Modeling Electric Vehicle Adoption at the ZIP Code Level: A Bass Diffusion and Machine Learning Approach

Angelina Li
Enloe Magnet High School
Raleigh, NC 27610
angelina.li.00301@gmail.com

Zuzhao Ye, Nanpeng Yu
Department of Electrical and Computer Engineering
University of California, Riverside, CA 92521
zye066@ucr.edu, nanpeng.yu@ucr.edu

***Abstract*—With the gradual transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs), accurate forecasts of EV adoption are essential for planning local charging infrastructure and assessing impacts on the power grid. However, most existing forecasts are conducted at national or state levels, which lack the spatial granularity needed to guide local power system upgrades. Moreover, constructing reliable models for EV adoption is challenging in areas without sufficient historical data. In this study, we analyze New York State's EV registration data using the Bass Diffusion Model and estimate the model parameters, including innovation, imitation, and market potential, at the ZIP code level. We then model how demographic, socioeconomic, and infrastructural characteristics influence these parameters using multiple linear regression and neural networks, enabling the estimation of Bass model parameters for regions with limited EV history. The proposed framework achieves high predictive accuracy and can be applied to other regions to generate fine-grained EV adoption forecasts for grid planning and infrastructure investment.**

***Index Terms*—Electric vehicle adoption, Bass model, Public data analysis**

I. Introduction

Electric vehicles (EVs) have emerged as a popular alternative to traditional Internal Combustion Engine (ICE) vehicles. Early commercial success in the 2010s with Tesla, the plug-in hybrid Chevy Volt, and the all-electric Nissan LEAF resulted in the further development of EVs and charging infrastructure [1]. Now, with reduced costs for charging and maintenance, growing environmental consciousness, and government incentives [2], United States EV sales are experiencing rapid growth, with 1.56 million units sold in 2024 and a market share of approximately 10%. Today, there are over 5.7 million EVs on the road [3]. Strategic preparation is needed to accommodate the growing charging demand of EVs. Studies such as penetration effects on local power grids and optimal infrastructure investment [4]–[6] require accurate forecasts of EV adoption.

However, predicting EV growth is complex. Widespread EV adoption is a key component of governmental policies for improving air quality and reducing climate impact, so tax incentives and rebates are commonly used to encourage the purchase of EVs [2], [5]. Development of charging infrastructure and technological advancement also contribute to their popularity. At the same time, EV adoption is slowed by several consumer concerns, including affordability compared to ICE vehicles, lack of accessible charging stations, and range anxiety [5], [7]. The regional variation of these factors further increases the difficulty of accurately predicting EV adoption.

The Bass model is widely used for forecasting the adoption of innovative technologies such as EVs [8]–[10]. Developed by Frank M. Bass in 1969 [11], the Bass model is a mathematical model that considers consumer characteristics of innovation, imitation, and market potential to forecast cumulative product adoption. Previous studies have applied the Bass model to predict EV diffusion in China [8], [12], the United States [13], France, and Germany [10], while incorporating factors such as policy incentives, green premiums, and availability of charging stations. One study of EV adoption in California divided the population into eight demographic and vehicle usage clusters before applying the Bass model [14].

However, existing studies are largely performed on state or national scales, and do not examine how these consumer characteristics directly influence the Bass model parameters. Power distribution networks will receive greater benefits from local EV demand forecasts, which will enable more granular and proactive decisions for upgrades. Developing such local forecasts is challenging due to variations in data availability, consumer preferences, and charging station accessibility, among other factors. To address these gaps, this paper introduces the following key contributions:

- First, we perform EV adoption forecasting at the ZIP code level using the Bass model and vehicle registration data from New York State. Such fine-grained forecasts provide valuable insights for local utilities to plan infrastructure upgrades and prepare for growing EV integration.
- Second, we investigate how the Bass model parameters, i.e., innovation (p), imitation (q), and market potential (m), are influenced by demographic and socioeconomic factors. Specifically, we employ multiple linear regression and neural network models to predict Bass model param-

eters from these factors and to interpret how innovation, imitation, and market potential respond differently to various data features.

This framework not only reveals how local demographic data influences EV adoption but also enables Bass model applications in regions lacking historical EV data, supporting broader applications of EV forecasting and grid planning. Furthermore, by relying solely on public data, our methodology ensures reproducibility and scalability, and allows the framework to be extended beyond New York State to other regions.

The rest of this paper is structured as follows: Section II details the public data used in the study. Section III introduces the technical methods for predicting EV adoption. Section IV analyzes the prediction results and model performance, using New York State as a case study. Section V states the conclusion.

II. Data Overview

In this section, we introduce the data used in the study. All data is sourced from reliable public databases maintained by official United States agencies, including the U.S. Census Bureau and U.S. Department of Energy. Electric vehicle registration records are sourced from the New York State Energy Research and Development Authority (NYSERDA). We select independent variables that broadly capture demographic and geographic factors. The following is a detailed overview of each data source and the predictors used for this study.

1) EV Registration Data: The New York State Energy Research and Development Authority (NYSERDA) publishes downloadable New York State EV statistics and registration records [15]. The dataset provides the date, ZIP code, and vehicle details for each EV registration, allowing us to calculate annual cumulative adoption counts. These cumulative values are essential for fitting the Bass model and estimating its parameters—innovation (p), imitation (q), and market potential (m)—at the ZIP code level.

2) Demographic Data: This study uses the latest 5-year American Community Survey (ACS), the 2019-2023 ACS 5-Year estimates [16]. The ACS provides consistent, high-resolution data at the ZIP code level, enabling us to investigate how local population features (e.g., income, education, age, and commuting behavior) affect consumer adoption behavior. These variables are critical to explaining spatial variations in the Bass model parameters and predicting adoption potential in regions lacking sufficient historical EV data.

3) Charging Infrastructure Data: The U.S. Department of Energy's Alternative Fuels Data Center provides detailed charging station data, including ZIP code-level counts of charging ports [17]. Charging availability directly influences the convenience of EV ownership, thus playing an important role in adoption decisions. Including infrastructure data allows us to account for geographic differences in charging accessibility when modeling adoption trends.

The variables used to predict EV adoption are summarized in Table I along with their data sources and descriptive statistics. We define the working-age population as individuals aged 18 to 65 years. Several demographic features are expressed as percentages to minimize the influence of population magnitude, improve comparability across regions, and reduce predictor collinearity.

To ensure robust and generalizable results, we only include ZIP codes with a working-age population greater than 1,000. A total of 1,112 ZIP codes meet this criterion. Nonzero charging infrastructure data is available for 700 of these ZIP codes.

III. Methodology

In this section, we describe the proposed framework used to forecast EV adoption and to identify the key factors influencing adoption patterns. As illustrated in Fig. 1, the process begins with forecasting EV adoption at the ZIP code level and estimating the Bass model parameters that characterize the adoption process. These parameters are then analyzed using multiple linear regression and neural networks to determine how they are impacted by demographic, socioeconomic, and infrastructural factors.

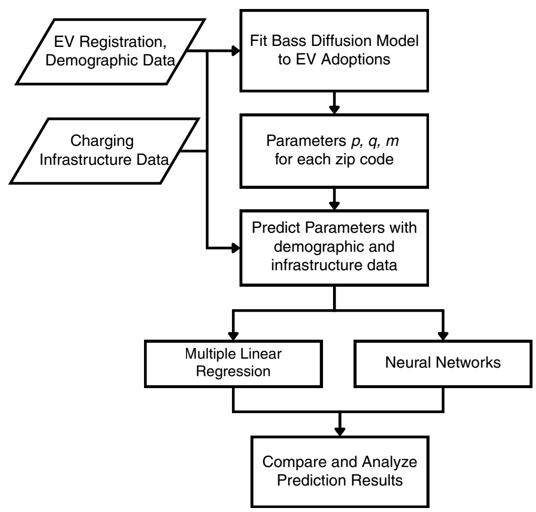

Fig. 1: The proposed framework for forecasting EV adoption and understanding the impact factors of adoption.

A. Method for EV Adoption Forecasting

We employ the Bass model to forecast EV adoption across New York State at the ZIP code level. The Bass model is a widely used diffusion model that describes how new technologies and products are adopted over time. It assumes that the adoption rate of a new product is driven by two main mechanisms, innovation and imitation, which together shape the "S-curve" of cumulative adoption. The differential equation of the Bass model is expressed as:

$$\frac{dF(t)}{dt} = m(p + qF(t))(1 - F(t)), \tag{1}$$

where $F(t)$ describes the cumulative fraction of adopters at time t. We set $t = 0$ as the year 2011 when EVs became

TABLE I: Summary Statistics and Sources of Predictor Variables (ZIP Code Level)

Variable	**Description**	**Source**	**Mean**	**SD**	**Median**	**Min**	**Max**
Working-Age Population (Thousands)	Count of population aged 18–65	Table S0101 – Age and Sex	10.76	12.73	5.29	1.00	70.82
Male-to-Female Ratio*	Calculated by count of males divided by count of females	ACS Derived	1.05	0.59	1.00	0.38	16.41
Median Age (Years)	Median age in years	Table S0101 – Age and Sex	42.1	6.2	42.4	19.5	63.3
Median Income (Thousands of Dollars)	Median annual household income (2023 USD)	Table S1903 – Median Income (past 12 months)	94.45	40.45	83.30	23.26	250.00
College Education Rate	Proportion of population with Bachelor's degree or higher	ACS Derived	0.278	0.138	0.252	0.023	0.811
Work from Home Proportion	Proportion of employed residents working from home	Table S0801 – Commuting Characteristics by Sex	0.120	0.065	0.107	0.000	0.462
Mean Commute Time (Minutes)	Average one-way commute time to work	Table S0801 – Commuting Characteristics by Sex	29.15	8.41	27.80	10.50	54.20
Charging Ports per 100 People	Public EV charging ports expressed as per 100 people	Alternative Fueling Station Locator [16]	0.180	0.282	0.096	0.001	3.642

* Calculated with the working-age population (ages 18–65).

commercially mainstream in the United States. The Bass model characterizes product diffusion using three parameters:

- Innovation (p): Captures adoption driven by external influences such as marketing, policy incentives, or personal initiative. Innovators are typically early adopters who decide independently of others.
- Imitation (q): Represents adoption through social influence, such as word-of-mouth, community visibility, and peer effects. As more individuals adopt, the likelihood of others following increases.
- Market Potential (m): Defines the maximum number of potential adopters in the market, representing the theoretical saturation level of EV adoption within a region.

Intuitively, at the early stage of adoption, innovation dominates as a small number of consumers adopt independently. As adoption grows, imitation effects take over, accelerating the adoption rate until the market nears saturation and the rate slows again, producing an S-shaped adoption curve typical of new technologies.

In this study, we fitted the Bass model to cumulative EV registration data for each ZIP code, using a nonlinear least squares method to estimate the parameters p, q, and m.

We set the upper bound for market potential m to an estimate of future EV drivers in each ZIP code: m^{max} = Working-age population $\times 75\% \times 50\%$. Here, 75% is the estimated proportion of U.S. consumers who drive their own car [18]. 50% is a moderate estimate of EV share on U.S. roads by 2050, which varies from 34% [19] to 70% [20]. To assess the Bass model parameter sensitivities to this assumption, we also evaluated 40% and 60% EV share scenarios. The parameters p and q remained relatively stable across all scenarios, while m increased in several ZIP codes with increasing EV adoption rate. We focused on the 50% scenario as a reasonable middle case.

B. *Methods for Explaining EV Adoption*

After estimating the Bass model parameters, we examine how they are influenced by demographic and socioeconomic characteristics. Specifically, we investigate whether local factors can predict the coefficients of innovation (p), imitation (q), and market potential (m) at the ZIP code level. To achieve this, we employ and compare two approaches: multiple linear regression (MLR) and neural networks (NN).

1) Multiple Linear Regression: Multiple linear regression (MLR) was implemented using the ordinary least squares (OLS) method to estimate the relationships between Bass model parameters and the selected predictors. Overall explanatory power was assessed using the adjusted R^2. To reduce skewness and improve model fit, we applied logarithmic transformations to median income, male-to-female ratio, working-age population, and the Bass model parameters p and m. This transformation allows model coefficients to be interpreted on a percentage scale, facilitating intuitive comparison of relative effects.

2) Neural Networks: Neural networks (NNs) enable the modeling of nonlinear relationships between demographic factors and Bass model parameters. We evaluated several architectures with varying depths and hidden neuron counts. Based on performance, we adopted a two-layer feed-forward neural network consisting of seven input neurons (corresponding to the predictors), one hidden layer with five neurons, and a single output neuron. This architecture balances model flexibility with overfitting prevention for our moderate dataset size, while maintaining comparable accuracy to deeper architectures [21]. Unlike for MLR, we did not apply log transformations to the variables because neural networks introduce their own nonlinearity to fit the data. To improve model results, we use robust scaling to normalize each variable with the median and interquartile range. This method is resistant to outliers such as populous urban areas.

Before model training, we checked for multicollinearity among predictors and confirmed that all variance inflation factors (VIFs) were within acceptable limits. Working-age population was included only when predicting market potential (m), as it represents the potential market scale rather than individual adoption behavior. Because p and q describe behavioral tendencies among consumers, we excluded population size from those models.

We first used a holdout approach by randomly dividing the ZIP code data into training and testing subsets (912 ZIP codes vs. 200 ZIP codes). The training data were used to fit the MLR and NN models, while the testing data were reserved for evaluating predictive performance. Model accuracy was quantified using the Root Mean Square Error (RMSE) on the test set. We then applied 5-fold cross validation on the entire dataset to validate our estimates of model performance and obtain a measure of model stability.

IV. Numerical Results

In this section, we present the study results. We begin by fitting the Bass model with EV registration data and exploring the fitted Bass model parameters with descriptive statistics. Then, we evaluate how demographic and socioeconomic factors predict these parameters using MLR and NN. Finally, we compare model performance and feature importance.

A. Bass Model Fitting

We fitted the Bass model for ZIP code areas in New York State with a working-age population above 1,000. Table II summarizes descriptive statistics for the Bass model parameters. To examine the reasonability of our fit parameters, we compare them with a previous study that used the Bass model to predict adoption of plug-in electric vehicles (PEV) in France and Germany, which found p values of 4.31×10^{-5} and 1.44×10^{-4}, and q values of 0.32 and 0.31 [10]. Our p and q values align with the scale of these reference values, while m, market size, varies based on the consumer population in the specific region.

TABLE II: Descriptive Statistics for ZIP Code-Level EV Adoption Bass Model Parameters

Parameter	p - innovation	q - imitation	m - market cap.
Mean	6.23×10^{-4}	0.407	5,808
SD	1.26×10^{-3}	0.158	5,482
Min	1.04×10^{-7}	6.94×10^{-18}	10
Max	4.91×10^{-2}	1	25,451

Note: mean and standard deviation are weighted by ZIP code working-age population.

These smaller magnitudes of innovation parameter p reflect a lower willingness to innovate, due to the large lifestyle change associated with switching to an EV. This trend can be found in studies of similarly innovative technology, such as solar photovoltaics in California [22]. The larger standard deviation for p results from a small subset of ZIP codes with relatively higher values. The imitation parameter q values fall within typical Bass model ranges, indicating that consumer imitation behavior of EVs is similar to other technologies.

Fig. 2 shows the forecasted EV adoption for ZIP codes 10021 and 10038 as typical examples of slow and fast adoption, respectively. Historical EV registration data is shown in red dots. ZIP code 10021 predicts that adoptions will continue increasing for several decades, while ZIP code 10038 is forecasted to reach market capacity by 2030. Most ZIP codes fall between these two extremes. For validation, we also fit the Bass model using county-level registration data (results not shown for brevity), which displayed similar overall trends but lower variability across regions.

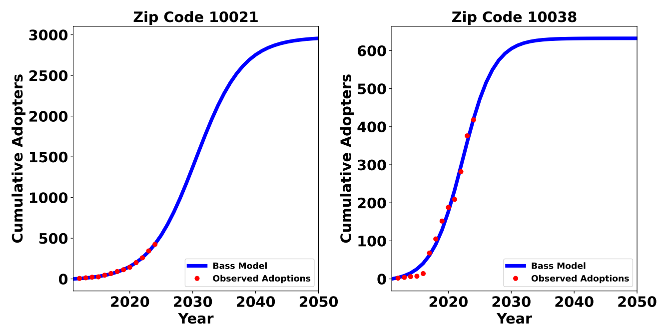

Fig. 2: Typical Bass model forecasts of EV adoption at the ZIP code level.

B. Predicting Bass Model Parameters Using Demographic Data

1) Multiple Linear Regression: To understand the variations of Bass model parameters across ZIP code areas, we first use multiple linear regression to predict the Bass model parameters. Table III shows the regression coefficients for each predictor.

For the innovation parameter p, mean commute time had the highest significance, where a 1-minute increase in average commute time was associated with a 6% decrease in p. In contrast, higher household incomes significantly increased p, where a 1% higher median income predicted a 0.58% higher p. For the imitation parameter q, ZIP codes with a higher median income showed less tendency to imitate, where a 1% increase in median income was associated with a 0.0494 decrease in q. Mean commute time had a significant positive effect on imitation, while college education rate had a strong negative correlation. Finally, for the market potential parameter m, larger working-age population and higher median income strongly predicted greater market capacity. A 1% increase in working-age population corresponded with a 1.19% increase in m, and a 1% higher median income corresponded with a 1.27% increase. Decreased commute times and increased charging ports per 100 people were significantly associated with higher market potential.

TABLE III: Regression Coefficients and p-values for ZIP Code-Level EV Bass Model Parameters.

Predictor	**ln(p)**	q	**ln(m)**
Working-Age Population (ln)	-	-	** 1.1899
Male-to-Female Ratio (ln)	0.0597	† 0.0477	* -0.3470
Median Age	* 0.0169	† -0.0014	** 0.0336
Median Income (ln)	** 0.5828	* -0.0494	** 1.2662
College Education Rate	** 2.7228	-0.0748	** -1.6334
Work from Home Proportion	1.3503	0.1983	* -2.1720
Mean Commute Time	** -0.0591	** 0.0059	** -0.0205
Charging Ports per 100 People	0.0990	0.0149	** 0.4648
Adj. R^2	0.231	0.086	0.574

Notes: † $p<$ 0.1; * $p<$ 0.05; ** $p<$ 0.01. The symbol p in "p-values" refers to statistical significance and should not be confused with the Bass model's innovation parameter p.

2) Neural Networks: Next, we discuss the results of using neural networks to predict the Bass model parameters. We use SHAP values [23] to evaluate the importance and directionality of each explanatory variable in predicting the parameters, as shown in the beeswarm summary plots in Fig. 3.

For predicting p, work from home proportion and male-to-female ratio had strong positive effects, while median age and mean commute time contributed strong negative effects. Charging ports per 100 people had a positive correlation with innovation. For predicting q, mean commute time was the largest contributor and had a positive correlation. Work from home proportion was also positively correlated with q, while median income and college education rate were negatively correlated. Lastly, for predicting m, working-age population had the largest SHAP values, as it directly captures the scale of the market. Other strong contributors included median income, which positively correlates with market potential, as well as work from home proportion and mean commute time, which negatively correlate with m.

C. Comparing Predictive Methods

1) Model Performance: Next, we evaluate the performance of MLR and NN using RMSE values. We first calculated RMSE on the holdout dataset, then applied 5-fold cross validation on the entire dataset to obtain more stable estimates of model performance and variance. Table IV reports the RMSE from the holdout dataset as well as the RMSE mean and standard deviation across all cross validation (CV) folds. NN improvement over MLR was calculated using mean RMSE from cross validation.

The NN consistently outperformed the MLR, implying non-linearity better captures demographic trends in consumer behavior. This performance gap was larger for the parameters with higher variance explained, p and m, and may continue to

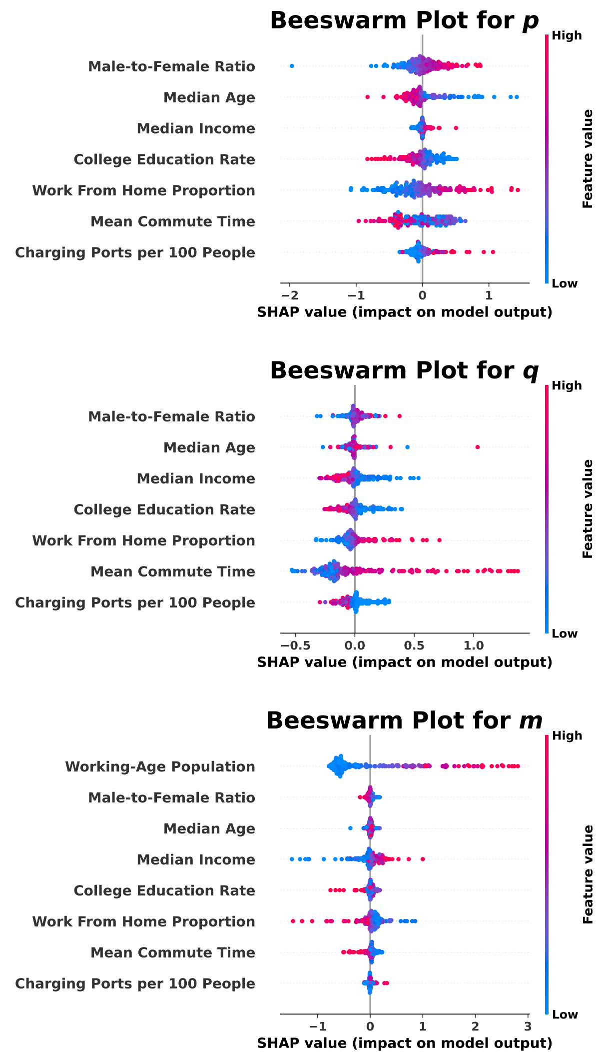

Fig. 3: Beeswarm summary plots for predicting p, q, and m at the ZIP code level using neural networks.

TABLE IV: Bass Model Parameter Prediction RMSEs

Model	**Statistic**	p - innovation	q - imitation	m - market cap.
MLR	**Holdout**	2.7×10^{-3}	0.1719	2,520
	CV Mean	2.3×10^{-3}	0.1565	2,521
	CV SD	1.4×10^{-3}	0.0138	258
NN	**Holdout**	2.6×10^{-3}	0.1637	2,355
	CV Mean	2.2×10^{-3}	0.1529	2,186
	CV SD	1.3×10^{-3}	0.0201	336.1
NN Improvement		4.35%	2.30%	13.3%

increase with predictors that account for a higher proportion of variance in the Bass model parameters. The largest contributors to NN RMSE were ZIP codes with relatively extreme Bass model parameter values, such as $p \approx 0.04$ and $q \approx 1$, with underprediction and overprediction occurring at similar rates. Future work could improve these forecasts by exploring further predictors, such as age structure, policy incentives, and social network metrics.

2) Model Consistency: Next, we interpret the MLR and NN results for p, q, and m using predictor relative importance shown in Fig. 4, which displays normalized semipartial correlations and mean absolute SHAP values averaged across all cross-validation folds. We also cross-reference correlation directions shown in Table III and Fig. 3 in the comparison.

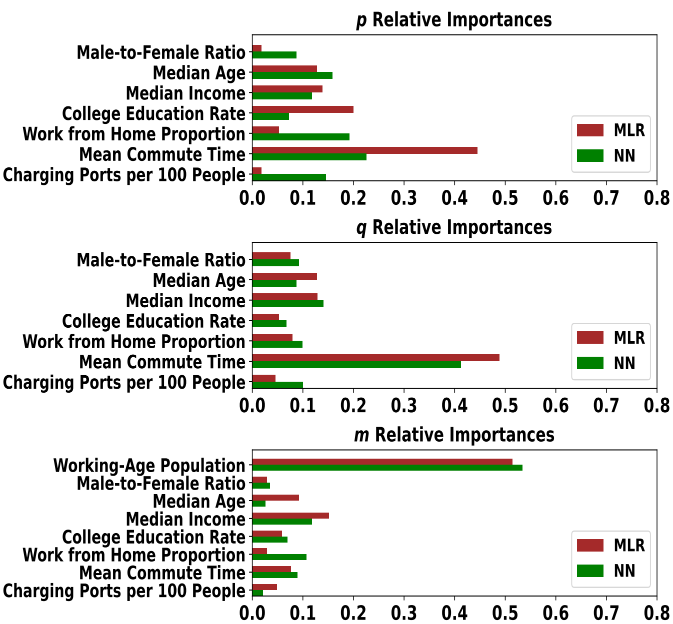

Fig. 4: Comparing MLR and NN relative feature importance for p, q and m at the ZIP code level.

We pay special attention to patterns where both models agree. p (innovation) was largely predicted by work patterns, median income, and college education. q (imitation) was the most difficult to explain on the ZIP code level with the current predictors, though MLR and NN agreed on variable directions that also oppose those of p, supporting that median age, median income, and mean commute time are important for predicting and distinguishing innovators and imitators. m (market potential) had the highest variance explained, with the strongest predictors being working-age population, median income, commute time, work from home proportion, and charging ports per 100 people.

In summary, both MLR and NN accurately capture the relationships between socioeconomic status, demographic characteristics, work patterns and EV consumer behavior at the ZIP code level, quantifying previously studied effects of affordability, charging accessibility, range anxiety, and education level. We find each method provides its own benefits: MLR offers an interpretable, directionally clear model for quick parameter estimation, while neural networks provide higher predictive accuracy by capturing non-linear relationships.

V. Conclusion

In this paper, we introduced a new methodology for predicting electric vehicle adoption at the ZIP code level, and assessed its performance with a case study for New York State. We used the Bass Diffusion Model to explain EV adoption with innovation, imitation, and market potential. Then, we employed multiple linear regression and neural networks to analyze how demographic, socioeconomic, and charging infrastructure influence these Bass model parameters. Comparing model performance and results, we find agreement on predictor correlations and relative importance, allowing both methods to make accurate predictions. This framework can be applied to other regions, even those without historical EV registration data, to analyze and forecast fine-grained EV adoption for load estimation, infrastructure investment, and power grid planning.

References

[1] U.S. Department of Energy. "Timeline: History of the electric car." (2015), [Online]. Available: https://www.energy.gov/timeline-history-electric-car.

[2] New York State Energy Research and Development Authority. "Top five reasons that drivers are contemplating the switch to an EV." (n.d.), [Online]. Available: https://www.nyserda.ny.gov/Featured-Stories/Top-5-Reasons-Drivers-Are-Choosing-EVs.

[3] Argonne National Laboratory. "EV model availability and sales." (2025), [Online]. Available: https://www.anl.gov/ev-facts/model-sales.

[4] "Impact of electric vehicles on the grid." (2024), [Online]. Available: https://www.energy.gov/eere/evgrid-assist-resources-reports-and-tools.

[5] C. R. Knittel and S. Tanaka, "Challenges to expanding EV adoption and policy responses," in *Handbook on Electricity Regulation*, Edward Elgar Publishing, 2025, pp. 405–447.

[6] W. Wang, Z. Ye, N. Yu, and P.-C. Chen, "Prediction of electric vehicle penetration and its impacts on distribution systems: A real-world case study in Maryland," in *2024 IEEE Conference on Technologies for Sustainability (SusTech)*, IEEE, 2024, pp. 390–396.

[7] C. Threewitt. "Reasons people don't buy electric cars (and why they're wrong)." (2025), [Online]. Available: https://cars.usnews.com/cars-trucks/advice/why-people-dont-buy-electric-cars.

[8] Y. Li, G. Ma, and L. Li, "Development of a generalization bass diffusion model for Chinese electric vehicles considering charging stations," in *2017 5th International Conference on Enterprise Systems (ES)*, IEEE, 2017, pp. 148–156.

[9] J. Massiani and A. Gohs, “The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies,” *Research in Transportation Economics*, vol. 50, pp. 17–28, 2015.
[10] A. Ensslen, C. Will, and P. Jochem, “Simulating electric vehicle diffusion and charging activities in France and Germany,” *World Electric Vehicle Journal*, vol. 10, no. 4, p. 73, 2019.
[11] F. M. Bass, “A new product growth for model consumer durables,” *Management science*, vol. 15, no. 5, pp. 215–227, 1969.
[12] Z. Li, H. Fan, and S. Dong, “Electric vehicle sales forecasting model considering green premium: A Chinese market-based perspective,” *arXiv preprint arXiv:2302.13893*, 2023.
[13] T. A. Becker, I. Sidhu, and B. Tenderich, “Electric vehicles in the United States: A new model with forecasts to 2030,” Center for Entrepreneurship & Technology (CET), University of California, Berkeley, Technical Brief 2009.1.v.2.0, Aug. 2009, Revision Date: August 24, 2009.
[14] T. V. Ramadoss, J. H. Lee, A. W. Davis, S. Hardman, and G. Tal, “Classifying electric vehicle adopters and forecasting progress to full adoption,” *npj Sustainable Mobility and Transport*, vol. 2, 2025.
[15] ATLAS Public Policy. “Evaluateny.” (2025), [Online]. Available: https://atlaspolicy.com/evaluateny/.
[16] U.S. Census Bureau. “American community survey 5-year data (2009-2023).” (2024), [Online]. Available: https://www.census.gov/data/developers/data-sets/acs-5year.html.
[17] U.S. Department of Energy. “Alternative fueling station locator.” (2025), [Online]. Available: https://afdc.energy.gov/stations.
[18] B. Bunce. “Car ownership statistics 2025.” (2025), [Online]. Available: https://www.consumeraffairs.com/automotive/car-ownership-statistics.html.
[19] M. Dwyer. “EIA projects global conventional vehicle fleet will peak in 2038.” (2021), [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=50096.
[20] F. Cage. “The long road to electric cars.” (2022), [Online]. Available: https://www.reuters.com/graphics/AUTOS-ELECTRIC/USA/mopanyqxwva/.
[21] Y. Meir, O. Tevet, Y. Tzach, S. Hodassman, R. D. Gross, and I. Kanter, “Efficient shallow learning as an alternative to deep learning,” *Scientific Reports*, vol. 13, no. 1, p. 5423, 2023.
[22] C. Dong, B. Sigrin, and G. Brinkman, “Forecasting residential solar photovoltaic deployment in California,” *Technological Forecasting and Social Change*, vol. 117, pp. 251–265, 2017.
[23] S. Lundberg and S.-I. Lee. “A unified approach to interpreting model predictions.” (2017), [Online]. Available: https://doi.org/10.48550/arXiv.1705.07874.