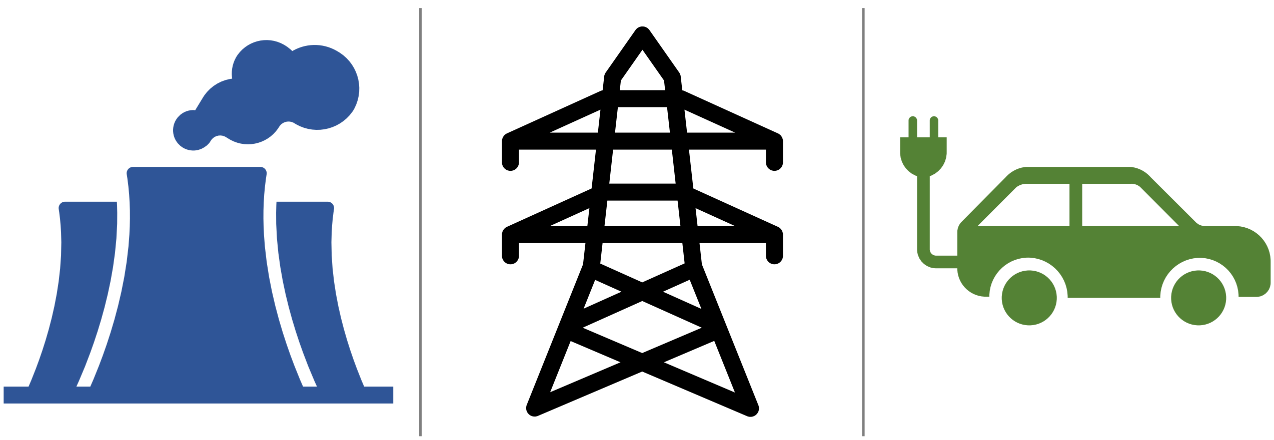
LOCATIONAL MARGINAL EMISSION EVALUATION FOR ELECTRIC VEHICLE CHARGING FACILITY PLANNING



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7. Author(s)
Yuanrui Sang
Ivonne Santiago

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16. Abstract
Transportation and electricity generation are the two largest sources of air pollution, however, the pollutants caused by these two sectors are becoming increasingly intertwined in today's world due to the increasing popularity of electric vehicles (EVs). In recent years, EVs have become the trend for automobiles around the world, and many automobile manufacturers have invested heavily in EVs. Although EVs do not produce emissions directly, they do induce indirect emissions from the electric power grid when being charged because most electric power generation sources are not emission-free. To reduce such indirect EV emissions, it is essential to situate EV charging facilities at locations that induce low emissions from the generation sources. The identification of these low-emission locations requires real-time, system-wide analyses for the power grid. The electric power grid includes a mix of generation units that are powered by different types of fuels, such as coal, natural gas, and renewable resources like solar and wind energy. These generation units have different emission rates for each pollutant, and different combinations of generation units are dispatched to meet a time-varying load demand. Due to transmission congestion, charging an EV at different locations may result in different pollutant emission rates. Such real-time, system-wide analyses will provide us with information on locational marginal emissions (LMEs), which are the emissions caused by the next unit of electric power consumption at a given location and time. It is the very indicator that provides us with insights on which locations have lower emission rates at a given moment. Through long-term LME analyses, an infrastructure planner could identify locations with low emission rates to build EV charging facilities, thus reducing the indirect pollutant emissions caused by EV charging. This project aims to develop an LME assessment framework for gases that impose public health hazards, such as sulfur dioxide and nitrogen oxides.

17. Key Words
Air pollution, electric vehicles, locational marginal emissions, power system emissions

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Executive Summary

Problem statement: Transportation and electricity generation are the two largest sources of air pollution, however, the pollutants caused by these two sectors are becoming increasingly intertwined in today's world due to the increasing popularity of electric vehicles (EVs). In recent years, EVs have become the trend for automobiles around the world, and many automobile manufacturers have invested heavily in EVs. According to Bloomberg New Energy Finance, EVs will take a 55 percent share of the automobile market by 2040. Although EVs do not produce emissions directly, they do induce indirect emissions from the electric power grid when being charged because most electric power generation sources are not emission-free. To reduce such indirect EV emissions, it is essential to situate EV charging facilities at locations that induce low emissions from the generation sources. Identification of these low-emission locations requires real-time, system-wide analyses for the power grid. The electric power grid includes a mix of generation units that are powered by different types of fuels, such as coal, natural gas, and renewable resources like solar and wind energy. These generation units have different emission rates for each pollutant, and different combinations of generation units are dispatched to meet a time-varying load demand. Due to transmission congestion, charging an EV at different locations may result in different pollutant emission rates. Such real-time, system-wide analyses will provide us with information on locational marginal emissions (LMEs), which are the emissions caused by the next unit of electric power consumption at a given location and time. It is the very indicator that provides us with insights on which locations have lower emission rates at a given moment. Through long-term LME analyses, an infrastructure planner could identify locations with low emission rates to build EV charging facilities, thus reducing the indirect pollutant emissions caused by EV charging. This project aims to develop an LME assessment framework for gases that impose public health hazards, such as sulfur dioxide (SO_2) and nitrogen oxides (NO_x). It aligns with CARTEEH's focus on the impact of transportation emissions on human health and CARTEEH's priority of investing in integrated research projects in transportation infrastructure planning that consider a nexus of transportation emissions, energy, and health.

Although LME data are essential for EV charging facility planning, no accurate LME model presently exists that considers the network constraints of power systems. Currently, device-level SO_2 and NO_x emissions have been widely studied, including the analysis of emissions from each type of generator and the design of low-emission generators. In the 1990s, when the 1990 U.S. Clean Air Act Amendments took effect, the utility industry used multiple methods to limit the emissions of hazardous gases such as SO_2 and NO_x. These methods included setting allowances of emissions in energy transactions, adding surcharges to emissions, and adding emission constraints in generation dispatch. Subsequent studies focused on limiting overall emissions; none considered marginal emissions across the system. To date, studies on marginal emissions remain rather limited, especially for hazardous gases. Existing power system marginal emission studies focused on carbon dioxide (CO_2) emissions, with models that can only estimate marginal emissions rather than accurately calculate them. Currently, two main approaches exist for estimating marginal emissions. One approach is to find out the marginal generator based on merit order and then calculate marginal emissions based on the type of the marginal generator. The drawback of this approach is that it only works in a system without transmission congestion. When transmission congestion exists, out-of-merit-order dispatch exists in the system, and more than one marginal generator exists, each of which may have a different emission rate. Also under this condition, marginal emissions will be different at different locations, but the merit-order-based method can only provide an overall estimate for the entire system. An alternative approach is to estimate the type of generator from locational marginal prices using statistical methods and then calculate the marginal emissions. Although the results obtained from this method can reflect the differences between different locations, it is a challenge to accurately estimate the generation level combination of different marginal generators when transmission congestions exist. Additionally, previous studies were limited to CO_2; the marginal emissions of hazardous gases such as SO_2 and NO_x have been extremely under-investigated. Thus, a need exists to develop a framework to accurately calculate LMEs in a congested network, especially for hazardous emissions such as SO_2 and NO_x, so that infrastructure planners can take public health into

consideration when making decisions on the locations of EV charging stations or electrified roads with imbedded dynamic charging facilities.

This project aimed to fill this gap by developing a computationally efficient LME evaluation framework for hazardous gas emissions. The framework can provide accurate real-time LME information in a congested network on a locational basis. Using this framework, LME data in a power system can be obtained and used to optimize EV charging facility locations. Infrastructure planners can make informed decisions regarding charging facility locations with the emission information we provide, taking into account socioeconomic information that would minimize environmental and health impacts and ensure equitable distribution of health benefits. Also, the LME data can be provided to EV owners, allowing them to choose a charging facility with a relatively low emission rate at their convenience and thus reduce the emissions caused by transportation.

Technical objectives: The overarching goal of this project was to develop a framework for hazardous gas LME evaluation and EV environmental impact mitigation. The framework includes an accurate LME evaluation model for hazardous gases, such as SO_2 and NO_x, and an optimization model to identify EV charging facility locations that minimize hazardous gas emissions. This framework will guide infrastructure planners in keeping public health in mind and choosing low-emission locations for EV charging facilities. The project included the following two objectives:

- Objective 1. Develop an accurate hazardous gas LME evaluation model for power systems. Transmission congestion exists commonly in power systems. In such congested systems, increasing load demand at different locations may result in different emission rates for hazardous gases. However, existing emission evaluation models fail to reflect such locational differences. In this objective, we aimed to develop an accurate LME evaluation model for hazardous gases from power systems. The model was intended to calculate the marginal emission rate based on locations with load increases. This model was also intended to provide real-time power system LMEs to EV charging infrastructure planners and EV owners so that infrastructure planners can choose an EV charging facility location with relatively low LMEs and EV owners can choose to charge their EVs at a charging facility that induces low emissions.
- Objective 2. Develop a model to analyze and mitigate the impact of EV charging on hazardous gas emissions from power systems. Because of a volatile load demand, the LMEs in power systems vary not only locationally but also temporally. To identify locations where EV charging facilities may induce low emissions, it is essential to analyze LME data at each location over the long term. Also, to enhance EV adoption, public opinion needs to be analyzed at each location. In this objective, we aimed to analyze the LMEs and public opinion for future EV charging station allocation.

Key findings: We established models to analyze the LMEs of power systems. The emission data can be used to optimally allocate EV charging stations based on the environmental impact of EV charging. The following are some key findings from the emission tracking studies:

- The generations from different generators can be tracked in a spatiotemporal manner.
- The emissions induced by EV charging can be tracked in real time based on the charging location.
- EV charging stations can be allocated based on their environmental impacts.

We also conducted research regarding public opinions of EVs and EV charging in the Paso del Norte Region to facilitate EV adoption. The key findings include the following:

- Underrepresented communities (URCs) expressed remarkable interest in EVs, charging stations (ChSs), and electrified roadways (ERWs).
- Most participants had some knowledge of EVs, less knowledge of ChSs, and no knowledge of ERWs.

- Results indicated that the evident gap in essential knowledge of EV technology in URCs was the main barrier to EVs widespread diffusion and adoption.
- Because most URC residents lacked EV technology knowledge, they expressed the need to have their doubts and concerns addressed before even considering an EV purchase.

Project impacts: Although EVs do not generate emissions by themselves, the electric power consumed by EVs is not completely emission-free. In this project, we developed models to evaluate the LMEs from power systems. LMEs can be used to analyze the emissions induced by EVs and facilitate analysis of their environmental impacts. We also considered the emissions induced by EV charging in the optimal allocation of EV charging stations. Additionally, public opinions on EV and EV charging were analyzed. This study revealed differences among groups of people with different socioeconomic statuses and shed light on the concerns that need to be addressed in the adoption of EVs. This project supported two graduate students—one student pursuing their master's degree and one student pursuing their doctoral degree—in their work toward their thesis or dissertation. Additionally, the students and principal investigators of this project were actively involved in outreach activities that enhanced public knowledge of EVs.

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Background and Introduction

Introduction

Transportation and electricity generation are the two largest sources of air pollution 1–3, however, the pollutants caused by these two sectors are becoming increasingly intertwined in today's world due to the increasing popularity of electric vehicles (EVs). In recent years, EVs have become the trend for automobiles around the world, and many automobile manufacturers have invested heavily in EVs. According to the Bloomberg New Energy Finance, EVs will take a 55 percent share of the automobile market by 2040 4. Although EVs do not produce emissions directly, they do induce indirect emissions from the electric power grid when being charged because most electric power generation sources are not emission-free. According to the U.S. Energy Information Administration, more than 1 million metric tons of sulfur dioxide (SO_2) and nitrogen oxides (NO_x) are produced each year in the United States due to electric power generation 5. With an increasing number of EVs hitting the road, electric power consumption will increase due to EV charging, resulting in more emissions from the electric power systems. To reduce such indirect EV emissions, it is essential to situate EV charging facilities at locations that induce low emissions from the generation sources. Identification of these low-emission locations requires real-time, system-wide analyses for the power grid. The electric power grid includes a mix of generation units that are powered by different types of fuels, such as coal, natural gas, and renewable resources like solar and wind energy. These generation units have different emission rates for each pollutant, and different combinations of generation units are dispatched to meet a time-varying load demand. Charging an EV at different locations may result in different pollutant emission rates 6 due to transmission congestion. Such real-time, system-wide analyses will provide us with information on locational marginal emissions (LMEs), which are the emissions caused by the next unit of electric power consumption at a given location and time. It is the very indicator that provides us with insights into which locations have lower emission rates at a given moment. Through long-term LME analyses, an infrastructure planner could identify locations with low emission rates to build EV charging facilities, thus reducing the indirect pollutant emissions caused by EV charging. This project aimed to develop a framework for LME evaluation and impact mitigation for hazardous gases, such as SO_2 and NOx, induced by EV charging. It aligns with CARTEEH's focus on the impact of transportation emissions on human health and CARTEEH's priority of investing in integrated research projects in transportation infrastructure planning that consider a nexus of transportation emissions, energy, and health.

Although LME data are essential for EV charging facility planning, no accurate LME model presently exists that considers the network constraints of power systems. Currently, device-level SO_2 and NO_x emissions have been widely studied, including the analysis of emissions from each type of generator 7 and the design of low-emission generators 8–10. Although reducing emissions at the device level sets the foundation for reducing overall emissions, system-level optimization is still necessary for reducing the emissions due to the complexity of power systems. Each power system has a mix of generators with different emission rates, and generators need to be properly used to meet the electricity demand considering different constraints related to transmission, generator ramping, and minimum up and down times. In such a complex environment, meeting all the constraints while minimizing emissions is a critical task. System-level emission studies for electric power generation were initiated in the 1990s when the 1990 U.S. Clean Air Act Amendments took effect. Starting then, the utility industry used multiple methods to limit the emissions of hazardous gases such as SO_2 and NO_x. These methods included setting allowances of emissions in energy transactions 11, adding surcharges to emissions 12, and adding emission constraints in generation dispatch 13. Subsequent studies focused on limiting overall emissions; none considered marginal emissions 14. Although overall emissions are important environmental impact indicators for the existing system, they do not reveal the impact on emissions imposed by an additional load, such as an EV charging station. To know how much impact an additional load could have on the system's emissions, it is important to evaluate the marginal emissions of the system (i.e., the change in system emissions caused by a one-unit increase of the load). To date, studies on marginal emissions remain rather limited, especially for hazardous gases. Existing power system marginal emission studies focused on carbon dioxide (CO_2) emissions, with models that can only estimate marginal emissions rather than accurately calculate them. Currently, two main approaches exist for estimating marginal emissions. One approach is to find out the marginal generator based on merit order and then calculate marginal emissions based on the type of the marginal generator 15. The drawback of this approach is that: (1) it only works in a system without transmission congestion, and (2) the locational differences of marginal emissions cannot be reflected. Without transmission congestion, the system only has one marginal generator, and the marginal emissions for each gas are the same across the system. Under a one-unit load increase, this one marginal generator will produce the one unit of power to meet the demand, and system-wide marginal emissions can be calculated based on the emission rate of this generator. When transmission congestion exists, there will be multiple marginal generators in a system due to the out-of-merit-order dispatch. These marginal generators may have different emission rates, and under a one-unit load increase, the distribution of the additional generation among these generators cannot be revealed using this approach. Also with transmission congestion, the distribution of the additional generation among the marginal generators depends upon the location of the load increase, but this marginal emission evaluation approach cannot reveal such locational differences. An alternative approach is to estimate the type of generator from locational marginal prices using statistical methods and then calculate the marginal emissions 16. Although results obtained from this method can reflect the differences in marginal emissions between different locations, it is a challenge to accurately estimate the generation level combination of different marginal generators when transmission congestions exist. Additionally, previous studies on marginal emissions only focused on CO_2; the marginal emissions of hazardous gases such as SO_2 and NO_x have been extremely under-investigated. Because of the lack of studies on marginal emissions of hazardous gases from power systems, the public health impact of electric power usage cannot be properly evaluated. However, with the electrification of transportation systems, it is paramount to understand the impact of hazardous gas emissions imposed by the increased use of electric power so that the public health impacts of electric vehicles can be evaluated and approaches to mitigate such impacts can be developed. Thus, an urgent need exists for a framework to accurately calculate the LMEs for hazardous gases in congested power systems and effectively reduce the emissions caused by EV charging facilities. This framework will assist EV charging infrastructure planners in making decisions that consider public health.

This project aimed to fill this gap by developing a framework for evaluating the hazardous gas LMEs in power systems and the environmental impact mitigation for electric vehicles. This framework includes: (1) a computationally efficient LME evaluation model for hazardous gas emissions, such as SO_2 and NO_x; and (2) an approach for minimizing hazardous gas emissions induced by EV charging. The LME evaluation model can provide accurate real-time LME information in a congested network on a locational basis and identify EV charging locations that can potentially induce relatively low emissions from the power system. Also, the LME evaluation model can be used to generate data for EV owners, allowing them to choose a charging facility with relatively low emissions at their convenience, thus reducing the environmental and public health impact imposed by transportation. An optimization model was also developed to find the EV charging facility locations that result in relatively low environmental and public health impacts while considering the physical constraints of the power and transportation systems and environmental and public health equities. Using this framework, infrastructure planners can make informed decisions regarding charging facility locations that would minimize environmental and public health impacts, ensure equitable distribution of environmental and public health benefits, and satisfy the physical requirements for power system operations.

Tracking the Source of Marginal Electricity Generation

Moving toward sustainability has become a key focus for companies and policymakers in the past few decades due to rapidly increasing greenhouse gas (GHG) emissions in our atmosphere. These emissions have been widely attributed to the global increase in temperatures observed since the mid-20th century caused by the burning of fossil fuels to generate electric power 17. According to the Fifth Assessment report by the Intergovernmental Panel on Climate Change (IPCC), the increase in CO_2 emissions in the atmosphere was 2,040 ± 310 Gt CO_2 between 1750 and 2011. About half of this increase in emissions occurred in the last 40 years, and emissions are projected to continue rising despite a growing number of climate change mitigation policies 18. It is important to note that the total CO_2 levels in our atmosphere today are unprecedented in the last 800,000 years and are estimated to cause negative consequences 19. According to the U. S. Environmental Protection Agency (EPA), the emissions from burning fossil fuels for energy production constituted about 78 percent of the total increase in emissions from 1970 to 2011 and is the largest contributor to global greenhouse emissions 20. In the United States alone, electricity production is the second largest emitter, producing 25 percent of the GHG emissions in 2019 **Error! Reference source not found.**. Due to the problems encountered from the generation of emissions from the electric power industry, a need exists to find solutions to meet our power demand using a more sustainable approach.

Renewable energy is a viable solution to curbing GHG emissions and mitigating the impacts on our environment because it produces virtually no emissions. The U.S. Energy Information Administration (EIA) estimates that renewable energy in the United States will increase from 21 percent in 2020 to 42 percent in 2050 21. As recently as 2019, the total renewable consumption in the United States grew to a record high of 11.5 quadrillion Btu 22. Even with substantial growth, renewable sources only make up about 11.4 percent of the energy in the United States 23. Many policies have been used to encourage the adoption of renewable energy. The U.S. Renewable Portfolio Standards (RPS) is a policy program that requires electricity providers to meet a specific amount of a consumer's electricity with renewable resources 24. The RPS program in 2013 reduced CO_2 equivalent emissions by 59 million metric tons and air pollution emissions like SO_2 by 77,400 metric tons 25. An example of an RPS implementation is the Renewable Energy Credit (REC) program established by the Public Utility Commission of Texas, which mandates that 10,000 megawatts (MW) of renewable energy capacity be added in Texas by 2025 26. According to a compliance report by the Electric Reliability Council of Texas (ERCOT), this program exceeded its 10,000 MW target, producing over 26,045 MW of renewable capacity and showing the viability of such programs to increase investment in renewable generation 27. The accuracy in which renewable energy is tracked in an electricity market is important in the implementation of policies that seek to incentivize specified amounts of renewable energy generation.

In recent years, many studies have been done on renewable generation consumption and greenhouse gas emission reduction. In **Error! Reference source not found.**, the authors proposed an economic dispatch that analyzed the operation of conventional plants with wind generation and determined the amounts of CO_2, SO_2, and NO_x emissions that were produced. It is important to note that this study incorporated wind forecasts into the dispatch decisions for more computational efficiency. The authors in 28 and 29 proposed a combination of economic dispatch and unit commitment models to show that wind curtailment can reduce costs and CO_2 emissions due to factors like network constraints and increased ramp capability. In 30, the authors developed a model that minimized both costs and emissions in power system operations by considering a high penetration of renewable energy. Using the Northwest power grid, this study was able to show that the proposed model can be used in the research of wind and photovoltaic consumption capacity. In 31, an optimal microgrid operations model was proposed to minimize the net present cost. This study analyzed the reductions in costs and emissions in serving the load by comparing the results from the proposed method with results when the load was only served by the grid. The authors in 32 investigated the operational flexibility and costs of low-emission power systems using simulation over different time horizons. In 33, a dispatch model was used on the 2012 All Ireland system to determine the savings in CO_2 emissions for a year. In 34, the authors proposed a unit commitment model to analyze the cost and emission impacts of wind generation when energy prices were negative. In 35, the authors proposed a multi-objective optimization model to minimize the cost and emissions of hybrid power systems. Finally, the authors in 36 proposed a method of evaluating the reduction in emissions due to power grid interconnection using an integrated transnational generation-transmission planning model.

With the increase in renewable energy integration to the electric grid, an urgent need exists to accurately track consumption amounts. However, optimal models that track renewables with consideration to location and time constraints are lacking. None of the aforementioned studies considered the location of renewable integration/curtailment with regard to costs and emissions. The combination of different generation technologies and a constrained transmission system can make reducing CO_2 emissions heavily reliant on the location and time 38, 37. The main contribution of this study was the development of a proposed optimization model that tracks renewable generation while considering location and time. Researchers proposed a model to calculate the marginal generation from each marginal generator under increased loads at certain locations in the power system based on economic dispatch results. It can effectively track the sources of electricity generation in a locational and temporal manner. Compared to the cumulative renewable energy consumption of an electricity customer over a certain period, this model focuses on marginal generation tracking and allows electricity consumers the ability to see in real time how much of their electric power will be from renewable energy sources if they use an additional appliance at a certain time point. This information allows environmentally aware consumers to strategically plan their energy consumption over the day. A modified IEEE reliability test system (RTS-96) was used to analyze the results of tracking renewable generation using this model. Results showed that the proposed model can be used to determine the sources of marginal generation at specific buses at different times in a computationally efficient manner.

Reducing Marginal Emissions in Power Systems with Distributed Flexible Alternating Current Transmission Systems

The increasing implementation of renewable energy sources in the electricity market poses significant challenges to power system operation due to their irregular and variable nature 38. As a result, grid operators may impose a restriction on the output of renewable energy sources to maintain system stability and reliability. This restriction on renewable energy, also known as renewable energy curtailment (REC), has become a major concern for the efficient integration of renewable energy into the electric grid 39. Transmission congestion is a major cause of REC 40. To reduce congestion, a variable impedance series distributed flexible alternating current (AC) transmission system (D-FACTS) can be used to reduce REC by improving grid flexibility.

A D-FACTS is essentially a scaled back version of a traditional flexible AC transmission system (FACTS) 41. Rather than being placed in a substation, these systems are placed along the transmission line, using several smaller devices rather than a single large one 42. In terms of reliability, a D-FACTS can also help provide stability to a grid that has been affected by failures. This study focused not only on the cost-benefit of a D-FACTS in the power grid, but also considered the environmental benefits it will have on the system. Because a D-FACTS can improve the transmission capacity of a network, it is anticipated that by improving the flow capacity of the electric grid, renewable energy integration will be enhanced, and the environmental impact of power systems can be reduced 43.

Renewable energy presents a promising option for reducing GHG emissions and environmental impacts because it produces virtually no emissions during generation. A total of 6,347.7 million metric tons of CO2 were produced in the United States in 2021, accounting for all land sectors. Compared to 2020, emissions increased by a total of 6.8 percent due to the burning of fossil fuels to produce energy 44. However, as mentioned in 45, 17 percent of the world's electric energy is being obtained from renewable sources, mainly from large hydroelectric dams. New rules have been implemented to encourage the use of renewable energy in the United States. One such regulation is the previously mentioned Renewable Portfolio Standards (RPS) program, which requires electricity providers to supply a specific consumption of renewable energy. Also mentioned previously, another example of a program aimed at encouraging renewable energy consumption is the Renewable Energy Credit program established by the Public Utility Commission of Texas, which requires that 10,000 MW of renewable energy be added to the generation mix in Texas by 2025.

With the increasing penetration of renewable energy, a growing interest has emerged in tracking the source of emissions. Marginal emissions can be used to evaluate the emissions induced by one unit of power consumption at a certain location in real time. This metric can be used to track the emissions 46 because a combination of different generation technologies and a constrained transmission system can make reducing CO_2 emissions reliant on the location and time **Error! Reference source not found.**. With the integration of flexible transmission technologies, such as D-FACTS, marginal emissions can be affected. However, studies are still lacking on how flexible transmission technologies affect the emissions in power systems, especially marginal emissions that differ depending on the location and time. Therefore, this research aimed to investigate the impacts of an optimized D-FACTS deployment on marginal emissions in power systems. This research contributed to the understanding of changes in power system environmental impacts as a result of a D-FACTS deployment, ultimately leading to further decarbonization of the power grid.

Achieving an Environmentally Aware Allocation of Electric Vehicle Charging Stations

The U.S. Department of Energy reported that the sale of light-duty plug-in electric vehicles increased from 308,000 in 2020 to 608,000 in 2021 47. Furthermore, the sale of light-duty vehicles is predicted to increase to about 2.21 billion vehicles by 2050, according to the U.S. Energy Information Administration. The sale of vehicles with plug-in charging is expected to grow by 31 percent in this same time 48. As a result, the increased load from charging these vehicles could affect the stability and reliability of the grid. The consumption of a level 2 electric car charger is 7.2 kW, but this can increase with the fast chargers 49. For instance, the Model S charger uses the Tesla wall connector with an output of up to 11.5 kW 50. The individual charging output for each vehicle is negligible to the grid. However, hundreds of vehicles charging in the same location and time could increase the load by a range of megawatts. Several long-haul trucks would need to use heavy-duty EV chargers, which could also increase the load by multiple MWs 51. One solution to ensure that the load is not impacted would be to use charging management to schedule the charging of vehicles when needed 52. In this study, the primary focus was on the planning and placement of these charging stations to maintain grid functionality with a reasonable cost and minimal environmental impact.

Many studies have been conducted on EV charging station allocation and planning in recent years. In 53, the authors used a two-step linear programming (LP) solution to determine the placement of EV charging stations to minimize the supply cost. The authors in 54 proposed an optimization problem to minimize the placement cost of the charging infrastructure by using a branch and bound algorithm. The authors in 55 proposed a multi-objective framework that considers the characteristics of the power grid, economic factors, reliability, and power loss to place EV charging stations in Guwahati, India. In 56, the authors proposed an adaptive particle swarm optimization algorithm for EV charging station placement with an objective function to minimize the cost of construction and operation. The authors in 57 developed a particle swarm optimization problem with the objective of finding an optimal location for EV charging stations in the IEEE-33 Bus Distribution System. In 58, a bilevel optimization problem was proposed to determine the optimal locations for EV fast charging stations. The model was converted into a single-level optimization problem to be used by the proposed algorithm to compute the optimal placement of charging stations. The authors in 59 investigated the optimal transit stops to place EV charging stations for electric buses. The authors used a linear programming relaxation algorithm with the objective of minimizing the cost of installation. In 60, the authors proposed a spatial temporal expanding power grid model to allocate the EVs, charging stations, and distributed generation units using the constrained Markov decision process. The authors in 61 used the grey wolf optimization and whale optimization algorithms to find the optimal location for EV charging stations that would minimize the power loss while maintaining the voltage profile of the system. Finally, the authors in 62 proposed a location optimization model based on a genetic algorithm to allocate EV charging stations in Ireland with the objective of minimizing the operating cost.

With the electrification of transportation and rise in sales of EVs, a need exists to optimally allocate charging stations for these vehicles. However, models that evaluate the electricity costs and emissions produced by the increase in demand from EV charging are still lacking. None of the previous studies considered the reduction in marginal costs and emissions in a spatial-temporal manner. A constrained transmission system combined with different generation technologies can make the reduction of CO_2 emissions dependent on the location and time 38, **Error! Reference source not found.**. The main contribution of this study is the development of a proposed optimization model that determines the costs and emissions produced by an increase in load from EV charging stations. The proposed model calculates the marginal generation from each marginal generator caused by the increase in demand based on unit commitment and economic dispatch results. From there, the marginal emission factor (MEF) is calculated with the objective of minimizing the cost to meet the demand. These results were tracked every hour for one year to determine the optimal locations to place EV charging stations that would minimize both the cost of electricity to the consumers and the environmental impacts of emission production. The model in this study was simulated using a modified IEEE RTS-96. Results showed that the proposed model can be used in a computationally efficient manner.

Ensuring Equity in Access to EVs and EV Charging by Examining the Perceptions, Opinions, and Knowledge in Underrepresented Communities in the Paso del Norte Region

As EVs make their way into the market as a sustainable solution to reduce fuel-use dependency and lower GHG emissions and environmental pollution 63–66, attention has turned to previous studies addressing consumer perceptions, behaviors, and tendencies regarding EV adoption. These studies found that cost, style, size, and range anxiety were among the main influential factors affecting the potential purchase and use of the vehicles 67–70. This study, however, provided insights from the unique perspective of underrepresented communities (URCs) in El Paso, Texas, that go beyond these factors. In this study, we evaluated how these communities perceive EVs, EV charging stations (ChSs), and electrified roadways (ERWs). We also examined access to each of these technologies by these communities, explored the potential of having ChSs and ERWs installed in their neighborhoods and measured their desire for the technologies to develop and be equally accessible for all.

Although consumers in general share a familiarity with EVs to some extent, basic knowledge of the technology, capable of influencing consumer perceptions and potentially leading to adoption, seems to be absent in the general public. The lack of this basic knowledge—perhaps one of the major barriers between EVs and consumers in URCs—goes beyond misconception, range anxiety, style, and pricing that have been addressed in previous studies on EV adoption and consumer behavior 63–65. Participants from URCs showed greater concern about electrification costs, health impacts, the variety of EV charging options, initial and ongoing maintenance costs for EVs, and EV safety. After learning of their availability, government incentives and tax rebates also sparked particular interest from URC participants when considering an EV purchase.

Acknowledging and addressing the existing knowledge gap between consumers, EV manufacturers, and EV-related infrastructure developers is essential for the widespread diffusion and adoption of EVs. Making the information accurate, easily accessible to the public, and effective in addressing their specific needs can make a significant difference in EV adoption in new and unexplored markets like URCs.

Approach

To develop an accurate LME evaluation framework, three steps were carried out.

The first step was to develop an economic dispatch (ED) model to determine generation dispatch. ED is an optimization problem that minimizes the dispatch cost considering different physical constraints of power systems. The ED model was developed using C++ and the C++ application programming interface of Gurobi, a commercial optimization solver, to ensure computational efficiency. The model was implemented on a modified IEEE RTS-96, and the generation level of each generator and the power flow through each line were obtained as results. From the results, marginal generators and binding transmission lines were identified—marginal generators are generators that are online but not generating at their full capacity, and binding transmission lines are lines that are utilized at their rating limits.

In the second step, a linear model was built to obtain the generation level change from the marginal generators under a load demand increase of 1 MW in the power system, considering transmission constraints and the relationship between generation injection and power flow changes on the transmission lines. The model, which included a set of linear equations, was implemented using the data obtained in Step 1 and was solved using the MATLAB Symbolic Math Toolbox. In this step, the marginal generation of each marginal generator was obtained.

In the third step, an LME calculation method based on the marginal generation and the hazardous gas emission rate of each marginal generator was developed. The LMEs were calculated using MATLAB. Figure 1 illustrates these three steps.

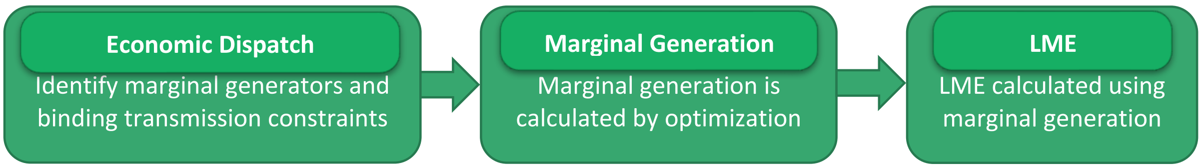


Figure 1. Three steps for MEF calculation.

After the LME evaluation framework was developed, we used it to optimally allocate EV charging stations based on the environmental impacts. Additionally, we learned about public opinions regarding EVs and EV charging that set a foundation for future EV adoption.

Methodology

Nomenclature

Indices

b	Binding transmission line.
g	Generator.
k	Transmission line.
m	Marginal generator.
n	Node.

Sets

$\sigma^+(n)$	Transmission lines with their *to* bus connected to node n.
$\sigma^-(n)$	Transmission lines with their *from* bus connected to node n.
$g(n)$	Generators connected to node n.

Variables

ΔF_b	Change of power flow through transmission line b.
ΔP_m	Change of generation level of marginal generator m.
$b_{k,t}$	Susceptance of transmission line k at time t.
$F_{k,t}$	Real power flow through transmission line k at time t.
$P_{g,t}$	Real power generation of generator g at time t.
$u_{g,t}$	Generator status (1=generator g is on at time t, 0=generator g is off at time t).
$v_{g,t}$	Startup variable (1=generator g starts up at time t, 0=generator g does not start up at time t).
$w_{g,t}$	Shutdown variable (1=generator g shuts down at time t, 0=generator g does not shut down at time t).
$\theta_{b,t}$	Voltage angle at bus b at time t.
$\theta_{fr,k,t}$	Voltage angle at the *from* node of line k at time t.
$\theta_{to,k,t}$	Voltage angle at the *to* node of line k at time t.

Parameters

B	Total number of binding transmission lines.
$B+1$	Total number of marginal generators.
b_k	Susceptance of transmission line k.
b_k^{max}	Upper susceptance limit of transmission line k.
b_k^{min}	Lower susceptance limit of transmission line k.
c_g^{NL}	No-load cost of generator g.
c_g^{linear}	Linear cost of generator g.
c_g^{SD}	Shutdown cost of generator g.
c_g^{SU}	Startup cost of generator g.
F_k^{max}	Thermal capacity/voltage drop limit of transmission line k.
L_n	Marginal load increase at bus n.
$L_{n,t}$	Load at bus n at time t.
N_g	Total number of generators.
P_g^{max}	Upper generation limit of generator g.
P_g^{min}	Lower generation limit of generator g.
RR_g	Hourly ramp-rate for generator g.
T	Length of investigated time period.
T_g^{down}	Minimum down time for generator g.
T_g^{up}	Minimum up time for generator g.
μ_m	Emission factor of generator m.
μ_{MEF}	Marginal emission factor.
$\Delta\theta_k^{max}$	Maximum voltage angle separation for line k to maintain stability.
$\Delta\theta_k^{min}$	Minimum voltage angle separation for line k to maintain stability.
φ_m^b	Change of power flow through transmission line b with power injection at bus with generator m.
φ_n^b	Change of power flow through transmission line b with power injection at bus with marginal load increase.

The Power System Operation Model

To build the renewable energy tracking system, an economic dispatch was implemented to identify marginal generators and binding transmission lines. A unit commitment (UC) problem was used to identify the generator unit commitment and generation dispatch during a given day. This model uses a mixed-integer linear program based on a multi-period optimal direct current (DC) power flow formulation that takes into consideration the time of operation. Then, the distribution of power on each transmission line can be calculated to monitor the power generation of each marginal generator that contributes to an increase in load using the following formulations:

$$min\left(\sum_{t=1}^{T}\sum_{g=1}^{N_g}\begin{pmatrix}c_g^{linear}P_{g,t}+c_g^{NL}u_{g,t}\\ +c_g^{SU}v_{g,t}+c_g^{SD}w_{g,t}\end{pmatrix}\right) \tag{1}$$

$$u_{g,t}P_g^{min} \leq P_{g,t} \leq u_{g,t}P_g^{max} \tag{2}$$

$$-F_k^{max} \leq F_{k,t} \leq F_k^{max} \tag{3}$$

$$b_k(\theta_{fr,k,t} - \theta_{to,k,t}) = F_{k,t} \tag{4}$$

$$\sum_{k\epsilon\sigma^+(n)} F_{k,t} - \sum_{k\epsilon\sigma^-(n)} F_{k,t} + \sum_{g\epsilon g(n)} P_{g,t} = L_{n,t} \tag{5}$$

$$v_{g,t} - w_{g,t} = u_{g,t} - u_{g,t-1} \tag{6}$$

$v_{g,t} + w_{g,t} \leq 1$ (7)

$-RR_g \leq P_{g,t} - P_{g,t-1} \leq RR_g$(8)

$$\sum_{t=m}^{m+T_g^{up}-1} u_{g,t} \geq T_g^{up}\left(u_{g,m} - u_{g,m-1}\right), 2 \leq m \leq T - T_g^{up} + 1 \quad (9)$$

$$\sum_{t=m}^{m+T_g^{down}-1} (1 - u_{g,t}) \geq T_g^{down}\left(u_{g,m-1} - u_{g,m}\right), 2 \leq m \leq T - T_g^{down} + 1 \quad (10)$$

$$\Delta\theta_k^{min} \leq \theta_{fr,k,t} - \theta_{to,k,t} \leq \Delta\theta_k^{max} \quad (11)$$

$$\theta_{1,t} = 0 \quad (12)$$

The objective function was intended to minimize the total operating cost, which included the generation, no-load, start-up, and shut-down costs of the system, as formulated in Equation (1). The constraints were represented by Equations (2)–(12). The real power output limits of the generators were determined by Equation (2). The thermal limits of the transmission lines were determined by Equation (3). The DC power flow was determined by Equation (4), while the nodal power-balance constraints were determined by Equation (5). The variable calculations for start-up and shutdown were determined in Equations (6) and (7). Ramping constraints were determined by Equation (8). The minimum up/down times of the generators were determined by Equations (9) and (10), respectively. The voltage angle difference limits between two connected busses were determined by Equation (11). Finally, the reference voltage angle was set to 0, as shown in Equation (12).

Calculation of the Marginal Generation from Each Marginal Generator

The marginal generation is defined as the amount of generation from each generator when the load at a certain bus increases by 1 MW. The total marginal generation from all the generators should be equal to the load increase (1 MW), the power flow through the binding transmission lines should remain unchanged with the load increase, and the generation and load changes should result in no changes of power flow through the binding transmission lines. Based on these relationships, the following system of linear equations can be solved to obtain the marginal generation:

$$min\left(\sum_{m=1}^{B+1}\left(\Delta P_m c_g^{linear}\right)\right) \quad (13)$$

$$\sum_{m=1}^{B+1} \Delta P_m = L_n \quad (14)$$

$$\Delta F_b = 0, \forall b \quad (15)$$

$$\Delta F_b = \sum_{m=1}^{B+1} \Delta P_m \varphi_m^b - L_n \varphi_n^b, \forall b \quad (16)$$

The marginal generation is defined as the next 1 MW of power used in the system, which can be supplied by multiple generators. The objective function of the MEF model was intended to minimize the total cost of meeting the load increase, as formulated in Equation (13). The change in generation of the marginal generators must add up to the load increase of 1 MW, as formulated in Equation (14). It is unlikely that an increase in load would alleviate transmission congestion, which means the power flow changes on binding lines must remain 0, as shown in Equation (15). The relationship between the changes in generation at the buses of marginal generators, the power flow through binding transmission lines, and load were found using a power transfer distribution factor (PTDF) matrix, as formulated in Equation (16). This matrix used a sensitivity factor to determine the change in power flow through a transmission line due to a change in load at a bus.

Calculation of the LMEs

The LMEs were calculated using the marginal generation and emission rate of each generator, as formulated in Equation (17) as follows:

$$\mu_{MEF} = \sum_{m=1}^{B+1} \Delta P_m \mu_m \tag{17}$$

Impact of Flexible Transmission Systems on LMEs

The mathematical formulations in this study involved the use of a two-step optimization problem; the first step optimally allocated the D-FACTS, and the second step evaluated the MEFs considering the effects of the installed D-FACTS.

The first step, in which we optimized the allocation of the D-FACTS, used a model based on the DC optimal power flow formulation to allocate the D-FACTS modules in each phase. The proposed model addressed a multi-objective problem that aimed to minimize both operating costs and global warming potential (GWP). In addition, the D-FACTS devices were allocated per line rather than per mile on each line, providing greater flexibility. A multi-objective evolutionary algorithm (MOEA) was used in this model to solve the problem in a computationally efficient manner. Because the implementation of these modules on transmission lines also adjusted their reactances, the effects were dependent upon the direction of power flow 71. These relationships are formulated in Equations (18) and (19) as follows:

If $\theta_{fr,k,t} - \theta_{to,k,t} \geq 0$,

$$\theta_{fr,k,t} - \theta_{to,k,t}/X_k^{max} \leq F_{k,s} \leq \theta_{fr,k,t} - \theta_{to,k,t}/X_k^{min} \tag{18}$$

If $\theta_{fr,k,t} - \theta_{to,k,t} \leq 0$,

$$\theta_{fr,k,t} - \theta_{to,k,t}/X_k^{min} \leq F_{k,t} \leq \theta_{fr,k,t} - \theta_{to,k,t}/X_k^{max} \tag{19}$$

Equations (20)–(42) outline the formulation of the model used to optimally allocate the D-FACTS devices as follows:

$$\min OF_1 = \sum_{t=1}^{N_t} P_t \left(\sum_{g=1}^{N_g} \begin{pmatrix} \sum_{seg=1}^{N_{seg}} C_{g,seg}^{linear} P_{g,t}^{seg} + C_g^U R_{g,t}^U \\ + C_g^D R_{g,t}^D + C_g^{NL} \end{pmatrix} + \sum_{r=1}^{N_r} c_r P_{r,t}^C \right) + C_{inv}^D \tag{20}$$

$$\min \mathrm{OF}_2 = \left(\sum_{t=1}^{N_t} \left(P_t \sum_{g=1}^{N_g} \sum_{c=1}^{N_c} GWP_{g,c,t} \right) \right) \tag{21}$$

$$P_{g,t} = \sum_{seg=1}^{N_{seg}} P_{g,t}^{seg} \tag{22}$$

$$P_g^{min} \leq P_{g,t} \leq P_g^{max} \tag{23}$$

$$-F_k^{max} \leq F_{k,s} \leq F_k^{max} \tag{24}$$

$$\sum_{k\in\sigma^+(n)} F_{k,t} - \sum_{k\in\sigma^-(n)} F_{k,t} + \sum_{g\in g(n)} P_{g,t} + \sum_{r\in r(n)} \left(P_{r,t} - P_{r,t}^C\right) = L_{n,t} \tag{25}$$

$$\sum_{g=1}^{N_g} R_{g,t}^U \geq S^U \tag{26}$$

$$\sum_{g=1}^{N_g} R_{g,t}^D \geq S^D \tag{27}$$

$$R_{g,t}^{U} \leq P_{g}^{max} - P_{g,t} \tag{28}$$

$$R_{g,t}^{D} \leq P_{g,t} - P_{g}^{min} \tag{29}$$

$$R_{g,t}^{U} \geq 0 \tag{30}$$

$$R_{g,t}^{D} \geq 0 \tag{31}$$

$$\Delta\theta_{k}^{min} \leq \theta_{fr,k,t} - \theta_{to,k,t} \leq \Delta\theta_{k}^{max} \tag{32}$$

$$\theta_{1,t} = 0 \tag{33}$$

$$f_{k,t}\left(1 + \frac{x_k^D}{l_k}\eta_L\right)X_k F_{k,t} \geq f_{k,t}\left(\theta_{fr,k,t} - \theta_{to,k,t}\right) \tag{34}$$

$$f_{k,t}\left(1 + \frac{x_k^D}{l_k}\eta_C\right)X_k F_{k,t} \leq f_{k,t}\left(\theta_{fr,k,t} - \theta_{to,k,t}\right) \tag{35}$$

$$0 \leq x_k^D \leq i_k^{max} \tag{36}$$

$$\sum_{k=1}^{N_k} \frac{x_k^D}{\max\left(x_k^D, 1\right)} \leq l_{max}^{alloc} \tag{37}$$

$$GWP_{g,c,t} = \sum_{seg}^{N_{seg}} H_{g,seg}^{linear} P_{g,t}^{seg} G_{g,t} W_c \tag{38}$$

$$C_{inv}^{D} = \sum_{k=1}^{N_k} 3 C_{sh}^{D} x_k^D \tag{39}$$

$$C_{inv}^{D} \leq C_{inv}^{max} \tag{40}$$

$$C_{sh}^{D} = C_{single}^{D} \frac{I(1+I)^N}{8760\left((1+I)^N - 1\right)} \tag{41}$$

$$0 \leq P_{r,t}^{C} \leq P_{r,t} \tag{42}$$

The objective of the first problem was to minimize the total operating system costs, which included D-FACTS investment, reserve, and generation costs, as formulated in Equation (20). The objective of the second problem—to minimize the GWP—was included in the formulation of Equation (21). The linear segments of the generation cost curve were determined by Equation (22). Equation (23) was used to determine the upper and lower generation limits of each generator. The transmission line limits were determined by Equation (24), and the power balance at each bus was determined by Equation (25). The reserve requirements were defined by constraints formulated in Equations (26)–(31). The reserve capacities were determined by Equations (28) and (29). The voltage angle limits between two buses were defined by Equation (32), while Equation (33) was used to determine the reference voltage angle. The DC power flow equations for each line are formulated in Equations (34) and (35). The maximum number of D-FACTS devices that can be installed on a line was determined by Equation (36). Equation (37) was used to determine the maximum number of lines that these devices can be installed on. The GWP of each generator was determined based on each contaminant the generator emits using the linearized heat-based emission curves formulated in Equation (38). The factors for the GWP calculations were obtained from 72. The total investment cost was determined by Equation (39); Equation (40) was used to define the limit of this investment. The total investment costs were expressed as an hourly interval using Equation (41). Finally, the renewable energy curtailment limits were determined by Equation (42).

Evolutionary algorithms are increasingly popular thanks to their quick convergence and low computational burden. The MOEA was implemented to produce a Pareto front with solutions to the D-FACTS allocation problem in which every objective to optimize is not objectively better than the other (i.e., each objective is considered nondominant). The first iteration of the algorithm generated random candidate solutions, while subsequent iterations resulted in better solutions by performing a crossover operation. Each solution was fed into a simplified linear model formed by Equations (3)–(8) and (15)–(25), where nonlinearities formed by the x_k^D variable were solved by the MOEA's assignment of these values. This process minimized the operating costs and the GWP at the same time, where the cost was prioritized.

The algorithm first generated a set of possible solutions. A reduced linear model was used to allocate the power generation through the network to meet demand and satisfy all constraints. Next, a greedy algorithm was used to allocate the reserve requirements before obtaining objective function values for each candidate solution. The Pareto dominance of each solution was checked, and nondominant solutions were stored separately before using a unified fitness metric to rank the solutions and generate new candidates that return for testing. After a set number of iterations, all the stored solutions were checked again for dominance, and the nondominant solutions were returned by the algorithm. After using the MOEA to allocate the D-FACTS devices to the transmission lines, set points were obtained, and this data were then inputted into the models described in Equations (1)   (17) to determine the marginal generators and binding transmission lines needed to solve for the MEFs.

Impact of EV Charging Stations on LMEs

Based on the MEF model, we were able to identify several location candidates for EV charging facilities. These location candidates had relatively low LMEs for hazardous gases, promoted environmental equity, and were close to neighborhoods with relatively large numbers of EV owners. However, electricity price was also an important factor for consideration. In term of costs, the locational marginal price (LMP) was considered. The MEFs and LMPs were obtained from the model on an hourly basis for a desired period of time and then analyzed at different buses. Locations with relatively low MEFs and LMPs were identified for EV charging stations.

Equity in Access to EVs and EV Charging in URCs in the Paso del Norte Region

In this study, we examined the perceptions, opinions, and knowledge of EVs, EV ChSs, and ERWs in URCs in the Paso del Norte region of Texas, and determined whether participants had a desire to have these technologies installed in their own neighborhoods. Toward this purpose, we conducted 3 focus groups and obtained 221 completed surveys. Herein, we present the focus group findings only.

The research included a focus group questionnaire that followed the Institutional Review Board (IRB) approval protocol. Key participants included current residents of each community, who were considered to be the best candidates to convey their experiences and perspectives regarding residency in the neighborhoods. Participation was open to any resident of these areas who was at least 18 years of age. The questionnaire included the following sections and topics:

- Section I: Perceptions of local AQ and EVs as environmental benefit.
- Section II: Knowledge and perceptions of EVs.
- Section III: Knowledge and perceptions of EV purchases and incentives.
- Section IV: Knowledge and perceptions of EV ChSs and ERWs.

The data were analyzed using qualitative research methods with the use of the MAXQDA qualitative data analysis software. The study considered the following vehicle types [73], [74], [75]:

- Battery electric vehicles (BEVs): EVs fully powered by plug-in rechargeable electric batteries.

- Hybrid electric vehicles (HEVs): EVs powered by an electric motor and a fuel engine simultaneously (the fuel engine recharges the battery that powers the electric motor).
- Plug-in hybrid electric vehicles (PHEVs): EVs powered by an electric motor and gasoline engine (the electric motor is powered by a plug-in rechargeable electric battery and the gasoline engine is used as a backup).
- ICEVs: Conventional gasoline and diesel engine vehicles.

Selection of Communities

The EPA environmental justice screening and mapping tool (EJScreen) [76] and the Texas Commission on Environmental Quality monitoring stations [77] were used to select the communities for study based on their majority-minority populations, proportions of low-income residents, and high levels of GHG and fine particulate matter ($PM_{2.5}$) pollutants. The communities selected for study were Chihuahuita, Montana Vista, and Anthony, Texas. These locations are shown in Figure 2 and described in **Error! Reference source not found.**.

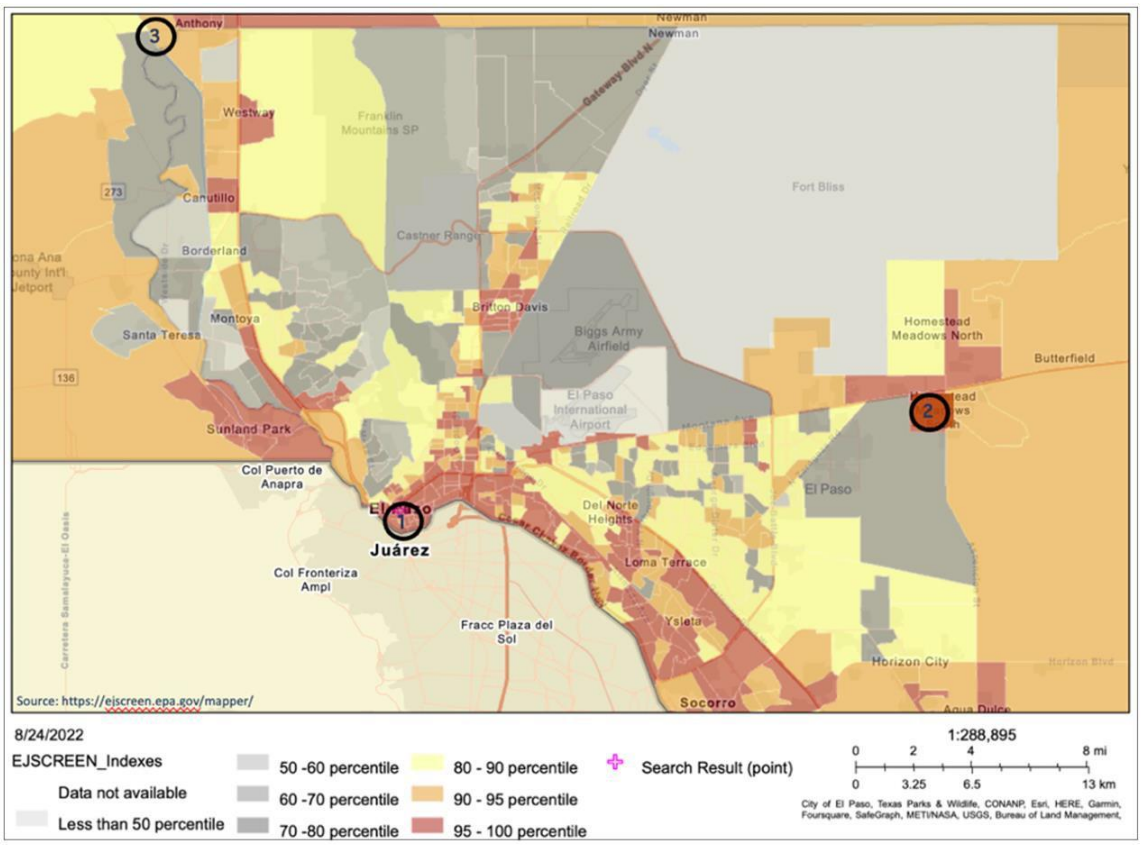


Figure 2. Communities selected using EJScreen: 1=Chihuahuita, 2=Montana Vista, and 3=Anthony, Texas.

Table 1. Overview of Selected Communities

Community	Age Group (years)	Education Level	Annual Household Income ($1,000)	Technology Perceptions	Neighborhood Overview
Chihuahuita	35–65	Some high school and associate's degrees	17–38	*Advantages:* EVs could potentially enhance community's air quality. *Disadvantages/ Concerns:* Initial EV costs and historic district design restrictions that prevent installation of ChSs and ERWs.	Affected by pollution from a bus station and downtown commercial areas nearby, US-62 and Loop 375, a commercial railroad that bisects the neighbor and blocks access to/from the community, the neighboring Mexican border city of Juarez, and the continuously operated Santa Fe international port of entry [15], [40]. Participants were unaware of their downtown access to EV ChSs, EV purchase incentives, or ERWs.
Montana Vista	25–55	High school and college	38–75	*Advantages:* EVs (especially pickups) could potentially facilitate work activities. Especially interested in at-home ChSs. *Disadvantages/ Concerns:* Initial EV cost, ERW potential for increasing taxes and causing community power outages, and ERW construction and maintenance cost responsibilities.	Rural, middle-age, working-class community located in far east El Paso County [82]. Affected by pollution from US-62 and a nearby electric plant. Participants perceived EVs as useful for their unincorporated work, had some knowledge of in service EV ChSs and their locations but were unaware of EV purchase incentives and ERWs.
Anthony	45–65	High school and college	49–75	*Advantages:* EVs viewed as highly beneficial for cleaner air and cost-effective compared to ICEV's fuel expenses. *Disadvantages/ Concerns:* Initial EV cost and potential for helping drivers prevent accidents, ERW potential for causing traffic congestion or community power outages.	Unincorporated town in far west El Paso County [82] with mostly retirees. Affected by pollution from nearby commercial areas, I-10, and gas stations that include rest areas. Participants perceived EVs to be beneficial but had no knowledge of EV purchase incentives or ERWs.

Chihuahuita, Texas

Chihuahuita is a historic district located in south downtown El Paso on the border between Mexico and the United States. It is the oldest neighborhood in the city, and most participants have lived there for over 20 or 30 years [78], [79]. This community is vulnerable to multiple environmental hazards including pollution from the commercial areas of the nearby downtown; the urban bus terminal; US-62 (Paisano Drive) located a few blocks away; Loop 375 that passes above the community; the commercial railroad that bisects the community and blocks the only entry/exit point to and from the community when a train travels through; the neighboring Mexican border city of Juarez that is located immediately south of the neighborhood; and the Santa Fe international port of entry that operates 24 hours a day, seven days a week. As a historic district, this community has specific design guidelines established by the city for restoration and/or new construction in the neighborhood that could modify or affect its original historic construction and preservation [80]. This, in turn, prevents them from any contemporary additions or modifications, such EV ChSs or ERWs.

The perceptions of EVs from most members of this community were positive. They felt that EVs could make a considerable difference in improving their air quality (AQ) due to the pollution they face, specifically from different sources of traffic. Nevertheless, they considered EVs out of their reach mainly due to initial costs. Regarding ChSs and ERWs, they again perceived these technologies to be out of their reach due to the historic district restrictions that could prevent ChSs and ERWs from being installed in their neighborhood. These factors made them lack interest in EV adoption. They were also unmoved by the existence of incentives and tax rebates available for EV purchase and the easy access to a public EV ChSs within one mile of their downtown neighborhood. The community members had never heard about ERWs before. Although they considered them to be a great resource because they would eliminate the need to drive to a charging station, they noted that most of their community members could not afford an EV, and thus, ERWs would not be useful for them.

Montana Vista, Texas

Montana Vista is an unincorporated rural community located in far east El Paso County and part of the metropolitan statistical area [81]. Some participants have lived in this neighborhood for less than 3 years, while other have lived here for over 10 years. Although Montana Vista has a power plant nearby and the highly trafficked US-62/180 (Montana Avenue) going through their neighborhood, the community members do not have big environmental concerns.

Participants of this middle-age, working-class community were in favor of the EV technology. Although they perceived it as costly, they showed great interest in the benefits that the technology could provide for their work. Their main EV inquiries included the availability of heavy-duty pickups, maximum payload capacities, and maximum distance traveled per charge on a full load. Regarding ChSs, they knew that El Paso had a public ChSs in service and that no similar ChSs were located near their community.

With respect to ERWs, the topic was fully unknown to this community. They perceived ERWs as useful because they would eliminate ChSs and EV range anxiety but unnecessary for now given the small number of EVs in their neighborhood. The topic did, however, generate particular interest about the effects of electrification on human health, user safety, and construction and maintenance costs, as well as its effects on their community power supply.

Anthony, Texas

Anthony is an unincorporated rural community located in far west El Paso County [81]. This community—comprised mostly of retirees—perceived EVs as highly beneficial because they help provide better air quality and are cost-effective compared to a regular internal combustion engine vehicle's ICEV's) fuel expenses. The community is vulnerable to nearby traffic pollution from I-10, commercial areas, gas stations that include rest areas for travel trailers, and a local elementary school.

The members of this community were particularly interested in what EVs can offer them in terms of safety, comfort, and savings. Their primary inquiries included whether EVs offer new technologies, such as movement and vehicle detection to prevent accidents (i.e., whether EVs can drive autonomously if the driver experiences a heart attack or other medical emergency), and whether EVs require less maintenance than ICEVs. They also perceived EVs as costly and had no knowledge of incentives or tax rebates availability for EV purchases. Once they were made aware of the potential for cost savings, their interest to learn about the topic increased.

Regarding ChSs, this community had some knowledge about stations in service in the city but did not know much about the locations or approximate numbers. Thus, they perceived having charging stations installed in their neighborhood as beneficial if they eliminate the need to drive some distance to a station and EV range anxiety.

Regarding ERWs, this community had never heard about this technology. Their perceptions were positive yet they expressed concerns about ERWs construction and maintenance that may cause traffic issues and the effects on their community's power supply.

Results

Tracking the Source of Marginal Electricity Generation

To build the energy source tracking system, a modified RTS-96 was used to implement the models. This test system included renewable generation from nuclear and hydroelectric generators. The system determines the change in generation of the marginal generators according to a 24-hour period of operation. Each bus was injected with an increased load of 1 MW to solve for each scenario of marginal generation change. This model uses a mixed-integer linear program based on a multi-period optimal DC power flow formulation and was solved using the Gurobi Optimization Solver in the Linux environment. Furthermore, the ramping constraints were modified to be one-fifth of the original.

In this study, the change in generation was in response to a load increase of 1 MW at a predetermined bus. This increase in load would be serviced by several generators, and the exact amount of power they contributed was determined by the program. In this way, the amount of power from renewable generators can be accurately tracked.

Load Increase Cost Comparison

Figure 3 shows the cost comparison for hours 1 and 5 when the load was increased by 1 MW at all 24 busses in the test system. Specifically, this figure compares the costs in U.S. dollars for the marginal generators to provide the extra load at each bus for hours 1 and 5. As can be seen from the results, the cost to meet this load can vary depending on the bus injection and hour of operation. In this case, the costs at hour 5 were almost always lower than the costs at hour 1 across all busses. Changing the hour of operation can consistently decrease costs.

Figure 4 and Figure 5 show the cost comparisons over 24 hours for bus 13 and bus 17, respectively. At bus 13, all hours yielded an increase in costs to serve the load, while the extra load caused the price to decrease at bus 17. From these results, the cost will always be positive or negative for certain busses (i.e., the locational marginal price was positive at bus 13 and negative at bus 17). During all hours of operation, if the load is increased at bus 17, the price will always decrease. This phenomenon related to the reduction in price is interesting to note if certain load zones are specifically targeted to be increased.

Finally, Figure **6** illustrates the functional relationship between the cost, bus injection, and time to meet the 1 MW load increase. The surface plot displays all hours and busses for the RTS-96 simulation. The costs fluctuated based on the location of the load increase and the hour of operation. Additionally, most hours had a similar price depending on the bus load increase, making it possible to predict the cost for meeting the load in the next hour.

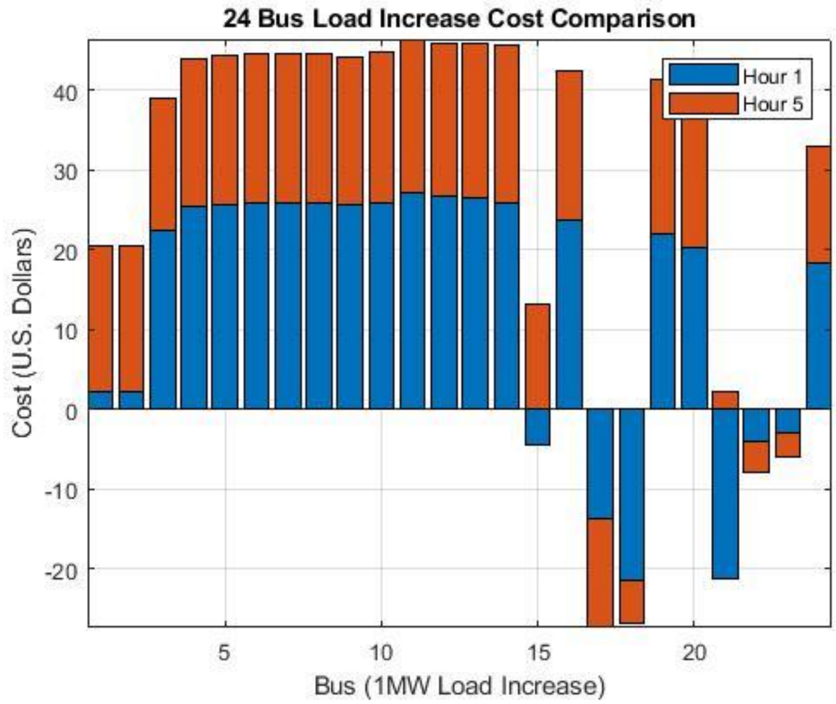


Figure 3. Load increase cost comparison (hours 1 and 5).

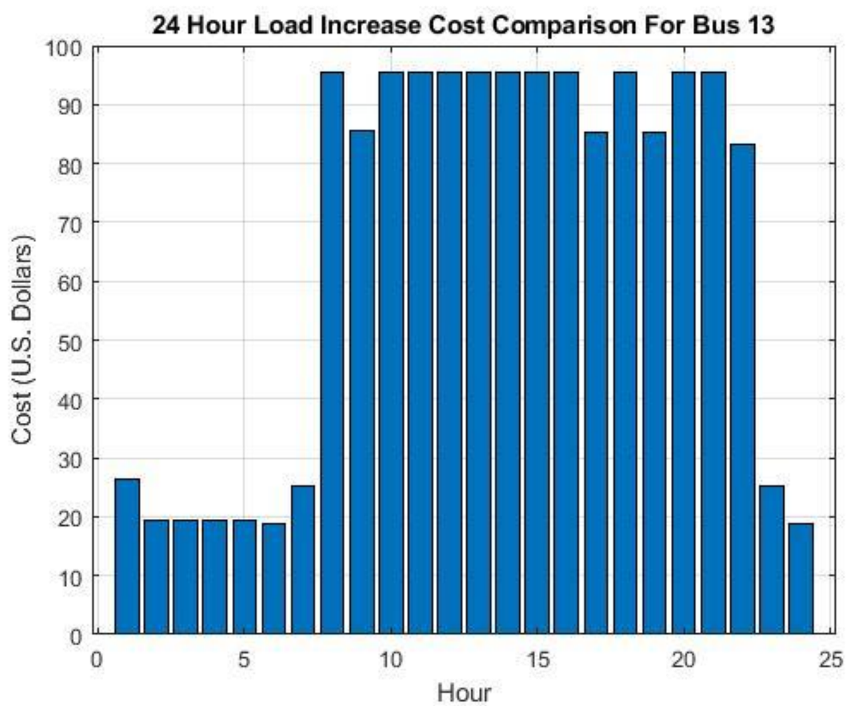


Figure 4. Load increase cost comparison for bus 13.

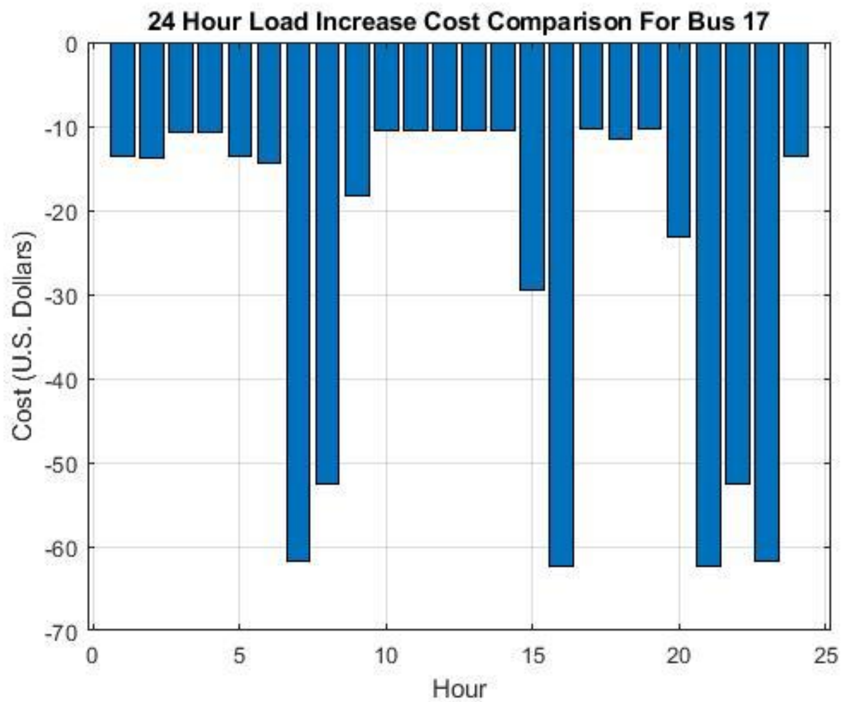


Figure 5. Load increase cost comparison for bus 17.

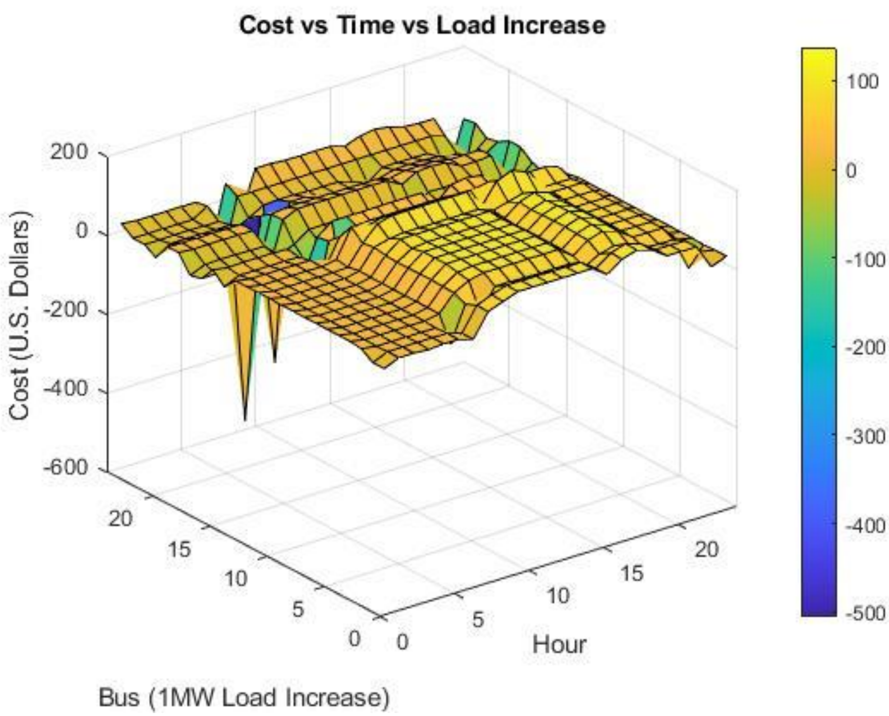


Figure 6**. Load increase cost comparison (all busses and hours).**

Change in Generation Analysis

Table 2 shows the change in generation for several marginal generators for a load increase at bus 1 and hour 14. It lists the kind of generators being used as well as the exact amount of generation in MW to meet the demand. As mentioned previously, the change in load is always consistent for each bus meaning the change in generation shown in the table must add up to 1 MW. Marginal generators 8, 11, 22, and 31 contributed to this 1 MW load. Marginal generator 22 is a nuclear generator that produced 0.0336222 MW of power and marginal generator 31 is a coal/steam generator that produced 0.0337058 MW of power. All other contributing marginal generators are oil/steam generators. The purpose of this study was to track renewable generation, which was determined using this method. The exact amount of nuclear generation was determined for this location and time. Although nuclear energy is not renewable, this example demonstrates how this method could be used to track renewable generators when implemented into the test system, which was the next step in this study.

Table 2. Change in Generation at Bus 1 (Hour 14)

Marginal Generator Number (Hour 14)	Generator Type	Change in Generation at Bus 1 (1 MW Load Increase)
8	Oil/Steam	0.925789
10	Oil/Steam	0
11	Oil/Steam	0.0068832
12	Oil/Steam	0
21	Nuclear	0
22	Nuclear	0.0336222
31	Coal/Steam	0.0337058

Table 3 shows the change in generation at bus 21 and hour 8. The 1 MW load increase at this bus was served solely by nuclear generator 22 at this hour; marginal generator 22 is located directly on bus 21 and was thus most feasible for serving the whole load. This capacity would not be possible if the generator was not marginal or if it were to be turned off in a different hour.

Table 3. Change in Generation at Bus 21 (Hour 8)

Marginal Generator Number (Hour 8)	Generator Type	Change in Generation at Bus 21 (1 MW Load Increase)
8	Oil/Steam	0
10	Oil/Steam	0
11	Oil/Steam	0
12	Oil/Steam	0
13	Oil/Steam	0
21	Nuclear	0
22	Nuclear	1
31	Coal/Steam	0

Table 4 and Table 5 show the change in generation at bus 11 and hours 10 and 1, respectively. At hour 10, nuclear generator 21 decreased in generation by –0.00840193 MW, while all other fossil fuel generators increased in generation. This trend can be used to track the increase/decrease of renewable generation for certain hours by the test system. At hour 1, marginal generation changed despite being at the same bus. First, the number of marginal generators significantly increased compared to hour 10. Depending on the time, certain generators will change generation and be turned off or on, causing the number of marginal generators to change; this dynamic must be accounted for in the test system. In this case, the higher number of generators can also include those generators that were generating at their minimum. Thus, the excess marginal generators may not be needed in hour 1, but they may be needed to make this approach feasible across all hours. Also, nuclear generator 22 produced 0.0395054 MW this hour compared to the decrease in generation at hour 10. Most of the load was still met by marginal generator 6, which is a coal/steam generator.

Table 4. Change in Generation at Bus 11 (Hour 10)

Marginal Generator Number (Hour 10)	Generator Type	Change in Generation at Bus 11 (1 MW Load Increase)
8	Oil/Steam	0.48919
10	Oil/Steam	0
11	Oil/Steam	0.405232
12	Oil/Steam	0
21	Nuclear	–0.00840193
31	Coal/Steam	0.11398

Table 5. Change in Generation at Bus 11 (Hour 1)

Marginal Generator Number (Hour 1)	Generator Type	Change in Generation at Bus 11 (1 MW Load Increase)
2	Coal/Steam	0
3	Coal/Steam	0
6	Coal/Steam	1.29285
7	Coal/Steam	0
8	Oil/Steam	0
10	Oil/Steam	0
11	Oil/Steam	0
12	Oil/Steam	0
13	Oil/Steam	0
19	Coal/Steam	–0.332352
21	Nuclear	0
22	Nuclear	0.0395054
29	Coal/Steam	0
31	Coal/Steam	0

Reducing Marginal Emissions in Power Systems with Distributed Flexible AC Transmission Systems

Step 1: D-FACTS Allocation Results

This simulation was run with 100 possible solutions over 100 iterations. The cost of a D-FACTS device was estimated at $3,000 with a discount rate of 6 percent over 30 years, based on previous literature [5]. Figure 7 shows the Pareto-optimal solutions.

The solution marked in red was selected as the most ideal for use in the marginal load and marginal emission analysis. The base case with no D-FACTS devices installed had an expected hourly cost of $39,237 and an expected GWP of 40,230. By comparison, the selected solution also had an expected hourly cost of $39,237, including the expected hourly cost of the D-FACTS, but a much-reduced GWP of 40,002.

Table 6 summarizes the D-FACTS allocation results for the selected solution. Next, the new reactances of the lines and the marginal emissions were calculated.

Table 6. D-FACTS Allocation Results

Line	Number of D-FACTS Devices	Set Point (%)
1	18	0.14
10	9	0.18
31	12	2.53

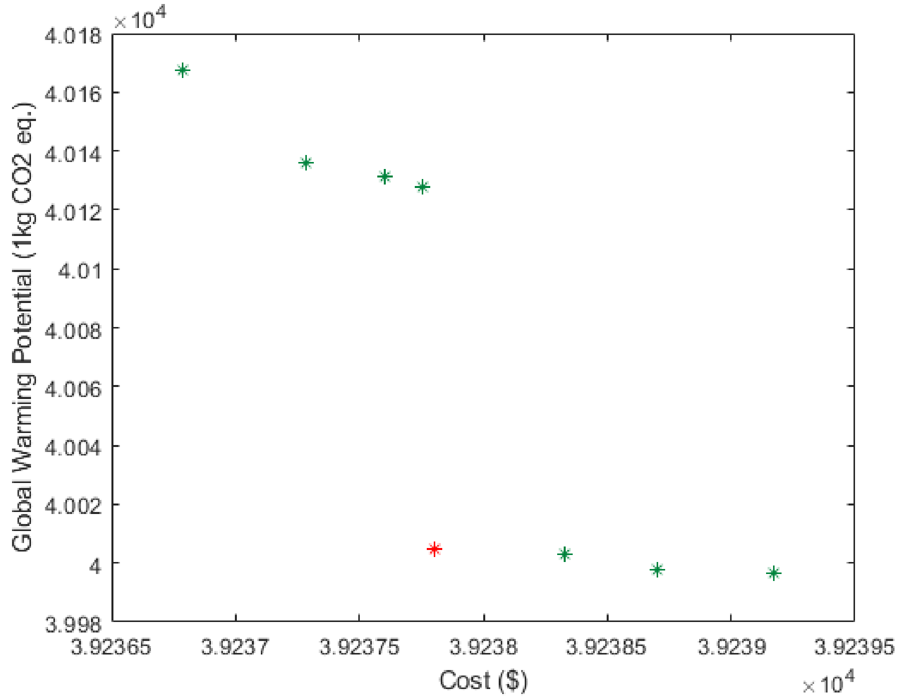


Figure 7. Pareto front: Cost vs. GWP.

Because the investment cost of the D-FACTS is considered in the objective function, the objective value for the case with the D-FACTS is lower than the case without the D-FACTS, indicating that the total savings in power system operating costs over the lifetime of the D-FACTS were higher than the system's investment cost. The operating cost savings were due to the transmission flexibility and redeployability that D-FACTS devices provide. In addition to the cost savings, the D-FACTS reduced the CO_2 emissions, reducing the GWP by approximately half a percentage point. Because the annual CO_2 emissions from electricity generation is more than 1.5 million metric tons in the United States, a half a percentage point reduction equates to more than 7,500 metric tons, which is a significant amount. With more variety of generating resources being integrated, the emissions can be further reduced.

Step 2: Marginal Emission Results

Figure 8 shows the marginal CO_2 emissions produced every hour of the day when the load was increased by 1 MW at the bus representing Fort Bliss. This figure shows the results of the emissions generated without the allocation of D-FACTS devices in the El Paso power system. Between hours 7 and 22, the marginal emissions remained at a constant value of about 820 lb/MWh. In addition, the emissions decreased to about 709.6 lb/MWh during the morning and evening hours, which is consistent with the behavior of real power plant load curves. Less power is consumed at hours of less activity for consumers. The total marginal emissions produced at this location for the whole day was found to be 19,197.65 lb/MWh. Finally, the total marginal emissions for all buses and hours were 460,743.7 lb/MWh without the allocation of D-FACTS devices.

Next, Figure 9 shows the marginal CO_2 emissions produced every hour of the day when the load was increased by 1 MW at Fort Bliss with the allocation of D-FACTS devices. The data shown in this figure were generated based on the changes in reactances of each transmission line when D-FACTS devices were installed in the same test system. The emissions emitted during the morning and evening hours were constant at around 709.6 lb/MWh. However, the emissions decreased sharply throughout the day instead of remaining mostly constant as was the case without the allocation of D-FACTS devices (Figure 8). Thus, the allocation of D-FACTS devices caused a notable decrease in the marginal emissions produced in the same test system. Furthermore, the total marginal emissions produced at this bus during a 24-hour period of operation were 18,231.21 lb/MWh; 966.44 lb/MWh less than the emissions produced without the allocation of D-FACTS devices (Figure 8).

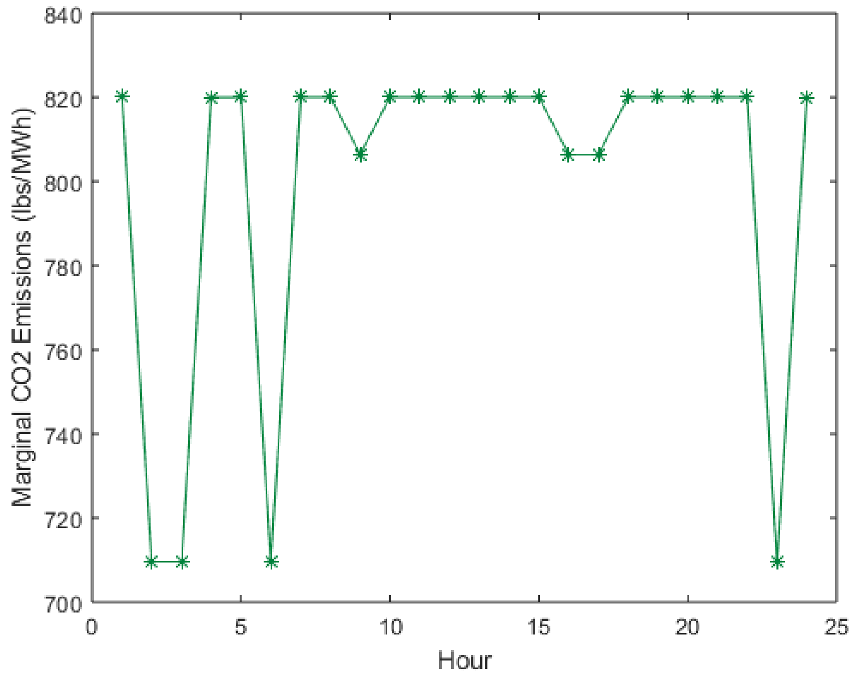


Figure 8. Marginal emissions vs. time without D-FACTS allocation.

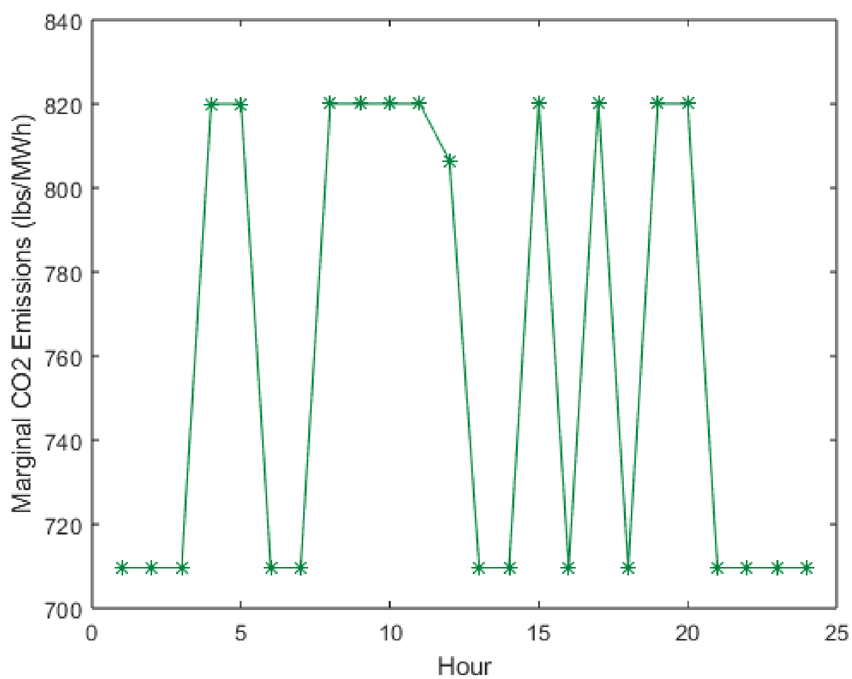


Figure 9. Marginal emissions vs. time with D-FACTS allocation.

The total marginal emissions across all locations and times with the allocation of D-FACTS devices yielded 437,549.1 lb/MWh; 23,194.6 lb/MWh less than the emissions produced without the allocation of D-FACTS devices (Figure 8). These findings further illustrate the environmental benefits of optimally allocating D-FACTS modules into a system. Figure 10 further illustrates these improvements by showing the differences in marginal emissions between a system with and without D-FACTS devices. Across almost all hours, the emissions decreased when D-FACTS devices were installed compared to when they were not. During some hours, such as hour 1, significant reductions in emissions of up to 110.4 lb/MWh occurred. The noticeable savings in emissions are important for increasing the sustainability of the grid.

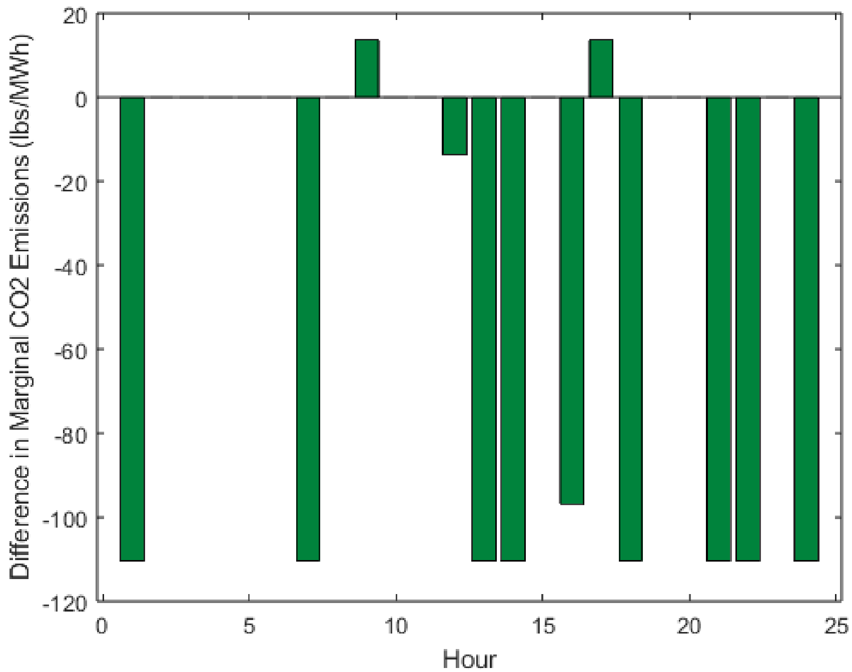


Figure 10. Difference in marginal emissions with D-FACTS allocation.

Achieving an Environmentally Aware Allocation of Electric Vehicle Charging Stations

The simulation executed the model for every hour of a representative year. The problem was solved using the Gurobi Optimization Solver in the Linux environment and the ramping constraints were changed to be one-fifth of the original. The generators operating at their minimum production levels were considered as marginal generators in this study to maintain feasibility during some hours of operation.

From the simulations, the MEFs and generation costs induced by a 1 MW load increase at different buses in each hour were obtained. This section describes the selection process for potential EV charging station installation locations and presents analysis results for the MEF and power system operating cost increases induced by a 1 MW EV load at each of the selected locations.

EV Charging Station Location Selection

In this study, buses 18, 21, and 23 were chosen for as EV charging station locations. Bus 18 was selected due to its lowest average MEF. Bus 21 was chosen because of its lowest average cost throughout the year. Finally, bus 23 was selected because it had the second lowest average cost and the fifth lowest average MEF for the year. Table 7 shows the five lowest average costs and emissions corresponding to each bus. Several buses overlapped; selecting certain locations can minimize both cost and emissions when charging. Both LMPs and MEFs can be negative when transmission congestion exists in the system.

Table 7. Lowest Average Costs and Emissions

Bus	Costs ($)	Bus	Emissions (lb/MWh)
21	-64.6924	18	-725.247
23	-52.4895	17	-720.028
18	-45.3587	21	-165.681
17	-24.7879	22	-101.379
22	-16.8267	23	211.82

Load Increase Emission Analysis

Figure 11 shows the average emissions produced by the 1 MW load increase, or MEFs, at buses 18, 21, and 23 for a typical day of the year. The curves show the MEFs in different hours of a typical day at these three locations. Bus 18 had the lowest emissions throughout the day. In fact, all the MEFs were negative for this bus except at hours 6 and 7. The highest emissions occurred at hour 6, reaching about 142.8 lb/MWh. In comparison, the MEFs at bus 21 were higher than those found in the previous bus except at certain times. The highest value reached was 3,905.8 lb/MWh at hour 7, which was higher than any of the chosen buses. Next, the figure illustrates that most of the MEFs at bus 23 were positive. The negative MEFs for this bus occurred between hours 10 and 15. Thus, bus 23 produced more emissions overall than the other buses when the load was increased. In addition, the peak emissions for this location (1,793.6 lb/MWh) were reached at hour 7.

Figure 12 shows the total emissions produced by a 1 MW load increase at buses 18, 21, and 23 during each season of the year. As can be seen from the results, the sum of emissions for each season at bus 18 were negative, indicating that the increase in load from EV charging at this location would reduce the emissions produced in the power system throughout the year. The summer and winter seasons yielded the largest decreases in emissions. The reduction in emissions during winter was found to be –3,006,271 lb/MWh, which was the lowest of the three buses. The total emissions during fall and spring were negative for bus 21. However, the sum of emissions for summer and winter were positive. The largest rise in emissions at this location occurred during the winter, reaching a total of 88,949.9 lb/MWh. Finally, the total emissions for all seasons except winter were positive for bus 23. The winter season showed a total decrease in emissions of –20,611 lb/MWh, while the fall season showed an increase of 903,857.4 lb/MWh (the highest of the three buses). Based on the sum of emissions, bus 18 showed the highest reduction in emissions, while bus 23 showed the highest production of emissions.

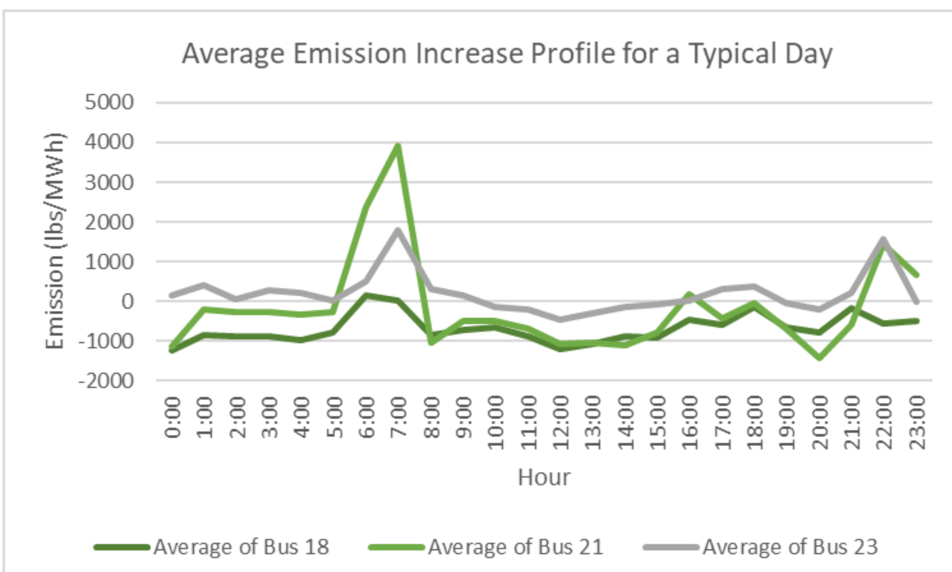


Figure 11. Average emission increase profile for a typical day (buses 18, 21, and 23).

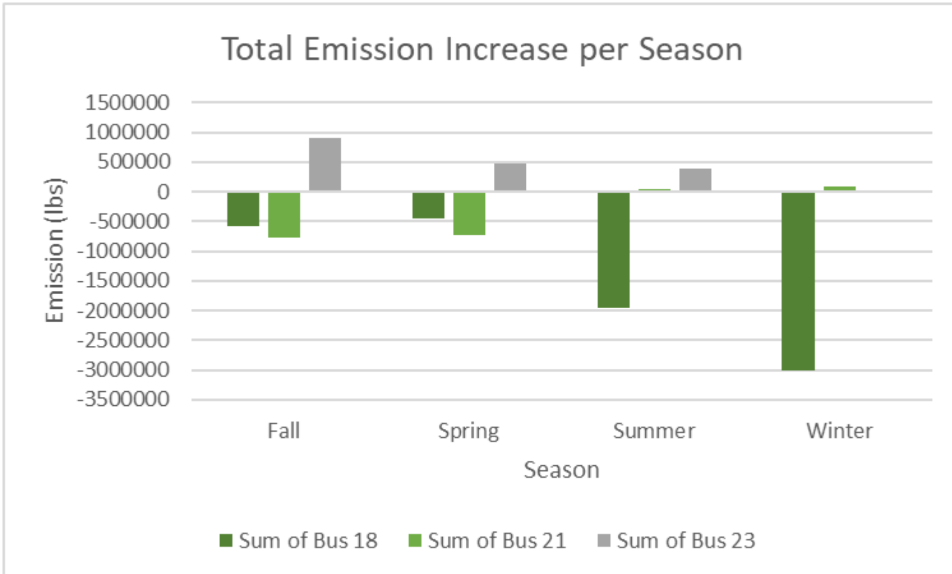


Figure 12. Total emission increase per season (buses 18, 21, and 23).Load Increase Cost Analysis

Figure 13 shows the average costs to meet the 1 MW increase in demand at buses 18, 21, and 23 for a typical day of the year. The cost for each hour at bus 18 was negative and fluctuated according to time. The lowest cost was found to be –$87.4 at hour 16. Like bus 18, bus 21 also had all negative costs associated with the increase in load. In select instances, the costs were higher at bus 21 than bus 18, but the costs for bus 21 were lower overall due to the sharp decreases in cost at certain hours. In fact, the lowest cost was found to be –$209 at hour 7. The costs of meeting the demand at bus 23 was also found to be mostly negative throughout the day. The highest cost ($4.6) was found at hour 1. The costs at all buses decreased sharply between hours 5 and 8. Furthermore, bus 21 had the lowest average cost because of sharp drops in price throughout the day. Additionally, bus 23 showed lower prices overall when compared to bus 18 between hours 7 and 23. For this reason, bus 23 had the second lowest average cost.

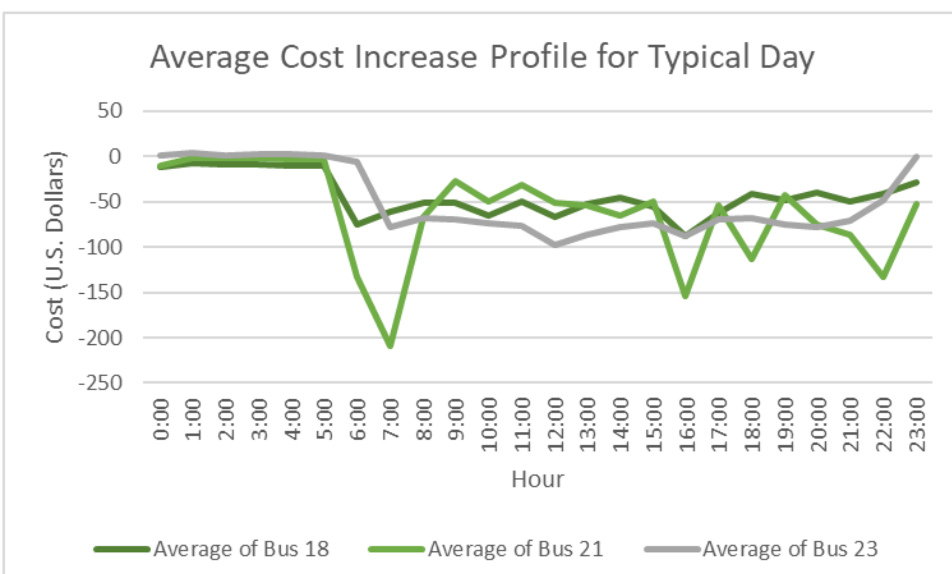


Figure 13. Average cost increase profile for a typical day (buses 18, 21, and 23).

Figure 14 shows the total costs of meeting the increase in load at buses 18, 21, and 23 during each season of the year. The total costs for each season at all buses were negative due to the objective function's aim of minimizing the cost, which made the prices negative. Bus 18 had the lowest total costs during summer and winter. The lowest cost for this bus was found to be –$201,942.9 in the winter, which was the lowest total cost observed among the three buses. Bus 21 had the lowest costs during the fall and winter seasons. The lowest total cost for this bus was found to be –$189,928.7 in the winter season. Finally, the lowest costs for bus 23 were found during summer and winter. Again, the lowest total cost for this location was found to be –$189,477 in the winter season, which was slightly lower than the lowest total cost found at bus 21. The results showed that the reduction in overall cost was highest at bus 21 because it had the lowest prices consistently throughout the seasons.

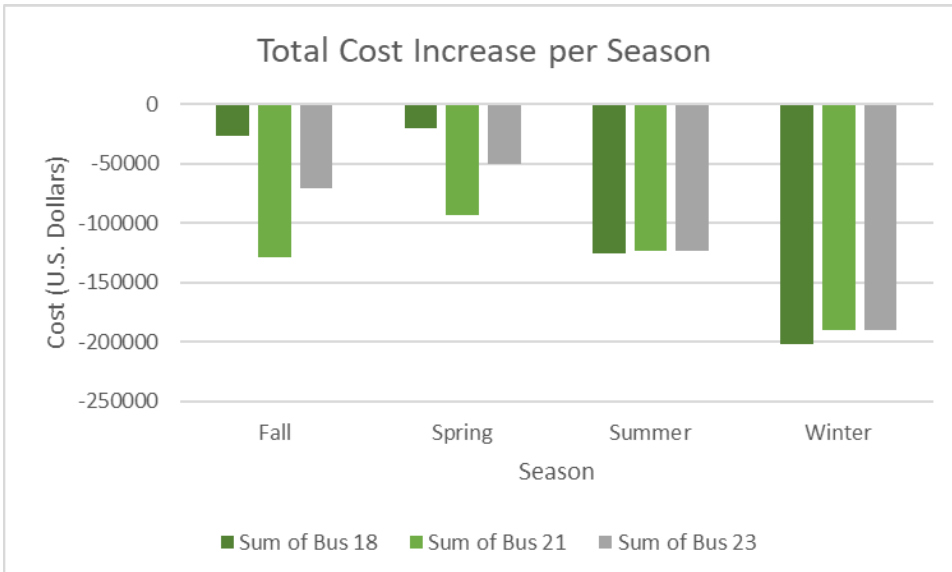


Figure 14. Total cost increase per season (buses 18, 21, and 23).

Change in Generation Analysis

Table 8, Table 9, and Table 10 show the change in generation for the marginal generators in response to a 1 MW increase in load at hour 17 on day 190. Table 8 shows that marginal generators 14, 23, and 32 contributed toward meeting the increase in load. During this time of day, the MEF was found to be –533.8 lb/MWh, and the cost to meet the demand was –$10.55. Reducing the generation from fossil fuel generators at this hour, while not emitting any new emissions through the nuclear generator, reduced this impact on the power system. In addition, the cost for meeting the demand was negative because the generators that reduced their power were operating in segments that were more expensive. Furthermore, the cost of the nuclear generator at segment 4 was only $2.36, which further contributed toward the reduction in price.

Table 9 shows the change in generation at bus 21 at the same hour and day. Marginal generators 13, 14, and 23 contributed to meeting the increase in demand. The MEF was found to be –2645.7 lb/MWh, and the cost to meet the demand was –$158.8. The significant reduction in emissions can be explained by the curtailment of –39.4 MW at generator 14. The program offset this curtailment by increasing the generation at generator 13 by the same amount. The emission rate at generator 14 was higher than generator 13, leading to the high reduction in emissions. The load was also met by nuclear generator 23, which produced no emissions. The cost also decreased; generator 13 was less expensive to operate than generator 14 at segment 4, and generator 23 only cost $2.36.

Next, Table 10 shows the change in generation for bus 23 at the same hour and day. The increase in load was met in part by generators 13 and 14, similar to bus 21. However, unlike bus 21, the remaining portion of the 1 MW of demand was met using coal/steam generator 31 instead of the nuclear generator. This generator produced more emissions than the nuclear generator, which changed the MEF to –776.7 lb/MWh. Additionally, the cost was found to be –$141.3 because the cost in the piecewise linear segment 3 for generator 31 was $19.85.

Table 8. Change in Generation at Bus 18 (Day 190)

Marginal Generator Number (Hour 17)	MEF: –533.80 lb	LMP: –$10.55	Change in Generation at Bus 18 (1 MW Load Increase)
	Emission rate (lb/MW)	Generation Cost ($/MW)	
14	1635.40	99.66	-0.096
23	0	2.36	1.290
32	1941.24	20.61	-0.194

Table 9. Change in Generation at Bus 21 (Day 190)

Marginal Generator Number (Hour 17)	MEF: –2645.71 lb	LMP: –$158.79	Change in Generation at Bus 21 (1 MW)
	Emission rate (lb/MW)	Generation Cost ($/MW)	
13	1568.25	95.57	39.4
14	1635.40	99.66	-39.4
23	0	2.36	1

Table 10. Change in Generation at Bus 23 (Day 190)

Marginal Generator Number (Hour 17)	MEF: –776.71 lb	LMP: –$141.30	Change in Generation at Bus 23 (1 MW)
	Emission rate (lb/MW)	Generation Cost ($/MW)	
13	1568.25	95.57	39.4
14	1635.40	99.66	-39.4
31	1869	19.85	1

Ensuring Equity in Access to EVs and EV Charging by Examining Perceptions, Opinions, and Knowledge in URCs in the Paso del Norte Region

Demographics

The survey sample (n=221) included comparable participation of males (45 percent) and females (54 percent), a high percentage of Hispanics (87 percent), a low percentage of Whites (8 percent), and lower percentages of Asians (1.5 percent) and American Indians (0.5 percent). The sample included mainly young participants belonging to the 18–24 (40 percent) and 25–34 (27 percent) age groups. The lowest participation of both males and females occurred for the 56–64 (3 percent) age group. Regarding highest level of education, respondents reported having completed some college, meaning they attended college and did not graduate or are still attending college (32 percent); graduated from high school (18 percent); and earned an associate's degrees (16 percent). Regarding annual household income, respondents reported earning $25k–49k (26 percent), $50–74K (23 percent), and less than $25K (16 percent). Fewer respondents reported earning $75–99K (13 percent), $100–149K (7 percent), and more than $150K (1 percent), and 14 percent preferred not to answer. Table 11 presents the demographics of the sample.

Perceptions of the Environment

Participants were asked to indicate their familiarity with air pollution impacts on health and their level of concern with the air quality of their neighborhoods (Table 12) using a 5-point scale, with 1=not at all familiar to 5=extremely familiar). Results showed a moderate familiarity regarding air pollution health impacts from almost half of the respondents (43 percent) and a slight familiarity from 20 percent of respondents. Neutral and extreme familiarities were reported by 17 and 16 percent of respondents, respectively. Only 4 percent of respondents reported being not at all familiar. Regarding AQ concerns in their neighborhoods, participants reported being moderately concerned (32 percent), neutral (26 percent), extremely concerned (21 percent), slightly concerned (16 percent), and not at all concerned (5 percent).

Table 11. Overview of Sample Demographics

Attribute	Number of Responses	Percent (%)	Attribute	Number of Responses	Percent (%)
Gender			Education level		
Female	120	54	Less than high school	11	5
Male	100	45	High school graduate	39	18
No response	21	1	Some college	72	32
			Associate's	36	16
Ethnicity			Bachelor's	35	16
Hispanic	192	87	Graduate	20	9
White	17	8	Other	8	4
No response	8	3			
Asian	3	1.5	Household income		
American Indian	1	0.5	<$25K	35	16
			$25–$49K	57	26
Age group			$50–$74K	51	23
18–24	89	40	$75–$99K	29	13
25–34	59	27	$100–$149K	15	7
35–44	29	13	>$150K	3	1
45–54	25	11	No answer	31	14
55–64	6	3			
65+	13	6			

Table 12. Familiarity with Pollution Health Effects and Concerns with Local AQ

Attribute	Number of Responses	Percent (%)	Attribute	Number of Responses	Percent (%)
Familiarity with pollution health effects			Concerns with local AQ		
			Not at all concerned	11	5
Not at all familiar	8	4	Slightly concerned	36	16
Slightly familiar	44	20	Neutral	58	26
Neutral	38	17	Moderately concerned	69	32
Moderately familiar	95	43	Extremely concerned	47	21
Extremely familiar	36	16			

Driving and Transportation Habits

Participants were asked about their driving and transportation habits (Table 13), including their driving frequencies, approximate weekly vehicle miles traveled (vmt), and monthly fuel expenses.

The majority of respondents (76 percent) reported driving daily, with weekly distances of 20–60 vmt (27.6 percent), 60–120 vmt (25.8 percent), more than 120 vmt (16.7 percent), and less than 20 vmt (5.9 percent). Another 12 percent of respondents reported driving more than three times per week, with weekly distances of 20–60 vmt (7 percent), 60–120 vmt (3 percent), more than 120 vmt (1 percent), and less than 120 vmt (1 percent). Smaller percentages of the sample had a driving frequency of once a week (4 percent) or rarely driving (4 percent); the smallest percentage of the sample only drove once a month (2 percent). Figure 15 depicts these driving frequency results based on the weekly vmt.

Regarding fuel expenses, participants reported monthly expenses of $60–99 (33 percent), $100–199 (30 percent), $40–59 (13 percent), and more than $200 (13 percent). Only 4 percent reported expenses of $20–39, and 2 percent reported expenses less than $20. The remaining participants either did not know their approximate fuel expenses (2 percent) or did not have a vehicle (4 percent). Figure 16 depicts these fuel expenses based on the weekly vmt. Some of the vmt results may seem inaccurate when contrasted with monthly fuel expenses. However, it is important to note that vehicles differ in size and fuel efficiency and that responses were presented exactly as given by participants.

Table 13. Driving and Transportation Habits

Attribute	Number of Responses	Percent (%)*	Attribute	Number of Responses	Percent (%)*
Driving frequency			Average weekly vmt		
Every day	168	76	<20 miles	21	39
>3 times per week	28	12	20–60 miles	85	30
2–3 times per week	8	4	60–120 miles	67	18
Do not own a vehicle	8	4	>120 miles	40	10
Once a week	4	2	Do not own a vehicle	8	4
Rarely	4	2			
Once a month	1	1			
Monthly fuel expenses					
<$20	4	2			
$20–39.99	10	4			
$40–59.99	29	13			
$60–99.99	72	33			
$100–199	65	30			
>$200	29	13			
Do not know	4	2			
Do not own a vehicle	8	4			

*Percentages may not equal 100 percent because they were rounded to the nearest 10.

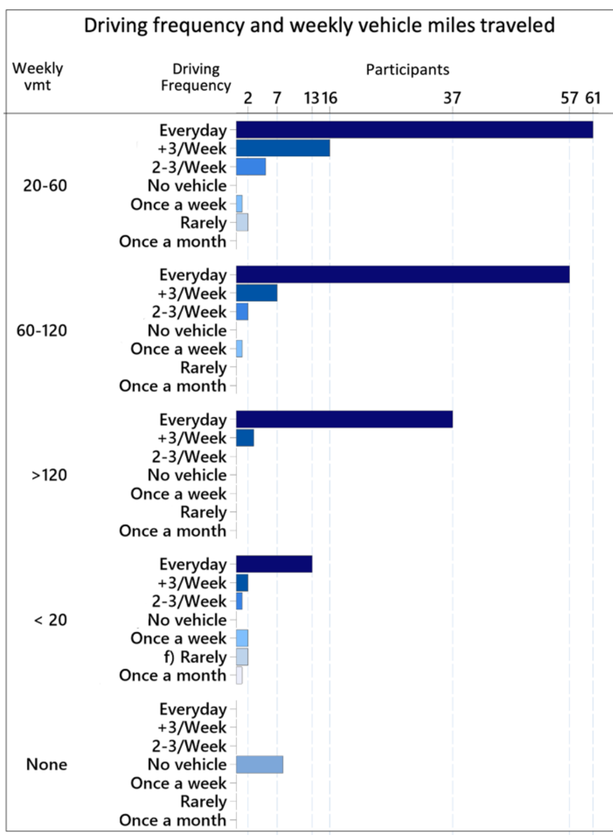


Figure 15. **Driving frequency and weekly vmt.**

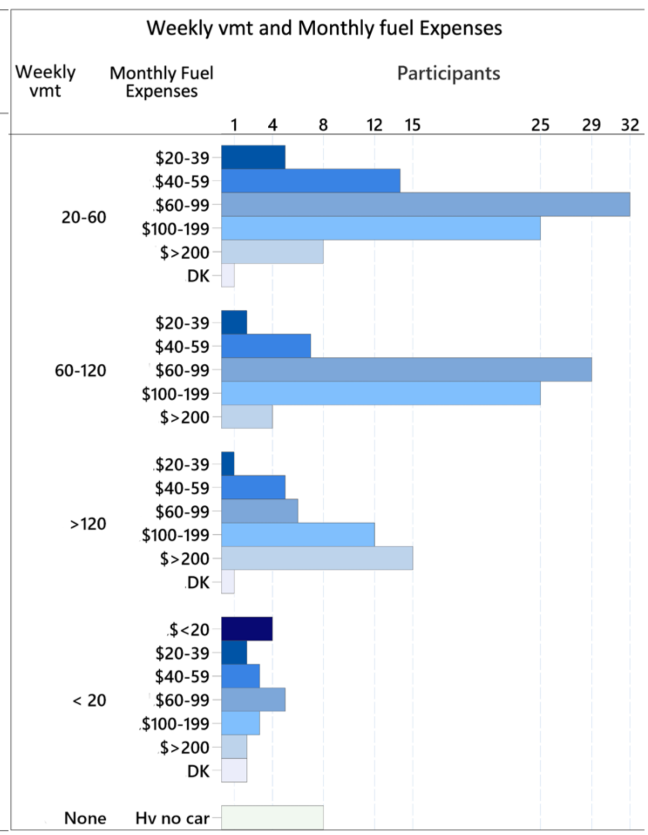


Figure 16. **Weekly vmt and monthly fuel expenses.**

Knowledge of EV Technologies

The focus group sessions provided valuable information regarding consumer perceptions, opinions and knowledge that could potentially affect EV adoption, including the use of ChSs and ERWs. As stated earlier, topics included local AQ, EVs, EV ChSs, and ERWs. No specific response was provided or required from participants; instead, they were asked to share only their personal perceptions and ideas. Table 14 presents the results of the sentiment analysis for the three communities. Responses per community are summarized in separate columns. Sentiment is represented with a square; a larger square size indicates a greater feeling or emotion intensity. Community responses can be compared horizontally across rows. No square indicates that no responses were obtained.

Table 14. Focus Group Sentiment Analysis

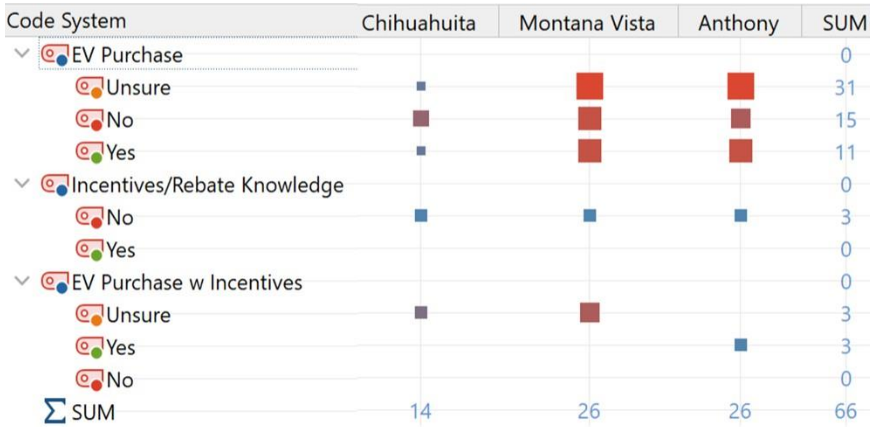
Section I: Perceptions of local AQ and EVs as an environmental benefit

Code System	Chihuahuita	Montana Vista	Anthony	SUM
AQ Community				0
Bad	■			2
Regular	■	■	■	3
Good		■	■	5
Factors affecting AQ				0
Transportation	■	■	■	8
Industries	■	■		3
Juarez city	■			2
Another	■			2
EVs on AQ				0
Unsure				0
Positive Impact	■	■	■	9
Negative Impact				0
Σ SUM	16	7	11	34

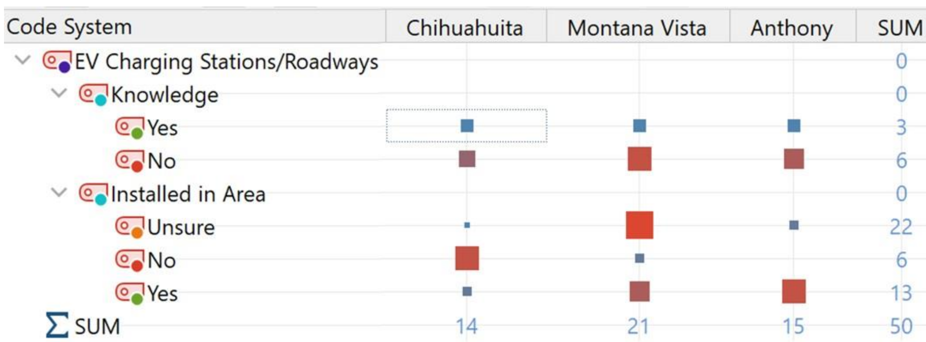
Section II: Knowledge and perceptions of EVs

Code System	Chihuahuita	Montana Vista	Anthony	SUM
EV Knowledge				0
No				0
Unsure	■		■	2
Yes	■	■	■	10
EV Perception				0
Negative	■	■	■	14
Concern	■	■	■	62
Positive	■	■	■	8
Σ SUM	25	39	32	96

Section III: Knowledge and perceptions of EV purchases and incentives



Section IV: Knowledge and perceptions of EVs, ChSs, and ERWs



Source: MAXQDA qualitative data analysis software.

Perceptions of Local AQ and EVs as an Environmental Benefit

The focus group sessions sought the respondents' perceptions, opinions, and knowledge of major factors that affect their local AQ, AQ improvement needs, and EVs as a beneficial factor to improve local AQ.

As shown in Section I of Table 14, participants from Montana Vista, in far east El Paso County, considered their AQ to be good, while participants from Chihuahuita expressed more concern regarding the pollution and fumes from nearby interstate highway traffic, commercial railroad traffic, activities in Ciudad Juárez in Mexico, and International Paso del Norte Port of Entry traffic. For participants from Anthony, major AQ concerns stemmed from the nearby I-10, gas stations, trailer rest areas, commercial areas, and schools. The three communities identified EVs as a technology able to positively improve their AQ. Participants from Anthony had the highest positive sentiments. Participants from Chihuahuita, despite having more factors affecting AQ, had lower positive sentiments due primarily to initial EV costs. Participants from Montana Vista had the lowest positive sentiments because they perceived their local AQ to be good. Participants from both Chihuahuita and Montana Vista agreed that replacing the current ICEVs transiting the interstates in their areas with EVs would be highly beneficial for their local AQ.

Knowledge and Perceptions of EVs

In the focus group sessions, we also evaluated EV perceptions, opinions, and knowledge in URCs to identify factors that may influence consumer preferences and behavior toward EV adoption in low-income minority populations.

As shown in Section II of Table 14, each of the three communities showed some degree of EV knowledge, although they felt unsure regarding its accuracy. They knew that EVs are available in the marketplace, that they help the environment and human health by reducing fuel emissions, and that they are more expensive than ICEVs. Participants from Montana Vista had some knowledge about different EVs in the marketplace, although they did not know them by name—only as cars that “use electricity only” (i.e., BEVs) or “use electricity and fuel” (i.e., HEVs). They did not know about PHEVs and their different components or characteristics. They also had some knowledge about home EV chargers. Participants from Anthony also knew about EVs as a new and cost-effective technology that could reduce their fuel expenses.

Purchase cost was perceived as the main disadvantage of EVs by the three communities. They stated that the higher purchase cost limits equal access for all, compared to the more affordable cost of ICEVs. Additional disadvantages noted by participants related to their lack of knowledge regarding an EV’s driving range under normal and congested conditions, charging time and costs, maintenance costs, and charging station locations. These unknowns limited their ability to make informed decisions about whether to buy EVs. Participants from Chihuahuita also noted that, as a historical district, the city would not allow infrastructure modifications in their neighborhood such as installing charging stations. This restriction was perceived as a disadvantage of EV use. Regarding positive sentiments on the benefits and advantages of EVs, the three communities expressed only two opinions: (1) EVs help the environment by reducing fuel emissions and (2) EVs can be a cost-effective technology due to fuel expense savings. Participants wanted to learn more about the actual monetary benefits of EVs and the time frame for the return on investment.

Beyond considering advantages or disadvantages of EV adoption, participants from the three communities expressed mostly concerns and inquiries about EVs that they were not able to articulate because they lacked information. Safety drew particular interest from participants with questions regarding whether it is safe to charge more than one vehicle at home, whether batteries can affect cellular phones or vice versa, and whether it is safe to one’s health to spend long periods of time inside an EV while charging. Regarding battery safety, the main concerns included whether high or low temperatures affected battery performance and life span and specifically whether batteries would be safe and not “explode” under the extreme heat temperatures in El Paso. They also questioned whether using or being close to an EV battery affected human health in the long term and whether batteries would be safe for pacemaker users.

Participants from the three communities had the same general questions about EVs, relating to the different charging options in the marketplace and their costs, maintenance requirements, safety, and environmental benefits. Regarding vehicle types available in the marketplace, they wanted to know why EVs cost more than ICEVs and what components or features make different EVs cost more than others. Participants also asked if EV repair shops are available in the city or limited to EV dealerships, if EVs require more frequent maintenance, and if EV repairs and insurance will cost more than ICEV repairs and insurance. They also inquired about EV batteries, including their types, maintenance, life spans, and replacement costs. Regarding home chargers, their main concerns related to available charging levels, purchase and installation costs, life spans, electricity consumption rates and costs, and installation requirements (i.e., regular electrician vs. specialized electrician). They also asked if a home charger was safer and faster than a public ChSs and asked what happens to both chargers and batteries once they complete their life span.

Participants from the three communities had other similar concerns regarding whether EVs are safe at high speeds, whether EVs are as safe as ICEVs in a car crash, whether EVs are at a lower risk of explosion in an accident compared to ICEVs, whether EVs offer new technologies like contact and movement sensors to help prevent accidents, whether EVs can be driven autonomously if a driver passes out or has a heart attack, and whether EVs safe for blind and deaf pedestrians given their quiet operation.

Knowledge and Perceptions of EV Purchases and Incentives

Regarding EV purchase (Section III of Table 14), participants from Montana Vista and Anthony were generally unsure about EV technology mainly due to their high initial cost and the lack of information regarding the different EV options and benefits. Participants from Chihuahuita showed the most interest in EVs. However, their interest waned when they considered the initial purchase cost of EVs (they felt they could not afford them) and historical district restrictions that would prevent a public charging station from being installed in their neighborhood. They had no knowledge that a public charging station already existed less than one mile from their neighborhood. Regarding EV purchases, the Montana Vista participants had questions about the availability of electric heavy-duty pickups in the marketplace, including their maximum payload/towing capacity, maximum travel distance on a single charge at full payload capacity, and costs. These participants also had questions regarding the availability of insurance and road assistance. Participants from the three groups also wanted to learn how to calculate the actual costs/benefits of owning an EV and the associated savings on fuel expenses, especially for long-distance work trips.

Ultimately, as previously mentioned, initial cost was the main limitation expressed by the participants in the three communities. No participant had any knowledge about federal tax credits or state and local incentives and rebates. This topic generated significant interest among all participants and improved their perceptions of EVs when presented as an affordable option for them, given the available incentives and rebates. Participants wanted to know what the maximum incentive amount is based on, which vehicles are eligible for the maximum amount, how the incentive applied, whether incentives are applicable for retirees, whether more than one incentive can be applied per household, whether used EVs are available for purchase, and whether ICEVs can be traded in for EV purchase.

Knowledge and Perceptions of EVs, ChSs, and ERWs

The last topic discussed was participant knowledge and perceptions of EVs, ChSs, and ERWs (Section IV of Table 14). Although the three communities had knowledge about public ChSs in El Paso, participants from Anthony and Chihuahuita did not know the specific number of stations available or their location. Only the participants from Montana Vista knew of some locations, but these stations were far from their homes. None of the participants from the three communities had knowledge of the different charging levels (e.g., Level 2 or DC fast charging) currently available in El Paso, or the charging times or costs. Also, none of the participants had knowledge of Internet applications or search engines that can be used to find locations of public ChSs.

Perceptions and opinions about having ChSs installed in their neighborhoods varied. Participants from the rural communities of Anthony and Montana Vista, in far west and far east El Paso County, respectively, were receptive and saw benefits to having ChSs installed in their neighborhood because they currently do not have any nearby. They felt that these installations could keep them from driving long distances to charge an EV, if they chose to purchase one, and could promote EV adoption in their communities, contributing to a decrease in traffic pollution as EV adoption increases. Their concerns about ChSs included cost responsibilities for station installation and maintenance and potential electricity supply issues the community if new stations are installed.

The participants from Montana Vista asked if the ChS installations would result in more emissions from electricity generation at the power plant located near their homes. On the other hand, participants from Anthony were concerned whether having ChSs in their neighborhoods could cause more traffic issues because they already struggle with traffic from the interstate, gas stations, trailer rest stops, commercial areas, and schools nearby. Participants from Chihuahuita reiterated that EVs are unaffordable to most members in their community and that public ChS installations are prohibited because of their historic district restrictions. They also reported feeling uncomfortable or unsafe about having “random strangers” coming to their small neighborhood to use the station, especially at night.

The topic of ERWs inspired the greatest interest. ERWs aim to replace charging stations with inductive embedded charging elements in the pavement, allowing vehicles to wirelessly charge as they drive or park on electrified roadways 83. This last section describes the perceptions, opinions, and knowledge of ERWs in URCs and considers their willingness to have this technology installed in their neighborhoods. None of the communities had previously heard about the electrification of roadways, which generated diverse perceptions and concerns in line with the specific needs of each group.

General perceptions of ERWs were positive among participants for their ability to eliminate the need for public ChSs and driver range anxiety, but participants expressed reservations about the timing of implementation given the state of EV adoption. The three communities agreed that promoting and making EVs accessible to all, including their URCs, should be prioritized before investing in roadway electrification, considering the low percentage of EVs in the market currently compared to ICEVs. The participants expressed concerns about the costs, health effects, and safety of ERWs. Cost-related questions included who will assume construction and maintenance cost of ERWs, whether ERWs construction will increase property taxes, and whether ERWs will be freely accessible or include an access fee. Most concerns about human health related to ERW safety for vulnerable users, including cancer survivors, people undergoing chemotherapy, people with pacemakers, and pregnant or lactating women. Additional safety concerns considered ERW safety during rainstorms, flooding, and extreme heat/freezing temperatures. Other concerns related to the life span of an ERW, electrification impacts on ICEVs, and safe circulation of specialized ICEVs such as cranes or ambulances to assist in road accidents.

Regarding EWRs installed in their neighborhoods, participants from Chihuahuita considered it unnecessary because none of their residents could afford an EV currently and such installations may be limited by their historic district restrictions. Participants from Montana Vista and Anthony showed mixed attitudes toward EWRs. They expressed concerns about electrification, including whether electrification would cause community electricity outages, and whether electrification construction and maintenance would cause lengthy roadway closures and traffic congestion as the highway extension currently does. Participants from Montana Vista suggested that after the number of EVs in El Paso increased considerably, electrification could begin by focusing only on highways and main roads.

Conclusions and Recommendations

In this project, we proposed a method for tracking energy sources by identifying the marginal generators and their marginal generation to meet an increase in demand. The aim of the proposed optimization model was to determine the exact amount of power being supplied by each generator due to an increase in generation at a certain location. A unit commitment optimization model was utilized to determine marginal generators and binding transmission lines. Then, the marginal generation was calculated and used to determine the amount of power being produced to serve a load that is increased at a certain bus. The model described in this study considers the time of operation and calculates the cost for meeting the increase in load at each bus and at different times. The proposed tracking system was examined through simulations based on the RTS-96 with a 24-hour period of operation. The results showed that the sources of electricity generation can be accurately tracked in a spatial-temporal manner using the proposed optimization model. The model can be solved quickly with high computational efficiency, making it possible to run this system using standard computational hardware.

A two-step method to evaluate the impact of a D-FACTS on marginal emissions in a realistic test system in a spatial-temporal manner was proposed in this project. Using this method, D-FACTS devices were first optimally allocated in a transmission network using a multi-objective optimization model. The model considers the cost of operating the system, the D-FACTS investment cost, and the GWP when solving the problem. An MOEA was utilized to solve the problem with high computational efficiency. In addition, UC and ED models were used to identify marginal generators and binding transmission lines based on the results of the D-FACTS allocation. These parameters were used in the proposed optimization problem with the aim to calculate the exact power produced by each marginal generator to meet an increase in load at each location. This allowed the program to discern the magnitude and origin of the emissions produced by the demand increase, known as the MEF. The models were implemented on a test system partially based on the RTS-96. This new test system was established to mirror the geographic locations of each substation in the city of El Paso, Texas. In addition, the transmission network topology was mapped to the El Paso Electric service territory. The models were used in conjunction with this test system to show the benefits of D-FACTS devices on real electric grids. The results showed that the implementation of D-FACTS devices on the test system can reduce transmission congestion, and thus, emissions. The findings showed a notable reduction in the GWP and marginal emissions of up to 16 percent, compared to the absence of these devices. This optimization problem showed how the use of a D-FACTS in a power system can be beneficial to the reduction of GHG emissions. This tool can be valuable for decision-makers to optimally allocate D-FACTS devices to reduce emissions and operating costs of the grid.

A method for allocating EV charging stations by evaluating the cost of meeting the increase in demand and the emissions that are produced at these locations was also proposed in this project. Using this method, the marginal generators and their marginal generation were first identified. The optimization model then determined the exact amount of power utilized by these generators to meet the increase in demand from EV chargers and calculated the MEFs and LMPs accordingly. By analyzing the MEFs and LMPs over a desired period of time, EV charging station locations can be identified to minimize the power system operating costs and environmental impacts. The proposed method was implemented on a modified RTS-96 with transmission congestion, and the results showed that the MEFs and LMPs varied both spatially and temporally. Based on the results, three potential locations for EV charging station installations were identified. Installing EV charging stations at these locations can mitigate the environmental impacts of the system and reduce the cost for power system operations.

Lastly, a study on public opinions regarding EVs was carried out in this project. This study helped understand the perceptions, opinions, and knowledge of EVs, public EV ChSs, and EWRs in URCs in both urban and rural areas in the Paso del Norte Region. Results from the focus groups provided valuable information that can help to increase equity and inclusion as EV adoption increases, bridging engineering with social and environmental justice. In engineering, these considerations must be a part of any design criteria that involves deployment of technologies within communities. If the needs and concerns of the communities are not understood and addressed through outreach and education, it will not be possible to increase adoption of EVs. Additionally, this study provided a foundation that can be used to choose locations for the deployment of electrified technology based on the resilience of the power grid and the public perceptions of infrastructure development.

The results showed that URCs have remarkable interest in EVs, ChSs, and ERWs. Most participants showed some knowledge of EVs, lesser knowledge of ChSs, and no knowledge of ERWs. Results also indicated an evident gap of essential knowledge of EV technology in URCs, which served as the main barrier to widespread EV diffusion and adoption. Given the fact that most URC residents lacked EV technology information, they expressed the need to have their doubts and concerns clarified before even considering the purchase of an EV.

This study provided evidence that the markets in URCs are all different, and concerns about EVs, ChSs, and EWRs are diverse, based essentially on the specific needs of each community. To increase EV adoption in URCs, comprehensive outreach and education that is easy to access and tailored to each community must be provided because one size does not fit all. Information that is lacking varies in degree by community but generally includes the following:

- Types of EVs and their benefits and costs.
- Government incentives and tax rebates available to inclusive and diverse URCs.
- Locations and charging costs of public ChSs.

- Home charging stations and purchase rebates that could help reduce upfront costs.
- Environmental and health effects and benefits of roadway electrification.

The provision of knowledge and understanding of EVs is an essential step in advocating EVs as an accessible technology. This outreach helps address the public's main adoption barriers, increases public interest, and encourages adoption for all, including historically minoritized populations. In the same manner, it prepares the market for the future of electrified infrastructure. This step also raises awareness in bridging the gap between higher engineering education and community outreach when planning and developing equitable transportation infrastructure, including ChSs and ERWs. This methodology showed that fostering equity and social and environmental justice in engineering education—by taking into account public perceptions and needs and including underrepresented groups during the process of planning and developing public transportation infrastructure—is extremely important.

Outputs, Outcomes, and Impacts

Although EVs do not generate emissions by themselves, the electric power consumed by EVs is not completely emission-free. In this project, we developed models to evaluate the locational marginal emissions from power systems. LMEs can be used to analyze the emissions induced by EVs and facilitate the analysis of the environmental impacts of EVs. We also considered the emissions induced by EV charging in the optimal allocation of EV charging stations. Additionally, public opinions on EV and EV charging were analyzed. The results revealed the concerns of groups of people with different socioeconomic statuses and shed light on the concerns that need to be addressed in the adoption of EVs. Four papers were published from this project and two papers are under preparation. This project supported two graduate students—one student pursuing their master's degree and one student pursuing their doctoral degree—in their work toward their thesis or dissertation. Additionally, the students and principal investigators of this project were actively involved in outreach activities that enhanced public knowledge of EVs.

Research Outputs, Outcomes, and Impacts

- Peer-reviewed publications include the following:
  - Kenji Santacruz and Yuanrui Sang, "Analyzing the Global Warming Potential and Human Toxicity Potential on a Spatial-Temporal Basis in an Electricity Market," manuscript under preparation.
  - Kenji Santacruz and Yuanrui Sang, "Tracking the Source of Marginal Electricity Generation on a Spatial-Temporal Basis in an Electricity Market," manuscript under preparation.

- Conference papers include the following:
  - Eduardo Castillo, Kenji Santacruz, Haveeair Caballero, and Yuanrui Sang, "Reducing Marginal Emissions in Power Systems with Distributed Flexible AC Transmission Systems," in *Proceedings of The 55th North American Power Symposium*, Asheville, NC, October 2023.
  - Liliana Lozada-Medellin, Ivonne Santiago, and Yuanrui Sang, "Increasing Equity in Access to Electric Vehicles and Electrified infrastructure through Perceptions, Opinions and Knowledge of Underrepresented Communities in the Paso del Norte Region," *2023 ASEE Annual Conference & Exposition*, Baltimore, MD, June 2023.
  - Kenji Santacruz and Yuanrui Sang, "Environmentally Aware Allocation of Electric Vehicle Charging Stations by Analyzing Locational Marginal Emissions," in *Proceedings of The 54th North American Power Symposium*, Salt Lake City, UT, October 2022.

- Kenji Santacruz and Yuanrui Sang, "Tracking the Source of Marginal Electricity Generation on a Spatial-Temporal Basis in an Electricity Market," in *Proceedings of The 53rd North American Power Symposium,* College Station, TX, November 2021.

- Presentations at conferences and technical meetings include the following:

    - Liliana Lozada-Medellin, Isabel Lopez, Ivonne Santiago, and Yuanrui Sang, "Disparities, Perceptions, Opinions, and Knowledge of the Electrified Technology in Underrepresented Communities in the Paso del Norte Region," Transportation Research Board Annual Meeting and Technology Showcase, Washington, D.C., January 8–12, 2023.
    - Kenji Santacruz and Yuanrui Sang, "Environmentally Aware Allocation of Electric Vehicle Charging Stations by Analyzing Locational Marginal Emissions," The ASPIRE NSF ERC Annual Meeting, October 2022.
    - Kenji Santacruz and Yuanrui Sang, "Tracking Renewable Energy Consumption in an Electricity Market," UTEP COURI Spring 2021 Symposium, May 2021.
    - Kenji Santacruz and Yuanrui Sang, "Tracking Renewable Energy Consumption in an Electricity Market," 2021 Texas Undergraduate Research Day at The Capitol, February 2021.

Technology Transfer Outputs, Outcomes, and Impacts

- An algorithm to analyze MEFs was developed. The algorithm was able to analyze the MEFs of power systems in a spatiotemporal manner.
- Four papers were published and two papers are under preparation.

Education and Workforce Development Outputs, Outcomes, and Impacts

- A doctoral student in civil engineering at the University of Texas—El Paso (UTEP) was supported by this project as a research assistant.
- A master's student in electrical and computer engineering at UTEP was supported by this project as a research assistant.
- The project was conducted as part of a doctoral dissertation in the civil engineering program at UTEP.
- The project was conducted as part of a master's thesis in the electrical and computer engineering program at UTEP.
- Training and education on obtaining IRB approval, carrying out focus groups, and administering questionnaire surveys were conducted.
- Training and education on the usage of qualitative software, MAXQDA, were conducted.
- Training and education in C++ programming, use of the Gurobi Optimization Solver, and analysis of power system emissions were conducted.

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