DESIGNING ELECTRIC VEHICLE INCENTIVES TO MEET EMISSION REDUCTION TARGETS

BY

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THESIS

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ABSTRACT

Electric vehicles are expected to reduce transportation emissions. We design and allocate rebates and charging infrastructure investments to induce electric vehicle adoption and achieve emission reduction targets. A nonlinear mixed-integer mathematical model is proposed to optimize the investment allocation over a planning horizon. Logistic functions describe the vehicle demand driven by capital and ownership costs and network externalities. A simulated annealing algorithm is used to solve the nonlinear programming problem that is applied using data representative of the United States and the State of Illinois markets. Our analysis indicates that rebates should be provided earlier than chargers due to neighborhood effects of electric vehicle adoption and the minimization of expenditure; availability of home charging influences consumers' choice and the drivers electrified travel distance; rebates are more effective for modest drivers while charging stations should be prioritized for frequent drivers; network externalities should be further investigated because of their impact on electric vehicle demand.

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CHAPTER 1: INTRODUCTION

Transportation is one of the primary energy consumers in the United States and the only sector depending almost exclusively on petroleum (U.S. Energy Information Administration (EIA), 2021a). Introducing electric vehicles into the transportation market promises diversification of this sector's fuel sources. Plug-in electric vehicles have zero tailpipe emissions due to operating solely on electricity. Hence, substituting conventional gasoline vehicles with electric ones can reduce carbon dioxide and greenhouse gas emissions (depending on the source of electricity used for charging) and gasoline consumption for the transportation sector (Rietmann et al., 2020). U.S. Energy Information Administration (EIA)'s (2021b) outlook of net electricity generation by fuel type shows that the proportion of renewable energy is estimated to increase over time, which implies that the emissions associated with electric vehicle charging will also decrease. However, due to the higher purchase price of electric vehicles than comparable conventional vehicle products, the lack of dense charging station infrastructure, and induced range anxiety, consumers have little intention to purchase electric vehicles (Canepa et al., 2019; Carley et al., 2013). Countries with higher electric vehicle penetration rates implement various policies to stimulate demand and accelerate environmental gains from their use. Such policies and incentives include rebates, tax credits, charging station deployment, etc. (Zhou et al., 2015). Monetary incentives, like rebates, discount an electric vehicle's capital cost and investments in a dense charging network result in driver savings that are accrued from lower operating costs. Policymakers promote electric vehicles through tax credits and other incentives partly because of their potential to reduce tailpipe emissions (Kontou et al., 2017) and gradually improve regional air quality (Brady and O'Mahony, 2011).

To design an effective incentives program, we need to understand how different policies might influence electric vehicle adoption and which programs play a crucial role in accelerating the electrification transition. Hardman et al. (2017) find that 91% of pertinent studies indicate that electric vehicle rebates play a significant role in increasing electric vehicle adoption. Hardman et al. (2017) and Narassimhan and Johnson (2018) also point out that rebates are usually more effective in driving ownership decisions than tax credits. Charging availability is another important electric vehicle demand determinant. Hardman et al. (2018) conclude that access to electric vehicle charging at home, work, or public locations increases consumers' willingness to purchase electric vehicles. Kontou et al. (2019) show the importance of charging availability on electric vehicle daily trip feasibility and coverage. Recognizing that rebates and charging infrastructure provision promote the electrification of personal mobility, we aim to assist policymakers with a framework to determine priorities for incentives investments that mathematically captures the electric vehicle market penetration. Monetary incentives in the form of rebates discount significant capital costs associated with purchasing electric vehicles in the introductory years of this new technology when economies of scale are not yet achieved (Helveston et al., 2015). At the same time, investing in public charging infrastructure placement contributes to reducing the operational costs borne by electric vehicle drivers and decreases environmental externalities associated with conducting daily trips by electrifying more miles.

We study the problem of dynamic electric vehicle incentives allocation from the policymaker's perspective, who aims to meet national or state-wide level emission reduction targets for the United States and Illinois light-duty vehicle sector and provide policy recommendations. Our research contributes to the transportation planning and policy literature in the following ways: (i) we introduce a new and dynamic electric vehicle incentive design problem with emission reduction targets and demand functions that capture network externalities; (ii) we present a simulated annealing algorithm to solve the highly nonlinear problem; and (iii) we provide a plethora of policy and planning recommendations from two real-world case studies focusing on the US and the State of Illinois. By evaluating diverse EV investment portfolio outcomes, we aim to comprehensively describe the decision-making mechanism and provide suggestions for governmental policies that incentivize EV growth and transportation decarbonization.

In Chapter 2, we provide a literature review pertinent to EV incentives design. From Chapter 3 to Chapter 6, we focus on the national-level analysis. Specifically, in Chapter 3, we formulate the optimization model for minimizing the EV investment expenditure while ensuring that we reach the exogenously set emission reduction target. In Chapter 4, we present the proposed simulated annealing algorithm. In Chapter 5, we discuss the analysis of the relevant national and state data. In Chapter 6, we report the base case results and sensitivity analyses. In Chapter 7, we modify the model and apply it to the State of Illinois and present the results. In Chapter 8, we summarize insights from this study and identify directions for future work.

CHAPTER 2: LITERATURE REVIEW

Electric vehicle incentive design is often modeled as an optimization problem. Kang et al. (2015) propose an integrated decision-making framework that incorporates the objectives of marketing, engineering, and operations stakeholders to examine the tradeoffs between electric vehicle mechanical design, charging station location network, and electric vehicle demand. However, the government's incentive policies are not incorporated into this model. The researchers extend this work and propose a game-theoretic approach, including various stakeholders' goals in the decision-making process for subsidies that promote vehicle electrification (Milano and In, 2015). Their numerical experiment suggests that when the available budget is below a certain threshold, policymakers should invest in allocating subsidies; otherwise, charger investments are essential for increased environmental benefits. Cohen et al. (2016a) design government rebates as a two-stage Stackelberg game and a multi-agent (government and manufacturers) problem. The government's leader problem minimizes subsidies subject to meeting adoption target goals, and the manufacturers' follower problem maximizes profits. Their results show the importance of considering demand uncertainty when designing subsidies to avoid missing the desired adoption targets. Nie et al. (2016) determine optimal incentive schemes by incorporating the dynamic evolution of the vehicles' market over a discrete timeframe, a vehicle ownership decision model, and a macroscopic travel and charging model. Their findings highlight that the optimal strategy is prioritizing chargers' placement as early as possible and offering purchase rebates later in their planning horizon. Kang et al. (2016) consider three stakeholders (government, EV manufacturer, charging station operator) and develop time-independent models, which assume a steady market state. They find the optimal allocation of public investment to minimize transportation emissions for a city in the USA (Ann Arbor, Michigan) and one in China (Beijing). Their analysis suggests that the primary barrier to electric vehicle adoption in the US is the high vehicle price set by the manufacturer, while the number of charging stations, license plate costs, and vehicle prices are all obstacles for the Chinese market.

Existing literature also highlights the impact of electric vehicles on carbon emission reduction. Doucette and McCulloch (2011) compare the CO_2 emissions of battery electric and plug-in hybrid electric vehicles with conventional ones. They conclude that the carbon intensity of the power generation mix of the electricity used to recharge the vehicles plays a vital role in the CO_2 emissions reduction measure. Electric vehicles are the most reliable option to reduce CO_2 emissions in countries with a low and mid-range CO_2 intensity of electricity generation, like France and the US. Bastida-Molina et al.'s (2020) analyses indicate that the higher the proportion of renewable energy used for power generation, the greater the emission reduction that can be achieved. Alarfaj et al. (2020) consider various factors, such as electricity carbon intensity and travel demand, and predict the penetration rate of electric vehicles required to achieve various decarbonization goals. They find that a higher level of fleet electrification is necessary because of the high carbon intensity of the electricity generation mix and reduced fuel economy due to projected vehicle automation.

Our research determines optimal incentives distribution over a planning horizon that increases electric vehicle penetration and enables meeting environmental externalities reduction goals for passenger transportation. We formulate an optimization problem to minimize the total cost of the electric vehicle investment program while achieving a desirable emission reduction goal over a set planning horizon. The proposed macroscopic framework will determine the optimal level of charging infrastructure and rebate investment over the years and reduce emissions to a desirable level by substituting conventional gas vehicles with electric ones. Our policy optimization model is applied to two case studies focusing on the gasoline and electric vehicles markets of the United States and Illinois.

CHAPTER 3: MODELING FRAMEWORK

Our model's objective is the design of electric vehicle incentives to meet policymaking goals related to achieving minimum investment costs and transportation emission reduction targets.

We assume that the planning horizon for the policymaker, who is allocating electric vehicle incentives, is $t \in T = \{1,2,\ldots,Y\}$. Variables x_k^t denote the vehicle stock type $k \in \{g: gasoline, e: electric\}$ by year t. Consumers demand each year t, q_k^t, is a function of the rebate r^t provided at year t to the adopters of electric vehicles and the charging infrastructure deployed at year t, u^t. All vehicles have a lifespan of l years and are replaced with new vehicles after reaching that year. The existing vehicle stock x_k^t is a discrete-time system and is updated by the number of vehicles of each technology k sold each t and $t-l$, as shown in Eq. (1).

$$x_k^{t+1} = x_k^t + q_k^t(r^t, u^t) - q_k^{t-l} \tag{1}$$

The state transition function in Eq. (2) captures the dynamic nature of the charging infrastructure placement on the transportation network:

$$v^{t+1} = v^t + u^t, \tag{2}$$

where v^t is the number of chargers in place up to year t and u^t is the number of chargers installed in year t. The decision variable in this case is u^t, which has an upper bound of $\bar{v}$. This constraint ensures the realistic density of the charging network.

Demand q_k^t for the vehicle technologies is a control variable. A logistic function denotes the sales of each technology k in t, and the demand is a function of utility U_k^t. The perceived utility of an average consumer is the sum of the indirect utility and an error component, as $U_k^t(r^t, u^t) = V_k^t(r^t, u^t) + \epsilon_k^t$ (Ben-Akiva and Lerman, 1985). We assume that all consumers are utility maximizers, aligned with literature on EV adoption studies (Javid and Nejat, 2017; Nie et al., 2016). Their logistic demand functions are as in Eqs. (3) and (4):

$$q_e^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_e^t(r^t,u^t)}}{e^{V_g^t} + e^{V_e^t(r^t,u^t)}}, \tag{3}$$

$$q_g^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_g^t(r^t,u^t)}}{e^{V_g^t} + e^{V_e^t(r^t,u^t)}}, \tag{4}$$

where m^t is the incremental market size of new vehicle registrations, and q_e^{t-l} and q_g^{t-l} are the number of vehicles purchased l years ago that need to be replaced due to vehicle turnover. The probability of a consumer choosing an electric or a gasoline vehicle is $\frac{e^{V_e^t(r^t,u^t)}}{e^{V_g^t} + e^{V_e^t(r^t,u^t)}}$ and $\frac{e^{V_g^t(r^t,u^t)}}{e^{V_g^t} + e^{V_e^t(r^t,u^t)}}$, respectively.

Total cost, including capital and operational costs, and network externalities enter the utility functions, as in Eqs. (5) and (6). The network externalities play an important role in explaining a portion of the utility of innovative products by describing purchasing choice learning-by-doing effects and the impact of information spread. Information spreading by existing adopters is a factor that is accounted for in alternative fuel vehicle choice modeling studies: a portion of the electric vehicle market penetration is assumed to be explained by the positive impact of "neighborhood effects" (Eppstein et al., 2011). Neighborhood effects or word-of-mouth effects can drive electric vehicle social exposure (Shepherd et al., 2012). The electric vehicle indirect utility function could capture the impact of information spreading under the assumption that the probability of choosing this vehicle type is more likely to increase as the number of vehicles adopted increases in a certain region. A logarithmic function is used to capture such effects, penalizing low electric vehicle adoption or low charging infrastructure availability: when the electric vehicle stock or charging infrastructure approaches zero, the function goes to $-\infty$; as their levels increase, it becomes zero (Cohen et al., 2016b).

$$V_e^t(r^t, u^t) = \beta_1 \cdot \left(B_e^t(R) - r^t + O_e^t(u^t)\right) + \beta_2 \cdot ln\left(\frac{x_e^t}{x_e^t + x_g^t}\right) + \beta_3 \cdot ln\left(\frac{v^t}{\bar{v}}\right) + \beta_4 + \omega^t, \tag{5}$$

$$V_g^t = \beta_1 \cdot \left(B_g^t + O_g^t\right) + \omega^t, \tag{6}$$

where $O_e^t(u^t)$ and O_g^t are the annual vehicle operational costs for the corresponding type of vehicles, and ω^t is the random demand. Electric vehicles with different driving ranges R that correspond to different retail prices.

In our study, we use the logit model to capture consumers' choice and behavior, which accounts for features like vehicles' capital cost, operational cost, and network externalities. The utility shows consumers' attitudes and how they consider purchasing different types of vehicle technologies, and their decisions are based on the utility they perceive. Since we are planning for vehicle electrification at a macroscopic level, we hypothesize that charging infrastructure will be optimally located and provide adequate service, but we do not track network-level impacts of such infrastructure that might be associated with exact siting locations and their waiting times. Operational costs for each vehicle type k are given by:

$$O_e^t(u^t) = (d_1^t + d_2^t) \cdot \frac{P_e^t}{n_e^t} + d_3^t \cdot \left(\left(\frac{P_g^t}{n_g^t}\right) + f\right), \tag{7}$$

$$O_g^t = d_t^t \cdot \frac{P_g^t}{n_g^t}, \tag{8}$$

where d_1^t is the average distance traveled on electricity depleting the battery charged at home, d_2^t is the average distance traveled on electricity depleting the battery charged at public charging stations, d_3^t is the average distance traveled with a backup gasoline vehicle, while d_t^t denotes the average annual miles traveled as the sum of d_1^t, d_2^t, and d_3^t in year t. P_e^t is the cost of electricity for charging, n_e^t is the onboard electricity efficiency, P_g^t is the gasoline cost, n_g^t is the gasoline efficiency, and f is the fixed cost to own or rent a backup gasoline vehicle. Note that d_t^t, d_1^t, d_2^t, and d_3^t are calculated as in Eqs. (9)-(12):

$$d_t^t = \int_0^\infty p^t(x)xdx \cdot 312, \tag{9}$$

$$d_1^t = \gamma \cdot \int_0^R p^t(x)xdx \cdot 312, \tag{10}$$

$$\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \leq M(1-y^t), \tag{11a}$$

$$\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \geq -My^t, \tag{11b}$$

$$d_2^t = (d_t^t - d_1^t) \cdot y^t + \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t \cdot\ (1-y^t), \tag{11c}$$

$$d_3^t = d_t^t - d_1^t - d_2^t, \tag{12}$$

where $p^t(x)$ is the probability density function of the daily vehicle mile traveled in year t, and γ is the percentage of availability of home charging for electric vehicle drivers.

The average daily vehicle miles traveled are calculated as the integration from 0 to ∞, and the average distance that can be traveled with electricity charged at home as the integration from 0 to the vehicle driving range boundary denoted by R (Lin, 2014). The probability density function is the distribution of the daily vehicle miles traveled. To calculate the annual distance, the daily travel distance is multiplied by 312, as vehicles are assumed to be used on average 312 days per year (Melaina et al., 2016). Based on a Weibull distribution of daily travel, Greene et al. (2020) find that a logarithmic function of charging availability can describe well the proportion of annual miles traveled that can be electrified. Thus, the product $\left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t$ calculates the annual enabled electrified miles that could be traveled with the corresponding number of charging stations v^t. Parameters α_0^t and α_1^t are estimated based on the fitted logarithmic function, according to the daily VMT distribution and the vehicle's average driving range. If the electric vehicle's driving range is long enough and the number of charging stations is adequate (i.e., the enabled electrified distance by the number of public charging stations is long enough to cover all travel distances when the driver cannot charge at home), drivers would not need backup vehicles to complete non-habitual trips. Thus, binary variables y^t and a big M are introduced in Eq. (11). If the potential enabled electrified miles are greater than all travel distances covered without charging at home, y^t will become 1 due to constraints (11a) and (11b), otherwise y^t will be 0. When y^t equals 1, according to constraint (11c), d_2^t will be equal to $d_t^t - d_1^t$ instead of $\left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t$, and d_3^t will be zero.

Eqs. (12) and (13) represent the carbon emissions of each technology that have a similar form as the operational costs.

$$E_{\mathrm{e}}^t(v^t) = (d_1^t + d_2^t) \cdot C_e^t + d_3^t \cdot C_g^t, \tag{12}$$

$$E_{\mathrm{g}}^t = d_t^t \cdot C_g^t, \tag{13}$$

where C_e^t and C_g^t are the carbon emissions in grams per mile for each vehicle technology. Please note that although electric vehicles have zero tailpipe emissions, there are carbon emissions from the electricity generation that is consumed while charging. Thus, to calculate C_e^t, we convert the electricity generation carbon emission rate (gCO_2/kWh) into gCO_2/mile with the electric vehicle efficiency.

Optimization Model

TABLE 1 summarizes the mathematical notations used in the optimization model.

TABLE 1 Definitions of notations

$t \in T$	The set of years that policymakers allocate incentives
$k \in \{g, e\}$	g: conventional vehicle, e: electric vehicle
r^t	Rebate offered per electric vehicle in year t
q_k^t	Consumers' demand of vehicle type k in year t
u^t	Number of charging infrastructures installed in year t
τ	Charging infrastructure's cost
δ	Discount factor
x_k^t	Vehicle stock of vehicle type k in year t
l	Vehicle's life expectance
v^t	Number of charging infrastructures in place up to year t
m^t	The incremental market size of new vehicle registrations in year t
V_k^t	Utility of vehicle type k in year t
B_k^t	Purchase price of vehicle type k in year t
O_k^t	The operational cost of vehicle type k in year t
d_1^t	Average distance traveled on electricity charged at home in year t
d_2^t	Average distance traveled on electricity charged at public chargers in year t
d_3^t	Average distance traveled with a backup vehicle in year t
d_t^t	Average annual miles traveled in year t
P_e^t	Cost ($/kWh) of electricity for charging the vehicle in year t
P_g^t	Gasoline cost ($/gal) in year t
n_e^t	On-board electricity efficiency (mi/kWh) in year t
n_g^t	Gasoline efficiency (mi/gal) in year t
f	Fixed cost ($/mi) for the backup gasoline vehicle
γ	The ratio of people having access to home charging
R	Electric vehicle driving range (mi)
$p^t(x)$	The probability density function of daily miles driven in year t
α_0^t, α_1^t	Parameters for the annual enabled electrified miles in year t
y^t	Binary variable in year t to ensure the annual enabled electrified miles do not exceed the total annual driving distance.
E_k^t	Carbon dioxide emissions (gCO_2) of vehicle type k in year t
C_e^t	Carbon dioxide emission (gCO_2/mi) rate of electricity generation in year t
C_g^t	Carbon dioxide emission (gCO_2/mi) rate of gasoline vehicle in year t
$\bar{r}$	Upper bound of rebate
$\bar{v}$	Upper bound of the number of charging infrastructures in place

The complete nonlinear mixed-integer programming framework proposed for modeling this policy problem is presented below:

$$min\ z = \sum_{t\in T}(r^t \cdot q_e^t(r^t, u^t) + \tau \cdot u^t)/(1+\delta)^t \qquad (14a)$$

Subject to

$$x_k^{t+1} = x_k^t + q_k^t(r^t, v^t) - q_k^{t-l}, \forall k \in \{e, g\}, \forall t \in T, \tag{14b}$$

$$v^{t+1} = v^t + u^t, \forall t \in T, \tag{14c}$$

$$q_e^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_e^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}, \forall t \in T, \tag{14d}$$

$$q_g^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_g^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}, \forall t \in T, \tag{14e}$$

$$V_e^t(r^t, u^t) = \beta_1 \cdot \left(B_e^t(\mathrm{R}) - r^t + O_e^t(u^t)\right) + \beta_2 \cdot ln\left(\frac{x_e^t}{x_e^t + x_g^t}\right) + \beta_3 \cdot ln\left(\frac{v^t}{\bar{v}}\right) + \beta_4 + \omega^t, \forall t \in T \tag{14f}$$

$$V_g^t = \beta_1 \cdot \left(B_g^t + O_g^t\right) + \omega^t, \forall t \in T, \tag{14g}$$

$$O_e^t(u^t) = (d_1^t + d_2^t) \cdot \frac{P_e^t}{n_e^t} + d_3^t \cdot \left(\left(\frac{P_g^t}{n_g^t}\right) + f\right), \forall t \in T, \tag{14h}$$

$$O_g^t = d_t^t \cdot \frac{P_g^t}{n_g^t}, \forall t \in T, \tag{14i}$$

$$d_t^t = \int_0^\infty p^t(x) x dx \cdot 312, \forall t \in T, \tag{14j}$$

$$d_1^t = \gamma \cdot \int_0^R p^t(x) x dx \cdot 312, \forall t \in T, \tag{14k}$$

$$\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \le M(1 - y^t), \forall t \in T, \tag{14l}$$

$$\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \ge -M y^t, \forall t \in T, \tag{14m}$$

$$d_2^t = (d_t^t - d_1^t) \cdot y^t + \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t \cdot (1 - y^t), \forall t \in T, \tag{14n}$$

$$d_3^t = d_t^t - d_1^t - d_2^t, \forall t \in T, \tag{14o}$$

$$E_\mathrm{e}^t(v^t) = (d_1^t + d_2^t) \cdot C_e^t + d_3^t \cdot C_g^t, \forall t \in T, \tag{14p}$$

$$E_\mathrm{g}^t = d_t^t \cdot C_g^t, \forall t \in T, \tag{14q}$$

$$\sum_{t\in T} x_e^t \cdot \left(E_g^t - E_e^t(v^t)\right) \geq target, \tag{14r}$$

$$r^t \leq r^{t+1}, \forall t \in T, \tag{14s}$$

$$r^t \geq 0, r^t \leq \bar{r}, \forall t \in T, \tag{14t}$$

$$x_k^t, v^t \geq 0, \forall k \in \{e, g\}, \forall t \in T, \tag{14u}$$

$$v^1 = \zeta, u^t \geq 0, v^t \leq \bar{v}, \forall t \in T, \tag{14v}$$

$$x_k^1 = \theta_k, \forall k \in \{e, g\}, \tag{14w}$$

$$y^t \in \{0,1\}, \forall t \in T \tag{14x}$$

The decision variables of this model are the rebate and number of chargers built each year, i.e., r^t and u^t, respectively. Eq. (14a) is the objective function, which is the government's cumulative expenditure for the electric vehicle incentives allocation over the years. Our goal is to minimize the total expenditure. Note that τ is the charging infrastructure's cost and δ the discount factor. Constraint (14r) enforces the target of emission reduction savings due to electric vehicles substituting gasoline ones over a set planning horizon. A variety of potential incentive investment paths can achieve the cumulative emission reduction target, and we aim to find and analyze the incentive portfolio with the least expenditure among these pathways. To ensure a more realistic policy that policymakers would advocate for, Eq. (14s) ensures the rebate in each year would not exceed that of the previous year. Eqs. (14t) - (14x) are non-negativity and variable restriction constraints, setting feasibility intervals for the decision variables.

CHAPTER 4: SOLUTION METHODOLOGY

Algorithm

Our formulated mathematical model is a highly nonlinear mixed-integer problem, given the logit demand, the logarithmic function of network externalities, and the logarithmic-enabled electrified miles function. Existing state-of-the-art solvers cannot give us a feasible solution, let alone solve the problem optimally or within a reasonable timeframe. Therefore, we propose using the simulated annealing algorithm to solve the problem with a satisfactory solution in a reasonable time. Although the simulated annealing algorithm was initially developed for combinatorial optimization problems, several studies have shown that it is an effective technique for problems with continuous variables (Brooks and Verdini, 1988; Busetti, 2003; Corana et al., 1987; Kruger, 1993; Zhang and Wang, 1993) and it is widely used in continuous problems (Ghamami et al., 2020; Wang et al., 2016). Corana et al. (1987) introduce a simulated annealing algorithm for continuous problems and show that the algorithm is reliable in finding at least a solution close to the optimum. Brooks & Verdini (1988) present good computational performance and efficiency of the generalized simulated annealing algorithm. Zhang & Wang (1993) demonstrate a good performance of the simulated annealing algorithm on mixed-discrete constrained nonlinear optimization problems.

FIGURE 1 shows a schematic of the applied algorithm. A simulated annealing algorithm (Kirkpatrick et al., 1983) allows probabilistically uphill movement to avoid being trapped in a local minimum solution, and the probability is determined by a random number generator and a control parameter called temperature (Johnson David S. et al., 1989). The heuristic solution technique begins with an initial feasible solution and then via random perturbation yields a new nearby feasible solution. The approach involves a pair of nested loops: an inner loop and a main one. After each iteration of the main loop is performed, the temperature decreases at a certain rate. In each iteration of the inner loop performed, a neighbor solution is generated by perturbing the current solution. If the neighbor solution provides a smaller objective function value, it will always be accepted as the new current solution. Suppose the objective function value of the neighbor solution is greater than the current solution. In that case, a probability test will be performed to determine whether to accept the neighbor solution, which enables the algorithm to escape from local minimum solutions. The probability of accepting a worse solution is greater when the difference between the current solution and the neighbor solution is smaller and becomes smaller as the temperature decreases.

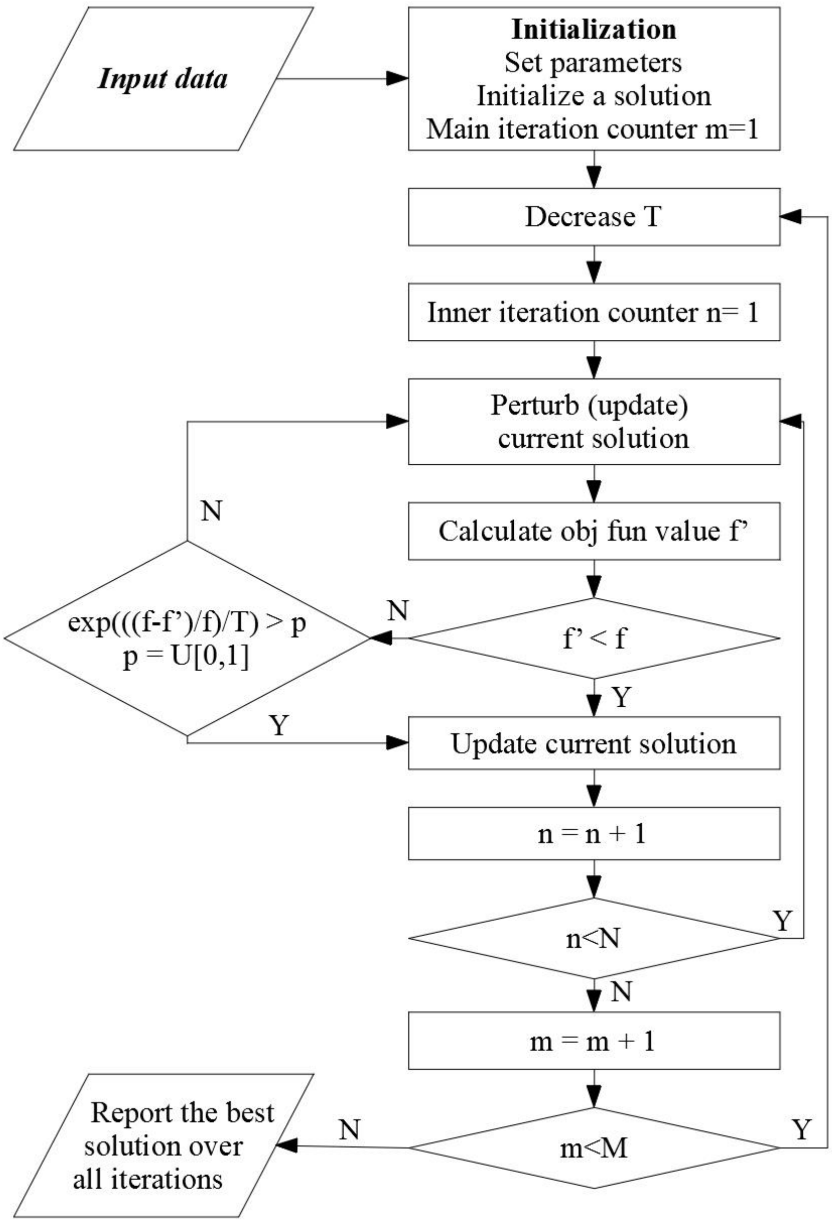

FIGURE 1 The procedure of the simulated annealing algorithm.

Before implementing the simulated annealing algorithm, we first check the feasibility of the problem. We set the rebate and the number of charging stations equal to the upper bound for every year in the planning horizon since this incentive allocation scheme gives us the maximum emission reduction that can be achieved. If the problem is feasible, we also set this as the initial feasible solution. Once the number of charging stations is determined, we can calculate the enabled electrified distance and examine if it is long enough to cover all travel distances. Thus, we can calculate the value of the binary decision variables y^t, after determining the aforementioned decision variables. The decision variables of rebate and the number of charging stations in our model are continuous. We generate a random number from the interval $[-\sqrt{3}, \sqrt{3}]$ (i.e., with zero mean and unit variance for the uniform distribution $U(-\sqrt{3}, \sqrt{3})$) for each decision variable independently (Corana et al., 1987; Vanderbilt and Eouie, 1984). Then, we multiply the random number by a step size (described in more detail in the Parameters Calibration section) and move the current solution along the direction to a neighbor solution, shown in Eq. (15). Every decision variable is perturbed one by one in each inner loop iteration and the probability test is performed if the neighbor solution is worse.

$$\boldsymbol{x}' = \boldsymbol{x} + round\left[\alpha U(-\sqrt{3}, \sqrt{3}), 0\right] \boldsymbol{e_h}, \tag{15}$$

where $\boldsymbol{x}$ is the vector of the current solution, $\boldsymbol{x}'$ is the perturbed solution, α is step size which decreases in each main loop iteration, $U(-\sqrt{3}, \sqrt{3})$ is the random number selected in the range $[-\sqrt{3}, \sqrt{3}]$ for decision variable x_h, and $\boldsymbol{e_h}$ is the vector of the hth coordinate direction. We round the number to an integer when perturbing the current solution.

As more electric vehicles are adopted, more charging stations are needed to serve the increasing demand. The built charging stations will continue to serve electric vehicle charging demand and should not be removed in later years. Besides, given that the government is promoting a vehicle product for emission reduction purposes, it is not aligned with set targets to let their constituents believe that they will save more if they purchase it later. The monotonically decreasing rebate plan can be seen in some empirical observations, such as the Climate and

Equitable Jobs Act (CEJA, SB2408) of the state of Illinois (*Public Act 102-0662*, 2021). Because of the policymaking implications of the decision variables, $\boldsymbol{r}$ is monotonically decreasing while $\boldsymbol{v}$ is monotonically increasing over time. Consequently, if the rebate of a certain year is perturbed to be greater than the one in the previous year, the rebates of all the years before that year are all modified to the same value as the perturbed value. When the number of perturbed charging stations is less than the number of charging stations in the next year, a similar method is adopted: all the numbers of charging stations after that year are modified to be equal to the perturbed value. Although the decision variables $\boldsymbol{u}$ capture the decision of charging infrastructure deployment over the years, we intuitively perturb $\boldsymbol{v}$ first and then use the resulting values to compute the decision variables $\boldsymbol{u}$ in the algorithm.

The details of the proposed simulated algorithm are shown in pseudocode form in FIGURE 2.

Step 0 (Initialization)

0.1 Initial solution: $\boldsymbol{v_0} = (v_1, \bar{v}, \bar{v}, ..., \bar{v})$, $\boldsymbol{r_0} = (\bar{r}, \bar{r}, ..., \bar{r})$;
Objective function value: $f_0 = f(\boldsymbol{v_0}, \boldsymbol{r_0})$.

0.2 Set initial step size α_{v0} and α_{r0}, initial temperature T_0.
Let $\alpha_v = \alpha_{v0}$, $\alpha_r = \alpha_{r0}$, $T = T_0$.
Set $\boldsymbol{v_{opt}} = \boldsymbol{v_0}$, $\boldsymbol{r_{opt}} = \boldsymbol{r_0}$, $f_{opt} = f_0$.

0.3 Set max main counter M and max inner counter N.

0.4 Set accepted solution counter $i = 0$; Set main iteration counter $m = 1$.

Step 1 (Perturbation)

1.1 Set inner iteration counter $n = 1$. $\boldsymbol{v_i} = (v_1, ..., v_j, ..., v_Y)$;
$\boldsymbol{r_i} = (r_1, ..., r_j, ..., r_Y)$

1.2 Perturb $\boldsymbol{v}$:

    $j = 2$
    while $j \le Y$ do
        $\boldsymbol{v}' = \boldsymbol{v_i}$; $\boldsymbol{r}' = \boldsymbol{r_i}$
        generate new solution $\boldsymbol{v}' = \boldsymbol{v}' + round\left[\alpha_v \cdot U(-\sqrt{3}, \sqrt{3}), 0\right]\boldsymbol{e_j}$
        (Note: The maximum and minimum values of v_j are $\bar{v}$ and v_1, set it to $\bar{v}$ or v_1 if more or less than the boundary. If $v_k' < v_j'$, $\forall k > j$, then $v_k' = v_j'$. If $v_k' > v_j'$, $\forall k < j$, then $v_k' = v_j'$.)
        do Step 1.4 and come back
        end while
        go to Step 1.5

1.3 Perturb $\boldsymbol{r}$:

    $j = 1$
    while $j \le Y$ do
        $\boldsymbol{v}' = \boldsymbol{v_i}$; $\boldsymbol{r}' = \boldsymbol{r_i}$
        generate new solution $\boldsymbol{r}' = \boldsymbol{r}' + round\left[\alpha_r \cdot U(-\sqrt{3}, \sqrt{3}), 0\right]\boldsymbol{e_j}$
        (Note: The maximum and minimum values of r_j are $\bar{r}$ and 0, set it to $\bar{r}$ or 0 if more or less than the boundary. If $r_k' > r_j'$, $\forall k > j$, then $r_k' = r_j'$. If $r_k' < r_j'$, $\forall k < j$, then $r_k' = r_j'$.)
        do Step 1.4 and come back
        end while
        go to Step 1.5

1.4 if $\boldsymbol{v}'$, $\boldsymbol{r}'$ feasible

    $j = j - 1$
    else
        if $f' \le f_i$
            accept the perturbed solution, $i = i + 1$; set $\boldsymbol{v_i} = \boldsymbol{v}'$, $\boldsymbol{r_i} = \boldsymbol{r}'$, $f_i = f'$
            if $f' \le f_{opt}$
                set $\boldsymbol{v_{opt}} = \boldsymbol{v}'$, $\boldsymbol{r_{opt}} = \boldsymbol{r}'$, $f_{opt} = f'$
            end if
        else
            if $exp\left(\frac{(f_i - f')/f_i}{T}\right) > a\ random\ number\ p = U(-\sqrt{3}, \sqrt{3})$
                accept the perturbed solution, $i = i + 1$; set $\boldsymbol{v_i} = \boldsymbol{v}'$, $\boldsymbol{r_i} = \boldsymbol{r}'$, $f_i = f'$
            else
                discard the perturbed solution
            end if
        end if
        $j = j + 1$
    end if

1.5 if $n < N$

    $n = n + 1$
    go back to Step 1.2
    else
        $m = m + 1$
        update the step size: $\alpha_v = \frac{m-1}{m}\alpha_v$, $\alpha_r = \frac{m-1}{m}\alpha_r$
    end if

Step 2 (Stop or not)

if $m < M$
    $T = \theta \cdot T$, where $\theta = 0.85$
    $i = i + 1$; $\boldsymbol{v_i} = \boldsymbol{v_{opt}}$, $\boldsymbol{r_i} = \boldsymbol{r_{opt}}$, $f_i = f_{opt}$
    go to step 1
else
    stop
end if

FIGURE 2 Proposed simulated annealing algorithm pseudocode.

Parameters Calibration

We calibrate the parameters of the simulated annealing algorithm as follows. The initial temperature is set to 0.05 with a constant decreasing factor of 0.85 after each main loop iteration (Ghamami et al., 2020; Zockaie et al., 2018, 2016). The number of iterations and initial step sizes are typically determined by trial and error (Brooks and Verdini, 1988). Due to the randomness of the algorithm, we cannot guarantee which value is the best; instead, we use the value that often results in better performance. To determine the number of iterations, we need to ensure that the objective value converges. We set the number of the main loop M and the inner loop N to 75, which implies that the objective value of at least the last 100 iterations remains unchanged.

FIGURE 3 demonstrates the convergence curve for the base case scenario in our study. The values of 8,000 and 142,000 are chosen for the initial step sizes of the rebate α_r and the initial step size of the charging stations α_u respectively, because the result of the objective function value is usually smaller with these values. In each iteration m of the outer loop M, we update the step size using the function $\alpha_m = \frac{m-1}{m} \alpha_{m-1}$ (Xu et al., 2009).

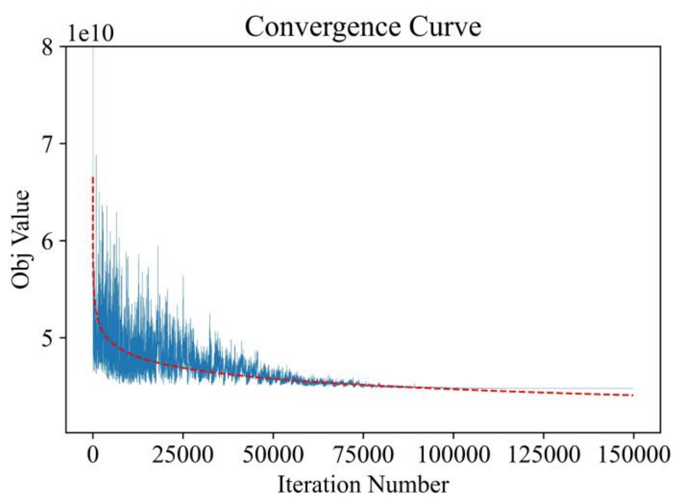

FIGURE 3 Convergence curve for the base case scenario.

CHAPTER 5: DATA

The planning horizon of this study is 30 years, and we optimize the incentive allocation between the years 2021-2050. We use the National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2021) trip data and the best estimate of annual vehicle miles to calculate the average daily VMT and fit the probability density function of the daily VMT. The probability density distribution is assumed to be a Weibull one, $f(x; k, \lambda) = \frac{k}{\lambda}\left(\frac{x}{k}\right)^{k-1} e^{-(x/\lambda)^k}$(Plötz et al., 2017). The mean and median of the NHTS data are used to compute the parameters k and λ for the Weibull distribution. We leverage historical data to fit the logit function of the vehicle ownership demand. We predict the average household's daily driving distance and changes over our planning horizon. That is achieved by fitting a linear regression of the mean and median VMT distribution values, leveraging the NHTS variables from the years 2001, 2009, and 2017. US travelers conduct short habitual daily trips, which account for a large share of VMT (e.g., daily travel distance less than or equal to 30 miles accounts for 55% of all travelers); thus, the fitted VMT distribution deviates from the actual distribution due to its small mean and median. Given our macroscopic model and our national-level case study, we leverage only daily VMT greater than 30 miles to capture primarily long-distance travel through highways. An example of the probability density function distribution of the year 2017 is shown in FIGURE 4.

Home charging plays an important role in the achieved electrified distance. With access to home charging, electric vehicle drivers can travel a distance equal to their vehicle's driving range without relying on public charging stations. On the contrary, if home charging is unavailable, all the electrified distance needs to be enabled by public charging, and drivers would need backup vehicles more often. Due to the lack of nationwide data on the percentage of electric vehicle owners accessing home charging γ, we use insights from the State of California survey data. This region has the highest share of vehicles electrified (Veloz, 2021). These resources show that 84% of electric vehicle owners have access to home charging (Tal et al., 2018). For the rest of the data trajectories from 2021 to 2050, (i) we leverage outlook data if these are already provided, or (ii) we use linear regression based on historical data and project future parameters. TABLE 2 presents the input parameters of our case study.

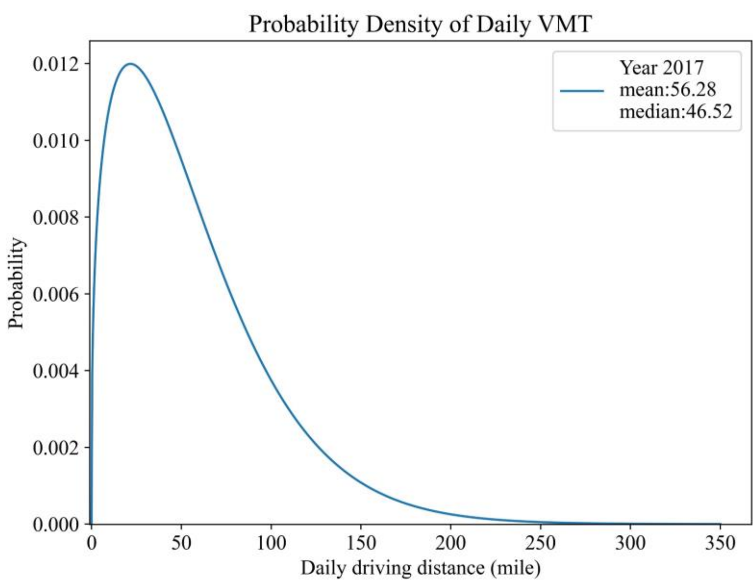

FIGURE 4 Probability density function of daily VMT, using 2017 NHTS data.

TABLE 2 Input parameters

Constant Parameters	**Unit**	**Value**
Vehicle range, R	mi	150
Access to home charging, γ [a]	--	84%
Vehicle's lifespan, l	year	12
Chargers upper bound, $\bar{v}$ [b]	--	142,000

TABLE 2 (cont.)

Rebate upper bound, $\bar{r}$	$	8,000			
No. of chargers in the first year, ζ [b]	--	29,738			
No. of EVs in the first year, θ_e [c]	--	1,124,906			
No. of GVs in the first year, θ_g [b]	--	12,673,33 62			
Cost to build a charging station, τ [d]	$	150,000			
Discount factor, δ	--	0.1			
Dynamic Parameters	**Unit**	**Value**			
		2021	**2030**	**2040**	**2050**
Incremental market size, m^t [b, e]	--	0	0	0	0
EV retail price, B_e^t [f]	$	25,347	28,180	31,328	34,476
GV retail price, B_g^t [f]	$	30,101	29,042	27,865	26,689
Electricity cost, P_e^t [g]	$/kWh	0.124	0.119	0.118	0.112
Electricity efficiency, n_e^t [g]	mi/kWh	2.924	2.932	2.931	2.931
Gasoline cost, P_g^t [g]	$/gal	2.356	2.796	3.110	3.231
Gasoline efficiency, n_g^t [g]	mi/gal	48.908	50.860	50.253	49.563
Emission rate of electricity, C_e^t [h]	gCO_2/mi	95.774	84.225	72.831	49.701
Emission rate of gasoline, C_g^t [b]	gCO_2/mi	177.199	153.542	127.256	100.970
Mean of daily VMT	mi	54.761	53.100	51.254	49.408
Median of daily VMT	mi	45.613	44.289	42.818	41.346

[a] Due to the lack of nationwide data, we use survey data from California from Tal et al. (2018).
[b] The upper bound of the number of charging stations is set to the number of existing gasoline refueling stations to ensure the realistic density of the charging network. Data is from Transportation Energy Data Book. See https://tedb.ornl.gov/.
[c] We add up the data of EV sales (excluding PHEV) from the Transportation Research Center at Argonne National Laboratory, https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates
[d] Adopted from Nie et al. (2016).
[e] After using linear regression, R square is found close to 0, meaning there is no evident trend. Thus, we assume there is no growth in vehicle registrations over time.
[f] We fit a linear function using historical data of the most popular vehicle of each fuel technology to predict their future retail price. For the electric vehicle, we use Nissan Leaf, and for the gasoline vehicle Toyota Camry. Data stem from https://cars.usnews.com.
[g] Data is collected directly from the outlook data of the US. Energy Information Administration. See https://www.eia.gov/outlooks/aeo/data/browser/.
[h] We use the mid-case outlook data of the CO_2 from electricity generation [kg/MWh] (equivalent to gCO_2/kWh) for the whole United States from https://cambium.nrel.gov/. We then convert the emission rate of the electricity generation into gCO_2/mi, by using the electricity efficiency data.
Note: 1 mi = 1.609344 km; 1 gal = 3.785411784 L

We also collect historical electric vehicle registration data from the year 2011 (when electric vehicles entered the market) to the year 2020 and fit the logit demand model to estimate the coefficients of each variable, as shown in Eqs. (14f) and (14g). We use a deterministic demand model, so the random ω^t are set to zero. The coefficients, estimated after fitting the logit model are shown in the "Model" columns of TABLE 3. Coefficient β_2 of the network externality of electric vehicle market share is negative in Model (0), an outcome caused due to collinearity with the network externality of chargers variable.

Additional regression results are shown in Model (1) and Model (2) columns of TABLE 3. Letting the network externality of chargers directly enter the utility function of electric vehicles may force charging stations to be prioritized. Thus, we decide to keep the network externality of electric vehicle market share in the electric vehicle utility. Therefore, our base case model uses the β estimates fitted in Model (1). We explore the implication of this choice by creating a scenario with the application of Model (2) in our sensitivity analysis.

TABLE 3 Coefficients of the logit model of vehicle demand

Variables	**Coefficients**	**Model (0)**	**Model (1)**	**Model (2)**
Intercept	β_4	-0.12991038	0.26064139	0.00382173
Cost	β_1	-0.00013944	-4.3061E-05	-0.00011916
Network Externality of EV Share	β_2	-0.14286841	0.65931248	--
Network Externality of Chargers	β_3	2.16032955	--	1.80423541

CHAPTER 6: RESULTS

The proposed simulated annealing algorithm, which is used to solve the electric vehicle incentive design problem, contains a certain degree of randomness; therefore, the incentive allocation solution is not guaranteed to be the global optimum. However, we gain important insights from this heuristic application since it allows us to provide various policy recommendations. For each scenario, we run the proposed simulated annealing algorithm 10 times and select the one with the smallest final value of the objective function to present from now on.

Base Case

We define a do-nothing scenario that examines the following: If the government does not incentivize electric vehicles, based on the logit model, a certain share of the market will still choose electric vehicles. In such a case we can estimate the emission reduction achieved without any incentives as a benchmark. On the other hand, if the annual rebate allocated is set to its upper limit, and the upper limit of installed charging stations is reached from the first year, then the emission reduction, in this case, will be the maximum target value that can be reached. Our goal is to accelerate electric vehicle adoption and to reduce emissions associated with passenger transportation; thus, we set the emission reduction target as 50% more than the do-nothing emission reduction achieved. We calculate the level of emission reduction without any incentives and the maximum emission reduction with max incentives that promote vehicle electrification from the very first year in our planning horizon.

The emission reduction without any incentives is $2.12 \cdot 10^8$ metric tons of CO_2 and the maximum emission reduction is $4.05 \cdot 10^8$ metric tons of CO_2. The maximum emission reduction is 1.91 times of the do-nothing case. We set the base case target to $3.18 \cdot 10^8$, which is 1.5 times the emission reduction without any incentives. The relationship between the do-nothing case, maximum emission reduction, and the target is shown in FIGURE 5 (a).

FIGURE 5 (b) and FIGURE 5 (c) show the optimization results for the decision variables. Over the planning horizon, policymakers should invest in rebates earlier and charging infrastructure later. In the early years, the rebate per electric vehicle value equals the upper bound, which may be influenced by the network externalities captured in its demand function. Because the number of electric vehicles is cumulative, if more electric vehicles are adopted in earlier years, the penalty of the network externality term in the utility function will be smaller, and thus the utility will be greater. Similarly, rebates in later years will not be so effective since benefits accumulated from the operation of electric vehicles in that timeframe will be lower, which justifies rebates per vehicle reaching zero starting in the year 2039. Investments in charging station installation should begin around the year 2030 and increase to around 8,000 by 2040. The upper bound of charging stations is 142,000, but the number of charging stations is only increased to approximately 9,000. It is not necessarily beneficial to build charging stations that meet the upper bound level; instead, only a certain number is required in the planning horizon. Moreover, we know that electric vehicles can use charging stations as long as they are built, so the sooner they are built, the more effective they are in electrifying greater mileage shares. However, the discount factor in the objective function should also be considered, given that the installation expenditure is lower if charging stations are built later. Consequently, charging stations will be built when the share of adopted electric vehicles justifies the investment and will reach the required number within a short period and remain at that level until the end of the planning horizon.

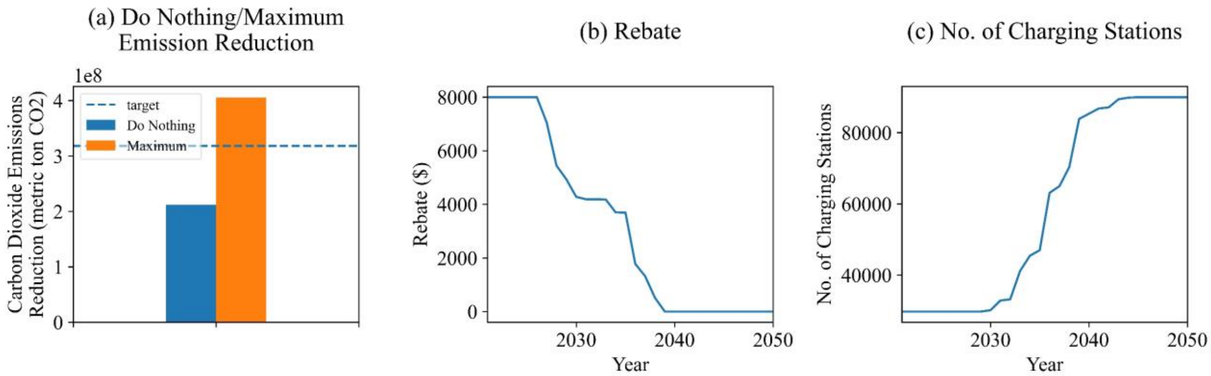

FIGURE 5 Electric vehicle incentives allocation results for the base case scenario.

Sensitivity Analyses

We conduct sensitivity analyses to uncover how the modeling mechanisms influence the decision-making on the allocation of electric vehicle incentives over time and provide insights for policymakers. The analyses include the impact of setting alternate emission reduction targets on the electrification transition, as well as the effect of rebates' upper bound, home charging availability, fuel prices, planning horizons, electricity generation mix, and renewable energy integration, charger costs, traveler types, and network externalities on the incentive allocation outcomes.

Emission Reduction Target

For this sensitivity analysis, we use the same data parameters as the ones presented in the base case scenario. We examine the electric vehicle incentive outcomes under different emission reduction targets. Even though in the base case we set the emission reduction target to 1.5 times the do-nothing case, in this section, we set this target as 1.1, 1.3, 1.5, 1.7, or 1.9. The relationship between the do-nothing case, maximum emission reduction, and the emission target for each case is shown in FIGURE 6 (1)(a). From the optimization results shown in FIGURE 6 (1)(b) and FIGURE 6 (1)(c), we observe that every single case results in a similar policy timeline to the base case. For example, rebates should be distributed to the public earlier than the investment in charging infrastructure, while the rebate value per vehicle is reduced in the later years since they would not be that effective. When the number of charging stations reaches a certain level, there is no need to increase charging station placement, given that they can electrify the desired share of electric vehicle miles.

When comparing the difference between each case, we observe that as the emission reduction target increases, the longer the rebate per vehicle needs to be maintained at the upper bound level, and the greater the final number of charging stations in the transportation network that is necessary. The final investment and number of charging stations increases exponentially as the emission reduction target increases. TABLE 4 (a) demonstrates the final electric vehicle shares needed to meet the emission reduction targets and the total expenditure for each case; these values are compared to the base case ones. The results imply that to achieve better environmental performance, more electric vehicles need to be adopted and used, more incentives should be provided, and thus the total expenditure on incentives ends up being greater.

Rebate Upper Bound

The data we use in this analysis is the same as the base case, apart from the rebate upper bounds, which are set to \$3,000, \$4,000, \$5,000, \$6,000, \$7,000, \$8,000, and \$9,000 per electric vehicle, respectively. To set a comparison benchmark, the value of the emission reduction target for each case is set to be the same as the base case, which is $3.18 \cdot 10^8$ metric ton CO_2. Before solving each problem, we calculate the maximum emission reduction that can be achieved for each case. In FIGURE 6 (2)(a), we observe that the target set is greater than the maximum emission reduction when the rebate upper bound is $3,000 or $4,000, and we have set too ambitious goals, resulting in these two cases being infeasible. The results of other feasible cases are shown in FIGURE 6 (2)(b) and FIGURE 6 (2)(c). When the rebate upper bound is greater, the year that the rebate per electric vehicle decreases shifts earlier. When the rebate upper bound is higher than $7,000, the final number of the charging stations needed of them is similar, but more charging stations are needed if the rebate upper bound is $5,000 or $6,000. This suggests to policymakers that when the rebate upper bound is greater than some certain value, the number of charging stations needed will not significantly vary. However, below that value, even if the rebates per vehicle are set equal to the upper bound for a longer period, the electric vehicle share is still lower than in other cases. Since the emission reduction is cumulative over the years, more charging stations are needed in the later years to compensate for the low rebate values to reach the same target. In addition, the total expenditure is greater if the rebate upper bound is low due to the longer time that rebates need to stay equal to their upper bound as well as the greater need for charging infrastructure deployment, as shown in TABLE 4 (b).

Home Charging Availability

We examine the incentive allocation with alternate home charging availability since the nationwide data might vary from the California use case, which sets the base case example's parameter. We assume the same emission reduction target as the base case, which serves as a benchmark for comparison purposes. As shown in FIGURE 6 (3)(a), we uncover that the set emission reduction target is infeasible when the home charging availability share is low, i.e., 0%, 25%, or 50%. The results of this analysis shown in FIGURE 6 (3)(b) and FIGURE 6 (3)(c) are intuitive. The lower the availability of home charging, the longer the time that electric vehicle rebates need to be maintained at the upper bound, the earlier the charging stations need to be built, and the greater the number of charging stations needed. An important insight for policymakers is that the availability of home charging greatly impacts emission reduction since the resulting incentive allocation timelines and magnitudes vary significantly with different levels of availability. The same thing holds with the resulting electric vehicle shares and the expenditure, as shown in TABLE 4 (c). Due to a lower level of home charging availability, the distance covered with electrified miles depends entirely on the number of public charging stations that policymakers invest in. If the electrified distance is shorter, the operational cost of drivers is higher since more backup vehicles are needed to complete long-distance trips annually, which will reduce people's willingness to choose electric vehicles and curb emission reduction.

Fuel Price

The U.S. Energy Information Administration (EIA) (2021) provides the outlook data on electricity costs and gasoline costs. We use their reference case as the base case: "the reference case serves as a baseline to investigate the impact of different assumptions about the economy, policies, and technology. It is expected that renewable energy such as solar and wind technologies will become the fastest-growing source of electricity generation by 2050." (U.S. Energy Information Administration (EIA), 2021) To test the sensitivity of the results to different fuel pricing trajectories, we leverage the high oil price and the low oil price cases from the outlook data provided by EIA. The high oil price case has higher gasoline prices than the reference case and similar electricity prices. In comparison, the low oil price case has lower gasoline prices than the reference case and similar electricity prices. In FIGURE 7 (4), we observe that under a scenario of low oil prices, higher rebates and more charging stations need to be distributed and installed, respectively, to reach the base case's emission reduction target. That is because fuel prices influence drivers' willingness to purchase electric vehicles due to operational costs. In the case of high gasoline prices, the operating cost of gasoline vehicles will become higher. As the utility function values change, a higher proportion of people will tend to choose electric vehicles. However, given the small differences in the prices under these scenarios, the results end up similar. This indicates that as long as the fuel price does not deviate from these trajectories, the electric vehicle incentives allocation is not sensitive to this parameter, and impacts of such pricing should not be the primary consideration for policymakers in the incentives planning stage.

Planning Horizon

The planning horizon for the base case is assumed to be 30 years, starting from 2021 to 2050. We analyze alternative scenarios with planning horizons of 20, 25, 30, 35, and 40 years. The result in FIGURE 7 (5)(a) shows that the problem is infeasible when having a planning horizon of 20 or 25 years if the emission reduction target is set the same as the base case, since more time is needed to meet strict targets. Moreover, when we set a 40-year planning horizon, the emission reduction without any incentives is already greater than the set target, which suggests that no incentives would be needed. FIGURE 7 (5)(b) and FIGURE 7 (5)(c) show intuitive results: to meet the same environmental target, having a longer planning horizon and deadline for achieving these reductions requires lower rebates per vehicle and charging station deployment. The rebates may only be needed in the very early years of the electrification transition, and the charging stations can be installed later when a greater electric vehicle share can use them. Furthermore, the amount of emission reduction is accumulated over a longer period and thus the number of electric vehicles on the road and the total expenditure are less, as shown in TABLE 4 (e). To formulate reasonable targets and effective incentive allocation strategies given a planning horizon, policymakers should first assess the emission reduction target that can be achieved without any incentives distribution and the maximum environmental standard that could be set under early and max incentive allocation.

Electricity Mix

In the base case, we choose the mid-case outlook data to account for the carbon intensity of the future U.S. electricity generation sector, as documented by the National Renewable Energy Laboratory Cambium database, based on their standard transition scenarios (Cole et al., 2021; NREL, 2020). To better understand how the electricity generation mix influences the emission of electric vehicles associated specifically with their charging externalities, we examine the cases of high and low renewable energy costs. High renewable energy cost corresponds to a future where less renewable energy is used for electricity generation and, thus, a higher emission rate is associated with electricity production. The opposite holds for the low renewable energy cost future, which results in greater integration of renewable energy sources to the electricity generation mix and lower emissions rates of electricity production. For the high renewable energy cost case, our sensitivity results portrayed in FIGURE 7 (6)(a) show that if we set the emission reduction target to be the same as the base case, our problem is infeasible and the target too ambitious under a high-cost renewables integration future in the US electric sector. Although emissions associated with vehicle operation can still be reduced in this scenario, the maximum emission reduction is lower, corresponding to approximately $2.94 \cdot 10^8$ metric tons of CO_2. From FIGURE 7 (6)(b) and FIGURE 7 (6)(c), we show that with a less carbon-intensive electricity generation sector, the emission reduction target with incentives allocation for new electric vehicles is easier to meet, while fewer rebates and charging stations are required to hit this milestone.

Charger Cost

We modify the objective function and include charging replacement costs and maintenance costs in the sensitivity analysis. The lifetime of the charging infrastructure is assumed to be ten years; in the aftermath of that period, chargers start being replaced. The replacement cost is 75,000 US dollars, and the maintenance cost is 400 US dollars annually per charger (U.S. Department of Energy, 2021). The result is shown in FIGURE 8 (7) and TABLE 4 (f). The base case results and the scenario that includes maintenance costs are similar because the maintenance cost is a small portion compared to the charging station unit's capital and installation costs. There is a jump in the number of charging stations in 2041 for the scenario that accounts for the chargers' replacement cost, as shown in FIGURE 8 (7)(c). Since our model's objective function is set to minimize the total incentives expenditure and we assume that a charging station needs to be replaced every 10 years, if the cumulative expenditure until 2050 is counted, for any charging stations built after 2041 we do not need to consider the replacement cost.

Traveler Type

We leverage data with daily VMT greater than 30 miles to fit the VMT daily distribution of US drivers in the base case. We investigate the impact of different types of travelers: (a) modest drivers (daily VMT greater than 20 miles) and (b) frequent drivers (daily VMT greater than 40 miles). If people travel more, the substitution of conventional gasoline vehicles with electric ones will reduce a greater volume of emissions. However, this is because frequent drivers produce more emissions in total. Therefore, it is not a nuanced decision to set the emission reduction target at the same level for different types of travelers. To provide comparable scenarios, we use the same ratio based on the maximum emission reduction and the reduction without any incentives for the drivers. Knowing the difference between the upper and lower boundaries of the emission reduction, we set the target to half of that value compared to the lower boundary. For example, for the modest drivers case, the emission reduction without any incentives is $1.79\cdot 10^8$ metric tons of CO_2 and the maximum reduction is $3.19\cdot 10^8$ metric tons of CO_2. Thus, the target is set to $2.49\cdot 10^8$ metric tons of CO_2, which can be calculated by $1.79\cdot 10^8+(3.19\cdot 10^8-1.79\cdot 10^8)/2$. For the frequent drivers' case, the emission reduction without any incentives is $2.39\cdot 10^8$ metric tons of CO_2, and the maximum reduction is $5.14\cdot 10^8$ metric tons of CO_2, so the target is set to $3.76\cdot 10^8$ metric tons of CO_2. Similarly, the target is set to $3.09\cdot 10^8$ metric tons of CO_2 for the average driver's case. The optimization results are shown in FIGURE 8 (8) and TABLE 4 (f). To achieve the emission reduction target, rebates are needed for modest drivers; however, fewer charging stations must be installed. For modest drivers, deploying charging stations is less effective because their travel distance is, on average short, and the demand for charging stations is not high. This suggests that policymakers should allocate rebates to promote electric vehicles to modest drivers. On the contrary, charging infrastructure extends the electrified distance of frequent drivers, which can effectively reduce operational costs. Therefore, for frequent travelers, policymakers should allocate more investments to install charging stations.

Network Externalities

In the DATA section, we present the result of the fitted parameters of the logit model. We use the network externality of the EV market share as part of the EV demand model in the base case. Still, we also compare the result under different electric vehicle owners’ utility functions. We let the network externality for charging stations (Electric Vehicle Supply Equipment (EVSE)), using the data of Model (2) columns of TABLE 3, enter the electric vehicle demand model. In FIGURE 8 (9)(a), we demonstrate that the maximum reduction of carbon emission under the scenario of capturing the network externality of the electric vehicle share in the demand function is smaller than the lower boundary for the scenario where the network externality of charging stations enters the function. This suggests that setting the environmental target at the same level for both demand function scenarios is not feasible since one of them will be infeasible. To provide comparable scenarios, we set the emission reduction targets similarly for different types of travelers.

In the case of a demand function that accounts for the network externality of charging stations, the emission reduction without any incentives is $0.83 \cdot 10^8$ metric tons of CO_2 and the maximum reduction is $13.96 \cdot 10^8$ metric tons of CO_2, so the target is set to $7.39 \cdot 10^8$ metric tons of CO_2. In the case of a demand function that accounts for the network externality of electric vehicle share, the emission reduction target is set to $3.09 \cdot 10^8$ metric tons of CO_2. The optimization results of these two cases, shown in FIGURE 8 (9)(b) and FIGURE 8 (9)(c), differ substantially. The latter case results show that rebates are not needed at all, but more charging stations need to be installed. To avoid the large penalty imposed on the electric vehicle utility by the lack of charging stations, charging infrastructure placement is prioritized since it will lead to a significant increase in the utility function. On the other hand, both rebates and charging stations are needed in the former case. Different network externalities and demand functions lead to different EV incentive allocation results. Therefore, before making decisions on the utility functions of vehicle owners, policymakers should conduct in-depth research on which network externalities can better capture vehicle purchasers’ choices.

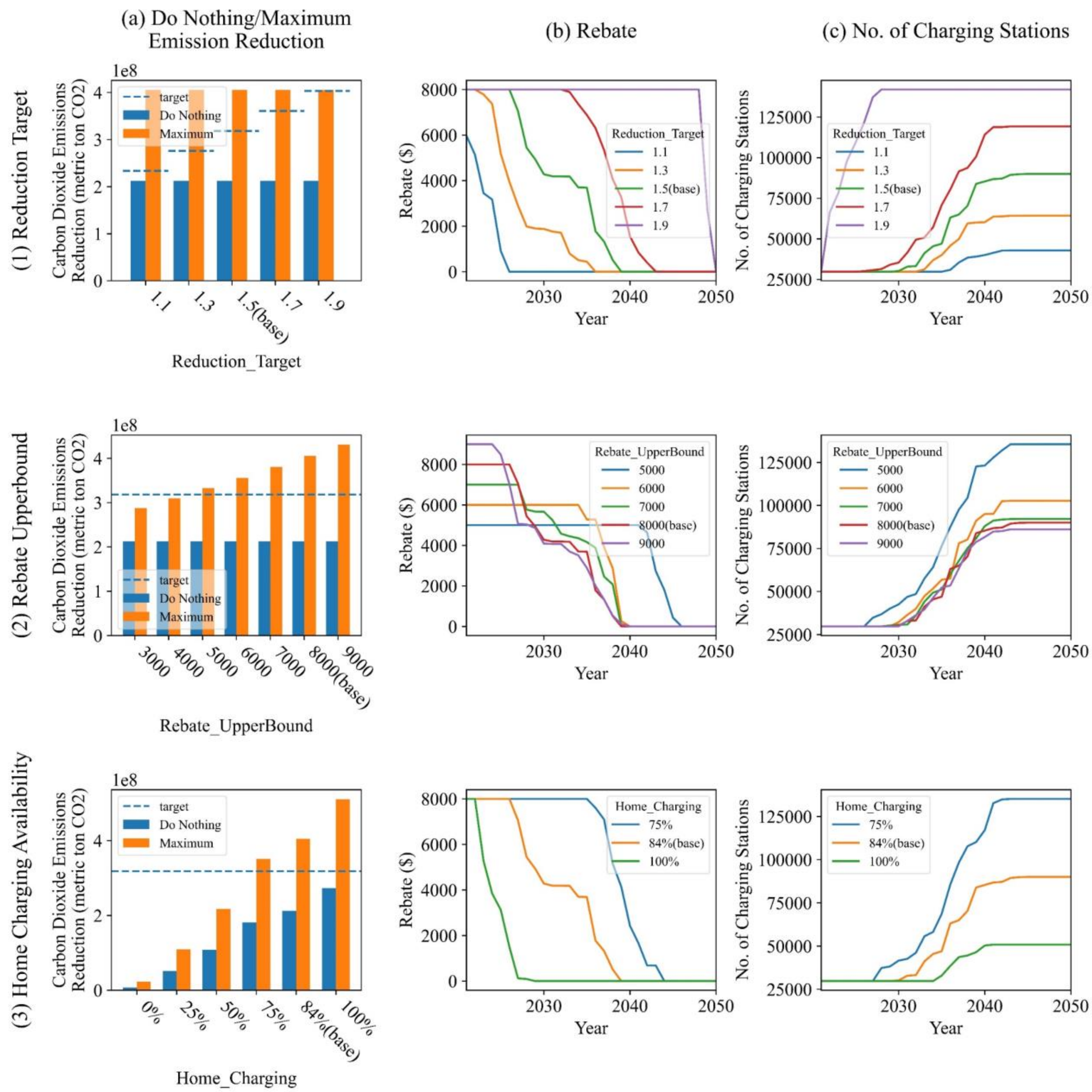

FIGURE 6 Optimization results for a variety of sensitivity scenarios, including alternate (1) emission reduction targets, (2) EV rebate upper bounds, and (3) levels of home charging availability.

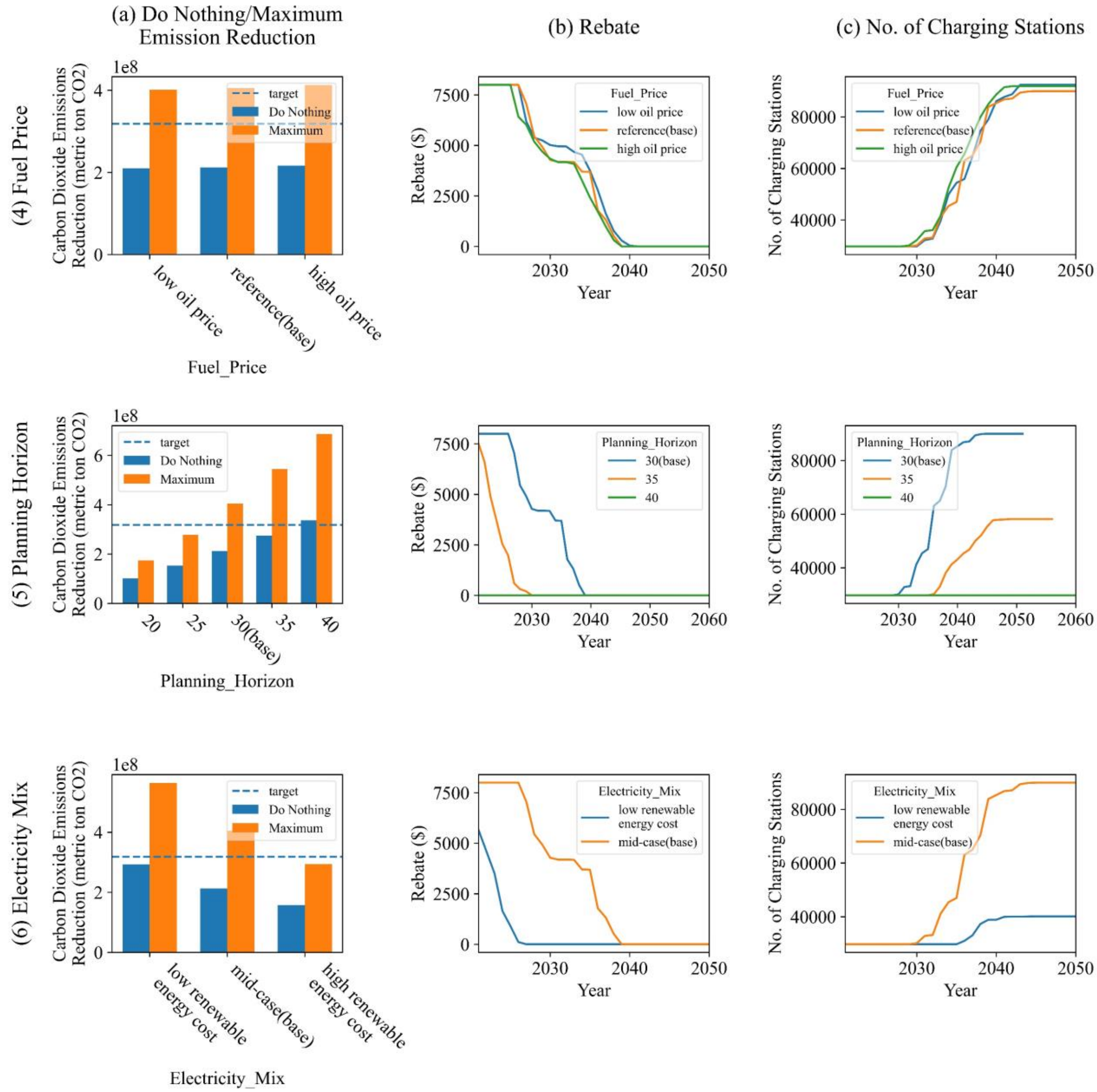

FIGURE 7 Optimization results for additional sensitivity scenarios, including (4) different fuel pricing outlooks, (5) alternate lengths of planning horizons, and (6) different electricity generation mixes.

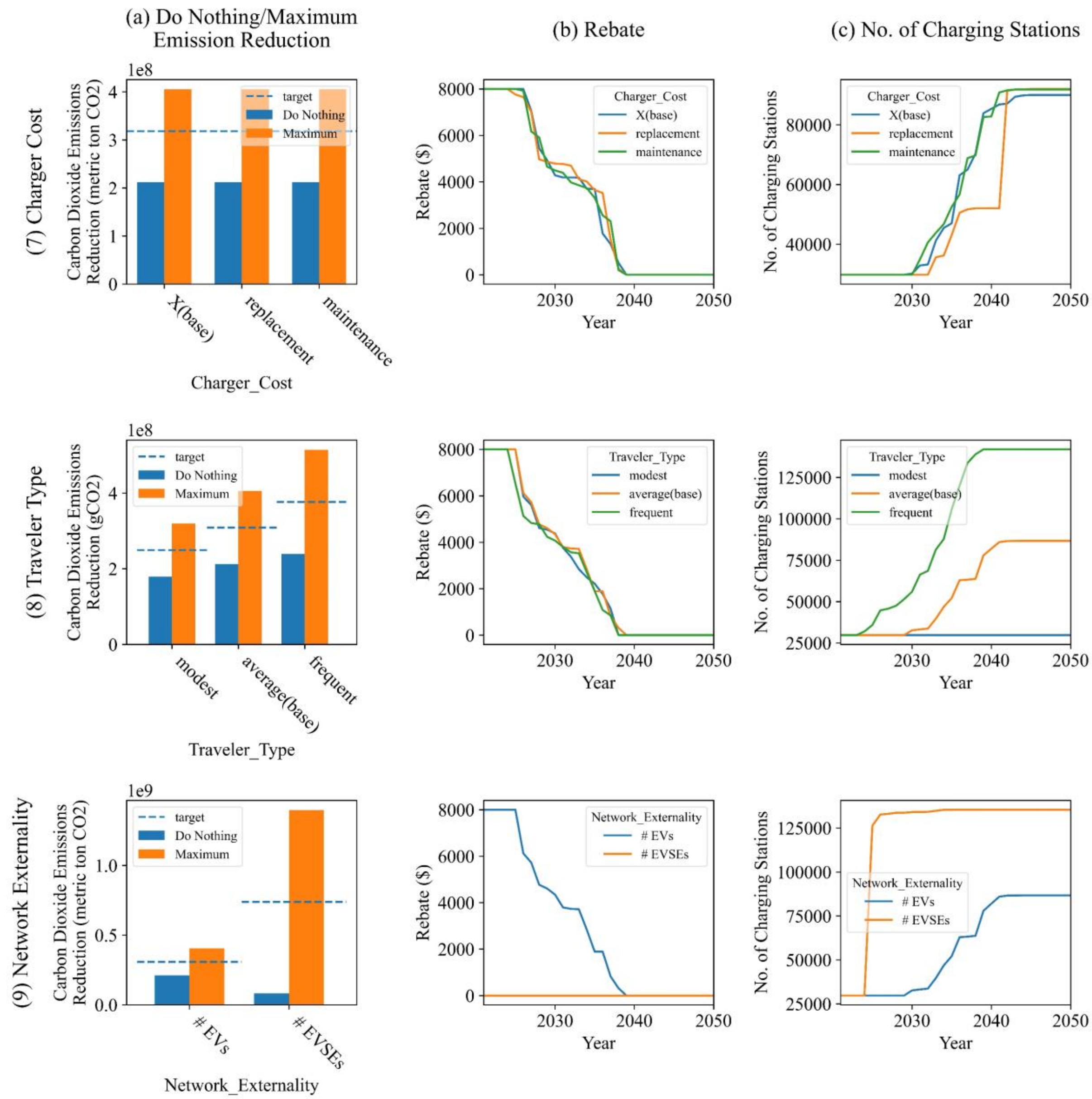

FIGURE 8 Optimization results for additional sensitivity scenarios, including (7) inclusion of different charger infrastructure costs, (8) different traveler types, and (9) different types of network externalities accounted for in the EV demand function.

TABLE 4 Final EV market shares and total expenditures

Sensitivity analysis	Scenario	Final EV market share		Total expenditure (obj. value)	
		EV share (%)	Compared to base case (%)	Expenditure ($) (billion)	Compared to base case (%)
Base case		23.57	--	44.450	--
(a) Emission reduction target	1.1	17.38	-26.27	6.548	-85.27
	1.3	20.40	-13.46	23.505	-47.12
	1.5 (base)	23.57	--	44.450	--
	1.7	27.11	15.01	69.494	56.34
	1.9	32.69	38.68	109.705	146.80
(b) Rebate upper bound	5000	24.61	4.41	48.623	9.39
	6000	23.95	1.60	45.907	3.28
	7000	23.76	0.81	45.010	1.26
	8000 (base)	23.57	--	44.450	--
	9000	23.54	-0.16	44.086	-0.82
(c) Home charging availability	75%	26.77	13.55	71.790	61.50
	84% (base)	23.57	--	44.450	--
	100%	20.00	-15.15	12.675	-71.48
(d) Fuel price	Low oil price	23.61	0.14	45.905	3.27
	Reference (base)	23.57	--	44.450	--
	High oil price	23.54	-0.15	41.947	-5.63
(e) Planning horizon	30 years (base)	23.57	--	44.450	--
	35 years	21.76	-7.70	11.069	-75.10
	40 years	21.50	-8.78	0.000	-100
(f) Electricity mix	low renewable energy cost	17.18	-27.14	5.657	-87.27
	average (base)	23.57	--	44.450	--
(g) Charger cost	capital cost (base)	23.57	--	44.450	--
	replacement cost	23.66	0.38	44.768	0.71
	maintenance cost	23.59	0.07	44.624	0.39
(h) Traveler type	modest driver	22.37	-5.10	36.334	-18.26
	average (base)	23.57	--	44.450	--
	frequent driver	23.13	-1.86	40.005	-10.00

CHAPTER 7: ILLINOIS CASE STUDY

Our modeling framework can be applied to different spatial scales; this chapter focuses on a state-level analysis. We choose the State of Illinois as the area of our case study. According to the Climate and Equitable Jobs Act (CEJA, SB2408), the State of Illinois plans to provide a \$4,000 rebate starting July 1, 2022, \$2,000 starting July 1, 2026, and \$1,000 starting July 1, 2028, for the purchase of an electric vehicle and aims to adopt 1,000,000 electric vehicles by 2030 (*Public Act 102-0662*, 2021). We aim to determine the number of charging stations needed to induce adoption levels aligned with CEJA goals.

Data

Vehicle adoption data and parameter values need to be collected and analyzed to accurately estimate the utility function coefficients of a higher resolution vehicle ownership model and capture consumers' behavior. The national-level data like vehicle range, vehicle lifespan, vehicle efficiency, etc., can be adopted directly to the state-level analysis. However, different values for the data of the number of vehicles, fuel prices, emission rates, and daily VMT need to be included in the study to represent the Illinois vehicle market. TABLE 5 presents the Illinois data, which differs from the national-level analysis.

TABLE 5 Input parameters of the Illinois vehicle market

Constant Parameters	**Unit**	**Value**			
Chargers upper bound, $\bar{v}$ [a]	--	4,113			
No. of chargers in the first year, ζ [b]	--	637			
No. of EVs in the first year, θ_e [c]	--	26,153			
No. of GVs in the first year, θ_g [c]	--	6,997,674			
Dynamic Parameters	**Unit**	**Value**			
		2021	**2030**	**2040**	**2050**
Electricity cost, P_e^t [d]	\$/kWh	0.105	0.110	0.108	0.094
Gasoline cost, P_g^t [d]	\$/gal	2.326	2.723	3.038	3.587

TABLE 5 (cont.)

Emission rate of electricity, C_e^t [e]	gCO_2/mi	72.725	61.670	67.690	85.976
Mean of daily VMT [f]	mi	53.602	51.916	50.043	48.169
Median of daily VMT [f]	mi	44.644	42.680	40.450	38.313

[a] The upper bound of the number of charging stations is set to the number of existing gasoline refueling stations to ensure the realistic density of the charging network. Data is collected from the Office of the Illinois State Fire Marshal. See https://webapps.sfm.illinois.gov/USTSearch/Search.aspx.
[b] We download the data from the Alternative Fuels Data Center and calculate the number of charging stations installed in the State of Illinois.
[c] Data is from the Office of the Illinois Secretary of State. See https://www.cyberdriveillinois.com/departments/vehicles/statistics/home.html.
[d] Data is collected directly from the outlook data of the US Energy Information Administration. See https://www.eia.gov/outlooks/aeo/data/browser/.
[e] We use the mid-case outlook data of the CO_2 from electricity generation [kg/MWh] (equivalent to gCO_2/kWh) for the State of Illinois from https://cambium.nrel.gov/. We then convert the emission rate of the electricity generation into gCO_2/mi, by using the electricity efficiency data.
[f] We select the Illinois trip data from the National Household Travel Survey (NHTS) to predict the mean and median daily VMT.
Note: 1 mi = 1.609344 km; 1 gal = 3.785411784 L

Model Modification

The Climate and Equitable Jobs Act (CEJA, SB2408) (*Public Act 102-0662*, 2021) sets explicitly the Illinois plan for the EV rebates allocation. Thus, in this case study, we consider rebates as parameters instead of a set of decision variables. We apply the model proposed in Chapter 3 to the State of Illinois. We fit the logit demand model with the state-level data to estimate the coefficients of each variable, as shown in Eqs. (14f) and (14g) and run the simulation. However, due to the considerable difference in the magnitude of historical data on the number of electric vehicles and the number of gasoline vehicles, we get a β_2 (1304.19) much larger than β_1 (-0.000259) and β_4 (-4.512) in Eq. (14f). In later years, when the number of electric vehicles becomes greater, $\beta_2 \cdot \left(\frac{x_e^t}{x_e^t+x_g^t}\right)$ and V_e^t becomes too large, the value of $e^{V_e^t(r^t,u^t)}$ in Eq. (14d) approaches infinity. To capture spatial heterogeneity and dependence and other intangible factors such as views on new technologies that may vary continuously in space, we consider spatial effects, which could be significant in capturing the relative tendency of people to choose electric vehicles in different regions (Florax and Rey, 1995).

Considering the accuracy and computation time for the solution by our optimization model and heuristic algorithm, we divide the State of Illinois into five clusters based on current EV adoption trends. Eq. (14f) is substituted by

$$V_e^t(r^t, u^t) = \beta_1 \cdot \left(B_e^t(\mathrm{R}) - r^t + O_e^t(u^t)\right) + \beta_4 + \omega^t + \beta_5 y_1 + \beta_6 y_2 + \beta_7 y_3 + \beta_8 y_4, \tag{16}$$

where y_1, y_2, y_3, and y_4 is set to one for cluster 1, cluster 2, cluster 3, and cluster 4, respectively, and zero otherwise.

Clusters

We leverage Jenks natural breaks (Jenks, 1967) classification method to divide the State of Illinois into five clusters based on their electric vehicle share heterogeneity to account for regional demand differences. FIGURE 9 (a) shows the county-level electric vehicle share in January 2021. Based on current year 2021 adoption trends in Illinois, the five clusters are shown in FIGURE 9 (b), where cluster 5 is characterized by the highest electric vehicle adoption share and cluster 1 by the lowest. TABLE 6 demonstrates the number of gas stations, charging stations, and the number of gasoline and electric vehicles in the first year of our analysis for the five clusters.

We assume that the upper bound of the number of charging stations should be the same as the gasoline stations to achieve maximum coverage. Cluster 1 has the lowest electric vehicle share, and it consists of rural counties in Illinois with the highest current availability of gas stations but the fewest charging ones. Counties in clusters 4 and 5 are primarily concentrated in the greater Chicago area, where electric vehicle adoption share and charging station coverage are higher.

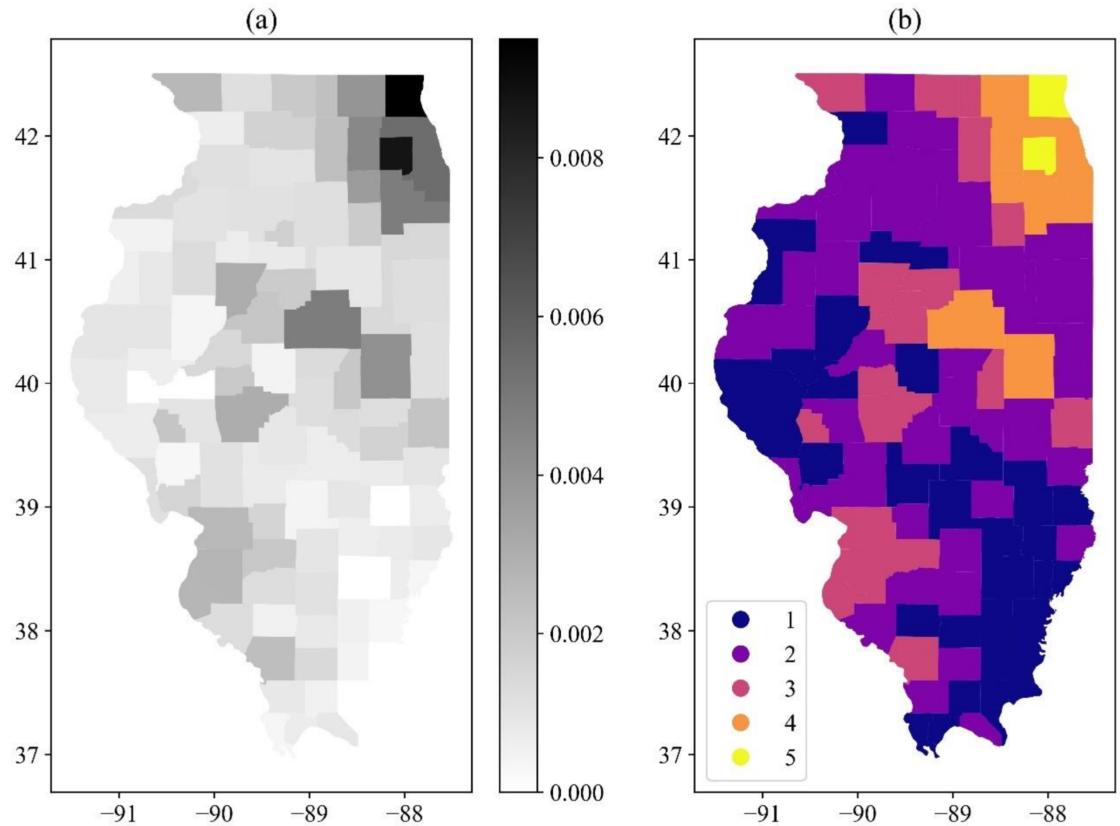

FIGURE 9 (a) EV share in January 2021 in the State of Illinois; (b) Five clusters of EV adoption in the State of Illinois (from lowest 1 to highest 5).

TABLE 6 Number of gas stations, charging stations, and gasoline and electric vehicles in each cluster in Illinois.

Cluster	No. of gas stations	No. of charging stations	No. of gasoline vehicles in the first year	No. of electric vehicles in the first year
Cluster 1	1,672	9	266,300	113
Cluster 2	879	32	815,717	713
Cluster 3	751	50	979,246	1,803
Cluster 4	459	417	3,862,688	15,497
Cluster 5	352	129	1,073,723	8,027

Results

Base case

We optimize the number of charging infrastructures for each cluster, compared to the do-nothing scenario and the maximum emission reduction scenario for each cluster. The emission reduction for the do-nothing scenario is $3.76 \cdot 10^7$ metric tons of CO_2 and the maximum emission reduction is $4.14 \cdot 10^7$ metric tons of CO_2. We set the emission reduction target for the base case to $3.76 \cdot 10^7 + 0.5 \times (4.14 \cdot 10^7 - 3.76 \cdot 10^7) = 3.95 \cdot 10^7$ metric tons of CO_2. TABLE 7, TABLE 8, and TABLE 9 demonstrate the predicted number of EVs and gasoline vehicles for each cluster in different years under the do-nothing scenario, base case, and maximum emission reduction scenario, respectively. If no incentives are provided, 997,212 electric vehicles will be adopted in 2030, which is close to the goal of the State of Illinois; while for the base case and maximum emission reduction targets, the one-million goal of CEJA is reached. The growth of the EV share in each cluster is presented in FIGURE 10. The relationship between the do-nothing case, maximum emission reduction, and the target is shown in FIGURE 11 (a). FIGURE 11 (b) shows the predicted trajectory of the total EVs; it indicates that the number of EVs will significantly increase after 2040. FIGURE 11 (c) shows that the investments in charging station installation should increase to provide around 2,200 stations by 2037 and remain at this level to support EV operation. We know that the earlier the charging stations are built, the more effective they are in electrifying driving distance; however, the later the charging stations are built, the lower the installation expenditure. Therefore, the required number of charging stations will keep increasing until reaching a critical coverage level and then remain at that same level until the end of the planning horizon. FIGURE 12 breaks down the EV share per cluster and the number of charging stations per cluster for the base case. From FIGURE 12 (a), we see that the EV share for every cluster will greatly increase after 2040, which is also shown in FIGURE 10, where the EV share is much higher in 2050 compared to 2030 and 2040. Moreover, the result shows that cluster 5 will always have the highest EV share and lead the electrification transition, reaching 100% in 2050; cluster 1 remains the lowest but can gradually reach about 60% in 2050; and clusters 2, 3, and 4 will reach more than 80% EV share at the end of the planning horizon. These EV trajectories enable meeting the set emission reduction target with increasing investments in charging infrastructure the first 15 to 18 years of the transition. FIGURE 12 (b) shows the required number of charging stations for each cluster; it indicates that charging stations should be invested in the earliest and the most in cluster 1, which currently has the fewest charging stations. This result demonstrates the pressing need for allocating investments for rural electrification to accelerate EV adoption in such lagger regions. EV transitions of lagger regions are very important for accruing emission savings for the state. Charging stations in clusters 2, 3, 4, and 5 should be installed and reach peak levels within the next 15-18 years.

TABLE 7 Results of the do-nothing scenario for the State of Illinois (GV stands for Gasoline Vehicle).

Scenario	Cluster		2030	2040	2050	Emission reduction (mtCO2)
Do-nothing	Cluster 1	EV	5,758	25,457	160,775	$3.78 \cdot 10^5$
		GV	260,655	240,956	105,638	
	Cluster 2	EV	53,032	193,018	682,193	$2.57 \cdot 10^6$
		GV	763,398	623,412	134,237	
	Cluster 3	EV	74,748	256,113	827,107	$3.45 \cdot 10^6$
		GV	906,301	724,936	153,942	
	Cluster 4	EV	567,291	1,507,540	3,510,779	$2.18 \cdot 10^7$
		GV	3,310,894	2,370,645	367,406	
	Cluster 5	EV	296,382	638,745	1,081,750	$9.39 \cdot 10^6$
		GV	785,368	443,005	0	
	Total	EV	997,212	2,620,873	6,262,604	$3.76 \cdot 10^7$
		GV	6,026,615	4,402,954	761,223	

TABLE 8 Results of the base case for the State of Illinois.

Scenario	Cluster		2030	2040	2050	Emission reduction (mtCO2)
Base	Cluster 1	EV	6,860	33,269	182,266	$4.86 \cdot 10^5$
		GV	259,553	233,144	84,147	
	Cluster 2	EV	58,999	238,941	754,193	$3.16 \cdot 10^6$
		GV	757,431	577,489	62,237	
	Cluster 3	EV	80,992	303,583	898,243	$4.06 \cdot 10^6$
		GV	900,057	677,466	82,806	
	Cluster 4	EV	567,985	1,515,974	3,521,819	$2.19 \cdot 10^7$
		GV	3,310,200	2,362,211	356,366	
	Cluster 5	EV	302,546	667,884	1,081,750	$9.87 \cdot 10^6$
		GV	779,204	413,866	0	
	Total	EV	1,017,382	2,759,651	6,438,270	$3.95 \cdot 10^7$
		GV	6,006,445	4,264,176	585,557	

TABLE 9 Results of maximum emission reduction scenario for the State of Illinois.

Scenario	Cluster		2030	2040	2050	Emission reduction (mtCO2)
Max	Cluster 1	EV	9,531	39,943	194,260	$5.94 \cdot 10^5$
		GV	256,882	226,470	72,153	
	Cluster 2	EV	79,985	270,086	790,483	$3.75 \cdot 10^6$
		GV	736,445	546,344	25,947	
	Cluster 3	EV	103,813	335,591	934,402	$4.68 \cdot 10^6$
		GV	877,236	645,458	46,647	
	Cluster 4	EV	573,276	1,521,265	3,527,110	$2.20 \cdot 10^7$
		GV	3,304,909	2,356,920	351,075	
	Cluster 5	EV	323,581	689,593	1,081,750	$1.04 \cdot 10^7$
		GV	758,169	392,157	0	
	Total	EV	1,090,186	2,856,478	6,528,005	$4.14 \cdot 10^7$
		GV	5,933,641	4,167,349	495,822	

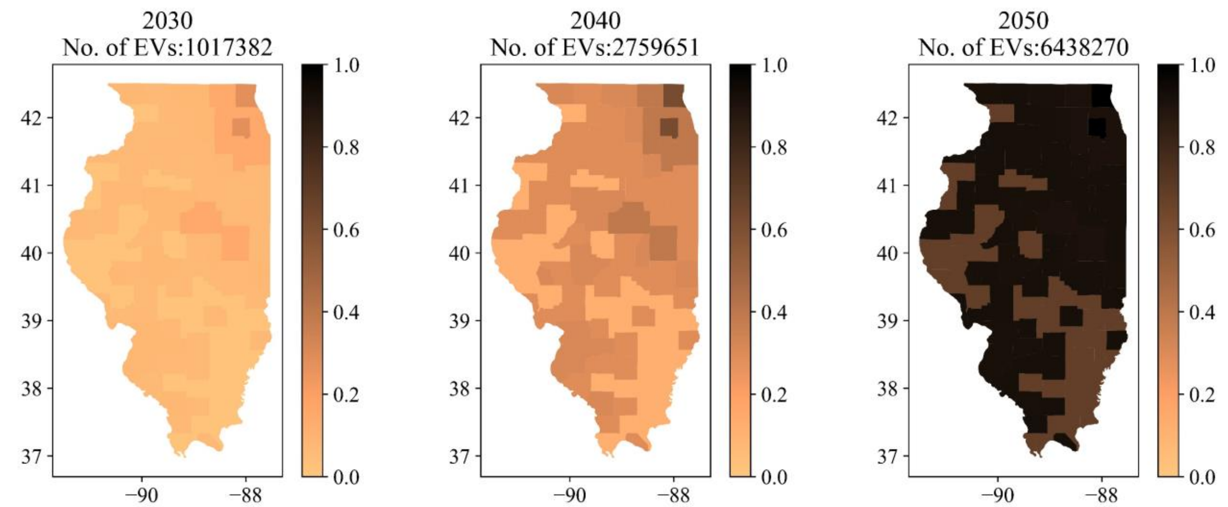

FIGURE 10 Growth of electric vehicle share for the State of Illinois.

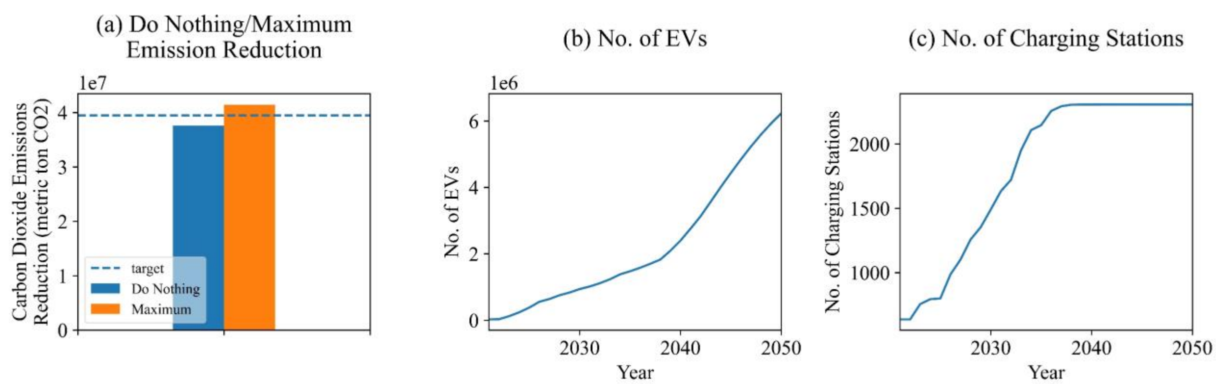

FIGURE 11 Optimization results for the base case scenario.

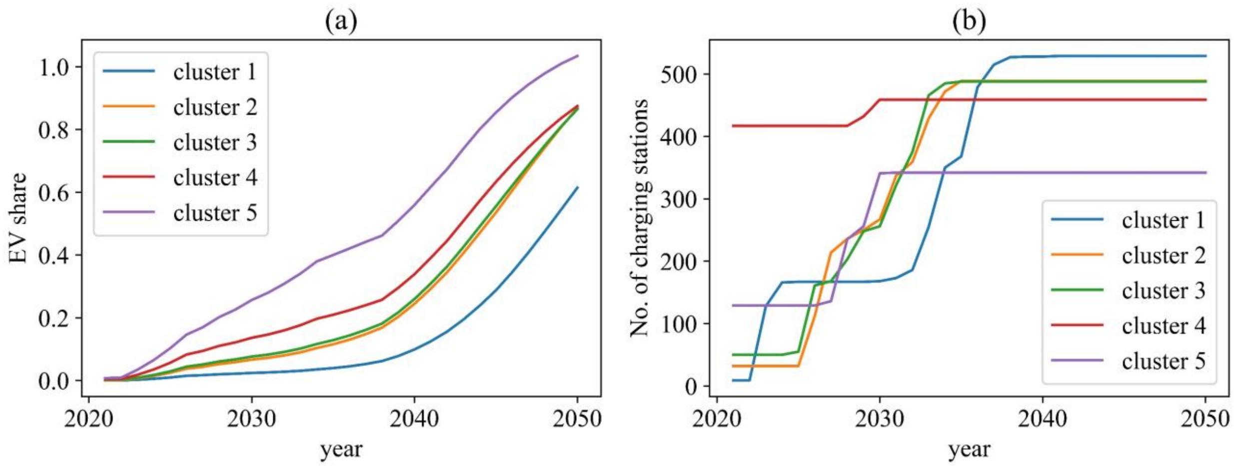

FIGURE 12 (a) EV share per cluster; (b) Number of charging stations per cluster.

Sensitivity Analyses

Aligned with the process that we followed for the US case study, we conduct sensitivity analyses for the State of Illinois case study. The analyses include evaluating the impact of different parameters that denote home charging availability, electricity generation mixes to infer charging carbon intensity, traveler type distances, fuel price outlooks, and alternate planning horizons.

The optimization results are shown in FIGURE 13 and FIGURE 14. The results provide insights that match the conclusions reached from our national case study:

(1) Home charging levels have a great impact on emissions reduction. FIGURE 13 (1)(a) shows that the set emission reduction target cannot be reached if home charging availability is 0%, 25%, 50%, and 75%. From FIGURE 13 (1)(c), we observe that when home charging availability is 100%, no charging stations are needed to achieve the emission reduction target. This is because the electrified distances are longer and enabled by universal and reliable home charging access, and the operational cost of drivers is lower since fewer backup gasoline vehicles are

needed. In addition, lower operating costs also drive more electric vehicle adoption, as shown in FIGURE 13 (1)(b).

(2) Low renewable energy cost corresponds to a future where more renewable energy is integrated and used for electricity generation and, thus, a lower emission rate is associated with electricity production. FIGURE 13 (2)(a) demonstrates the considerable differences in emission reductions for different electricity generation mixes: a less carbon-intensive electricity generation sector can lead to light-duty vehicle electrification emission reduction that is much greater than the base scenario. Therefore, as shown in FIGURE 13 (2)(b) and FIGURE 13 (2)(c), even though the number of electric vehicles in the transition trajectories is similar for the two cases, no significant additional investment in charging stations would be required to reach the target in the low renewable energy cost case.

(3) Three types of travelers are tested, based on their daily vehicle miles traveled: modest, average, and frequent. From FIGURE 13 (3)(c), we uncover that for modest drivers, their travel distance is on average short and the demand for charging stations is lower; on the contrary, charging infrastructure extends the electrified distance of frequent drivers, which can effectively reduce their operational costs.

(4) We also examine low gas prices high electricity prices and high gas prices low electricity prices scenarios. From FIGURE 14 (4)(c), we learn that with high gas prices and low electricity prices, people will be more willing to purchase electric vehicles, and therefore, to meet the same emission reduction target, fewer additional charging stations need to be provided. Note that if having high gas prices and low electricity prices, the emission reduction for the do-nothing scenario is higher than

the target, as shown in FIGURE 14 (4)(a), charging stations are still needed, as shown in FIGURE 14 (4)(c). This is because the emission reduction in FIGURE 14 (4)(a) is the summation of emission reductions for five clusters, and it does not mean that for every cluster, the do-nothing scenario has a higher emission reduction than the target. In fact, additional charging station investments are still needed in counties in clusters 1, 2, and 3.

(5) Similar to the analysis of different fuel prices, if the planning horizon is 35 years, although the total emission reduction for the do-nothing scenario is higher than the target, charging stations are still required to meet the target. FIGURE 14 (5)(c) shows that to meet the same environmental quality target, having a longer planning horizon to achieve this reduction requires fewer charging station deployments.

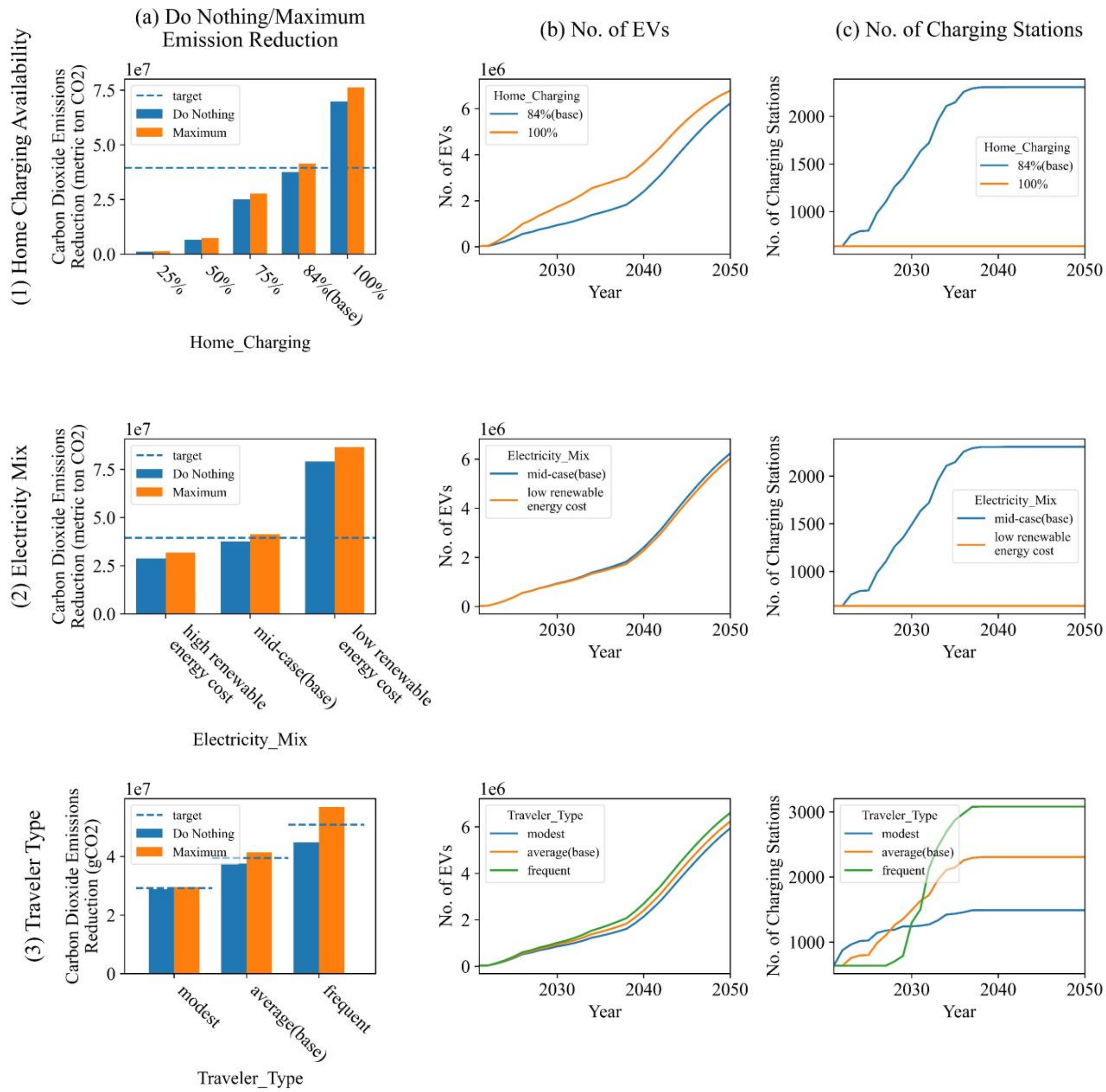

FIGURE 13 Optimization results for additional sensitivity scenarios for the State of Illinois, including (1) different home charging availabilities, (2) electricity generation mixes, (3) traveler types.

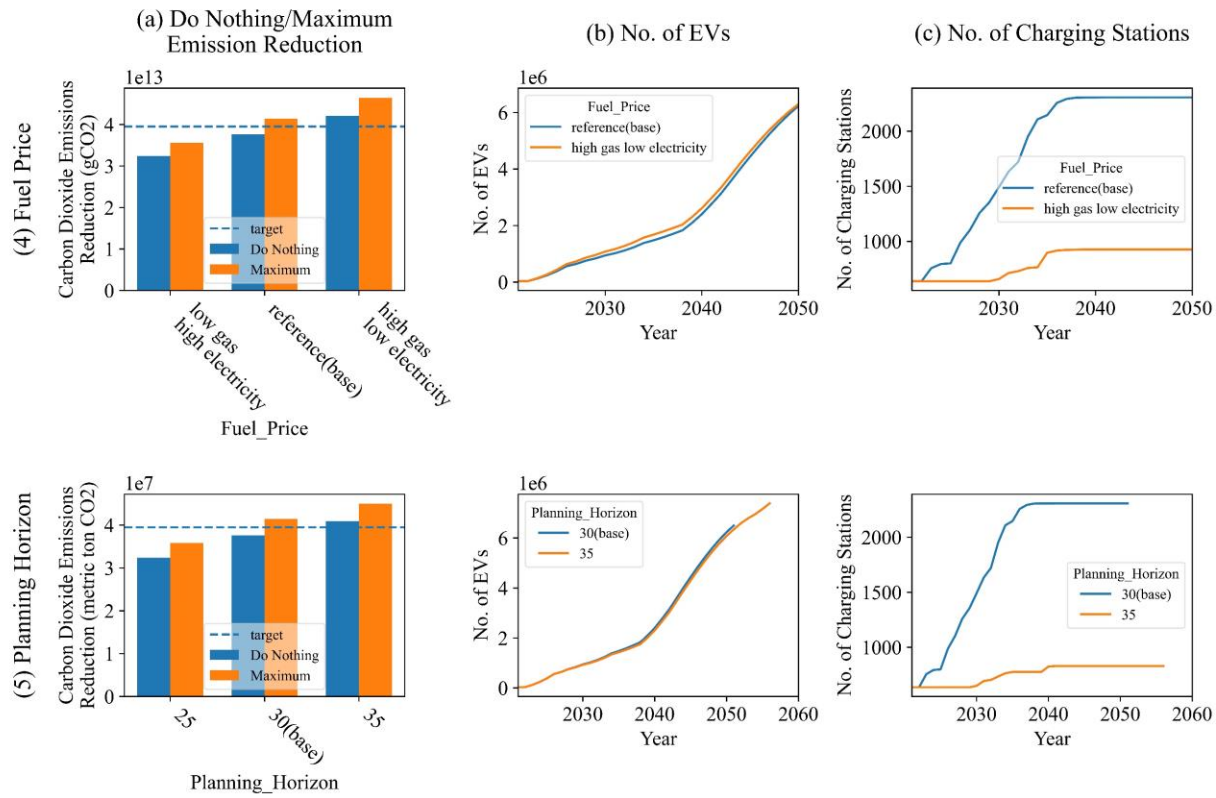

FIGURE 14 Optimization results for additional sensitivity scenarios for the State of Illinois, related to (4) different fuel pricing outlooks, (5) alternate lengths of planning horizons.

CHAPTER 8: CONCLUSIONS

In this paper, we propose a nonlinear mixed-integer programming framework to optimize the allocation of monetary incentives and charging infrastructure that accelerate consumers' adoption of electric vehicles to achieve a set emission reduction target. We capture the demand for gasoline and electric vehicles with logistic functions, accounting for both capital and operational costs and network externalities. Due to the high nonlinearity, we propose a simulated annealing algorithm to solve the problem. For the national-level study, our base case results show that if no electrification incentives are distributed, slower substitution of gasoline vehicles with electric vehicles will occur. On the other hand, if incentives are provided to accelerate electric vehicle adoption, the maximum emission reduction is 1.91 times the do-nothing case. If the emission reduction target is 1.5 times the emission reduction without any incentives, a total of 44.45 billion incentives are required by 2050, reaching a 23.57% electric vehicle share in the US. As expected, emission reduction levels depend on the carbon intensity of the electricity generation mix in the US. Under a high renewable energy cost scenario (conservative projections for renewable energy), the maximum emission reduction associated with the operation of light-duty vehicles is 27.36% less than the maximum emission reduction of the base case CO_2. The case study and the sensitivity analyses enable us to gain several policymaking insights. The main findings are summarized as follows: (i) rebates are more effective when provided in the early years of the planning horizon because of neighborhood effects that further incentivize electric vehicle adoption and due to discounting and the goal of minimizing the total expenditure, charging stations could be installed later; (ii) if the rebate upper bound is lower than a certain value, the electric vehicle share is lower in the early years, so more charging stations should be installed to compensate and incentivize adoption while the incentives expenditure increases; (iii) the availability of home charging significantly influences the volume of emission reduction that can be achieved due to its impact on consumer's willingness to purchase electric vehicles and the enabled electrified travel distance; (iv) different projections of fuel prices do not lead to significant changes in incentive allocation trends; (v) rebates should be prioritized for modest travelers while charging infrastructure plays a more critical role in accelerating the electric vehicle adoption of frequent drivers; (vi) incorporating different types of network externalities leads to very different outcomes and should be further investigated before making electric vehicle investment-related decisions. For the Illinois case study, if no incentives are offered, $3.76 \cdot 10^7$ metric tons of CO_2 can be reduced and 997,212 electric vehicles will be adopted in 2030, which does not meet the Illinois goal. If the maximum number of charging stations is provided in the first year of planning, $4.14 \cdot 10^7$ metric tons of CO_2 can be reduced and will reach the one-million-electric-vehicle goal of the state of Illinois. The EV share will significantly increase after 2040. In 2050, cluster 1 will reach about 60%, clusters 2, 3, and 4 will reach more than 80%, and cluster 5 will reach 100% EV share. Currently, cluster 1, the rural counties in Illinois, has the lowest charging infrastructure coverage, so charging stations should be invested in earlier and more than other clusters. The sensitivity analyses provide similar insights as the national case study.

Several studies on the lifecycle emissions of electric vehicles have been carried out, e.g., proposing assessment frameworks (Onat et al., 2019), evaluating air quality and emissions impacts (Tessum et al., 2014; Wu et al., 2018), and uncovering greenhouse gas implications of fleet electrification (Cai and Xu, 2013). Our analysis limitations are associated with the boundaries we set when measuring emissions: we focus on the operational emissions of the new market of light-duty vehicles in the US and Illinois. Even though our scope is to design electric vehicle incentives and understand mechanisms that can lead to meeting tighter operational carbon dioxide reduction targets, a more comprehensive well-to-wheel or lifecycle emissions analysis can holistically evaluate any benefits from this transition. In this study, we only focus on the two major vehicle technologies (i.e., gasoline and battery electric) to reduce the optimization model's complexity, aiming to gain insights into the incentive temporal allocation mechanisms. However, future research should aim to integrate more vehicle technologies in the model, such as hybrid and plug-in hybrid electric vehicles, due to the heterogeneous preferences of vehicle owners. Furthermore, in-depth research on network externalities' effects on electric vehicle adoption should be conducted. A more precise prediction model of consumer choice needs to capture how consumer demand is affected by the number of existing electric vehicles and the number of existing charging stations on the transportation network. Future research could integrate vehicle demand models (e.g., Jenn et al.'s (2020) and Shin et al.'s (2015) models) that capture intricacies and the heterogeneity of consumer behavior in greater detail and accuracy.

REFERENCES

Alarfaj, A.F., Griffin, W.M., Samaras, C., 2020. Decarbonizing US passenger vehicle transport under electrification and automation uncertainty has a travel budget. Environmental Research Letters 15. https://doi.org/10.1088/1748-9326/ab7c89

Bastida-Molina, P., Hurtado-Pérez, E., Peñalvo-López, E., Cristina Moros-Gómez, M., 2020. Assessing transport emissions reduction while increasing electric vehicles and renewable generation levels. Transportation Research Part D: Transport and Environment 88. https://doi.org/10.1016/j.trd.2020.102560

Ben-Akiva, M., Lerman, S.R., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press, Cambridge, Massachusets.

Brady, J., O'Mahony, M., 2011. Travel to work in Dublin. The potential impacts of electric vehicles on climate change and urban air quality. Transportation Research Part D: Transport and Environment 16, 188–193. https://doi.org/10.1016/j.trd.2010.09.006

Brooks, D.G., Verdini, W.A., 1988. Computational experience with generalized simulated annealing over continuous variables. American Journal of Mathematical and Management Sciences 8, 425–449. https://doi.org/10.1080/01966324.1988.10737248

Busetti, F., 2003. Simulated annealing overview.

Cai, H., Xu, M., 2013. Greenhouse gas implications of fleet electrification based on big data-informed individual travel patterns. Environmental Science and Technology 47, 9035–9043. https://doi.org/10.1021/es401008f

Canepa, K., Hardman, S., Tal, G., 2019. An early look at plug-in electric vehicle adoption in disadvantaged communities in California. Transport Policy 78, 19–30. https://doi.org/10.1016/j.tranpol.2019.03.009

Carley, S., Krause, R.M., Lane, B.W., Graham, J.D., 2013. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. Transportation Research Part D: Transport and Environment 18, 39–45. https://doi.org/10.1016/j.trd.2012.09.007

Cohen, M.C., Lobel, R., Perakis, G., 2016a. The impact of demand uncertainty on consumer subsidies for green technology adoption. Management Science 62, 1235–1258. https://doi.org/10.1287/mnsc.2015.2173

Cohen, M.C., Lobel, R., Perakis, G., 2016b. The impact of demand uncertainty on consumer subsidies for green technology adoption. Management Science 62, 1235–1258. https://doi.org/10.1287/mnsc.2015.2173

Cole, W., Vincent, J., Contributing, C., Brown, M., Brown, P., Cohen, S., Eurek, K., Frazier, W., Gagnon, P., Grue, N., Ho, J., Lopez, A., Mai, T., Mowers, M., Murphy, C., Sergi, B., Steinberg, D., Williams, T., 2021. 2021 Standard Scenarios Report: A U.S. Electricity Sector Outlook.

Corana, A., Marchesi, M., Martini, C., Ridella, S., 1987. Minimizing Multimodal Functions of Continuous Variables with the 'Simulated Annealing" Algorithm. ACM Transactions on Mathematical Software 13.

Doucette, R.T., McCulloch, M.D., 2011. Modeling the prospects of plug-in hybrid electric vehicles to reduce CO2 emissions. Applied Energy 88, 2315–2323. https://doi.org/10.1016/j.apenergy.2011.01.045

U.S. Energy Information Administration (EIA), 2021. EIA's Annual Energy Outlook 2020 projects consumption growing more slowly than production - Today in Energy [WWW Document]. URL https://www.eia.gov/todayinenergy/detail.php?id=42635 (accessed 7.27.21).

Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39, 3789–3802. https://doi.org/10.1016/J.ENPOL.2011.04.007

Florax, R.J., Rey, S., 1995. The impacts of misspecified spatial interaction in linear regression models. New directions in spatial econometrics.

Ghamami, M., Kavianipour, M., Zockaie, A., Hohnstadt, L.R., Ouyang, Y., 2020. Refueling infrastructure planning in intercity networks considering route choice and travel time delay for mixed fleet of electric and conventional vehicles. Transportation Research Part C: Emerging Technologies 120. https://doi.org/10.1016/j.trc.2020.102802

Greene, D.L., Kontou, E., Borlaug, B., Brooker, A., Muratori, M., 2020. Public charging infrastructure for plug-in electric vehicles: What is it worth? Transportation Research Part D: Transport and Environment 78. https://doi.org/10.1016/j.trd.2019.11.011

Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. Renewable and Sustainable Energy Reviews. https://doi.org/10.1016/j.rser.2017.05.255

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Plötz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transportation Research Part D: Transport and Environment 62, 508–523. https://doi.org/10.1016/j.trd.2018.04.002

Helveston, J.P., Liu, Y., Feit, E.M.D., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transportation Research Part A: Policy and Practice 73, 96–112. https://doi.org/10.1016/j.tra.2015.01.002

U.S. Energy Information Administration (EIA), 2021. Homepage [WWW Document]. URL https://www.eia.gov/ (accessed 7.15.21).

Javid, R.J., Nejat, A., 2017. A comprehensive model of regional electric vehicle adoption and penetration. Transport Policy 54, 30–42. https://doi.org/10.1016/j.tranpol.2016.11.003

Jenks, G.F., 1967. The data model concept in statistical mapping. International yearbook of cartography 186–190.

Jenn, A., Lee, J.H., Hardman, S., Tal, G., 2020. An in-depth examination of electric vehicle incentives: Consumer heterogeneity and changing response over time. Transportation Research Part A: Policy and Practice 132, 97–109. https://doi.org/10.1016/j.tra.2019.11.004

Johnson David S., Aragon Cecilia R., McGeoch Lyle A., Schevon Catherine, 1989. Optimization by Simulated Annealing: An Experimental Evaluation; Part I, Graph Partitioning. Operations Research 37, 865–892.

Kang, N., Feinberg, F.M., Papalambros, P.Y., 2015. Integrated decision making in electric vehicle and charging station location network design. Journal of Mechanical Design, Transactions of the ASME 137. https://doi.org/10.1115/1.4029894

Kang, N., Ren, Y., Feinberg, F.M., Papalambros, P.Y., 2016. Public investment and electric vehicle design: A model-based market analysis framework with application to a USA-China comparison study. Design Science 2. https://doi.org/10.1017/dsj.2016.7

Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by Simulated Annealing.

Kontou, E., Liu, C., Xie, F., Wu, X., Lin, Z., 2019. Understanding the linkage between electric vehicle charging network coverage and charging opportunity using GPS travel data. Transportation Research Part C: Emerging Technologies 98, 1–13. https://doi.org/10.1016/j.trc.2018.11.008

Kontou, E., Yin, Y., Lin, Z., He, F., 2017. Socially optimal replacement of conventional with electric vehicles for the US household fleet. International Journal of Sustainable Transportation 11, 749–763. https://doi.org/10.1080/15568318.2017.1313341

Kruger, J., 1993. Simulated Annealing: A Tool for Data Assimilation into an Almost Steady Model State. Journal of Physical Oceanography 23. https://doi.org/10.1175/1520-0485(1993)023<0679:SAATFD>2.0.CO;2

Lin, Z., 2014. Optimizing and diversifying electric vehicle driving range for U.S. drivers. Transportation Science 48, 635–650. https://doi.org/10.1287/trsc.2013.0516

Melaina, M., Bush, B., Eichman, J., Wood, E., Stright, D., Krishnan, V., Keyser, D., Mai, T., Mclaren, J., 2016. National Economic Value Assessment of Plug-In Electric Vehicles: Volume I.

Milano, I.C.O.E.D.; P. di, In, 2015. A Framework for Quantitative Analysis of Government Policy Influence on Electric Vehicle Market, in: International Conference on Engineering Design.

Narassimhan, E., Johnson, C., 2018. The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: Analysis of US States. Environmental Research Letters 13. https://doi.org/10.1088/1748-9326/aad0f8

U.S. Department of Transportation, 2021. National Household Travel Survey [WWW Document]. URL https://nhts.ornl.gov/ (accessed 7.13.21).

Nie, Y., Ghamami, M., Zockaie, A., Xiao, F., 2016. Optimization of incentive polices for plug-in electric vehicles. Transportation Research Part B: Methodological 84, 103–123. https://doi.org/10.1016/j.trb.2015.12.011

NREL, 2020. Cambium 2020 [WWW Document]. URL https://cambium.nrel.gov/ (accessed 1.27.22).

Onat, N.C., Kucukvar, M., Afshar, S., 2019. Eco-efficiency of electric vehicles in the United States: A life cycle assessment based principal component analysis. Journal of Cleaner Production 212, 515–526. https://doi.org/10.1016/j.jclepro.2018.12.058

Plötz, P., Jakobsson, N., Sprei, F., 2017. On the distribution of individual daily driving distances. Transportation Research Part B: Methodological 101, 213–227. https://doi.org/10.1016/j.trb.2017.04.008

Public Act. 102-0662. https://www.ilga.gov/legislation/publicacts/102/PDF/102-0662.pdf.

Rietmann, N., Hügler, B., Lieven, T., 2020. Forecasting the trajectory of electric vehicle sales and the consequences for worldwide CO2 emissions. Journal of Cleaner Production 261. https://doi.org/10.1016/j.jclepro.2020.121038

Veloz, 2021. Sales Dashboard [WWW Document]. URL https://www.veloz.org/sales-dashboard/ (accessed 7.23.21).

Shepherd, S., Bonsall, P., Harrison, G., 2012. Factors affecting future demand for electric vehicles: A model based study. Transport Policy 20, 62–74. https://doi.org/10.1016/J.TRANPOL.2011.12.006

Shin, J., Bhat, C.R., You, D., Garikapati, V.M., Pendyala, R.M., 2015. Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types. Transportation Research Part C: Emerging Technologies 60, 511–524. https://doi.org/10.1016/j.trc.2015.10.003

Tal, G., Lee, J.H., Nicholas, M.A., Org, E., 2018. UC Davis Research Reports Title Observed Charging Rates in California Publication Date.

Tessum, C.W., Hill, J.D., Marshall, J.D., 2014. Life cycle air quality impacts of conventional and alternative light-duty transportation in the United States 111, 18490–18495. https://doi.org/10.13020/D6159V

U.S. Department of Energy, 2021. Alternative Fuels Data Center [WWW Document]. URL https://afdc.energy.gov/ (accessed 1.27.22).

U.S. Energy Information Administration (EIA), 2021a. Use of energy for transportation [WWW Document]. URL https://www.eia.gov/energyexplained/use-of-energy/transportation.php (accessed 7.11.21).

U.S. Energy Information Administration (EIA), 2021b. Annual Energy Outlook 2021 [WWW Document]. URL https://www.eia.gov/outlooks/aeo/tables_ref.php

Vanderbilt, D., Eouie, S., 6,, 1984. A Monte Carlo Simulated Annealing Approach to Optimization over Continuous Variables. J. Computational Phys. 56 (2), 259–271. https://doi.org/10.1016/0021-9991(84)90095-0.

Wang, Yinglong, Bu, G., Wang, Yongkun, Zhao, T., Zhang, Z., Zhu, Z., 2016. Application of a simulated annealing algorithm to design and optimize a pressure-swing distillation process. Computers and Chemical Engineering 95, 97–107. https://doi.org/10.1016/j.compchemeng.2016.09.014

Wu, Z., Wang, M., Zheng, J., Sun, X., Zhao, M., Wang, X., 2018. Life cycle greenhouse gas emission reduction potential of battery electric vehicle. Journal of Cleaner Production 190, 462–470. https://doi.org/10.1016/j.jclepro.2018.04.036

Xu, T., Wei, H., Hu, G., 2009. Study on continuous network design problem using simulated annealing and genetic algorithm. Expert Systems with Applications 36, 1322–1328. https://doi.org/10.1016/j.eswa.2007.11.023

Zhang, C., Wang, H.P., 1993. Mixed-discrete nonlinear optimization with simulated annealing. Engineering Optimization 21, 277–291. https://doi.org/10.1080/03052159308940980

Zhou, Y., Wang, M., Hao, H., Johnson, L., Wang, H., Hao, H., 2015. Plug-in electric vehicle market penetration and incentives: a global review. Mitigation and Adaptation Strategies for Global Change 20, 777–795. https://doi.org/10.1007/s11027-014-9611-2

Zockaie, A., Aashtiani, H.Z., Ghamami, M., Marco Nie, Y., 2016. Solving Detour-Based Fuel Stations Location Problems. Computer-Aided Civil and Infrastructure Engineering 31, 132–144. https://doi.org/10.1111/mice.12170

Zockaie, A., Saberi, M., Saedi, R., 2018. A resource allocation problem to estimate network fundamental diagram in heterogeneous networks: Optimal locating of fixed measurement points and sampling of probe trajectories. Transportation Research Part C: Emerging Technologies 86, 245–262. https://doi.org/10.1016/j.trc.2017.11.017