processes used in approximating local drive-cycles [61]. This method relies largely on aggregate and estimated values for factors such as vehicle emissions standards and the measured VMT along a section of roadway and represents a middle road compromising between computational efficiency and accuracy. The process for calculating AQI proceeds as shown in Equations (10)–(14).

$$dM_{bin}(i) = \epsilon_{bin} \times V_{vmt}(i) \quad (10)$$

where $dM_{bin}(i)$ is the number of miles driven by vehicles in each emissions bin in the i th hour, ϵ_{bin} is from the PMF value for each bin from Equation (3), and $V_{vmt}(i)$ is the vector of vehicle miles traveled in the i th hour for the chosen section of highway.

$$dM(i) = dM_{bin}(i) \times E_{bin} \quad (11)$$

where $dM(i)$ is the mass in grams of pollutant emitted in the i th hour along the section of highway, $dM_{bin}(i)$ is from Equation (10), and E_{bin} is the vector of PM_{2.5} emissions regulations for each emissions bin given in the column headed “PM” in Tables 1 and 2.

$$M = \sum_{i=1}^k \alpha \times dM(i-1) + dM(i) \quad (12)$$

where M is the total mass in grams of accumulated PM_{2.5} pollution for one candidate design at the end of the design run, k is the total number of hours in the test run, α is the accumulation coefficient from Equation (4), $dM(i-1)$ is the mass of pollution emitted in the hour previous to the n th hour, and $dM(i)$ is the mass of pollution emitted in the i th hour both dM values are calculated in Equation (11).

$$\rho = \frac{M\lambda}{V} \quad (13)$$

where ρ is the pollutant concentration, M is from Equation (12), λ is a mass conversion factor, and V is the volume of the area containing the pollutants. This study considers PM_{2.5}, with $\lambda = 1 \times 10^6$ to convert grams to micrograms. Additionally, $V = 5.06 \times 10^8 \text{ m}^2$ for a 32 km long section of highway with an estimated immediate dispersion radius of 100 m, after which line-source pollution such as that emanating from roadways becomes an insignificant contributor to overall air quality [32,62]. While this equation does not

incorporate any dispersion models, it is assumed that as per [32], tailpipe emissions within a 100 m radius or major roadways are, if not uniformly distributed, at least present in significant concentrations to majorly influence air quality.

$$\chi = \frac{\chi_H - \chi_L}{\rho_H - \rho_L}(\rho - \rho_L) + \chi_L \quad (14)$$

where χ is the AQI, ρ is the calculated pollutant concentration from Equation (13), χ_H and χ_L are upper and lower AQI interpolation constants given in Table 4, and ρ_H and ρ_L the upper and lower concentration bounds for each AQI color category (Tables 3 and 4).

$$\Delta\chi = \chi_{actual} - \chi_{scenario} \quad (15)$$

where $\Delta\chi$ is the difference between the actual and scenario AQIs, χ_{actual} is the AQI as determined by the existing vehicle population and the hypothetical inversion and wind conditions, and $\chi_{scenario}$ is the AQI as determined by the EV adoption scenario and the same environmental factors.

2.2.3. Cost Model

After determining the change in AQI caused by each EV adoption scenario, the model also computes the costs involved in building, but not maintaining, the required charging infrastructure for each scenario. Section 2.1.7 explains the process used to determine how many public and workplace level 2 charging plugs and public level 3 fast-charging plugs would be needed in each scenario.

The cost per charging plug was taken from a study conducted in 2015 by the US DOE [46]. The study presents average costs per plug for various charger types. For level 2 charging plugs, it shows USD 3000 for installation costs and USD 3500 for component costs. For level 3 fast-charging plugs, it indicates USD 21,000 and USD 25,000 for the same cost categories. These numbers are similar to those presented by the International Council on Clean Transportation in 2019, though their estimates for L1/L2 chargers are somewhat lower and their estimates for L3 chargers are either closely matching or significantly higher, depending on the power capacity of the charger [63]. Equation (16) shows how these costs are used in the model.

$$C = 6500(\eta_{L2w} + \eta_{L2p}) + 46,000\eta_{L3p} \quad (16)$$

where C is the total charging infrastructure installation and component cost, 6500 is the total cost per level 2 charger, 46,000 is the total cost per level 3 fast-charger, and the η terms are found using Equation (9).

Note that these cost figures were derived for LDV and LDT charging needs, and not for HDVs. In the same way that engine size and horsepower increase dramatically for diesel-fuel HDVs as opposed to conventional-fuel LDVs and LDTs, electric HDVs will have much larger battery capacities than electric LDVs and LDTs. In order to achieve practical HDV charging times, recharge rates will have to be much higher at HDV charging plugs than at the LDV and LDT charging plugs referenced by this work. Such an increase in charging rate could require special equipment or grid access that could increase the cost associated with installing HDV charging infrastructure [64]. However, because little is known at this point about HDV charging infrastructure, the model simply assumes that it will cost the same as LDV and LDT charging infrastructure. Consequently, the projected costs associated with HDV infrastructure installation are likely an underestimate due to technological uncertainty.

3. Results and Discussion

The results discussed in this section are derived using sample vehicle population and VMT data from Salt Lake County, Utah [44,51]. The VMT data were taken from a 32 km segment of Interstate 15 that directly transects several of the major population centers in

the greater Salt Lake City metropolitan area. This corridor was chosen because over one million people live in its vicinity and it is the most heavily transited highway in the state.

Determining the AQI Reduction–Infrastructure–Cost relationship relies on multiple non-linear interactions between the five model input variables. The following sections describe these interactions generally and discuss the influence of the two major groups of independent variables, EV adoption rates and environmental factors, on both AQI levels and infrastructure costs. Additionally, a simplified, surrogate model that can quickly and reliably determine either air quality improvement or infrastructure cost as a function of the input variables and one of the two model outputs (AQI or infrastructure cost) is presented for use by decision makers and other system stakeholders.

3.1. Air Quality Improvement and Infrastructure Cost

Figure 3 shows the set of AQI improvement results from running a full factorial DOE with five inputs (LDV % EV, LDT % EV, HDV % EV, Inversion Factor, and Wind Factor) and 161,051 unique candidate scenarios. As can be seen, various echelons form within the results matrix (most notably at the extreme range for cost). Each echelon corresponds to a combination of inversion factors and wind speeds (i.e., accumulation coefficients). They form because the accumulation coefficient is a discrete, and not a continuous, value. Consequently, the results are not continuously distributed over the entire potential design space. Figure 4 shows specific results echelons for average summer and winter conditions and winter inversion conditions, respectively.

Pareto fronts can be used to easily determine the optimal set of vehicle electrification scenarios based on a given weather pattern. The overall Pareto front exists at the lower right edge of the data shown in Figure 3. In practice, however, that Pareto front is limited in its application to the specific echelon of pollution accumulation scenarios from which those data points were derived (in this case, extremely high inversion factors and low wind conditions that result in an accumulation coefficient of $\alpha = 0.9$). Though it shows density plots depicting the most likely AQI improvements versus infrastructure investment costs instead of Pareto fronts, Figure 4 provides a view of both low and a high pollution accumulation environmental scenarios that is generally consistent with the results from a similar but more detailed study in Kuwait City [59].

3.2. Pollution Accumulation Effects

The accumulation coefficient used to incorporate inversion patterns and wind speeds into the model is the first primary influencing factor on air quality predictions within the model. Pollution accumulation is only indirectly related to charging infrastructure costs through its impact on air quality and the need to adopt EVs at a higher rate to achieve the desired improvement in AQI.

Figure 5 shows the influence of increasing or decreasing wind speeds on a given EV adoption scenario's ability to improve air quality. There is a slight exponential effect, where high and medium wind speeds very successfully dissipate pollution, even during inversion events, and preempt the drastic impact that EV adoption can have on pollution accumulation when wind speeds are much lower. Conversely, however, it is evident that in low wind areas, high EV adoption can be more strongly correlated with substantial improvements in air quality.

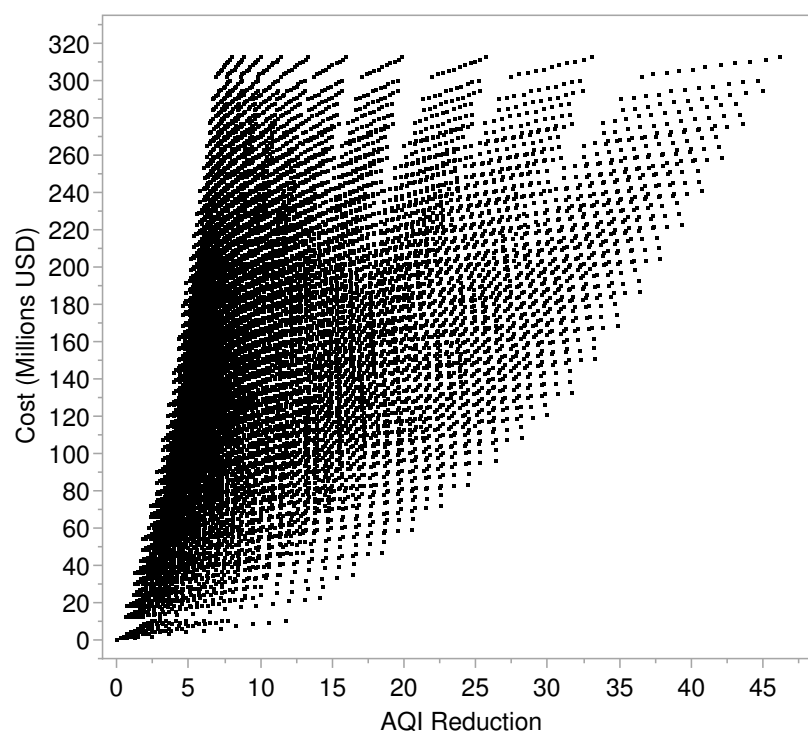


Figure 3. The full set of results from the Salt Lake County design of experiments input matrix. “AQI Reduction” on the x -axis shows the magnitude of air quality improvement in terms of AQI point reduction between the current and hypothetical vehicle populations’ pollution outputs. “Cost (Millions USD)” shows the infrastructure costs in millions USD to install the charging infrastructure to support the hypothetical vehicle population.

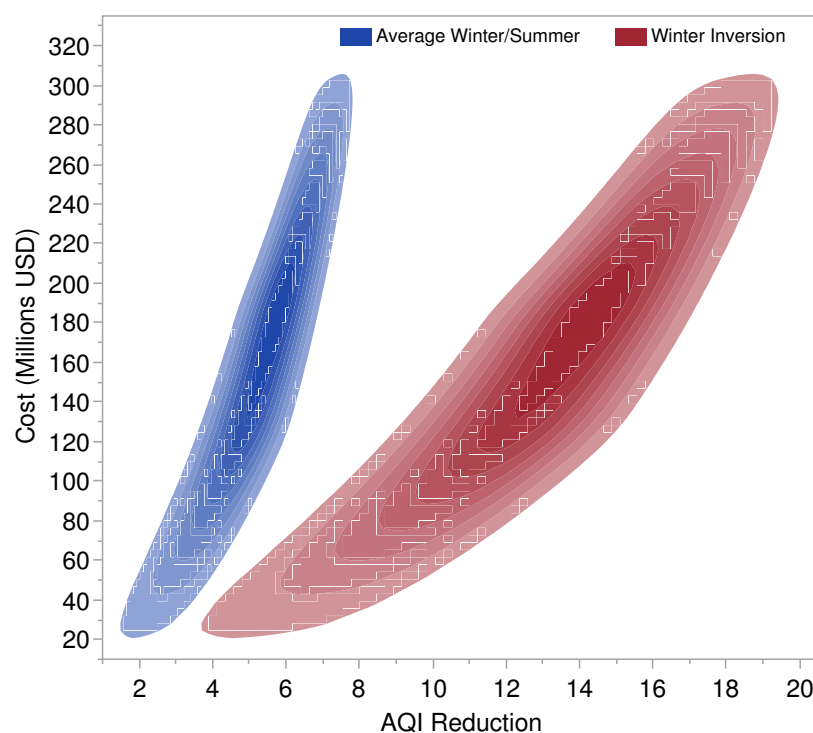


Figure 4. Model results for a typical winter inversion event ($INV = 8, W = 3$ MPH), such that $\alpha = 0.8$ as per Equations (4) and (6), are shown in red toward the right side of the chart. Model results for a typical summer or winter non-inversion weather pattern ($INV = 5, W = 5$ MPH), such that $\alpha = 0$ as per Equations (4) and (6), are shown in blue toward the left side of the chart [49].

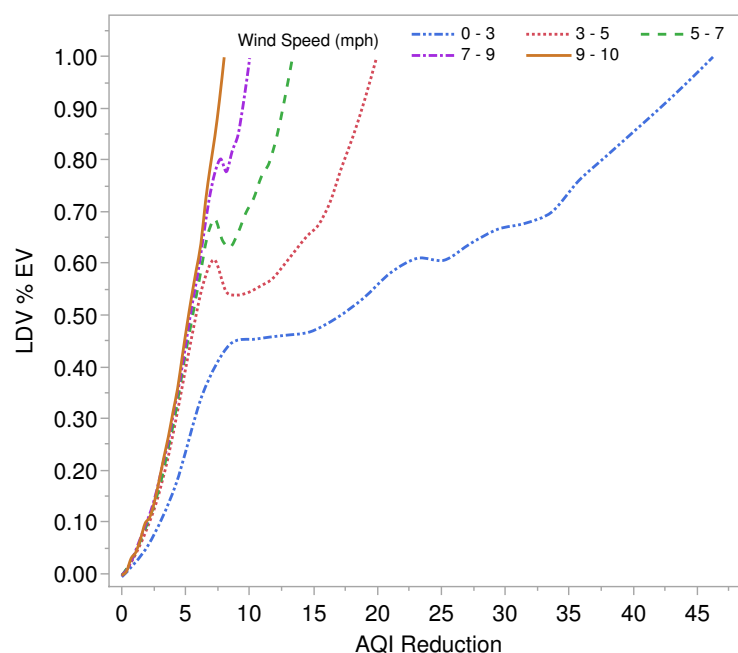


Figure 5. The correlation between AQI Reduction, LDV % EV (LDV EV adoption rate), and wind speed. LDT and HDV EV adoption follow very similar correlations.

Figure 6 shows the influence of varying magnitudes of inversion events on a given EV adoption scenario's ability to improve air quality. The apparent relationship between inversion events, EV adoption, and AQI reduction is not as strong as it is for wind speeds. At low EV adoption rates, inversion magnitude seems to have almost no relative effect on AQI improvement. Only at very high adoption rates is there a distinguishable difference between the impact a low magnitude inversion event would have on AQI and the impact that a more severe inversion event would have. This would indicate that, though inversion events are important in determining how much pollution might accumulate, the severity of the event has less to do with that accumulation than the fact that there is an inversion event in the first place.

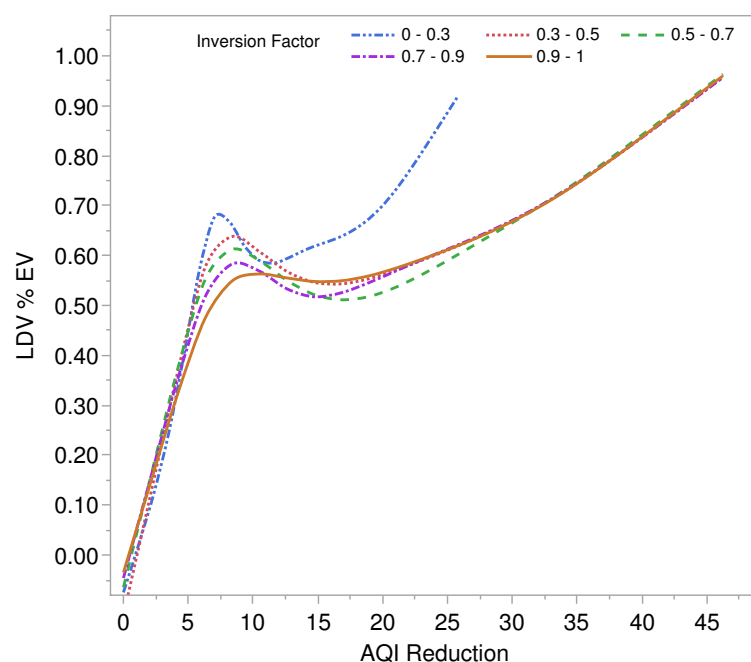


Figure 6. The correlation between AQI Reduction, LDV % EV (LDV EV adoption rate), and inversion events. LDT and HDV AQI-EV adoption correlations are very similar.

3.3. Vehicle Type Effects

Conversion from ICE vehicles to EVs is the second primary influencing factor on air quality and the only direct influencing factor on infrastructure cost in the model. EV conversion directly influences air quality by changing the amount of vehicle emissions along a highway and, after factoring in the pollution accumulation rate, the AQI level. Using the estimations provided by the DOE EVI-Pro calculator and INL charging plug cost estimation model, the size of the EV population is also used to directly compute the cost of EV supporting infrastructure for each EV adoption scenario.

Figure 7 shows the impact that exclusively adopting EVs from one of the vehicle categories (LDV, LDT, HDV) has as compared to adopting EVs at varying levels from each of the categories. The figure shows that, despite the likely underestimation of HDV charging infrastructure costs, an exclusive investment in HDV charging infrastructure and the corresponding support for HDV EV adoption could lead to marked improvements in air quality (an AQI reduction of up to 12 points). The HDV-first EV adoption scheme has been proposed and validated by studies in Germany and California [65,66]. By contrast, investment in LDV or LDT EV adoption and charging infrastructure would provide the same air quality improvement at costs an order of magnitude greater.

The exclusive adoption of one vehicle type or another, however, can only result in a limited improvement in air quality. While hybridizing the approach to EV adoption, as shown by the “non-exclusive” line in Figure 7, can be a more expensive option, it can also result in greater returns in terms of AQI reduction. Of particular note is the non-exclusive EV adoption strategy line’s low slope between 20 and 30 AQI. Though the model is subject to significant noise due to the effects of inversion events and wind speed across the EV adoption design space, that line segment shows that, for a marginal increase in cost (directly correlated with EV adoption rate), a significant improvement in air quality can be achieved.

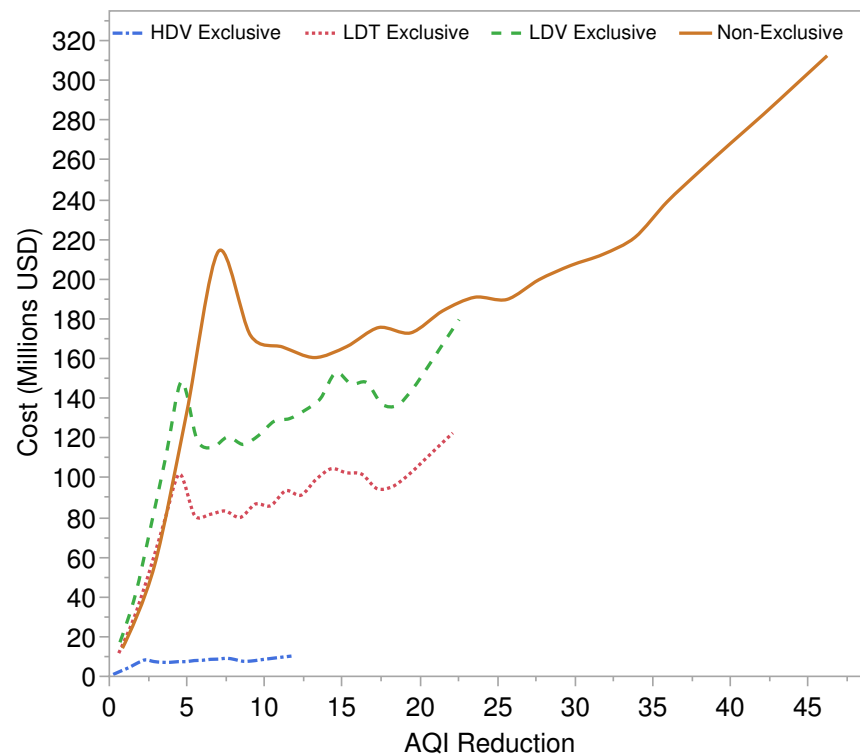


Figure 7. Infrastructure costs and air quality improvements based on vehicle type-exclusive EV adoption scenarios compared to the same results for vehicle type-hybrid EV adoption scenarios.

3.4. Decision Making Surrogate Model

The model presented in this paper is computationally expensive and requires some technical expertise to interpret. To help decision makers and other system stakeholders

decide how to best invest in EV adoption strategies that will achieve a certain air quality improvement within a certain budget, it must be more accessible and easily used [67]. Consequently, a surrogate model was developed using the same inputs and results discussed previously to allow for a set of candidate designs to be explored very quickly. Its intended purpose is to limit the users' interaction with the model to providing a few specified inputs and receiving the resultant outputs. Note that, because it was developed using the Salt Lake County test data, this surrogate model is only applicable in Salt Lake County; however, a similar model could be developed for other geographical regions using the primary model.

The surrogate model is a second-order linear regression equation. It was developed using forward sequential variable selection with the criteria of minimizing BIC (Bayesian information criterion) [68]. It incorporates each of the vehicle EV adoption rates, the pollution accumulation coefficient, and the cost in millions USD to identify the resulting reduction in AQI.

$$\begin{aligned}\Delta\chi = & -0.3 + 0.12C + \alpha(2.98 + 0.10C) \\ & - P_{LDV}(14.95 + 5.59\alpha + 0.01C) \\ & + P_{HDV}(0.96 + 5.52\alpha - 0.005C) \\ & - P_{LDT}(9.01 + 0.01C)\end{aligned}\quad (17)$$

where $\Delta\chi$ is the number of points by which the AQI is reduced; P_{LDV} , P_{LDT} , and P_{HDV} are the percentage of each vehicle class that will be converted to EVs; α is the accumulation coefficient from Equation (4); and C is the total infrastructure cost from Equation (16) converted into millions USD.

The surrogate model results fit the full model's results with a R^2 value of 0.903, indicating a reasonably tight fit with some marginal error. Much of the error likely results from the linear regression assumption that all input variables are normally distributed, which may not be the case for all input variables for the model. Mapping the residual values between the surrogate and full model AQI reduction values shows that the mean difference between surrogate and full model outputs is effectively zero (-1.3×10^{-12}) and the residuals are distributed along a standard deviation of $\sigma^2 = 2.11$. The surrogate model tends to produce larger residuals at extremely high values of the accumulation coefficient (i.e., $\alpha = 0.9$). An important attribute of the surrogate model is that large residuals produced by the model are almost exclusively conservative, which ensures that, when it is not as accurate as the full system dynamics model, it does not over-promise in terms of the air quality improvements that could be provided by an EV adoption strategy.

In any case, however, high accumulation events rarely occur in real life and users of the model should be cautious when considering in such extreme events. Considering its intended use case and the first-order approximation nature of this work, the surrogate model provides an appropriate substitute for the full model and is particularly accurate for more normal weather events with representative accumulation coefficients between 0.2 and 0.7.

3.5. Future Work

This work should be used as a springboard for additional research either in direct follow up or in related fields. Of particular potential value are the following opportunities.

- Developing a generalized traffic model from data from multiple locations that could be applied with greater confidence in major metropolitan areas where EV adoption could significantly improve air quality, (e.g., Los Angeles, Shanghai, London, Tokyo).
- Developing a more mature cost model using emerging data on the possible infrastructure costs associated with installing and maintaining (1) in-road wireless power transfer networks for LDV and HDV charging and (2) plug-in charging networks for LDV and HDV charging.

- Developing a model to identify the precise number and location of charging stations needed to support different electrification scenarios for LDV, LDT, and HDV segments in Utah and/or other locations.

While these suggested areas of research are by no means the only areas in which future research could be conducted adjacent to that presented in this work, they do represent areas of special concern in regions where EV adoption is on the rise and local governments have minimal knowledge to predict how infrastructure demands will change in parallel with those EV adoption rates.

4. Conclusions

This work's primary objective is to examine the effects of EV adoption across all vehicle types and environmental events on air quality near highways. Its secondary objective is to provide a reasonable estimate of the infrastructure costs associated with supporting an EV population capable of improving air quality to a predetermined level. Because pollution-trapping inversion events frequently occur in mountain valleys where pollution accumulation is already a concern, this study takes special interest in mapping these effects during such events.

The results of the Salt Lake County test case clearly indicate that high rates of EV adoption could drastically improve air quality, in particular during inversion events. Even during normal summer and winter weather scenarios, when exceptional pollution accumulation is not a concern, an AQI reduction of eight points when the typical AQI level in such conditions is between 20 and 50 cannot be considered insignificant. During inversion events, when the $PM_{2.5}$ AQI can reach upwards of 150 points [69], an AQI reduction of 20 points (or 40 to 50 points, as the 100 percent EV adoption scenarios estimate) is a massively important impact. Under the assumptions laid out for the model presented in this work, a 20 point reduction in $PM_{2.5}$ AQI would all but eliminate traffic-caused and weather-exacerbated "red air" conditions in Salt Lake County.

While a complete conversion from a conventional to an electrical-powered vehicle population may become a viable transportation scheme in the future, such a policy does not currently hold sufficient political or social priority. EV battery and charging technology and implementation strategies need to improve and be defined in order to meet the demands of a modern urban population [70,71]. Additionally, a sufficiently high capacity EV charging infrastructure does currently not exist, nor would the existing electrical grid infrastructure be capable of supporting it if it did [72–74]. These issues and others must be confronted and addressed before large-scale EV adoption can occur and its benefits discussed herein can be reaped; however, the outlook is by no means dim. Building the charging station infrastructure needed to support over two million electric vehicles of varying sizes in Salt Lake County would cost in the neighborhood of USD 300 million (Figure 3), an amount that seems large, but actually reduces to about USD 150 per vehicle. Added to the sticker price of a new EV or as a fraction-of-one-cent energy tax increase, for example, the number is almost unnoticeable. Though not considered by this work, updating the electrical grid would likely prove to be more expensive, though it could be incorporated into existing renovation projects and could even be supported by the EV population itself [75]. Charging station maintenance and staffing costs would also have to be considered. In short, though neither Salt Lake County nor most developed regions are fully prepared for rapid electrification, they are likely quite capable of a considered and aggressive movement in that direction.

As an intermediate step, this work presents an incremental EV adoption scheme. Because HDVs are much less heavily regulated in terms of emissions outputs than LDVs and LDTs, and simultaneously comprise a much smaller percentage of the total vehicle population than the other vehicle classes, they present an opportunity for early fleet electrification [76,77]. Figure 7 shows that even partial electrification of the HDV population in Salt Lake County could yield non-trivial results in air quality improvement at a very low relative price when compared to LDV and LDT fleet electrification. There is significant market potential and demand for HDV electrification, though the technology to support

that demand has yet to sufficiently develop [78]. Battery capacity, battery energy density, and charging technologies have not quite reached the levels needed to fully provide for all-electric HDVs [79–82]. However, as shown by the new developments in HDV electrification showcased by Tesla, Nikola Motors, and Daimler, among others, OEMs are more than capable of developing the required technologies [83–85]. The incentive need only be provided by regulators and other system stakeholders for the required improvements in electric HDV technology to be produced.

In addition to the direct positive results of an immediate push for HDV electrification, such a movement could also have an indirect impact on general transportation electrification. Market demand is already rapidly pulling LDV and LDT EV technology into the social and political mainstream. As an HDV charging infrastructure is developed, the increased access to charging locations could promote increased LDV and LDT EV adoption, which would provide an additional positive impact on air quality.

The background research, modelling, and analysis conducted by this work also indicate that both the inversion events and the wind patterns that contribute to their formation and help dissipate the pollutants that accumulate during them are important in considering future EV adoption strategies. Of particular note to policy makers are the exponential effect of wind on pollutant dispersal and the principle that inversion events, regardless of whether they are extreme or not, can cause significant pollution accumulation over time. Because of increasing urbanization and the ubiquity of personalized transport (i.e., LDVs and LDTs) and long-haul delivery (i.e., HDVs) in Utah and the world generally, government and community decision makers must realize the impact that natural weather patterns have on pollution accumulation. In particular, urban areas in mountain valleys, or even low-lying regions along the coast, are prone to having their human-caused pollution problems exacerbated by inversion events. Consequently, stakeholders in those regions must consider methods such as those proposed in this work to alleviate the negative consequences of interactions between human-generated pollution and natural weather patterns.

It follows further that by reducing vehicle pollution emissions in highly urbanized areas, especially during weather events such as inversions when that pollution can easily accumulate, human health can be improved. As discussed earlier, many acute and chronic respiratory diseases, especially in at-risk populations such as young children and the elderly, have been linked to the criteria pollutants that are emitted as part of vehicle exhaust. The observed concentration of low-income and underrepresented populations around major highways is also correlated with exposure of those populations to higher than average levels of dangerous pollution. The predicted improvement in air quality around roadways from transportation electrification would do a great deal in alleviating some of the physical and social health issues experienced by these groups.

As a final contribution, the decision-making surrogate model presented by this study provides policy influencers and other system stakeholders with an excellent tool for making informed decisions regarding vehicle electrification policies and opinions based on available funds, needed air quality improvements, and environmental factors. While the specific surrogate model provided here is specifically applicable to Salt Lake County, the principles behind its development can easily be translated for application in other cities and regions and allow for the development of informed and scientifically sound opinions and policies regarding key urban issues that involve the relationship between air quality, transportation, and public health.

In summary, this work concludes that HDV-oriented EV adoption and infrastructure development provides the best near-term option for air quality improvement by means of transportation electrification. It indicates that in near-term, and even more so in long-term, transportation electrification scenarios, EV adoption could drastically improve air quality around highways. That positive effect is crucially magnified in areas that are prone to winter inversion events. Finally, because an increasingly large segment of the general population lives near highways, such an improvement in air quality would undoubtedly have a meaningful and positive effect on human and societal health.

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