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Machine Learning Algorithms for Forecasting the Impacts of Connected and Automated Vehicles on Highway Construction Costs

Amirsaman Mahdavian
University of Central Florida

MACHINE LEARNING ALGORITHMS FOR FORECASTING THE IMPACTS OF CONNECTED AND AUTOMATED VEHICLES ON HIGHWAY CONSTRUCTION COSTS

By

AMIRSAMAN MAHDAVIAN
B.S. Amirkabir University of Technology (Tehran Polytechnic), 2013
M.S. Iran University of Technology, 2017
M.S. University of Central Florida, 2019

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ABSTRACT

A multitude of externalities affects transport efficiency and numbers of trips. Population expansion, urban development, political issues, fiscal trends, and growth in the field of connected, automated, shared, and electric (CASE) vehicles have all played prominent roles. While the market is keenly aware of the upcoming shift to the CASE vehicles, the transformation itself is reliant upon the development of technologies, customer outlook, and guidelines. The purpose of this research is to establish an overview of the possible network design problems, as well as potential consequences to vehicle automation systems by employing machine learning and system dynamics analysis. Finally, the cost of the required highway expansion for the critical links in the traffic network will be predicted. First, model was created for calculating traffic flow activity and necessitated highways to consider the impact of CASE vehicles between 2021 and 2050. Second, an economic evaluation outline was created to calculate optimum time and roadway improvement scenarios by a cost-prediction model using machine learning. Florida's interstate highways were employed as the subjects for the case study. The research showed that non-linear models had a better ability in the estimation of traffic flow, while linear models were better predictors of highway construction cost. These results also showed new technologies would add to traffic flow and capacity, with the increase in flow outpacing the increase in capacity. The consequences of this would be the level of service (LOS) of the current infrastructure decreasing. This study's results can assist discussion at the national and local level between government, networkers, automotive companies, tech-providers, logistics companies, and stakeholders for whom the practicality provided by the transportation infrastructure is crucial. This allows executives to create effective guidelines for subsequent transportation networks, ultimately accelerating the CASE vehicle network rollout to increase our current road network's level of service.

To my family…

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ARMA	Autoregressive Moving Average
ADAS	Advanced Driver Assistance Systems
ADSs	Automated Driving Systems
ACC	Adaptive Cruise Control
ARIMA	Autoregressive Integrated Moving Average
ABM	Activity-based Models
ACF	Autocorrelation correlogram function
ADT	Average daily traffic
AADT	Average Annual Daily Traffic
ACC	Adaptive Cruise Control
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASCE	American Society of Civil Engineers
ATRI	American Truck Research Institute
AV	Automated Vehicle
BEVs	Electric vehicle batteries
BR	Bayesian Ridge
BPNN	Back-Propagation Neural Networks
B2B	Business to business
B2C	Business to Customer
BP	Back Propagation
CASE	Connected, automated, shared, and electric

CAV	Connected and automated vehicles
CAT	Connected and automated trucks
CACC	Cooperative adaptive cruise control
CLD	Causal Loop Diagram
CPI	Cost performance index
CV	Connected Vehicle
DSHW	Double seasonality Holt-Winters
DT	Decision Tree
DOT	Department of Transport
DSR	Driving style recognition
DSRC	Dedicated short-range communication
EPA	Environmental Protection Agency
EVs	Electric vehicles
FNM	Fuzzy-neural model
FFS	Free flow speed
FLSWM	Florida Statewide Model
FCLASSIF	ANOVA F-value
FHWA	Federal Highway Administration
FDOT	Florida Department of Transportation
GPS	Global Positioning System
GIS	Geographic information systems
GDP	Gross Domestic Product
HCM	Highway capacity manual
I4	Interstate 4

IoT	Internet of things
I10	Interstate 10
ITS	Intelligent transportation systems
IEEE	Institute of Electrical and Electronics Engineers
KNN	K-Nearest Neighbors
LOS	Level of Service
Lidar	Light detection and ranging
MADT	Monthly average daily traffic
MLR	Multiple Regression Analysis
ML	Machine Learning
MAE	Mean absolute error
MAPE	Mean absolute percent error
MFCLASSIF	Mutual Information
MADTT	Monthly average daily truck traffic
NHCCI	National Highway Construction Cost Index
NASDAQ	National Association of Securities Dealers Automated Quotations
NN	Neural Network
NSF	National Science Foundation
NHTSA	National Highway Traffic Safety Administration
NPR	Nonparametric Regression
NFC	Near field communication
OEM	Original equipment manufacturer
OLS	Ordinary Least Squares
OD	Origin destination

PA	Passive-Aggressive
PV	Passenger vehicle
PACF	Partial autocorrelation correlogram function
PTMSs	Portable traffic monitoring sites
PCA-RBF	Principal component analysis - radial basis function
PCA-MLR	Principal component analysis - multiple linear regression
RSUs	Roadside units
RF	Random Forest
RFE	Recursive Feature Elimination
Ridge	Ridge Regression
RMSE	Root mean squared error
RFPs	Requests for proposals
SGD	Stochastic Gradient Descent
SAE	Society of Automotive Engineers
SAV	Shared Automated Vehicles
SVR	Support vector regression
TaaS	Transport-as-a-service
TTMSs	Telemetered traffic monitoring sites
TDM	Travel-demand modelling
TAZ	Transportation analysis zone
UCM	Unobserved component model
USDOT	U.S. Department of Transport
VSSA	Voluntary Safety Self-Assessment
V&V	Verification and validation

V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
VMT	Vehicle Miles Traveled
VTTS	Value of Time Savings
WTP	Willingness to Pay
Wi-Fi	Wireless fidelity
WTP	Willingness to Pay
ZOV	Zero occupant vehicles

CHAPTER ONE: INTRODUCTION

Overview

Automation and increased connectivity of personal vehicles could exacerbate current transportation problems driven by financial incongruities. Particularly the number of trips has increased due a plethora of disruptive forces, such as the emergence of connected automated vehicles (CAVs), urbanization and globalization, social and demographic changes, economic workforce changes, environment, and energy trends, and political and fiscal trends. Figure 1 shows the upcoming disruptive forces on the future transportation networks.

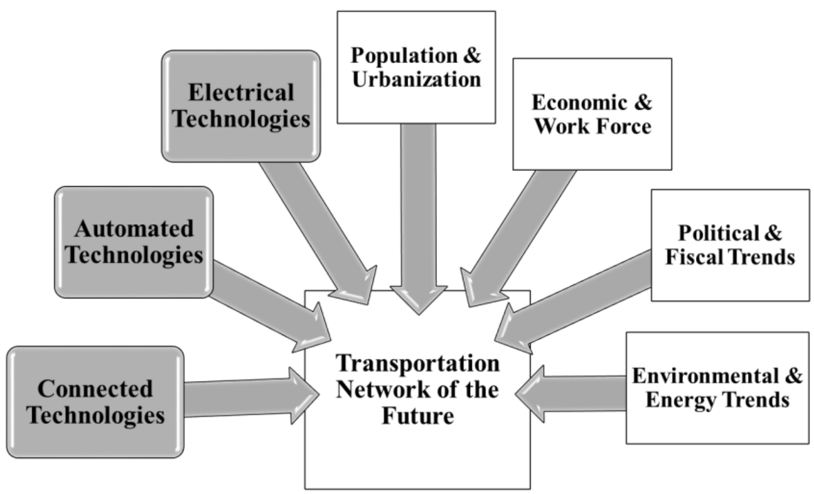


Figure 1: Upcoming disruptive forces on future transportation networks

Increased vehicle miles traveled for connected, automated, shared, and electric (CASE) vehicles emergence is due to consumer convenience, ease of use, higher safety levels, and consumers such as children, disabled individuals, and seniors who benefit from these factors. These changes happen quickly, and even though the evolution to a new mobility system may seem distant, market forces bring it closer by the day.

Considering both external and internal factors influencing the transportation network, the need for a solution to the United States' traffic gridlock is apparent. One must be inherently cautious when appraising the risks factors of the various forces involved with the efficiency of the transportation network. Traffic congestion has undesirable externalities on the quality of the life of the people it affects, decreasing human productivity, reducing driver health through increases in stress and fatigue. The issue compounds when you take into account that Americans drive nearly 3 trillion miles per year, which means a good deal of your life is behind a wheel of a vehicle. This is potentially dangerous, as increased time in a vehicle is accompanied by increased probability of crashes and increases air pollution. Automobile accidents lead to 34,080 fatalities in the US in 2012 alone. (USDOT 2015). Of those accidents, 90% were at least somewhat associated with driver error (McKinsey 2016). In 2012, the U.S. petroleum consumption for road transportation was ~11 million barrels per day: accounting for ~60% of the total U.S. petroleum consumption (Davis, Diegel, and Boundy 2014). The average commuter reported being delayed by on average 38 hours per year due to traffic congestion (Schrank, Eisele, and Lomax 2012).

To counter these megatrends that threaten traffic network numerous solutions are proposed: smart transportation, fleet conversion, shared mobility, and highway expansion. These Smart cities will be at the epicenter of IoT utilization employing CASEs, including smart transportation. Initially the use of CASE will be insulated and sector-specific (vertical). However, a diffusion of the technology will occur over time as a larger number of industries employee IoT to compete. Cities will compensate by creating horizontal IoT platforms, employing individual use cases that maximize performance, interconnectivity, and productivity across multiple sectors. As mobility is the key to competition in modern cities: Intelligent mobility is a system whose primary function is to connect people, places, and goods across all transport vectors. (McKinsey & Company 2016). As for fleet conversion, commercial and government vehicles make up a significant portion of the vehicles found on city streets, composing more than 25% of traffic. USDOT (2015) reports the vehicles in use as follows – government: 3,150,000, business: 3,025,000, police: 212,000, unassigned: 2,709,000, utilities: 815,000, and rental: 2,738,000. It is of particular interest that a low market penetration rate of CAVs will not lead to the expected benefits (a traffic capacity increase due to CAVs). A suitable entry point for growing market share would be through Taxis, commercial, and government vehicles. This would work to familiarizing the populace with ACES vehicles' technologies, allowing trust in the safety aspects of CAVs, and inspire the values of shared mobility transport. The process of switching or retrofitting these vehicles will occur on different timelines.

To achieve the goal of a shared mobility culture and ACEs vehicle it is important to diminish the desirability of CAV travel while simultaneously marketing the allure of public transit, dampening urban sprawl, and limiting the amount of driving that people can do, or a combination of the above. Just because a new technology hypothetically appears beneficial does not guarantee that consumers will adopt it. Many of the advantages of CAV can be achieved by using lower cost per mile shared mobility. Years of Automotive marketing has led most citizens to consider owning (and driving) their own vehicle as a status symbol, and a rite of passage. These same individuals fail to see the American dream as an eroding ideal. Taking these factors into consideration, one may find easier market saturation in countries with a less old-fashioned automobile ethos.

One would be hard pressed to find challenges against smart transportation, CAV fleet adaptation, and improvement of the culture around shared mobility to increase the efficiency of roadways. However, to integrate more frugal methods temporarily would make society highly dependent on existing physical infrastructure systems. As physical infrastructure is crucial to all walks of life: health care, public safety, trade, industry, and economic productivity, any disruption of existing transportation infrastructure services could have severe economic consequences on the well-being and the of the areas that they serve. Freeway infrastructures' expenditure is a tantamount responsibility of directors that lead state highway agencies. Highway developments involve elevated risks due to the complexities of these undeveloped environments. These unknowns can massively escalate the amount of work and cost (Zhang 2017). A multitude of elements may impact cost overrun in highway developments, including (but not limited too) project difficulty, duration, contractor experience, weather, site accessibility, economic situations, and local political and societal conditions. Budget discrepancies are challenging for highway contractors because they can result in bid or profit loss (Shahandashti and Ashuri 2016). They are also difficult for state Departments of Transportation as they can result in budgetary exigences, delays, cancellations, and an overall unreliability in scheduling. These problems can be mitigated if highway costs can be more accurately predicted (Shahandashti and Ashuri, 2016). Artificial neural networks (ANNs)(Wilmot & Mei 2005) and regression models (Wilmot and Cheng 2003) are the two most widely used methods for accurate highway construction cost prediction. Several studies have declared that ANNs outperform regression models.

When considering all architectural substructures, the cost of roadways in the United States was predicted to be approximated $2.6 trillion (based on US. BEA data). The requisite of infrastructure financing in the U.S. is an ongoing issue for officials as they continually are tasked with demand for infrastructure enhancements. Consequently, political parties across the aisle are focused on the issue of infrastructure costs at the local and federal level (PWC 2016). The Federal government encounters two major hindrances in improving the road system: one being the disparity between investments and the need for highway construction, and one being the cost of existing projects that already exceeds original estimates.

In 2017, these funding issues were already anticipated by the ASCE, who gave U.S. highways a grade of D+ based on transportation infrastructure. These speculated gaps are anticipated to cause significant losses in the U.S. economy. By 2025, the loss to the GDP is predicted to be roughly $4 trillion. By 2040, the loss is expected to reach over $18 trillion. While local government is attempting to solve these problems, there remains a lack of investment capital to follow through. It is predicted only 16% of U.S. cities would be able to pay for the needed projects through self-funding sources (Automated and Autonomous Spatial Mobility, 2018.

Reviewing the previous research

To date many of the articles published on the impact of CASE vehicles on the traffic network only speak to at most a few issues in relative seclusion. Research on the mid and long-term influences of ACES vehicles can be divided into two principal categories. First, there are specific analyses centered on relatively small datasets that result in strongly supported results and are bounded to marginal issues. Second, there are more contemplative arguments that include a thorough set of issues and hardly build on existing structures of the transportation system. Many safety studies have explored the effects of ACES vehicles, such as: the effectiveness of traffic flow (Spieser et al., 2014, Arvin. Et al. 2019, Mahdavian et al. 2019a, Lovejoy 2013, Fagnant and Kockelman 2013, Kok, et al. 2017, and McKinsey 2016) or the reduction in time needed for travel (Cyganski et al. 2015, Gucwa 2014, Childress et al. 2015, Wadud et al. 2016 and Litman 2017, Sonia Baee et al. 2019), and last but not least, new categories of users such as Children, Seniors, and Impaired People (Rodier 2018, Harper et al. 2016, Trommer, et al. 2016, Wadud et al. 2016, Fagnaut and Kockelman 2015, Sivak and Schoettle 2015, Childress et al. 2015, Brown et al. 2014, Kidando et al. (2018) and Fagnaut and Kockelman 2014).

Gap and the Questions

Some of the counter considerations have been paid to consequences such as social variations, influences on outlooks about changes to land-use, public transit, and the influence on local planning (Chin, 2014, Coughlin and Yoquinto, 2015, Nazari et al. 2019, Lee et al. 2018). Articles that give a more holistic approach to the impact of the emerging technologies of traffic may present valuable insights, they are unfortunately non-quantifiable and therefore difficult to incorporate into calculations:

1) How would CASE vehicles impact the number of trips of passenger vehicles in the mid- and long-term?
2) How would the CASE vehicles influence the number of trips of trucks in the mid- and long-term?
3) What is the worst and the best LOS scenario of this new technologies in the mid- and short-term on the traffic network?
4) What is the cost to expand a network link that is experiencing a low LOS in the mid- and long-term?

5) How much should the alternative solutions to highway expansion cost to meet the investment gap in construction and transportation projects?

Goal and Objectives

This research strives to recognize some of the consequences of CASE vehicles at the system level, by first developing a traffic flow prediction model considering the impact of CASE vehicles, and second, generating a highway expansion cost-prediction model to enhance traffic capacity. Overall, the study goals are:

Step 1. Create a highly accurate forecasting model for passenger vehicles traffic volumes using different types of nonlinear/linear algorithms that incorporate machine learning

Step 2. Generating a highly accurate prediction model for trucks traffic volumes employing the aforementioned algorithms

Step 3. Establishing a comprehensive range of possible CASE vehicles scenarios of their impact on the traffic network employing an extensive literature.

Step 4. Developing a highly accurate prediction model to forecast the highway construction cost items using the stated algorithms

Using the aforementioned steps, the model could accurately predict the cost of the network link expansion that would be affected by CASE vehicles, allowing for a cost benefit analysis.

Principal findings

This research employed FDOT historical traffic records as a case study to assess the projected standards. The study's findings confirm CASE vehicles will increase traffic flow along with highway capacity with the increase in flow being higher than the increase in capacity- shared ownership of passenger vehicles have been found to mitigate these impacts to some degree. The growth in projected demand for CASE is not accompanied by increased capacity resulting in even more significant congestion. Expediency is key when planning infrastructure for the adoption of CASE vehicles, thereby avoiding projected traffic flow and highway capacity congestion. This study provides valuable metrics, showing the value of CASE vehicles, and can be employed as a tool to increase engagement with traffic network stakeholders (including the government and private sector). This will allow those stakeholders the time to prepare critical regulations and policies in preparation for CASE vehicles.

Dissertation Structure

This dissertation will be composed of 7 total chapters. Chapter One offers a synopsis of the existing traffic network in the U.S., and the subsequent questions that this research seeks answers for. Chapter 2 affords a comprehensive examination of preceding research in traffic volume prediction, CASE vehicles, and roadway construction cost prediction models. Chapter 3 shows the methodology including gaps, contribution, scope of study, objectives, aim, data structure, and research general design are conducted. The data gathered is employed in chapter 4 to develop modeling strategies. The pipeline of the study consisting of data preprocessing, feature selection, model creation (including various linear and non-linear algorithms), parameter optimization, and evaluation of the model are represented in the modeling development section. Chapter 5 highlights the utilization of the modeling method to carry out a traffic and cost analysis on various highway in Florida and tallying the results. Chapter 6 offers a thorough examination of the 4-step model and the developed framework of the study. Finally, chapter 7 gives us a conclusion of the study, potential research broadenings, and presents suggestions that will be useful for policy- and decision-makers in public and private sector.

CHAPTER TWO: LITERATURE REVIEW

Overview

Research on the mid and long-term impacts of ACES vehicles can be divided into two fundamental categories. First, there are precise analyses based on small sets of data that result in strongly supported results, which are bounded to minimal issues. Second, there are thoughtful arguments on a more comprehensive set of issues that hardly build on existing structures of the transportation system. Many studies have explored the effects of ACES vehicles on safety, shared mobility, efficiency of traffic flow, value of travel time savings, and new categories of users. Studies investigated several factors that ACES vehicles would affect including safety and car-sharing (Spieser et al., 2014, Arvin. Et al. 2019, Mahdavian et al. 2019a, Lovejoy 2013, Fagnant and Kockelman 2013, Kok, et al. 2017, and McKinsey 2016) or on the efficiency of traffic flow (Fagnant and Kockelman, 2013, Arvin et al. 2019), or on the reduced travel time (Cyganski et al. 2015, Gucwa 2014, Childress et al. 2015, Wadud et al. 2016 and Litman 2017, Sonia Baee et al. 2019), and last but not least, new categories of users such as Children, Seniors, and Impaired People (Rodier 2018, Harper et al. 2016, Trommer, et al. 2016, Wadud et al. 2016, Fagnaut and Kockelman 2015, Sivak and Schoettle 2015, Childress et al. 2015, Brown et al. 2014, Kidando et al. (2018) and Fagnaut and Kockelman 2014).

To a lesser extent there has been some consideration paid to less-quantifiable consequences, such as behavioral fluctuations, impacts on attitudes about changes to land-use, public transit, and bearing on regional planning (Chin, 2014, Coughlin and Yoquinto, 2015, Nazari et al. 2019, Lee et al. 2018). Studies that provide a larger overview of the impacts on the traffic network are limited. Fagnant and Kockelman (2014), Spieser et al. (2014) and Lovejoy (2013) showed in their case studies that shared-vehicle mobility can provide for the mobility demand of a city with a much fewer number of vehicles. Burns et al. (2013) and Mahdavian et al. (2019b) applied analytical and simulation models to investigate a “new mobility system” based on shared, automated vehicles finding significant economic, environmental, and consumer benefits in such a system. Townsend (2014), Milakis et al. (2015), and Gruel, Stanford (2016), and Mahdavian et al. (2019b) devised multiple scenarios to observe the consequences that ACES vehicles had on the traffic network. Their scenarios are built along the dimensions of ownership models, the behavior of the users, technological development, and regulations and policies. Sterman (2000) developed a transportation model reflecting the attractiveness of making trips as a primary role. In his model, the attractiveness of making trips with cars is a function of travel time, public transit fares, desired travel time, and adequacy of public transit.

This research strives to recognize some of the consequences of CASE vehicles at the system level by first developing a predictive traffic flow model that considers the impact of CASE vehicles, and second, generating a highway expansion cost-prediction model to enhance traffic capacity. So that, to cover the literature, this section includes 4 subsections, namely, passenger vehicles traffic prediction models, trucks traffic prediction models, CASE vehicles and the traffic network, and lastly, highway construction cost prediction models.

Step 1: Traffic prediction model – Passenger vehicles

(Regarding this section, the Author employed the studies reviewed in the article published by author: Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Yuan, J.S. and Oloufa, A., 2021c. Automated Machine Learning Pipeline for Traffic Count Prediction. Modelling, 2(4), pp.482-513.)

Traffic flow prediction is a crucial tool for transport authorities and drivers to create a more efficient traffic management and minimize traffic congestion and to improve the efficiency of the traffic network. The field of traffic predictions is often categorized into 3 subsets; those that are short-term or long term, and those that are medium-length predictions. Short-term predictions include anything in the range for 5-30 minutes in the future. After 30 minutes, predictions for up to several hours into the future can be considered medium-term predictions. Finally, long term predictions include periods of more than a day into the future. In order to achieve these long-term predictions, different models are often employed. These include using NN's, models based on demand for travel, and econometric regression-based models (Kelly et al. 2017).

A. Short- and mid-term prediction models: Since the 1980s, scholars focused more on short or medium-term predictions and their associate with currently ongoing traffic (Okutani 1984). Algorithms with NNs are commonly incorporated into traffic predictions due to their success in considering non-linear datasets and appropriately modeling the behavior of traffic flow. (Zheng et al. 2006) used a combination of methods in the forecasting of traffic flow; including both neural networks, and Bayesian modeling. Outside of the neural networks, other feature-based approaches that have been widely utilized include Kalman filter (Mahdavian et al. 2021b), time series modeling, support vector regression (SVR) (Wang 2013), k-nearest neighbor (Wu 2015), hybrid modeling (Guo et al. 2014 and Kumar et al. 2015) and lastly gradient boosting tree regression (Sun et al. 2003).

B. Traffic volume prediction models: Regarding Econometric regressions, Marshment et al. researched econometric practices in traffic forecasting in a 1-to-5-year period for the Oklahoma Turnpike Authority employing an autoregressive integrated moving average (ARIMA) and regression modeling approaches in an effort to predict changes in traffic volumes. Bian et al. They employed an unobserved component model (UCM) as an econometric model to predict monthly traffic volume with several temporal aspects.

Travel-demand modelling (TDM) is commonly employed in long-term forecasting. This method utilizes ravel characteristics and operation of transport services, based on land-use types as well as social and economic elements. Travel demand modeling is most performed by a four-step process: trip generation, trip distribution, mode choice, and lastly, trip assignment. Using this an annual average daily traffic (AADT) can be produced. An advanced type of TDM is activity-based models (ABM) in which the focus is individual's plan and schedule to replicate actual traveler decisions. ABM on average allows for more accurate forecasts, particularly when one wishes to diversify to a broader range of strategies and policies.

While both TDM methods demonstrate accurate AADT inference, they are time-consuming to produce, and necessitate an inordinate amounts of data collection, resources, and modeling skills. Therefore, TDM results are useful in transportation planning decisions, as it is a continual challenge to derive more detailed information to advance traffic management.

Khatib et al. (2001) revealed that the types of centroids employed for traffic zone censuses could have a significant impact on the quality of TDM results. Mustafa et al. (2010) indicated that a higher specificity model (one using smaller units) can provide a more accurate estimation of AADT. Zhong and Hanson (2018) created a method considering geographic information systems (GIS) to forecast traffic counts. Yang et al. (2013) investigated the uncertainty of variables used in combined TDM dealings and the classic four-step model in traffic forecasting to determine the level of confidence on the model outputs along with identifying and treating uncertainties from inputs and parameters separately to enhance the accuracy of the models. Wang et al. (2013) presented a tool to estimate highway AADT using a TDM. By applying the TDM, their study included land-use data at the parcel level- allowing them estimate trips produced from or to each parcel. The trip assignment was carried utilizing free-flow travel times. The trips were then entered into a trip distribution gravity model at the parcel-level. Results showed the proposed model generated 52% MAPE, 159% lower than MAPE from regression models developed for the same area as the benchmark Wang et al. (2013).

Nonparametric Regression (NPR) regression is based on data-driven models emphasizing fundamental structures while not necessitating elucidation of the relations between inputs and outputs. The primary purpose of these methods is to identify data clusters with characteristics like the current state for a specific interval of prediction and then to define the same prediction from these. In this way, it is not required to consider a forecasting equation expressed mathematically by a set of parameters, as it happens to the parametric approach. The term “non-parametric” is misleading, as these models still have parameters. It is just the parameters are not set. Instead, they are scalable to fit the purpose of the study. Usually, more data is required to use a non-parametric model. However, ultimately, they may be more appropriate for predicating a dynamic process such as traffic flow.

Neural Networks (NNs): The neural network algorithm is the most used model in traffic prediction due to its excellent capability of appropriating non-linear datasets of data that undergoes real-time changes. The NN model considers connections between the data that may not be apparent at first glance, allow it to generalize an accurate prediction due to its non-parametric and nonlinear features. Neural networks were viewed as a black box and not straightforward to fully interpret since they have multiple complex neuronal structures and non-linear functions. Due to the amount of data, and quick variations within traffic patterns, they are inherently difficult to be modeled by linear algorithms. However, NN models allow an approximation of any degree of complexity without prior knowledge of problem-solving, and due to such has grown in popularity for traffic flow forecasting models Mustafa et al. (2010), and Yang et al. (2013). Yin et al. (2002) generated a fuzzy-neural model (FNM) to forecast traffic flow in an urban network, showing that the FNM more accurately predicted results than the Back-Propagation Neural Networks (BPNN) model. Vlahogianni et al. (2025), successfully predicted traffic flow patterns employing a genetic algorithm (GA) based multilayered structural optimization strategy to determine suitable NN structure.

Ratrouta and Gazdera (2014) employed two types of ANNs, comparing them with traditional parametric method of linear regression analysis. ANNs showed increased accuracy VS. linear regression method in daily traffic prediction. Fu and Kelly (2017) employed NN, logging-linear, and Ordinary Least Squares (OLS) to predict traffic volume. The comparison of results shows that the NN method with a MAPE of 28.58% outperforms logging-linear model with a 52.49% MAPE, and OLS with a MAPE of 66.6%. Duraku and Ramadani (2019) developed two combined models, principal component analysis - multiple linear regression (PCA-MLR) and principal component analysis - radial basis function (PCA-RBF), for projecting traffic volumes. Analysis of the results of these models shows that the PCA-RBF model giving more accurate results. ANN-based forecasting can approximate any function -including nonlinear functions- it has limitations, including difficulties interpreting operations of the model, and determining suitable network structure.

The KNN, or K-Nearest Neighbor, is one of the more commonly applied NPR approaches used. Forecasting is done using the k events of the historical database most like the current traffic situation, and then a weighted average is used to generate the results, giving more weight to events that are closer to the situation being studied. Based on research by Smith et al. (1997), the KNN technique has been found to be not only fast, but it performs better than some more simplistic methods of traffic volume prediction. Davis and Nihan's (1989) proposed KNN approach gave an alternative method for parametric regression approaches in short-term motorway traffic forecasting. They examined KNN results with the results of simple univariate linear time series forecasts to deal with the advantage of the NPR. Smith and Demetsky (1997) showed the advantage of the KNN approach (for forecasting the traffic volume) dealing with a variety data types and sizes and examining the distinctions between NN and ARIMA models. Pompigna and Rupi (2018) compared the precision of three parametric and non-parametric prediction models (K-NN regression model, Gaussian maximum likelihood model, and double seasonality Holt-Winter's exponential smoothing model), using data obtained from Italian highways. The parametric double seasonality Holt-Winters (DSHW) model and the KNN provided the best results.

The algorithms: Random Forest (RF), Decision Tree (DT), and Support Vector Regressor (SVR); are excellent for NPR models utilized traffic volume prediction. Decision tree (DT) allows for a highly interpretable traffic data model on the traffic data, which can be used to show traffic patterns (Alajali et al. (2018). Liu and Wu (2017) advocated the use of the random forest algorithm to forecast traffic due to its favorable generalization capabilities. Support Vector Regressor (SVR) has also been leveraged for modeling traffic volume and has proven superior performance when compared to linear models (Deshpande et al. 2016).

C. Leading independent variables (predictors): A variety of studies show linear regression models that use roadway characteristics and socioeconomic factors can estimate AADT with acceptable results (Wang et al. 2013, Doustmohammadi et al. 2017, Lowry et al. 2014, Zhao 2014). Other research has attempted using a variety of independent variables (predictors) including socioeconomic variables (population, employment, personal income, vehicle registrations), road characteristics (the total number of lanes and location type) to predict the traffic volume for high volume urban highways (Doustmohammadi et al. 2016, Doustmohammadi et al. 2017, Lowry et al. 2014, Zhao et al. 2001). Tennant (1975) created a model of traffic volume evaluation for use in more rural areas which also took into account these socio-economic variables as well as land data, and principles of traffic generation in Kenia employing Multiple Regression Analysis (MLR). Neveu (1982) developed several models that employed elastic parameters in MLR to predict traffic volumes as AADT for a variety of road types. The Variables included in model are population, number of households, vehicle ownership, and employment (Neveu 1982).

Duddu and Pulugurtha's (2013) generated a model employed statistical methodology as well as ANN in predicting AADT, which was based on land-use in the city of Charlotte (NC). Fu and Kelly (2017) used road type, residential and working density, speed limit, distance to motorways, region types, vehicle ownership ratio, and overall population in the creation of their NNs for traffic counts. Raja et al. (2021) developed a model using linear regression using known AADTs and the collection of socioeconomic and spatial variables to predict the AADT. This model relied on five independent variables: population, number of households, employment, employment rates, and major highway access (Raja et al. 2021).

Step 2: Traffic prediction model – Trucks

(Regarding this section the author employed his published study: Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Eluru, N. and Oloufa, A.A., 2021d. A Universal Automated Data-Driven Modeling Framework for Truck Traffic Volume Prediction. IEEE Access, 9, pp.105341-105356.)

Traffic volume prediction has become of particular interest with the recent advancements in incorporating ITS, or intelligent transport systems, in traffic forecasting. As traffic sensor technology advances to incorporate more variables, a greater volume of data is now collected, resulting in a new digital data age of automobiles. Consequently, transportation management is undergoing a paradigm shift, employing more data-driven methods. In contrast current estimation and freight modeling tools have become increasingly antiquated, failing to meet of today's demands. Because of the sheer amount of data and its complexity, it is essential to reassess traffic volume forecasting with the use of deep-structured non-linear models, that take full advantage of the volume of data of data available. Thus far, the forecasting of freight traffic uses methods that fall into either approaches that are vehicle based or commodity based.

As before, freight travel predictions are also can be classed as either short, medium, or long-term forecasting. Short-term forecasting is predicting five to thirty minutes out, medium-term forecasting goes up to several hours in the future, and finally those predictions that start to extend out beyond a day are long-term. Traffic volume falls under the category of long-term prediction and is performed using multiple approaches not limited to, modeling based on travel demand, NN models, and econometric regression (Okutani, 1984).

From the 1980s onwards academics have investigated short and mid-term traffic flow for traffic prediction (Mahdavian et al. 2019b). Neural networks have received considerable attention in traffic forecasting due to their modeling of more dynamic processes. They can also handle more uncertain variables. To give an example, Zheng et al. (2006) tried an approach that successfully used neural networks and Bayesian methods and provided accurate predictions. Other models are available that have been heavily studied in this field. Those include those that utilize Kalman filter (Guo et al. (2014)), models that are based on time series (Kumar et al. 2015, Sun et al. 2003), SVR models (Wang et al. 2013), k-nearest neighbor (as discussed) Wu et al. (2015). As stated, more detail is provided on these models in Vlahogianni et al. (2005) and Lippi et al. (2013).

Multiple states have developed models for use in freight movement forecasting, most of these are commodity-based. In Indiana, the state collected data on the flow of goods to create a massive directory based on data from a 1997 survey of commodity transport. This directory was then used in predictions for freight traffic for the whole of Indiana.

On the regional level of freight transport, prediction models are generally either dependent on the commodity or the vehicle type. Models that consider the vehicle type classify vehicles with a conducting mode split. They also consider trip generation. Models that are based on the commodity being transported, consider the average payload estimation based on both the number of trucks and the worth of the goods being transported. Use of the models is intended to predict truck travel based on mode or level of travel.

On average vehicle-based methods can offer predictions from a dataset that include historical land-use and socioeconomic data (Boile, 2000). These models can be further categorized into subgroups on the object of their use, namely: GIS-based, traffic count, those that offer gravity based self-calibration, partial matrix techniques (Mustafa & Zhong, 2011), heuristic models (Janssens et al., 2005), facility forecasting techniques (Cervero, 2007), etc. One of the more popular is the traditional four-step model, accomplished using a combination of the above techniques (as needed by the respective agency). This is the current model employed to forecast travel in a given area- according to a variety of factors such as type, time of day, route take, and others.

A. MATHEMATICAL VEHICLE-BASED TRUCK TRAFFIC PREDICTION MODELS: Algorithms are commonly used for the prediction of traffic networks (Meyer et al. 2001). They tend to be both expansive and highly complex; and use predetermined hypotheses. As a result, they could be readily improved through the incorporation of programming methods that reduce the number of calculations needed on the part of the user (Friesz 2000). More recently, forecasting has involved the use of models that emphasize traffic efficiency. Real-time traffic data have been employed by using the latest technology through ITS based detection systems. Traffic flow prediction using vehicle counts as well as variables that incorporate both roadway capacity and the impact of traffic on the environment allow for either short or mid-term forecasts (Do et al., 2019; Duan et al., 2018; Kim & Hong, 2015). For long-term predictions, the results are sorted based on the average daily traffic (ADT), the monthly ADT (MADT), as well as average ADT (AADT). These forecasts are made for subsets of vehicles as well, considering historical data for exploration (Bagheri et al., 2015; Roh et al., 2015; Tsapakis et al., 2013). Based on the parameters used, the methods utilized may be categorized differently. Categories include those that are parametric vs non-parametric, and naïve methods (Mahdavian et al. 2021d).

A1. Parametric Models (Mahdavian et al. 2021d): The structure of a parametric model is predetermined, and the parameters of the model must be determined by utilizing data. The intrinsic knowledge of traffic processes within traffic simulation models can be captured in these structures. Overall, a lower quantity of data is required compared to non-parametric models. Traffic simulation models utilize the OD traffic matrix by considering the theory of network equilibrium. Traffic simulation models consist of macroscopic, microscopic, and mesoscopic modeling. In macroscopic modeling the global variables of a roadway network are analyzed, including mean speeds, densities, and traffic flows. Macroscopic models are also known as kinematic wave models, and trip generation rates and multiple linear regression models are commonly used methodologies. This approach was termed the LWR model and introduced by Lighthill & Whitham, 1955. Meanwhile, in microscopic modeling the interactions between private vehicles are simulated based on the longitudinal (car-following) and lateral (lane-changing) behavior of vehicles in a network system. Kometani and Sasaki 1959 introduced the first car-following model, derived from Newton's equations. Lastly, mesoscopic modeling includes a blend of macroscopic and microscopic modeling (Burghout et al., 2005).

B. LEADING PREDICTORS FOR TRUCK VOLUME PREDICTION (Mahdavian et al. 2021d): Al-Deek et al. (2000) reported the primary factors affecting truck volume to be the amount and direction of cargo vessel freight and the weekday of operation. Furthermore, Tsapakis et al. (2013) developed 12 models based on regression and Bayesian analysis using data taken from 67 continuous data recorders to predict the AADT for heavy-duty trucks. Roadway functional class, population density, and spatial location had the highest importance factors in the created daily truck traffic prediction models. Golias et al. (2005) presented a statistical approach using a stepwise linear regression to create predictive models for estimating truck volumes. The number of employees estimated sales volume, while the number of establishments based on the standard industrial classification for the region were considered to be good predictors of truck volumes. Lu et al. (2009) also developed a truck volume prediction model, with results revealing that both linear and compound growth models fit truck traffic growth trends well. However, growth rates estimated from less than six years of data may exhibit considerable variation, which can lead to significant errors in pavement response prediction. In addition, roadway characteristics and socioeconomic factors cannot be used to directly predict truck traffic growth rates with high accuracy. However, some factors are strongly associated with traffic growth, and can assist pavement designers in selecting appropriate defaults for traffic growth rates. These factors include population density, population density growth rate, land use, and highway functional classification (Lu et al. 2009).

Step 3: Traffic CAVs CLDs – Scenario development

Regarding this section the author employed his published publications: *Mahdavian, A. Shojaei, A., Oloufa, A. 2019a. Service Level Evaluation of Florida's Highways Considering the Impact of Autonomous Vehicles. Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC). And: Mahdavian, A., A. Shojaei, and A. Oloufa. 2019b. Assessing the long-and mid-term effects of connected and automated vehicles on highways' traffic flow and capacity. International Conference on Sustainable Infrastructure 2019: Leading Resilient Communities through the 21st Century. Reston, VA: American Society of Civil Engineers. And also: Mahdavian, A., Shojaei, A., Mccormick, S., Papandreou, T., Eluru, N. and Oloufa, A.A., 2021a. Drivers and Barriers to Implementation of Connected, Automated, Shared, and Electric Vehicles: An Agenda for Future Research. IEEE Access, 9, pp.22195-22213.)*

The benefits and opportunities presented by CASE vehicles more than compensate for challenges against them, as their adoption that will ultimately lead to new behaviors in the traffic network. This section reviews studies conducted by academia and the private sector on the implementation of the network, barriers to market entry, and drivers of CASE vehicles, mainly in the U.S.. The speed and nature of transitioning to a well-penetrated market of CASE vehicles is not well understood (Fagnant et al. 2014). The transition depends largely on the markets technological maturity and sociological makeup of the consumers (i.e., acceptance rate), as well government policies.

A. TECHNOLOGICAL MATURITY: Technological development is the initial and main step in implementation of a CASE vehicle market. With access to the technology and the proper existing network, other steps and regulations can lay the groundwork for the transition preparing it for presentation to consumers. McKinsey and Company (2017) assert that the automobile sector is undergoing a digital revolution with waves of new business models. Atkins (2017) reported the emergence of CAVs as one of the most compelling developments ever to affect cities. Accordingly, CAVs and electric vehicles (EVs) are a quickly growing sector that merits further study.

A1. Electric Vehicle Technology: One of the few advantages that petroleum burning vehicles hold over electric vehicles is recharge vs refuel time. Notable efforts have been made to address pollution problems as well as fuel shortages. Transportation agencies in several countries under the auspices of the green movement have looked to different energy sources: electric, hybrid technologies, biodiesel, and hydrogen. (Mehar 2015). Some of the most promise shown under this new wave is the fact that vehicles entirely or partially powered by electricity are on the rise and hold great potential value. In 2019, 41% of U.S. citizens were interested in alternative powertrain technology, as opposed to only 29% wanted something other than gas or diesel (Deloitte 2020). The change in demand is partially a result of the lower operational costs and emissions of electric vehicles. One of the main concerns for fleet electrification include the high cost of battery technology, battery life, the number of charging stations, and charging wait times.

Bloomberg New Energy Finance and McKinsey (2016) show that the cost of lithium-ion batteries decreased approximately 65% in five years from 2010 to 2015- and that it is expected to fall to a low-range cost of $50 per kilowatt-hour by 2040. This would expunge the price/performance gap of CASE vs. internal combustion model engines. Moreover, researchers forecast that by 2040, one out of every three new cars sold worldwide will be completely electric. A trend of more affordable battery technology has also been seen in the market, costs decreasing to $273/ (kWh) from $599/ (kWh) in 2013 (2016). Trends show costs dropping even further, possibly reaching as little as $100/ (kWh) by 2026, presenting a highly viable choice for consumers. By 2030, a second transition will occur as the cost of electric vehicle batteries (BEVs) will decline rapidly with market saturation (Bloomberg Philanthropies, 2017).

The drivers behind CASE vehicle market penetration are shown in Figure 2.

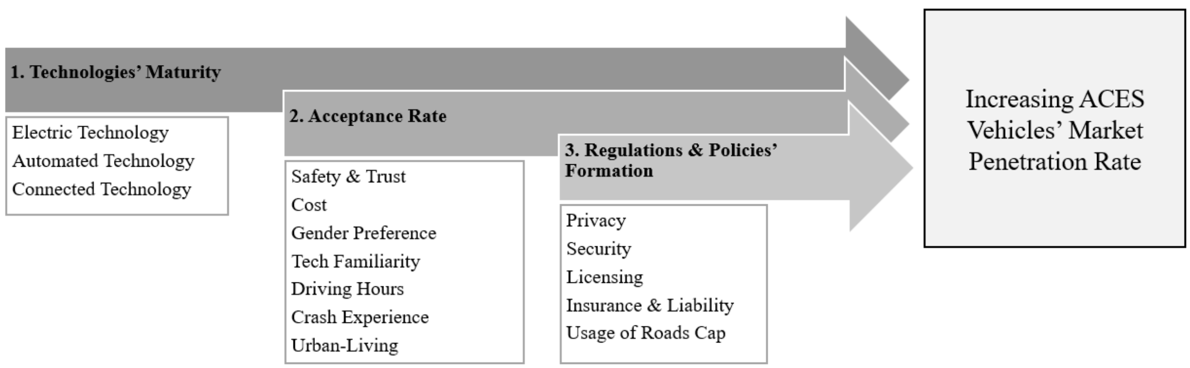


Figure 2: CASE vehicle drivers (by Mahdavian et al. 2021a)

A2. Automated Vehicle Technology (Mahdavian et al. 2021a): Automated vehicle (AV) technologies are electronic systems that control the longitudinal and lateral movement of a vehicle, as well as acceleration, geolocation, braking, and sensing via cameras, sensors, radar and lidar, demanding a high degree of precision. Due to the large variability encountered while driving, these systems are extremely complex, requiring an integrated relationship between hardware and software. In these technologies' vehicle software plays as crucial of role, if not a more important one than vehicle hardware. Moreover, AVs cannot require connected vehicle technology as the scope of their travel is not constrained to network covered locations.

The current criterion for vehicle automation is established by the Society of Automotive Engineers (SAE). The National Highway Transportation Safety Administration (NHTSA) also published AV policy guidelines. A broadly accepted policy for AV classification, authorized by the NHTSA first in 2013 and then updated in 2018, is comprised of five levels, ranging from no automation to full automation. In 2014, the SAE created a separate classification for AVs with the J3016 standard (Mahdavian et al. 2021a). SAE International (2018) also offers a viewpoint on AVs and the industries six levels of classification. The levels are established by the role of the AV system versus the role of the driver, consisting of fallback responsibility for the driving task, monitoring of the vehicles immediate surroundings, steering, acceleration, and driving mode. The automation levels include: no automation (Level 0); driver assistance (Level 1); partial automation (Level 2); conditional automation (Level 3); high driving automation (Level 4); and full automation (Level 5) SAE International (2018).

A3. Connected Vehicle Technology (Mahdavian et al. 2021a): Connected vehicle (CV) technology is a data depository system that allows highway infrastructures and vehicles to communicate information to reduce collisions, optimize traffic flow, and provide more general information. A CV system allows for the wireless transfer of digital data within a car and its outside environment. This technology combines a diverse set of hardware and software allowing bidirectional communication using established protocols, giving access to any device inside and outside the vehicle. This permanent connectivity allows for smart information management which is the key to zero emissions and zero collisions goals Medagliani (2020).

Forms of unidirectional communication includes satellite radio, global positioning systems (GPS), near field communication (NFC), and AM/FM/HD Radio. In contrast to this bidirectional communication includes cellular technology for communications, Wi-Fi for information, DSRC for safety, NFC for authentication, and Bluetooth for entertainment. Bidirectional technologies of this sort have various uses such as safety, infotainment, and mobility; all of which have a multitude of variables to manage (speed, security, distance, and bandwidth) Medagliani (2020). The most common connectivity consumer offerings include infotainment and convenience, navigation, safety, security, and maintenance. Moreover, driving style recognition (DSR) while EV-related features are just beginning to be incorporated. Some aspects, such as insurance and urban mobility-related features, still require additional research to better understand.

Established protocols include Bluetooth, Wi-Fi, satellite, DSRC, and cellular-5G. Bluetooth is relatively short range, limited to a 10-meter range, and in comparison, has limited functionality, as well as and requiring pairing. Wi-Fi due to its omnipresence has commonly known exploitative security issues. Satellites remain expensive and due to their nature tend to communicate unidirectionally. Dedicated short-range communication (DSRC) is a wireless transmission that allows for two-way communication of data within a 1,000-meter range. DSRC is extremely fast and secure and has no usage cost. This high reliability, safety, and security supporting the vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) are among the DSRC benefits. The technologies involved include:

- Sensors such as radar, lasers, high-powered cameras, sonar, and light detection and ranging (Lidar) technology.
- Sophisticated software that analyzes the data.
- GPS assist, routing, and navigation within the CV environment.

One must also consider the growth of 5G, (the fifth generation of the wireless broadband technology based on the IEEE 802.11ac standards) (Mahdavian et al. 2021a). 5G offers speeds 100 times quicker than 4G/LTE as well as boasting a better coverage zone with a 5GHz signal of up to 10Gb/s. This is a huge leap as 5G improves network potential by hundreds of connections (CVTA 2020). The expansion of 5G technology and DSRC promises to deliver intelligent transportation and looks to connect CASE vehicle data to the cloud, and transport infrastructure data centers. The U.S. Department of Transport (USDOT) has funded placements of CV equipment, transferring digital code over the licensed radiofrequency of 5.850 - 5.925 GHz, in an example of DSRC utilizing a language certified by SAE International 2018. One should note that due to the new nature of this field, SAE standard compliance is not mandatory as no government has begun regulations upon the technology.

Pioneering expertise and tech within driver assistance systems (ADAS) have been devised to increase highway safety in addition to increasing overall traffic capacity (Blythe 2004). This level of ADAS is appropriate for situations such as forward-collision alert, lane-keep support, and blind-spot monitoring. A recent analysis by the AAA Foundation for Traffic Safety (AAA 2018) showed that ADAS decreases accidents, injuries, and fatalities in passenger vehicles. The implementation of ADAS could result in the elimination of up to 37% of injuries, and 29% of deaths. There are four categories within these intelligent-vehicle systems: AV, CAV, cooperative adaptive cruise control (CACC), and adaptive cruise control (ACC). Established ADAS equipment can distinguish some objects and their proximity to the vehicle, alerting the driver of dangerous highway situations and slowing down or even stopping the car (Shladover 2018).

B. USER ACCEPTANCE RATE (Mahdavian et al. 2021a): If CAV is to gain high market penetration users are expected to accept this technology as a replacement for their daily means of transportation. Deloitte (2018) states that crucial boundaries that potential buyers of CAV technologies will be: cost, brand, trust, and safety. There are several hurdles to be overcome in the full adoption of CAV technologies. Market outlook: Consumers need to see the technology as safe, secure, and reliable. Individuals see enough appeal in CAV technologies to motivate their willingness to pay (WTP). Other variables that may correlate with the acceptance of CAV should be taken into account when formulating a market plan, including gender, income, and "tech-savviness" (Deloitte 2018, Menon 2019, Barbour 2019).

B1. Safety and Trust (Mahdavian et al. 2021a): Zmud et al. (2017) reported the primary reason for an individual to not use a technology is a lack of trust in that technology. Bansal et al. (2016) report that an established safety history increases the likelihood of U.S. consumers purchasing a CAV by 71%. This figure is up from the previous 68% reported in 2015.

B2. Cost and WTP (Mahdavian et al. 2021a): Drivers and passengers tend to have different values concerning travel time and are likely to display different WTP with the addition of CAV technologies to their vehicles. Cost is a common factor in choosing travel options. There are two types of costs to consider: upfront cost, and cost per mile. HERE (2017) reports that the current high cost of CAVs is a critical issue for consumers, one that must be overcome before high adoption rates and mass production of CAVs can increase Fagnant et al. 2014. The cost of automated and EV technologies is currently higher than those of traditional internal-combustion-engine passenger vehicles. However, the cost of AVs is projected to decline rapidly from 2020 onwards, owing to advancements in sensor and battery technology (Bloomberg 2017). Cost and WTP issues can be divided into categories of cost to buy and cost to access.

Cost to buy (Mahdavian et al. 2021a): The idea that customers will purchase AVs in the future is assumptive, as they are yet to be supported by changing demographics and ownership preferences. However, we can follow the well documented trend price changes of various elements of AVs. Upfront AV price reduction, Waymo 2020 showed that LIDAR cost approximately $75,000 earlier in the decade but dropped to $7,500 in 2017. The U.S. Environmental Protection Agency (EPA) NHTSA 2016 reported that automated manual transmission, which facilitates truck shifting dropped from $5,100 in 2013 to $3,750 in 2018. The DOT (2014) reported a price drop in adaptive cruise control (ACC) from nearly $3,000 in 2006 to $2,000 in 2014. The Texas A&M Transportation Institute (2017) approximates that by 2030 new technologies and advancing in manufacturing could reduce the cost of full autonomy to be less than $1,000 per vehicle.

Cost to access (Mahdavian et al. 2021a): Considering CAV cost per mile: widespread adoption of CAVs could lead to a decreased individual vehicle ownership, as more individuals opt to employ shared mobility because of the price saving per-mile cost to operate CAV vehicles, which is projected to be substantially lower for highly autonomous and EV vehicles VS. traditional internal-combustion-engine non autonomous vehicles. ARK Investment Management LLC (Kyriakidis 2015) studies showed the comparative cost of various modes of transportation, the price per mile is $3.50 for taxis, $0.70 for personal vehicles, and $0.35 for autonomous taxis. It is worth noting that the research and development costs of CAVs should be added to the above-mentioned operational costs.

B3. Age factor (Mahdavian et al. 2021a): Research seems to indicate younger drivers, regardless of nationality are more interested in owning CASE vehicles (Zmud et al. 2016). A survey done by Bansal et al. (2016) showed that 70% of Generation Y/Z individuals in the United States would be inclined to purchase a CASE vehicle produced by brand they trusted, opposed to a traditional vehicle from a less trusted brand. Individuals from Generation X showed a slightly lower acceptance rate of 62%.

B4. Gender factor (Mahdavian et al. 2021a): A multitude of studies show that men are more likely than women to acquire a CASE vehicle (Kyriakidis et al. 2015). This gender-specific preference can in part be due to men’s tendency to acquire vehicles earlier, willingness to pay more for new technologies, and their stronger belief in the safety associated with AVs Casley et al. (2013).

B5. Familiarity with technology (Mahdavian et al. 2021a): On average tech-savvy individuals show a higher likelihood of purchasing a CASE vehicle Bansal (2016)). Regarding passengers, lone drivers demonstrate the greatest interest in the new technologies and show the greatest WTP, and their decision seems to show little dependence on others’ adoption rates. Concerning accident experience, accident survivors have an increased interest in WTP with little dependence on others’ adoption rates (Bansal (2016)).

Considering issues of urban sprawl, Gurumurthy and Kockelman (2020) report that long commute drivers tend to prefer owning their own automated vehicles. Regarding shared automated vehicles (SAVs), moreover, middle-income households prefer renting SAVs for long-distance trips. SAVs are also preferred by customers for long-distance business trips of less than 500 miles. Moreover, the absence of a driver's license profoundly improves the willingness to share rides with strangers. The authors state higher incomes individuals as well as those that are younger in age are more likely to share rides in SAVs. The author noted their belief that people on average prefer private mobility, either private ownership or private access to shared fleets (Mahdavian et al. 2021a).

C. REGULATIONS AND POLICIES (Mahdavian et al. 2021a): Policy and regulation is a factor that can play a role in the purchase of a CAV. As a result, a framework to utilize these technologies more efficiently is needed for legislators to effectively create policies for the employment of CAVs. This set of legal, social, and ethical concerns need to be assessed along with their influences for CAVs to offer a substantial value for consumers.

C1. Privacy (Mahdavian et al. 2021a): CAVs employee a highly sophisticated advanced onboard system capable of transferring vast amount of data about their users and their location. There it goes without saying that electronic security is going to be a concern for automobile producers and consumers alike. The CAV network could stand to be vulnerable to dissatisfied employees or hackers who use exploits to induce crashes that cause traffic congestion and turmoil. This central control of vehicles has divided users on whether the benefits of increased connectivity are worth the risks. Currently solutions to CASE vehicle data collection, ownership, and accessibility are speculative. When American consumers ranked their choices for stakeholders, they would trust to maintain CASE vehicle information the results were: (Original equipment manufacturer) OEM 26%; no-one 26%; dealer 9%; government 5%, and other 34% (Deloitte, 2020). These figures show a mistrust of government with data handling, and more perhaps importantly that data security is a challenging issue for institution of CAVs.

C2. Licensing (Mahdavian et al. 2021a): As there is little legislation overall on CAVs, there is still no need for additional certification or classes to operate CASE vehicles. However, if individual drivers were obliged to receive a additional licensing for CAVs, this could represent an additional barrier to entry for market penetration, especially if an extra cost is associated. USDOT AV4.0. (USDOT, 2020) evaluates the premise of certifying users on the level of automation they display proficiency with. For example, the authors believe that today’s elderly may be a level 0, but a child would be in Level 4 and above.

C3. Insurance and liability (Mahdavian et al. 2021a): CASE vehicle collisions represent a particularly complicated issue in the case of accident liability. Current tort law fully elaborates on CAVs. USDOT AV4.0. USDOT (2020) states that with regard to the individual piloting, the vehicle is liable; but if the car is autonomous, the builder of the car is liable. However, this is a relatively new topic in courts and will be established in courts as precedent cases start to appear.

D. IMPACT OF CASE VEHICLES ON THE TRAFFIC NETWORK:

D1. Traffic Flow (Mahdavian et al. 2019b): Most likely, a fully CAV fleet of vehicles could possibly change saturation flow rates. CAV will increase traffic flow and capacity like the effect that urbanization, population growth and increase in the size of the economy has on traffic flow and capacity. This technology will allow enable improvements in vehicle energy efficiency including electrification, weight reduction, and size optimization, faster travel and full cycle smoothing. Moreover, they have the potential to provide efficient routing, efficient driving, platooning, higher occupancy, increased parking efficiency (as well as real-estate previously allocated to parking becoming free to other use), and ultimately result in increased travel especially in the case of underserved people.

D1.1. New category of users (Mahdavian et al. 2019b): The leap from partial to fully automated vehicles will open doors to vastly increased mobility for the majority of people. Speculation by various authors point out the fact AVs will add trips to the network by increasing the mobility of currently underserved populations. Three long-underserved groups that would benefit in this case would be: disabled people, children, and elderly people (seniors). Several studies used U.S. NHTS data to assess the limits of vehicle miles traveled (VMT) within these groups and how they will be affected with automated vehicles emergence.

Some studies looked at the impact of full AV adaption on these new categories of users. Regarding non-drivers (adult and children), CMU (2016) estimated approximately 196 billion new VMT annually (age 19 and over) to be added to the traffic. Corey et al. (2016) also estimated a 9% growth in VMT from this category of users. Moreover, while Corey et al. (2016) projected 2.2% expansion in VMT by using automated technologies in senior category, CMU (2016) predicted about 46 billion additional annual VMT (Senior Citizens person aged 65 and older). Ultimately, Corey et al. (2016) estimated 2.5% increase in VMT, and CMU (2016) foresaw more than 55 billion VMT annually involving disabled People (People with travel restrictive medical conditions).

D1.2. Ownership and shared mobility (Mahdavian et al. 2019b): There is an established body of research on the travel behavior effects caused by the ownership or availability of vehicles. Automobile ownership is seen as a critical variable in determining public transportation usage. Currently vehicle ownership is correlated with vehicle availability (Texas A&M Transportation Institute 2017). CAVs technology and shared mobility services are evolving today in parallel and stands to change future travel behaviors and change vehicle ownership concepts. Indeed, projections involving CAVs indicated a shift away from personal vehicle ownership toward a shared mobility marketplace. Many cities the world over have restricting construction and commuting patterns that have intensified urban sprawl significantly. Car ownership is all but necessity in these cities (McKinsey & Company 2016). The Preference and customization of represents their tastes, lifestyle, and beliefs. Here (2017) estimated that although by Emergence of CAV drive technology there is a high probability that people change their mobility, (as this technology is already proved to be viable, safe, convenient, and economical) that private ownership will continue to prevail. Many drivers that still choose owning their vehicles but want driverless functionality for its safety and convenience. It should be noted that consumer mobility behavior is being influenced by shared mobility as the incidence of private car ownership is declining, while shared mobility is increasing. Although not entirely clear, the speed of the change shows a fundamental shift away from personally owned driver-driven vehicles is occurring, possibly in the direction of a future mobility system that uses driverless vehicles and shared mobility (McKinsey & Company 2016). Existing data shows that CAVs' effects will depend on the extent that households move from vehicle owning to vehicle sharing. The changes brought about by shared mobility led to a decrease in overall vehicle travel, while it is not known whether CAVs increase or reduce total vehicle travel. Because of these continuing trends up to one out of ten new cars sold in 2030 is expected to be a shared vehicle. This could affect private-use vehicle sales which at least in part be offset by a faster replacement rate for shared vehicles (McKinsey & Company 2016). It would follow that more than 30% of miles driven in new cars sold could be shared mobility miles. Lovejoy (2013) estimates that Households tend to significantly reduce their overall vehicle travel, by 25% to 75%, when they shift from owning a vehicle to sharing. Kok et al. (2017) predicted that, by 2030, within ten years of regulatory approval of fully automated vehicles, 95% of all U.S. passenger miles will be served by transport-as-a-service (TaaS) providers.

D1.3. Empty vehicle travel (zero occupant vehicles) (Mahdavian et al. 2019b): Zero occupant vehicles will be used for goods delivery. It is argued that empty relocation travel will contribute significantly to VMT effects of automated vehicles. Some zero occupant cars will be employed as a part of the future traffic flow while dropping off or picking up travelers, or while waiting service assignment. It is thought that it is more reasonable for a car to continually move about rather than to pay parking charges (Texas A&M Transportation Institute 2017).

D1.4. Safety (Mahdavian et al. 2019b): Car travel is unsafe, costly, and burdensome (McKinsey & Company 2018). Safety continues to be the primary concern for the U.S. Department of Transportation (USDOT) as well as the prime focus of the National Highway Traffic Safety Administration (NHTSA), whose data shows 9 out of 10 severe roadway crashes happen due to human behavior. This loss of life from traffic deaths is a serious issue, and costs America at least $77 billion per year in forgone economic contributions. This amount is equal to the entire GDP of New Hampshire. More than 30 thousand persons die annually in the U.S. in automotive collisions (NHTSA 2012), with 2.2 million crashes ending in injury (NHTSA 2013). Considering the aviation industry, over time, the emergence of autopilot technology has reduced pilot-attributable crash rates by 90%. System improvements and increases in cockpit efficiency from the 1960s through the 1980s dramatically improved flight safety. If automated vehicles offer a similar advancement in safety, the introduction of the automated car could be one of the significant public health advances in history.

The scope of potential advantages is substantial. If automated vehicles can remove human error from the transportation system, it can be concluded that the number of accidents, injuries, and lives lost would also be significantly reduced (Mahdavian et al. 2019b). Texas A&M Transportation Institute (2017) stated that the most considerable impact of safety enhancements as a result of AV/CVs may come from the avoidance of non-recurrent delays on congested facilities created by vehicle crashes. Vehicle crashes that occur during peak periods on heavily used facilities can cause blockages in the traffic. FHWA (2015) estimated fewer crashes (which today cause 25 percent of traffic congestion) because of the emergence of AV. There is a consistency in the literature arguing that by removing humans and human error from the driving task, automated vehicles have the potential to lessen congestion and traffic accidents dramatically (Fagnant and Kockelman 2014). Kok, et al. (2017) claimed that, because human error contributes to 90% of crashes, automated vehicles will diminish crash rates and insurance costs by 90%. NHTSA (2008) also stated that over 90% of the primary factors behind crashes are due to human errors which could be reduced by the adoption of AVs. NHTSA (2011) stated that 40% of fatal accidents include driver alcohol or drug use and driver fatigue or other distractions. Morgan Stanley estimated that a 90% reduction in crashes would save nearly 30,000 lives and prevent 2.12 million injuries annually. Hayes (2011) suggested that motor-vehicle fatality rates could eventually approach those seen in aviation and rail, about 1% of current rates; KPMG and CAR (2012) advocated a goal of creating crash-less cars, while noting that connected vehicle solutions could decrease up to 80% of unimpaired accidents (Mahdavian et al. 2019b).

D1.5. Value of travel time savings (VTTS): Of the benefits of CAV use, travel is expected to become more comfortable and relaxing, allowing for more free time in the car during trips. This is expected to lead to lower VTTS, or higher acceptable travel times. How this VTTS reduction will relate to AV technology has been extensively research. Based on Cyganski et al. (2015), a 25% decrease in trips longer than 10 minutes is expected. While Gucwa (2014) estimated VTTS would be reduced by 25% of AVs. Research by Childress et al. (2015) reported even higher levels, expected a 35% decrease in AV travel times. Some reports are more variable, like Wadud et al. (2016) that speculate a VTTS reduction anyway from 5-80%, depending on the level of automation employed. Finally, Litman (2017) expected a 30% relative difference between the VTTS between car drivers and car passengers.

When looking out how VTTS will impact VMTs, this same study also predicted higher vehicle milage, and reduced fuel and insurance costs based on an elasticity analysis. Increases anywhere from 4-60% are anticipated based on automation, with a VTTS decrease of up to 80% needed for the highest values. Some research by Kröger et al. (2018) has suggested that this VMT increase will be higher than the total trip increase. Trip length can then increase, based on the expectations that AVs will more likely be used for longer trips.

D2. Traffic Capacity: Until now, may researchers have investigated the influence of AVs on traffic flow predictors such as traffic capacity (Hartman et al. 2017). Despite this, their focus has been vehicle automation on a longitudinal level, where following distances for vehicles depend on human vision and human response times. AVs are expected improve driving in part, through increases in vehicle to vehicle and vehicle to infrastructure connectivity. As discussed by Makridis et al (2018), connected vehicles will have quicker response times than human drivers, with much shorter headways through use of communication tools. These tools will both send and receive data via wireless transmission, including dedicated short-range communications, or DSRC. DSRC sends information both to the drive, and to other vehicles with V2V. It also can send information to roadside units (RSU), the cloud, and to infrastructures with V2I (Hartmann et al. 2017). By enabling this communication, traffic management data such as signal phasing can be sent in real time. V2V technology in particular will be the easiest to utilize because the changes include additions to transport operators or to the vehicles. V2I however, is going to need additional government assistance in the form of maintenance, operation, and upgrades to infrastructure. Ultimately, this information communicated that informs the vehicle could be anything relating to the shape, size, speed limit zone, or surroundings of the vehicle needed in order to help with vehicle control (Hartmann et al. 2017). When AVs use both V2I and V2V, the traveling distance between vehicles can ultimately decrease. These shorter headway distances mean higher lane capacity and is expected to provide the greatest benefits for CAV use. On application of this technology that is quickly becoming more popular is cooperative adaptive cruise control (CACC) (Charalampopoulos et al. 2016). As discussed by Bang and Ahn (2017), CACC allows for greater autonomy by letting vehicles communicate traffic information, speed, vehicle position, and relative acceleration, in order to engage in more advanced driving techniques. Research by Shladover et al. (2012) looked at the impact ACC/CACC could have on freeway capacity based on simulated changes in market penetration. They concluded that CACC had the potential to double freeway lane capacity if CACC market penetration was high. While the potential to ease congestion with CACC was high, the results of ACC uncoordinated was not as promising. These findings consistently estimated a > 10% increase in capacity with 40% CACC market penetration. Looking at work by Van Arem et al. (2006), MIXIC technology could be used to mimic a highway lane-drop from 4 to 3 lanes. They saw higher flow and capacity increases because or CACC. Finally, it was estimated by Shladover et al. (2013) that V2V in combination with ACC would increase capacity from 21-50% for relevant vehicles, or at max 80% with 100% vehicle fleet coordination.

D2.1. Capacity and speed: In a study by Maurer (2016), fully automating highway traffic with a mean speed v = 80 km/h, car length = 7.5 m, the impact of speed on the traffic capacity could be considered. His results indicated that with speeds of 200 km/h, capacity increased by 2-fold. With just 100 km/h, speed increased by 1.85 x the capacity; while with 38 km/h, the fold increase was 1.5.

D2.2. Capacity in relation to the market penetration: In the aforementioned study, it was determined that more AV market penetration results in more highway capacity. Based on his estimates, 20% of fleet vehicles would be able to increase capacity by 6%. If 50% of these vehicles employed this technology, there would be a 26% increase in capacity. While a 100% coordinated vehicle fleet would be needed for a 75% capacity increase. In order to compared different market penetration rates, Sadat Lavasani (2016) compared various market scenarios. With 61% market penetration, fleet vehicle capacity would be expanded 33-70% if a 74% coordinated vehicle fleet was used. However, Van Arem et al. (2006) found that rates > 40% had no impact of capacity. It was also found by Hartmann et al. (2017), that obvious benefits are unlikely to be seen until higher AV use into the traffic grid is applied.

D2.3. Capacity and the share of trucks: As found by Maurer (2016) the proportion of trucks is also likely to impact lane capacity. Based on his results, when truck shares reached 10%, capacity would decrease by almost 7%. With 30% truck shares, there was a 19% reduction in capacity. Correspondingly, with a 60% truck share increase a 30% reduction, and with 100%, a 42% reduction.

D2.4. Capacity and VMT: CAV technology and their VMT level impact was also analyzed. According to Pinijari et al. (2013), AVs are superior to human drivers when it comes to detecting their surroundings, making narrower lanes a possibility. With AV freights entering the equation, Chapin et al. (2016) predicted that highway truck capacity will go up. Based on estimated by Childress et al. (2015), network capacity could increase 2-4-fold depending on the size of the CAV fleet. The smaller headways specifically, have been reported by Rodier (2018) to allow for double or even triple roadway capacity. Rodier also stated VMT elasticity based on capacity could increase from 0.3-0.6 in the short term, and 0.6-1.0 in the longer time. Finally, Tientrakool et al.(2011) predicted a 43% increase in capacity on the highway by using vehicle sensors. With V2V communication system use, this value went up to 273%.

E. Predictions for CAV market penetrations: Because of the cost of current vehicles, and the long use period afforded by them, it is unlikely for customers to consider new vehicles based on progressing technology. As a result, it can take decades for new technology to become widespread in the vehicle market. Often these types of advances follow a pattern known as an ‘S-curve’, or ‘Gal’s Insight’. AVs also are predicted to follow these patterns. Taking this into account, the predictions for cost and sale of AVs for

2025-2060 based on the reviewed literature was considered. These results can be seen in Table 1, organized in 5-year intervals. Based on this, a majority of researchers show that over time the AV market share will increase. Following 2040, AVs are likely to make up most of the cars currently on the road.

Table 1: Sales and cost forecasts

Year	Study	Forecast
2025	Citi GPS 2014	$40B market for level 4 AVs
	McKinsey 2016	33% of new trucks sold have level 4 or better
	Litman 2014	17% U.S. vehicle sales in AVs
	Lavasani 2018	2-5% of vehicle sales in AVs
2030	Litman 2014	23% of U.S. vehicle sales in AVs
	Lux Research 2014	$21B revenues for U.S. of selling level 2 & level 3 AVs
	Goldman Sachs 2019	42% new U.S. AVs Level 3, and 17% level 4 or 5
	Morgan Stanley 2013	$6000 per vehicle to add level 3 automation
	Lux Research 2014	250,000 vehicle sales annually for level 5 AVs
2035	ABI Research 2013	50% of all new vehicle sales in level AVs
	Mosquet et al. 2015	10% of U.S. new light-vehicle sales level 4 AVs
	HIS Automotive analyst	50% of U.S. and Canadian vehicle sales in AVs
	Litman 2014	35% of U.S. vehicle sales in AVs
	Lavasani 2018	20-40% of vehicle sales in AVs
2040	Litman 2015	50% of U.S. vehicle sales in level 4 AVs
2045	Morgan Stanley 2013	$10000 per vehicle to add level 4 automation
	Lavasani 2018	40-60% of vehicle sales in AVs
	Litman 2014	65% of U.S. vehicle sales in AVs
2050	Deloitte 2018	80% of sales for shared vehicles
	Litman 2015	75%-90% of U.S. vehicle sales in AVs
2055	Lavasani 2018	80-100% of vehicle sales in AVs
	Litman 2014	95% of U.S. vehicle sales in AVs
2060	Litman 2014	88-97% of U.S. vehicle sales in AVs

The results forecasting VMT use can also be compared from the literature for 2025-2060. As before, these results are split into 5-year increments, as seen in Table 2. Not including one study by Hars (2014), researchers agreed in the direction of VMTs and CAV use. Also, a more conservative prediction by Lavasani 2018 suggested lower levels of VMT market rates and use than Litman 2014.

Table 2: VMT and use forecasts

Year	Study	Forecast
2025	Lavasani 2018 Litman 2014	1-4% of vehicle travel in AVs 16% of U.S. vehicle travel in AVs
2030	Hars (2014) Litman 2014	90% of person-trips in U.S. in level 4 AVs 20% of U.S. vehicle travel in AVs
2035	Lavasani 2018 Litman 2014 Trommer	10-30% of vehicle travel in AVs 30% of U.S. vehicle travel in AVs Fleet share of AVs can be up to 42% in Germany in 2035
2040	Litman 2015	40% of U.S. vehicle travel in level 4 AVs
2045	Litman 2014	50% of U.S. vehicle travel in AVs
2050	Litman 2015	65% of U.S. vehicle travel in level 4 AVs
2055	Lavasani 2018 Litman 2014	50-80% of vehicle travels in AVs 65-75% of U.S. vehicle travel in AVs
2060	Litman 2014	75-90% of U.S. vehicle travel in AVs

A similar analysis of 2025-2060 vehicle fleet forecasts is illustrated in Table 3. Researchers generally agreed upon the market penetration rates. However, overall, fleet increase rates were not as high as user, sales, and ownership estimates.

Table 3: Vehicle fleet forecasts

Year	Study	Forecast
2025	Lavasani 2018 Litman 2014	1-2% of vehicle fleet in AVs 9% of U.S. vehicle fleet in AVs
2030	Litman 2014	15% of U.S. vehicle fleet in AVs
2035	Lavasani 2018 Fehr and Peers 2014 Litman 2014	10-20% of vehicle fleet in AVs 25% of U.S. vehicle fleet in AVs 31% of U.S. vehicle fleet in AVs
2040	Litman 2016 Bansal 2016	30% of U.S. vehicle fleet in level 4 43% of U.S. vehicle fleet in AVs
2045	Lavasani 2014 Bansal 2016	20-40% of vehicle fleet in AVs Fleet of light-duty vehicles in the U.S. will not be near homogenous by 2045
2050	Litman 2014 Talebian 2020	50% of U.S. vehicle fleet in AVs Automobile fleet will be near homogenous in about 2050 only if CAV prices decrease at an annual rate of 15% or 20%
2055	Lavasani 2018 Litman 2014	40-60% of vehicle fleet in AVs 60-65% of U.S. vehicle fleet in AVs
2060	Litman 2014	70-85% of U.S. vehicle fleet in AVs

Table 4 represents the vehicle-ownership predictions from the reviewed literature for 2025 to 2060. It is evident ownership and access predictions are higher than fleet use/sale rates. Research generally accept that most people will own or have access to CAVs by the year 2030. A 5-year difference was identified from when level 4 automation would happen based on the results by Rowe (2015) and Stanley (2014).

Table 4: Ownership and access forecasts

Year	Study	Forecast
2030	Lux Research 2014	92% of vehicles, level 2 automation, and 8%, level 3
	Morgan Stanley 2013	100% of U.S. light-duty vehicles in level 3
2035	Harrop and Das 2015	8.5 million vehicles in AVs
2040	IEEE 2006	75% vehicles in AVs
2055	Morgan Stanley 2013	100% of U.S. light-duty vehicles in level 4
2060	Rowe 2015	100% of U.S. vehicles in level 4
	Fehr and Peers 2014	75% of U.S. highway traffic in AVs

One thing to consider, is that each year only 6.7% of fleets get replaced on a national level. Based on this, it will be nearly 14 years before a 90% market penetration rate for all OEM makes and models can occur.

Step 4: Highway construction cost prediction model

(Regarding this section the study published by the author were employed: Mahdavian, A., Shojaei, A., Salem, M., Yuan, J.S. and Oloufa, A.A., 2021b. Data-Driven Predictive Modeling of Highway Construction Cost Items. Journal of Construction Engineering and Management, 147(3), p.04020180.)

In order to develop any industry, a firm grasp of the expected revenue and cost is required in order to make decisions (Victoria Transport Policy Institute 2018). Based on methods discussed by Turochy et al. (2001), the US DOT methods used to predict roadway costs and assign a budget could initially be categorized into two stages. For the first stage, several DOTs consider the cost-per-unit, making use of engineering knowledge and expertise in order to implement cost items. For the second stage certain DOTs compare approximate predictions for the number of payments based on historical precedent from similar cases. On a statewide level, there is not a consistently applied method for cost estimation. Among some of these DOTs, different methods or techniques are used that depend completely on engineering practices (Zhang 2017).

Two of the most widely applicable methods of construction cost prediction include regression models (Wilmont & Cheng 2003), and artificial neural networks (ANN), better outlined in work by both Wilmot and Mei 2005,and Shojaei and Mahdavian, 2019. On study by Emsley et al (2002) used both ANN and linear regression for cost prediction, and found there was a substantial benefit to using the NN method, based on its capacity to model non-linear data. When model accuracy was examined in a report by Membah et. al. (2015), it was shown that using an approach based on unit cost was unreliable for predictions, could lead the a much lower predicted budget than needed, and did not consider project risks. Companies could then benefit also from a detailed risk analysis with predictions, prior to bid submission. With the unit cost method, the user is also limited in the volume of data they can analyzed. A parametric model was designed by Swei et al. (2017) to make construction cost projects by using a maximum likelihood estimator and a least angle regression for dimensionality. They utilized this model and 15 total bid items in order to transform datasets. Minchin et al. (2004) showed that using values provided by the DOT, they were able to generate an accurate regression model. The most important variable affecting lowest bid price vs. engineering prediction was the number of bidders. Mahamid (2011) used a polynomial regression model in estimating startup roadway construction. The model utilized bid quantity as an independent factor accomplished greater outcomes when compared to models using road dimensions.

A body of research has observed construction cost vs construction market using independent macroeconomic predictors. Chief parameters show high a correlation of overhead to resource price. This is to be expected as the economy is a common indicator of the price needed for the entirety of the construction project (Anderson et al. 2007, Williams 2003). The reasoning for this is that these costs include the use of both machine and human resources, and building materials which are a litmus of the economy (Zhang 2017). Williams (1994) foresaw Engineering News-Record changes in construction cost using housing trends (start price) and the average lending rate. In this instance, these variables were incorporated along with the month for back-propagation network modeling.

In another report, Wong & Ng (2010) determined that macroeconomic market factors common in construction were critical for calculating the TPI. In a separate study, Shahandashti and Ashuri (2016) used sixteen variables (a higher amount then likewise studies) and concluded that the factors "hourly gains" and "price of crude oil" were the key elements impacting highway construction costs. To distinguish appropriate attributes in modeling the price of building projects, previous research (Lowe et al. 2006, Ji et al. 2010, Kim and Hong 2012) has utilized step-by-step multiple linear regression (MLR) for their forecasts. Finally, a study by Shahandashti and Ashuri (2016) also utilized VEC modeling in order to project the leading variables that effect the cost of highway construction projects.

Assessing gaps, and delineation of contributions of dissertation

Most articles published on the impact of CASE vehicles on the traffic network to date, only address one or at most a few issues in relative isolation. To a minor degree, there has been some consideration paid to less-quantifiable consequences, such as behavioral changes, impacts on attitudes about changes to land-use, public transit, and the impact on regional planning. Articles that give a more holistic approach to the impact of the emerging technologies on the traffic network are limited.

This research strives to recognize some of the consequences of CASE vehicles at the system level, by first developing a traffic flow prediction model considering the impact of CASE vehicles, and second, generating a highway expansion cost-prediction model to enhance traffic capacity. To reach the goal of this study, four steps mentioned above were used. The assessment of the gaps in the literature and the delineation of contributions of dissertation research considering gaps are as follows:

Numerous well- organized traffic volumes prediction models that predict short-term periods accurately, even if their traffic models perform inadequate for mid- to long-term estimates. Successful enactment of this investigation type is delayed due to a lack of adequate traffic modeling methods, models, and data that properly represents the involvedness of the transportation network. Traffic count estimations must take these multipart traffic patterns into account, making it compulsory to employ deep structure models that are able to incorporate more IVs than past models. Because of the very nature of the unpredictability in traffic analysis due in no small part to the plethora of relevant factors mid- and long-term predictions tend to be unreliable for practical use. However, if one was able to take make use of the multitude of affecting factors, they very well could obtain level of accuracy that makes long and mid term predictions viable.

Current literature shows a need for a universal framework of this sort, as seeming discrepancy in earlier efficacious methods in terms of algorithms used selection method in addition to elements of the traffic prediction forecasting pipeline. In other words, of the investigated case characteristics in each previous study each had their own differing algorithms, and it reasons they would have different final parameters to be the optimal choice. It follows that in perfecting and adjusting a model for an individual cast study, a workflow needs to be designed as to establish the framework for standardization that would be needed for maximum market penetration, and in addition allows optional customizations based on specific applications.

This research represents a comprehensive attempt in developing, and comparing, an array of non-linear and linear models able to estimate traffic volumes of highways accurately, adding to the current body of research. A pipeline encompassing feature choice is constructed and enhanced to help train the models. We tested the models against the Florida Department of Transportation's (DOT's) average daily highway traffic for cars between 2001 and 2017. We chose this specific data because of Florida’s population growth, status as an immigrant destination, over all state logistics, tourist population, and hurricane frequency. The resulting model could provide valuable data to transportation planners and policymakers in the most efficient paths to expanding existing infrastructure, both to alleviate current congestion and to futureproof for possible issues.

Current paradigms and lacks a standardized workflow to process and forecast the volume of truck traffic. In this study, an expansive volume of diverse datasets from Florida highways, and 59 IVs. It also incorporates both linear and nonlinear algorithms, including five linear and four non-linear, and is robustly cross-validated. The steps outlined in this study are modeled based on a gride search for feature selction, followed by MAPE error reduction via model optimization. This study's scope is model generation that compensates for the variety of shortcomings in current modeling, allowing enhanced truck count estimation. Study results illustrate the high accuracy of the developed system, which could be easily employed by other users more generally. Using the methodology elaborated on in this research and collecting local data related to predictors and projects, users can optimize this truck volume prediction model accordingly. It should be carefully noted that the model illustrated in this study and its leading factors are customed tuned to Florida, and that factors are expected to vary from those shown in this study in other applications.

As there has been little effort to create a widely accepted workflow for forecasting highway construction costs, there has been little research about it. One existing study incorporates nonlinear (4) and linear (5) modeling of data from 2001-2017, with 69 IVs and multifactorial cross-validation. This studies workflow employed hyperparameter optimization framework in establishing which factors had the most impact on decreasing MAPE error. Without a universal standard, inconsistency arises during the feature selection stage, as well as other forecasting steps. Essential, the algorithms deemed optimal for a particular case in these past studies varied widely. An argument can then be made to forego optimizing on a case by case basis, and instead focus on the creation of a standard workflow that can be generalized.

A major goal of this dissertation study is to create a model that addresses these shortcomings, so that project planners will have access to more accurate cost predictions. Based on the results highlighted, this framework has the potential to be highly accurate, and readily employed. If the step-wise process outlined in this dissertation is followed, planners can optimize the forecast provided based on predictors relevant to their project. The factors that will then be identified as key to cost prediction are likely to vary from the exact ones selected for in this study of a Florida highway dataset.

CHAPTER THREE: METHODOLOGY

Overview

The study attempts a macro-overview of the transportation network design obstacles and attempts to delineate the results of vehicle automation at the systemic level, leveraging machine learning and system dynamics analysis. The study will accomplish this by:

- Step 1: Development of an accurate prediction model for passenger vehicles traffic volumes using nonlinear and linear machine learning

- Step 2: Create an accurate model to estimate truck traffic volumes utilizing nonlinear and linear machine learning

- Step 3: Forming a range of possible CASE vehicles scenarios of their impact on the traffic network employing an extensive literature.

- Step 4: Creation of an accurate prediction model to forecast highway construction cost using nonlinear and linear machine learning.

Using the previous steps, the hypothetical model could predict expansion cost of the network link considering CASE vehicles implementation and then compare that cost to the other market solutions to take the best course of action. The flowchart of the dissertation is shown in Figure 3.

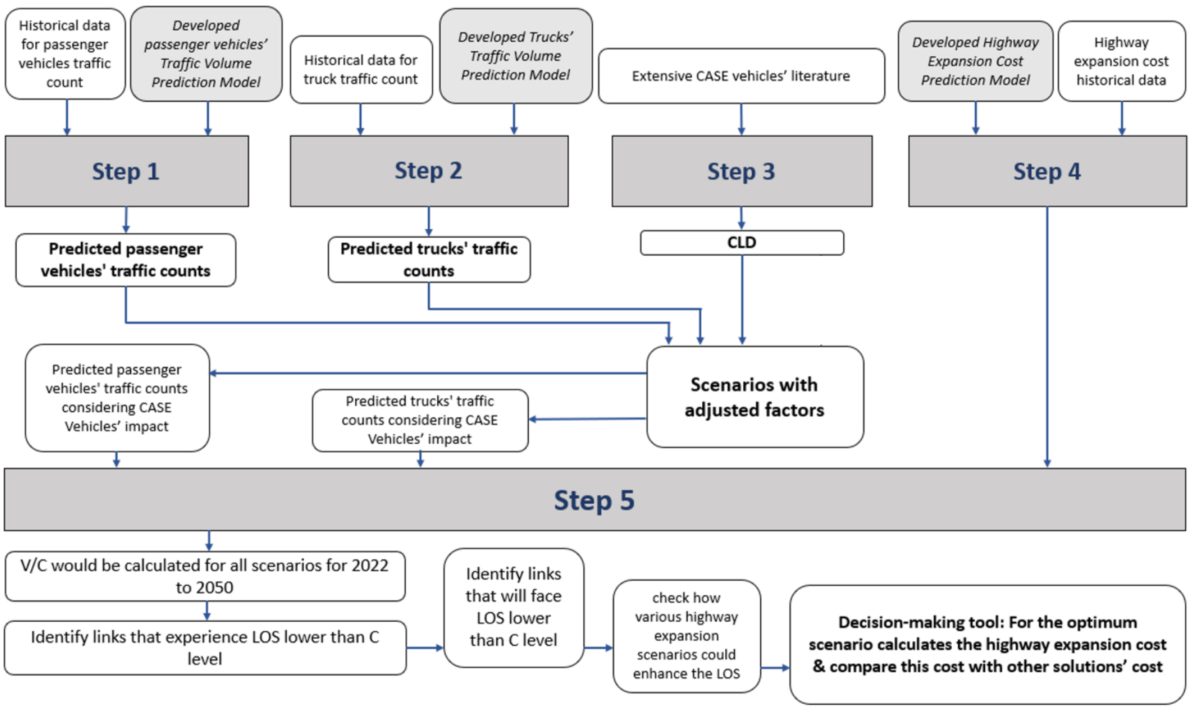


Figure 3: The flowchart methodology of the dissertation

<u>Steps 1 and 2: Traffic prediction model – for Passenger Vehicles and Trucks</u>

*(*Regarding this section, the Author employed the studies reviewed in the article published by author: *Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Yuan, J.S. and Oloufa, A., 2021c. Automated Machine Learning Pipeline for Traffic Count Prediction. Modelling, 2(4), pp.482-513.* And the study: *Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Eluru, N. and Oloufa, A.A., 2021d. A Universal Automated Data-Driven Modeling Framework for Truck Traffic Volume Prediction. IEEE Access, 9, pp.105341-105356.)*

Improved forecasting of passenger vehicle traffic volumes and truck traffic volumes through the generation of a highly accurate forecasting model was the prime reason for this step. To achieve this aim we employed a machine learning approach to examine a broad dataset of historical traffic volumes to develop a wide-ranging set of applicable independent variables. The key objectives of this step are as follows:

- Complete a comparative analysis of a variety of machine learning algorithms for traffic volume forecasting with consideration shown to linear and non-linear relationships among variables.
- Examine influences of a variety financial markets and the U.S. economy on traffic patterns.
- Consider how road characteristics may contribute to changes in traffic volumes.
- Determine the significance of spatio-temporal predictors in altering the traffic volumes.

This studies model pipeline identifies best option for bother variable selection and which model to use, in order to reduce the MAPE. It does so by leveraging hyperparameter optimization in generating a universal automated framework, which is a distinct then previous optimization techniques that employed in one off studies.

Dependent Variables

The Florida Department of Transportation (FDOT) database of historic vehicle traffic provided data that is used in this study. The data covers traffic volumes, MADT, and reporting from Florida highways linked to 259 different locations.

One study constraint was the authors had to scale traffic data to monthly level in order to match the the independent and dependent variables (predictors and traffic volumes). Preferably more specific timepoints at the hourly, daily, or weekly level be used for higher resolution. However the monthly predictors for 6 Florida interstate highways we studied for a total of 52,836 data points or an average of every 5.75 miles of road. Summarization of basic information seen this dataset can be found in Table 5.

Table 5: Highway sites included for analysis

Interstate ID	**Interstate type**	**Length (mi)**	**Number of cosites / interstate highway**	**Length of road per cosite (miles)**
I95	Primary interstate	382.0	82	4.6
I10	Primary interstate	362.2	52	6.9
I75	Primary interstate	470.6	68	6.9
I4	Primary interstate	132.2	47	2.8
I275	Auxiliary interstate	60.6	9	6.7
I 110	Auxiliary interstate	6.3	1	6.3
		Total = 1414.3	Total = 259	Mean = 5.7

This research employed PTMS (portable traffic monitoring sites) to record the traffic counts from 211 locations. TTMSs (Telemetered traffic monitoring sites) were employed in collecting data from the remaining 48 locations. PTMSs capture data through loop and axel sensors on the road that connects directly to a nearby weatherproofed cabinet. TTMSs in contrast employee wireless internet or landlines in order to send information to a TRANSTAT office offsite, thus reducing its accuracy. Figure 4 illustrates the majority coverage of Florida interstates by the 259 different co-sites.

Figure 4: 259 cosites of the study on the Florida interstates map

Statistical Analysis

Table 6 presents the results of analysis of of truck monthly traffic volumes.

Table 6: Monthly truck traffic results:

Item	N/E Trucks	S/W Trucks	Total Trucks
Mean	1,134,867	1,344,004	2,478,871
Std	97,695	102,439	199,560
Minimum value	943,280	1,157,397	2,100,677
First quartile	1,061,814	1,263,920	2,324,526
Median value	1,105,466	1,316,157	2,419,644
Third quartile	1,215,878	1,433,383	2,651,906
Maximum value	1,359,654	1,567,772	2,926,388

Also, Table 7 summarizes the passenger vehicle (PV) directional monthly traffic volumes used in this study. Determination of the data range by statistical analysis is also shown.

Table 7: Monthly cars traffic counts data statistical description

Item	N/E Cars	S/W Cars	Total Cars
Mean	10146551	11847260	21993811
Std	665397	762102	1413177
Minimum value	8378788	9802174	18180962
First quartile	9755700	11364921	21101325
Median value	10208572	11851693	21960358
Third quartile	10578486	12325489	22828754
Maximum value	11775017	13722702	25497719

The project compared global as well as local socioeconomic factors in Florida, like income and the labor force numbers. It considered the US economy, considering that the GDP can be a reasonable indicator of average national income. The consumer price index (CPI) is commonly as a measure of the rate of national inflation. Other factors such as national interest also good indicators of macroeconomic changes. Additionally, both the prime loan rate and rate of federal funds used are two commonly used metrics showing general interest rates. Finally, the stock market is a successful indicator to predict the cost ofa construction project, and they are widely available to the public for use.

As for construction spending, this can be applied as a metric to planned construction costs at residential or non-residential locations. Employment can also be considered to factor in the state of the labor force in the U.S. construction industry. Despite this, to take into account trends in building projects, you also must include data on private housing unit construction. A neglected variable thus far in traffic forecasting has been energy prices. Other values have be used instead, including the price of gas or crude oil. In this study, we also take into account the variables 'max speed', 'lane number', and 'toll road' as additional factors that impact the volume and pattern of truck traffic on the higway.

Figure 5 compares the general trends seen among the most likely indicators of traffic volume. A distinct trend was identified in each potential indicator related to U.S. macroeconomic, socioeconomic, construction, and energy markets.

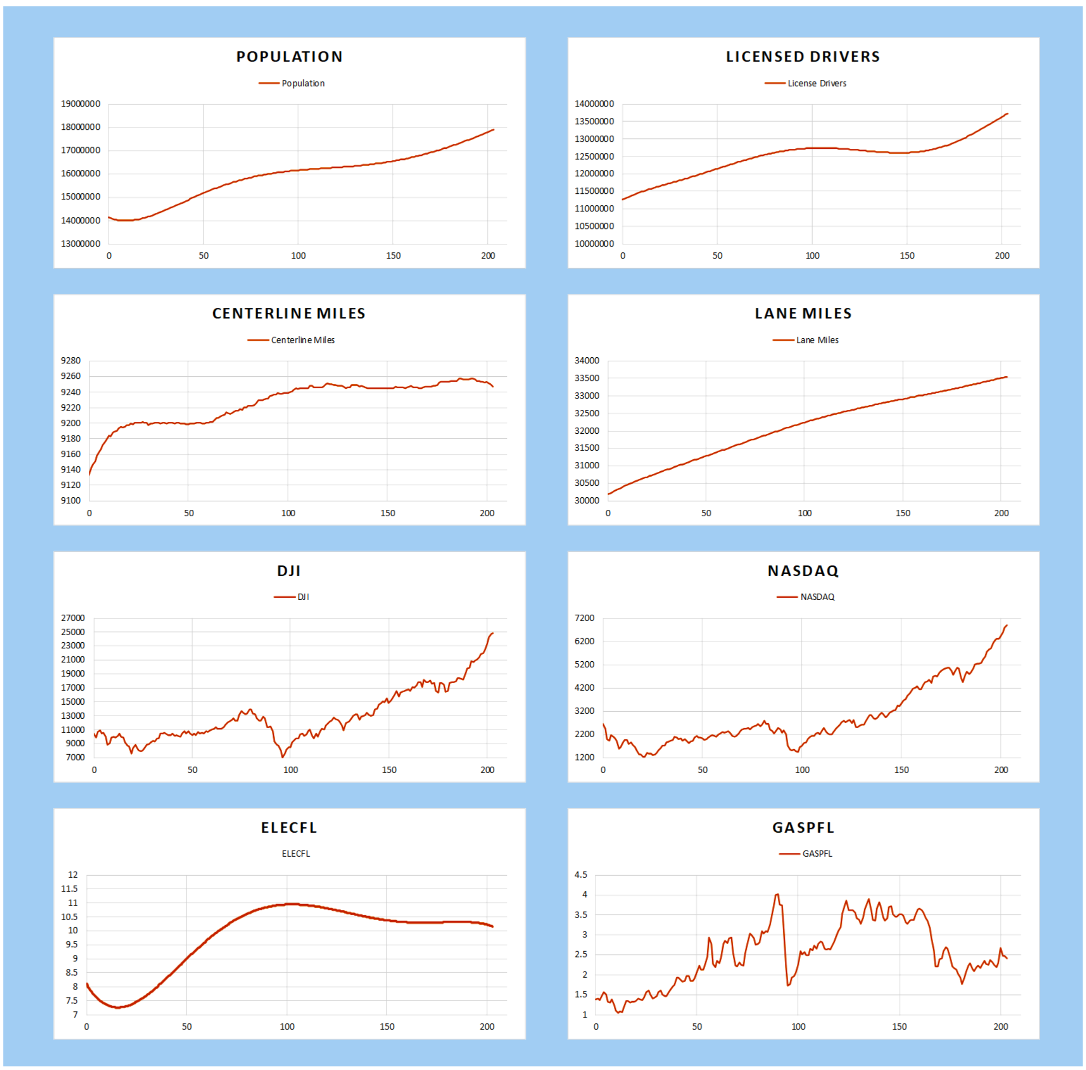


Figure 5: Samples trends of the potential leading indicators of car traffic counts

Step 3 Traffic CASE vehicles CLDs – Scenario development

This section elaborates the procedure and steps including literature research method, CASE Vehicles System Dynamic Causal Loop Diagram (CLD) development, that was followed by this study to develop the CASE vehicles scenarios for the framework in modeling development chapter (chapter 4).

A. Research method: To begin, a critical review of the available literature was performed. This was accomplished be researching trends with keyboards CAV implementation in transport studies, using Google Scholar. After this, different peer-reviewed databases were explored with additional keyword use. The keywords included, connected vehicles, automated vehicles, electric vehicles, CASE vehicle technology and implementation barriers, shared automatic vehicles, smart mobility implementation, and CASE vehicle regulations and user acceptance. At this stage, leading databases for transportation research were utilized including Sustainable Cities and Society (Elsevier), Transportation Research Parts A-F (Elsevier), Journal Transportation and Health (Elsevier), Journal of cleaner production (Elsevier), Transportation Research Institutes, Transport Policy (Elsevier), Journal of Technological Forecasting and Social Change, Transport Reviews Journal (Taylor and Francis), and Transportation Research Record. In order to obtain research regarding the system dynamics employed, authors also looked at reports by the National Highway Traffic Safety Administration (NHTSA), the Federal Highway Administration (FHWA), or transport consulting companies.

As this topic is evolving rapidly to properly convey current academia on the subject authors included the NHTSA's Automated Driving Systems (ADSs – SAE International Automation Levels 3-5) Voluntary Safety Self-Assessment (VSSA) Disclosure Index in the review process. This study reviewed National Science Foundation (NSF) requests for proposals (RFPs) to identify current gaps in this field. While the majority is on articles, projects, research, and reports published in the U.S.; there are several European countries as well as China have been included in the review process. Inclusion and exclusion range were set evaluating the significance of each study to the topic, and if applicable, only then was it applied. First, authors recognized and excluded manuscripts that were not specific to CASE vehicle implementation.

Second, the authors isolated the remaining periodicals to ones that addressed topics related to barriers in implementing CASE vehicles. The authors critically reviewed 131 articles (56 journal papers, 16 conference papers, 19 transportation research institutes, 16 federal reports, and 24 industry reports) to explore the various stakeholders' viewpoints regarding the subject of research from among the 367 articles initially identified.

B. CLD development: The CASE vehicles System Dynamic Causal Loop Diagram (CLD): Results of the assessment were used in developing a CLD offering a comprehensive model showing the consequences of CASE vehicles and CATs on traffic network. CLDs and system dynamics have been used to analyze complex, dynamic systems to investigate effects of vehicle automation on a systems level. This is because of the focus on the relationships between variables and the overall structure of the system, with our specific work being limited to the use of causal loop diagrams (CLDs). For the purpose of this study we improved upon the current CLD traffic and congestion model developed by Gruel and Stanford (2016). They in turn built their model based upon the work of John Sterman's (2000) baseline model.

The core purpose of this model is management and relief of roadway congestion. As is common in transport modeling the CLD considers factors such as: road capacity, trip generation, land use, mode choice, and public transit. This model provides an apt framework for our discussion as a basis for the scenarios of the study. Figure 6 shows the developed CLDs for the CASE vehicles impact on the traffic network.

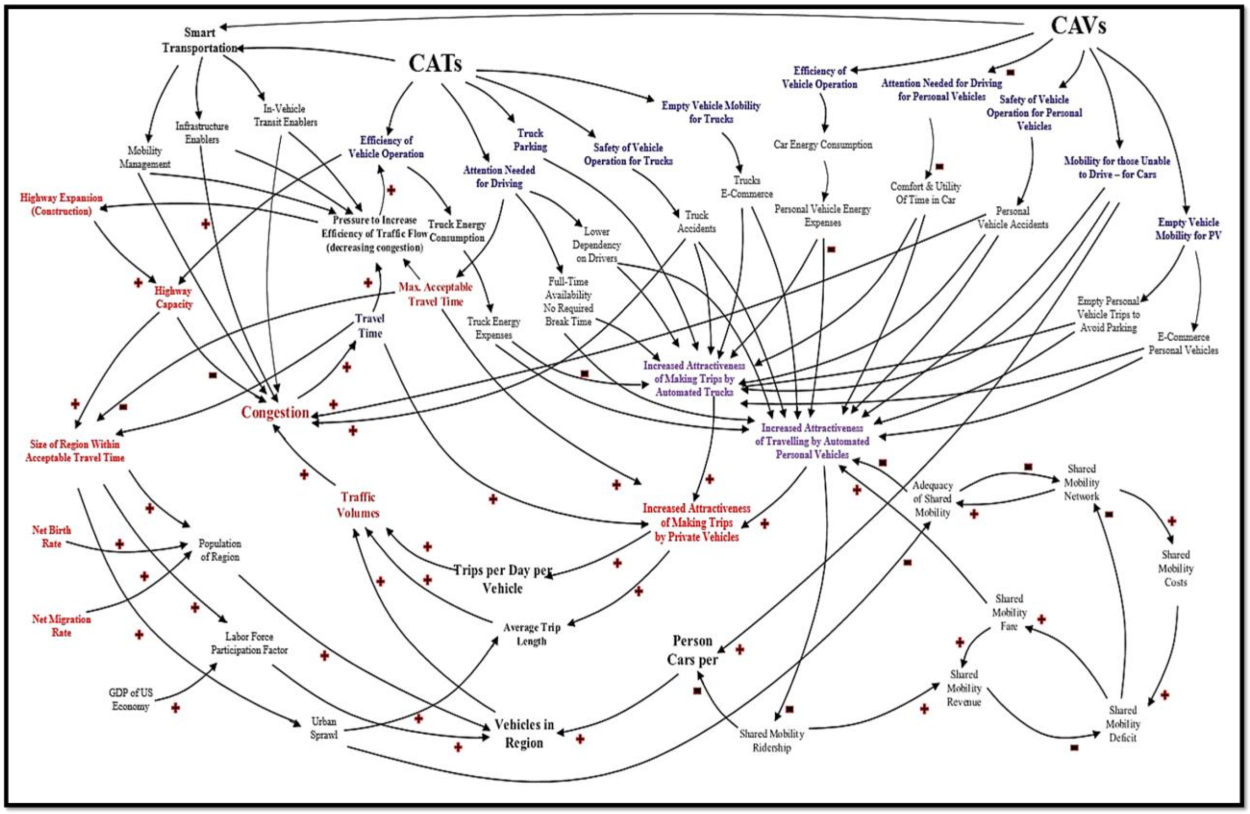


Figure 6: CASE Vehicles System Dynamic Causal Loop Diagram (CLD)

According to the CASE Vehicles CLD in Figure 6, the following Reinforcing loops (which generate growth and collapse) and the balancing loops (which generate stability) were identified:

REINFORCING LOOPS. Regarding the reinforcing loops, the increased attractiveness of travelling by CASE vehicles, would lead to more trips and lower LOS of the traffic network:

- *[Reinforcing Loop-1]: Attractiveness of Travelling by CASE vehicles / Trips per Day per Car / Traffic Volume/ Congestion / Travel Time / Attractiveness of Travelling by vehicles*
- *[Reinforcing Loop-2]: Attractiveness of Travelling by vehicles / Average Trip Length / Traffic Volume / Congestion / Travel Time / Attractiveness of Travelling by vehicles and*

BALANCING LOOPS. About the balancing loops, for the first four loops, the higher level of congestion would lead to more resources allocated to the traffic management. By employing various solutions (such as Highway Construction, In-Vehicle Transit Enablers, Mobility Management, and

Infrastructure enablers) the level of service of the highway will get higher (lower traffic congestion). Also, vehicle-sharing leads to increased Price Transparency as its per-trip-payment exposes many of the hidden costs of driving that most people usually do not consider. This transparency has the potential to reduce the Attractiveness of Travelling by Car.

- *[Balancing Loop-1]: Congestion / Travel Time / Pressure to decrease congestion / Highway Construction / Highway Capacity / Congestion*
- *[Balancing Loop-2]: Congestion / Travel Time / Pressure to decrease congestion / In-Vehicle Transit Enablers / Congestion*
- *[Balancing Loop-3]: Congestion / Travel Time / Pressure to decrease congestion / Mobility Management / Congestion*
- *[Balancing Loop-4]: Congestion / Travel Time / Pressure to decrease congestion / Infrastructure enablers / Congestion*
- *[Balancing Loop-5]: Shared Mobility Ridership / Shared Mobility Revenue / Shared Mobility Deficit / Shared Mobility Network / Adequacy of Shared Mobility / Attractiveness of travelling by car / Shared Mobility Ridership*
- *[Balancing Loop-6]: Shared Mobility Ridership / Shared Mobility Revenue / Shared Mobility Deficit / Shared Mobility Fare / Adequacy of Shared Mobility / Attractiveness of travelling by car / Shared Mobility Ridership*
- *[Balancing Loop-7]: Travel Time / Size of Region within Acceptable Travel Time / Urban Sprawl / Average Trip Length / Traffic Volume / Congestion / Travel Time*

Step 4 Highway construction cost prediction model

(Regarding this section the study published by the author were employed: Mahdavian, A., Shojaei, A., Salem, M., Yuan, J.S. and Oloufa, A.A., 2021b. Data-Driven Predictive Modeling of Highway Construction Cost Items. Journal of Construction Engineering and Management, 147(3), p.04020180.)

This step of the study aims to predict future highway construction costs accurately using internal and external variables. Particularly, this study strives to address the following objectives:

1. Evaluating the prediction accuracy of multiple machine learning algorithms considering multiple linear and non-linear relationships between variables to forecast the cost items

2. Evaluating the influence of temporal predictors on the prediction model on road construction cost items
3. Investigating the impact of the socio-economic, energy market, U.S. economy, and construction market on highway construction cost item

In order to accomplish these objectives, the steps of training, testing, and feature selection, a new model was designed to automatic workflow. This model was then tested on a dataset from the FDOT that contained itemized construction costs from 2001-2017 classified as 'critical highway costs'. This data included 60 individual item costs for both 4 and 6 lane rural or urban interstate highway construction/widening projects. Florida highways in particular were used due to multiple factors including, logistics, frequency of hurricanes, and population growth and demographics.

Figure 8 shows sixty cost items and their associated cost margin in each type of project. From the sixty cost items (dependent variables) covering 100% of the total cost of six highway expansion types (constructing and widening), ten cost items' monthly historical data were not available (about 7.4% of the total cost), so the remaining fifty cost items were considered to be fed to the pipeline of the study. These cost items covered about 92.6% of the average total cost of highway construction (both new construction and widening construction projects). In total, this included roughly 17,121 small, medium, or large sized projects and 1,027,260 individual data points. The data from these projects was then sorted for a feature analysis on a monthly level from 2001-2017 (17 years total, or 204 months). Analysis on a month to month basis was then maintained for the entire period covered by the dataset. The full list of dependent variables is shown in Figure 7, and with the 10 cost items not included in training highlighted in yellow. Construction types that did not include the remaining 50 cost items in factoring the total per-mile project costs were listed as ***x***.

	Dependent Varibles	Constructing New Urban 6L	Constructing New Urban 4L	Constructing New Rural 6L	Constructing New Rural 4L	Widening 6L to 8L	Widening 4L to 6L
1	MAINTENANCE OF TRAFFIC	8.18%	8.18%	4.29%	4.29%	8.17%	8.16%
2	MOBILIZATION	9.00%	9.00%	9.00%	9.00%	8.99%	8.98%
3	SEDIMENT BARRIER	0.16%	0.17%	0.30%	0.43%	0.38%	0.43%
4	FLOATING TURBIDITY BARRIER	0.02%	0.02%	0.04%	0.06%	0.02%	0.03%
5	STAKED TURBIDITY BARRIER- NYL REINF PVC	0.01%	0.01%	0.01%	0.02%	0.01%	0.01%
6	SOIL TRACKING PREVENTION DEVICE	0.02%	0.02%	0.04%	0.05%	0.05%	0.06%
7	LITTER REMOVAL	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
8	MOWING	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
9	CLEARING & GRUBBING	2.53%	2.74%	7.13%	8.30%	2.22%	2.49%
10	REGULAR EXCAVATION	1.61%	1.74%	3.87%	4.41%	2.12%	2.39%
11	BORROW EXCAVATION, TRUCK MEASURE	×	×	×	×	10.76%	12.10%
12	EMBANKMENT	5.11%	4.57%	14.15%	17.25%	2.46%	2.76%
13	TYPE B STABILIZATION	2.03%	1.73%	4.19%	3.58%	2.90%	3.26%
14	OPTIONAL BASE,BASE GROUP 04	2.56%	2.78%	4.94%	4.08%	3.54%	3.98%
15	OPTIONAL BASE,BASE GROUP 09	5.95%	4.33%	11.46%	8.97%	5.52%	6.21%
16	MILLING EXIST ASPH PAVT, 1" AVG DEPTH	×	×	×	×	0.66%	0.74%
17	MILLING EXIST ASPH PAVT, 4" AVG DEPTH	×	×	×	×	3.70%	2.77%
18	SUPERPAVE ASPH CONC, TRAF C,PG76-22,PMA	2.08%	2.25%	22.02%	18.29%	4.30%	4.84%
19	SUPERPAVE ASPH CONC, TRAF D,PG76-22,PMA	9.45%	6.82%	3.70%	2.85%	26.94%	23.45%
20	ASPH CONC FC,INC BIT,FC-5,PG76-22,PMA	1.92%	1.41%	×	0.08%	6.92%	5.86%
21	ASPH CONC FC,TRAFFIC B,FC-9.5,PG 76-22	×	×	×	×	0.07%	0.08%
22	CONC CLASS II, ENDWALLS	1.71%	1.55%	1.05%	1.23%	1.13%	1.27%
23	INLETS, DT BOT, TYPE D	0.06%	0.07%	0.06%	0.07%	0.09%	0.10%
24	INLETS, DT BOT, TYPE E	0.20%	0.22%	0.39%	0.59%	×	×
25	INLETS, BARRIER WALL	2.33%	2.10%	×	×	×	×
26	MANHOLES, J-7	0.11%	0.12%	0.22%	0.26%	0.15%	0.17%
27	DESILTING PIPE, 0 - 24"	×	×	×	×		
28	DESILTING PIPE, 25 - 36"	×	×	×	×		
29	PIPE CULV, OPT MATL, ROUND,24"SD	0.70%	0.59%	1.07%	1.34%	1.53%	1.72%
30	PIPE CULV, OPT MATL, ROUND, 24"S/CD	×	X	0.43%	0.50%	×	×

	Dependent Variables	Constructing New Urban 6L	Constructing New Urban 4L	Constructing New Rural 6L	Constructing New Rural 4L	Widening 6L to 8L	Widening 4L to 6L
31	PIPE CULV, OPT MATL, ROUND, 30"S/CD	4.94%	×	×	×	0.21%	0.23%
32	PIPE CULV, OPT MATL, ROUND, 36"S/CD	0%	6.19%	0.62%	0.67%	×	×
33	PIPE CULV, OPT MATL, ROUND, 42"S/CD	7.10%	8.49%	0.14%	0.15%	0.20%	0.23%
34	PIPE CULV, OPT MATL, ROUND, 54"S/CD	0.86%	0.93%	1.66%	1.90%	1.19%	1.34%
35	MITERED END SECT, OPTIONAL RD, 24" SD	0.52%	×	1%	1.17%	1.44%	1.62%
36	MEDIAN CONC BARRIER WALL	5.54%	6%	×	×	×	×
37	SHLDR CONC BARRIER, RIGID-SHLDR	16.83%	18.24%	×	×	×	×
38	CONCRETE DITCH PAVT, NR, 3"	×	×	1.57%	1.46%	×	×
39	RUMBLE STRIPS, GROUND-IN, 16" MIN. WIDTH	0.03%	0.03%	0.06%	0.07%	0.08%	0.09%
40	FENCING, TYPE B, 5.1-6.0', STANDARD	1.47%	1.59%	2.72%	3.85%	0.19%	0.21%
41	FENCE GATE,TYP B,SLIDE /CANT,18.1-20'OPEN						
42	PERFORMANCE TURF	×	×	0.01%	0.02%	×	×
43	PERFORMANCE TURF, SOD	0.41%	0.01%	1.18%	1.48%	0.87%	0.97%
44	SINGLE POST SIGN, F&I GM	0.01%	0.23%	0.01%	×	0.02%	0.02%
45	SINGLE POST SIGN, F&I GM, 12-20 SF	0.21%	0.08%	0.41%	0.53%	0.59%	0.67%
46	MULTI-POST SIGN, F&I GM, 21-30 SF	0.03%	×	×	×	0.01%	0.01%
47	SINGLE POST SIGN, REMOVE	×	×	×	×	0.02%	0.02%
48	MULTI-POST SIGN, F&I GM, 31-50 SF	0.07%	0.32%	0.14%	0.16%	0.20%	0.23%
49	MULTI-POST SIGN, F&I GM, 51-100 SF	0.30%	0.51%	0.57%	0.23%	×	×
50	MULTI-POST SIGN, F&I GM, 101-200 SF	×	×	×	1.14%	×	×
51	MULTI-POST SIGN, REMOVE	×	×	×	×	0.03%	0.03%
52	OH STATIC SIGN STR, F&I, C 21-30 FT			×	×	×	×
53	OH STATIC SIGN STR, F&I, S 31-40 FT	×		×	×	×	×
54	RETRO-REFLECTIVE/RAISED PAVEMENT MARKERS	0.02%	0.01%	0.04%	0.03%	0.07%	0.06%
55	PAINTED PAVT MARK,STD,WHITE,SOLID,6"	×	×				
56	PAINTED PAVT MARK,STD,WHITE,SKIP, 6"	×	×				
57	THERMOPLASTIC, STD-OP, WHITE, SOLID, 6"						
58	THERMOPLASTIC, STD-OP, WHITE, SKIP, 6"						
59	INITIAL CONTINGENCY AMOUNT (DO NOT BID)	0.99%	0.99%	0.99%	0.99%	×	×
60	RURAL LIGHT POLES - 52 AT $10,000.00			×	×	×	×

Figure 7: The cost items utilized in the study

For the predictor variables, 69 different independent/candidate variables were chosen, including 14,076 total data points from the 17 year period studied. Five different categories for the predictor variables as highlighted in Appendix B, Table B1. These categories included socioeconomic, economy, construction market, energy market, and temporal candidate variables. For the first category, socioeconomic candidate variables, 9 different variables were used; including but not limited to, household size, household income, the labor force used, and the length of paved road studied. The economy candidate variables specifically looked at factors of the U.S. economy, and included 28 different variables. Both gross domestic product (GDP) and the consumer price index (CPI) were utilized in this category. While the national U.S. income can be examined with GDP, CPI is important to consider federal inflation levels. The most widely referenced stock market indexes among the U.S. were also used, including the Dow Jones, S&P 500, and NASDAQ index. The category of construction market candidate variables also included 28 individual variables, not limited to construction spending and building/housing permits. Another critical variable included was the national highway construction cost index (NHCCI) in order to consider construction bids in the previous years. In addition, FDOT historical data on revenue and disbursement was used. Four total variables for the energy market candidate variables category were selected; and these include the price of crude oil, diesel, electricity, and natural gas. Finally, the category of temporal candidate variables included the number of months, the individual month, and the year.

Step 5: ARIMA Model

In order to predict the assigned values of future independent variables, this study utilized different univariate modeling techniques. For the temporal candidate variables, the univariate models used included smoothing, and the autoregressive moving average (ARMA); the latter of which is one of the most widely used prediction models for a time series involving one variable. For the purpose of this study, ARMA (p, q) is used to refer to this model type, with p and q being the AR and MA order, respectively. This order was selected using both an partial autocorrelation correlogram function (PACF) and a autocorrelation correlogram function (ACF). In contrast, the smoothing method consisted of Holt-Winters or exponential methods. The Holt-Winters methods included linear, multiplicative or seasonal additive; and the exponential methods included simple, and single or double exponential smoothing.

These methods, in addition to the categories previously listed (with the exception of licensed drivers, line miles, centerline miles, and population), were used together for future variable prediction. For the variables not included, the results from previously published studies were used. Results from Rayer et al. 2020 were used for the socioeconomic variables of licensed drivers and population; while the line miles and centerline miles that relate to the length of paved Florida highway roads in the future were considered to be constant. Both spatial variables, and variables relating to road characteristics were also left as constant for the prediction time span.

CHAPTER FOUR: MODEL DEVELOPMENT

Steps 1 and 2: Traffic prediction for Passenger Vehicles and Trucks

*(*Regarding this section, the Author employed the studies reviewed in the article published by author: *Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Yuan, J.S. and Oloufa, A., 2021c. Automated Machine Learning Pipeline for Traffic Count Prediction. Modelling, 2(4), pp.482-513.* And the study: *Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Eluru, N. and Oloufa, A.A., 2021d. A Universal Automated Data-Driven Modeling Framework for Truck Traffic Volume Prediction. IEEE Access, 9, pp.105341-105356.)*

To generate a model for trucks and passenger vehicles traffic volume prediction, a workflow was designed that consists of (1) data preprocessing, (2) feature selection, (3) model training, (4) hyperparameter optimization, and (5) machine learning based in Python (2020) that incorporates the Scikit-learn library (2011). The standardized data obtained during the preprocessing steps was further separated into the datasets training, test, and validation. Finally, key predictors of traffic volume were identified using a feature selection model based on the training and validation datasets. A summary of this workflow can be seen in Figure 8.

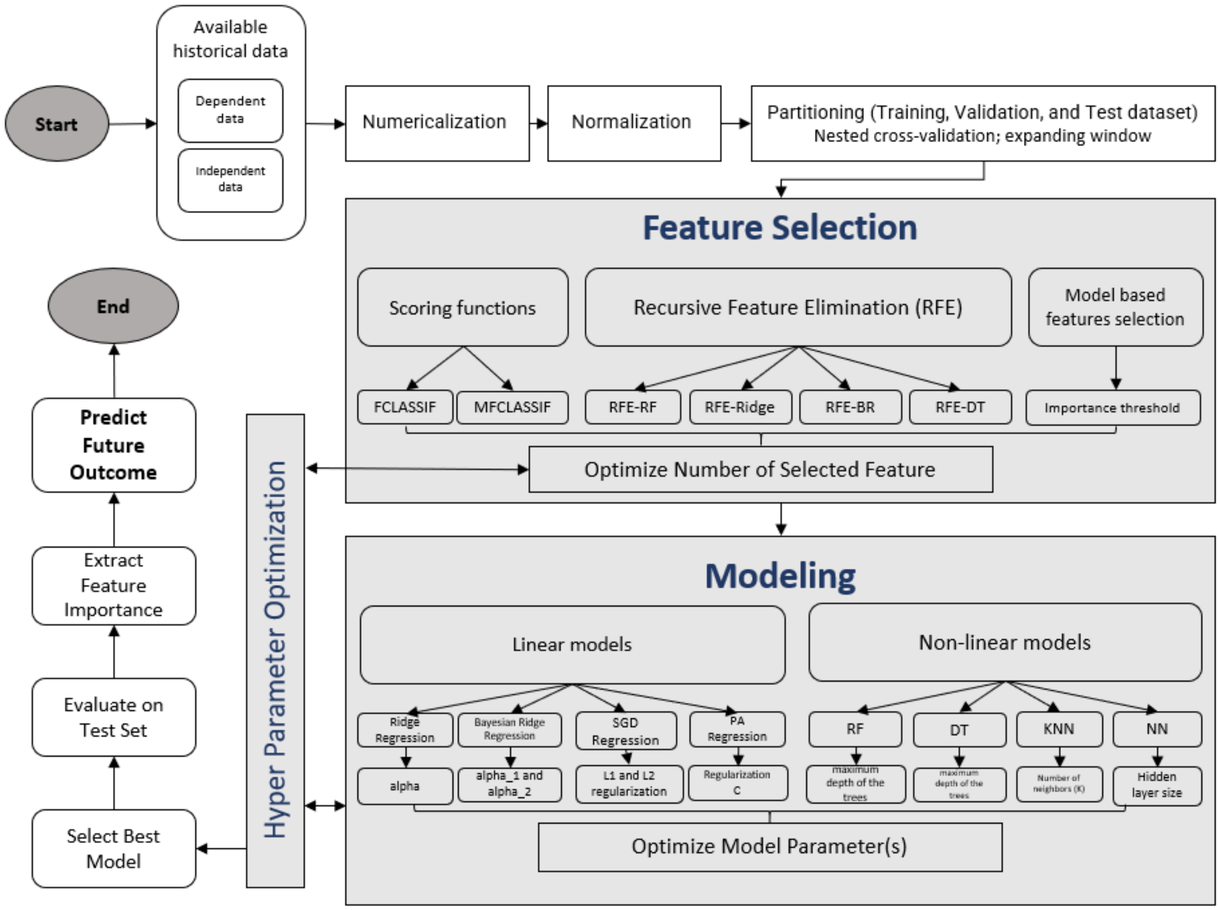


Figure 8: The Pipeline of the study

A. Data Preprocessing and Partitioning: At the data preprocessing stage, all independent variables (predictors) were transformed into a number. Then, the numeric data were standardized to normal distributions with an average of 0 and a standard deviation of 1 to support the regularization of the models. Following standardization, the prepared data were divided into training, test, and validation datasets. As time series data are used in this research, exploring the integrity and temporal continuity of the data was essential. Accordingly, randomly splitting the dataset into different parts for validation would not be appropriate. As shown in Figure 9, the evaluation method employed in this study relied on the nested cross-validation expanding window method. In this method, the training dataset has a training subset and a validation set in the inner loop (yellow dashed box) starting with three years of serial data for each dataset. The training set was increased by three years in each split. The testing dataset then consisted of the next three successive years of the dataset after those of the validation dataset. For the inner loop, each split went through the research pipeline presented in Figure 8. Then, concerning the outer loop, after employing the outcomes of each split, the error was averaged. This method ensures that the final model is robust and is not overfitted or randomly accurate.

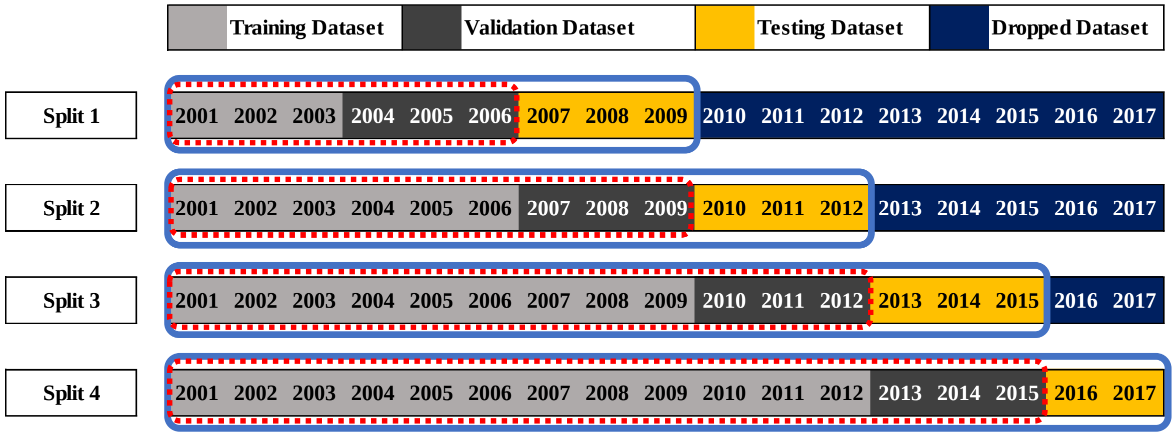


Figure 9: Nested cross validation (expanding window approach)

Performance measurement scales: To measure the reliability of the models used and the feature selection methods chosen, four measures of error were used. These included, the mean absolute percent error (MAPE), the mean absolute error (MAE), R-squared, and the root mean squared error (RMSE). The aforementioned error measurements were analyzed in order to best consider potential forecast errors, based on the dataset utilized (highway construction cost); with the goal of producing the most reliable forecast possible. To that end, MAPE and RMSE were identified as the superior methods of error measurement for accuracy, and also provided the most insight into potential forecast errors. By using RMSE and MAPE, this study was also able to consider both scale-dependent and -independent measurements, allowing significant error to be more easily interpreted in the results. Of the two, the RMSE however, can be easily impacted by significant error outliers. As a result, MAPE was chosen as the most appropriate method for determining mean and error in this study and was to evaluate the training results of the models used.

B. Feature Selection: Taking into account the model structure utilized, feature selection was used to increase model accuracy. During the feature selection process, superfluous variables are removed from the independent variables considered, and only the most appropriate variables are used. This is done by measuring the impact each variable has on model precision, and then removing an low-scoring variables that are deemed unnecessary. If these variables are not removed, they can negatively impact a models performance, precision, and predictive abilities. By using the nested cross-validation previously discussed, model testing, training, and validation for each of the remaining parameters was performed. The determine which features were critical to model development, three different steps were utilized. These steps included:

1. Bayesian Ridge Regression (BR), Ridge Regression (Ridge), Decision Tree (DT), and Random Forest Regression (RF) were utilized for implicit feature selection (SelectFromModel function from Scikit-learn (2011)). At this step, values tested for the importance threshold alternated between 0.25, 0.5, 0.75, 1, 1.25, 1.5, and 1.75 to consider the selection parameter.
2. To gradually pinpoint and remove superfluous features, Recursive Feature Elimination (RFE in Scikit Learn (2011)) was employed until only features of high import remained. This step utilized the previous models (FRE-RF, RFE-Ridge, RFE-BR, and REF-DT), and the resulting number of selected features chosen included 1, 3, 5, 10, 20, 30, 40, 50, and 60.
3. Finally, the K most appropriate dataset features are identified via a scoring function (SelectKBest in Scikit Learn (2011)). For the purpose of this study, Mutual Information (MFCLASSIF) and ANOVA F-value (FCLASSIF) were used. At this stage, the final number of selected features varied as before from 1, 3, 5, 10, 20, 30, 40, 50, and 60.

Each method was used within a grid search after which, the principle set of parameters chosen were compared.

C. Modeling Approaches: For the purpose of passenger vehicle traffic volume forecast, this study took advantage of multiple different machine learning (ML) algorithms. Neural Network (NN), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN) were chosen as the non-linear regression models for this study (SelectFromModel function from Scikit-learn (2011)). For the linear models, Ridge Regression (Ridge), Stochiastic Gradient Descent Regression (SGD), Passive-Aggressive Regression (PA), Linear Regression (Linear), and Bayesian Ridge Regression (BR) were selected (SelectionFromModel function from Scikit-learn (2011)).

The regression models chosen allowed for the manipulation of parametric models, while also ensuring methods with varying levels of non-linearity or linearity could be compared. As mentioned prior, data was previously split to train, validate, and test the model using a nested cross-validation approach. After this approach was performed, the aforementioned ML methods were applied. For training, an expanding data window was utilized. The following 3 years after dataset training were then used for validation. Finally, this process was tested on data from 3 additional years in sequence. The model parameter (MP) –or the highest value of the binary tree depth– ranged from 5, 20, 50, 75, 100, and 200 for all RF and DT algorithms used. The MP used for the K-Nearest Neighbors algorithm varied from 1, 3, 5, 7, 10, and 16. In the case of the Neural Network models, the MP alternated between 1, 2, and 4, and corresponds to the hidden layer size or number of neurons. MP selection for the linear algorithm was also performed. With BR Regression, the MP was used to illustrate the prior gamma distribution (alpha_1 and alpha_2) inverse scale parameters and shape. For the Ridge Regression, the MP is indicative of the regularization strength (alpha); and for the PA regression model, the MP is the maximum step size (regularization C). For all three of these algorithm's, the MP varied from 0.1, 1, 10, 100, 10,000, and 1e6. Finally, MP values fluctuated from 0, 0.15, 0.3, 0.5, 0.75, and 1 for the SGD regression, and can be attributed to the L1 ratios (L1 and L2 regularization) elastic net mixing parameter. As established in these last two sections, the hyperparameter optimization grid developed incorporates an extensive range of reasonably low to high parameter values, allowing it to be applied to multiple datasets containing distinctive features.

Step 3: CASE vehicles scenario development

(Regarding this section the author employed his published publications: *Mahdavian, A. Shojaei, A.,Oloufa, A. 2019a. Service Level Evaluation of Florida's Highways Considering the Impact of Autonomous Vehicles. Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC). And: Mahdavian, A., A. Shojaei, and A. Oloufa. 2019b. Assessing the long-and mid-term effects of connected and* *automated vehicles on highways' traffic flow and capacity. International Conference on Sustainable Infrastructure 2019: Leading Resilient Communities through the 21st Century. Reston, VA: American Society of Civil Engineers. And also: Mahdavian, A., Shojaei, A., Mccormick, S., Papandreou, T., Eluru, N. and Oloufa, A.A., 2021a. Drivers and Barriers to Implementation of Connected, Automated, Shared, and Electric Vehicles: An Agenda for Future Research. IEEE Access, 9, pp.22195-22213.)*

The scenario development process in this study included five sequential steps, namely the identification of the critical factors and driving forces of the development of solutions, assessment of the impact and uncertainty of the driving forces, construction of the scenario matrix, estimation of the penetration rates and potential implications of CAVs in each scenario, and finally review of the scenario and assessment of the overall impact of each of the 22 scenarios. To build the following scenarios, four important factors were considered including CASE vehicles impact on traffic flow (4 scenarios: No impact, Low impact, Medium impact, and High impact), impact of trucks automation on cars' trips (2 scenarios: Has an impact or does not have an impact), shared and ownership mobility (3 scenarios: All private ownership, half shared mobility, and All shared mobility), and shared mobility usage policies (3 scenarios: optimistic, most likely, and pessimistic).

To present the impact of CASE vehicles on the traffic network, this study investigated the Effects in 3 Main Scenarios:

1. Scenario A. Technology Changes, But We Don't
2. Scenario B. New Technology Drives New Behavior
3. Scenario C. New Technology Drives New Behavior & New Ownership Models

Scenario A. Technology Changes, But We Do not

In scenario A, it is assumed no changes are made to vehicle ownership or behavior. For the purpose of modeling, all vehicles are privately owned, and CAVs use is based on the current use of cars in society. In this case, no behavioral changes are cause by the expected improvements. In addition, shared automatic vehicle (SAV) policies in this instance refers to policies involving the use of shared AVs by various users. Table 8 shows the assumptions for scenario A.

Table 8: Scenario A

Scenarios	New Behavior	New Ownership Models	Shared Mobility Policies
Scenario A.1.	No Change	No Shared Mobility	Not Required

Scenario B. New Technology Drives New Behavior

In scenario B, it is assumed no charges are made to vehicle ownership choices (privately owned vs shared mobility vehicles), but major changes in behaviors related to vehicle use and travel are seen. In this case, new uses for cars are found (both for business use and use by private individuals). In addition, people are more willing to engage in longer trips, and at a greater frequency. Table 9 shows the assumptions for scenario B.

Table 9: Scenario B

Scenarios	New Behavior	New Ownership Models	Shared Mobility Policies
Scenario B.1.	High Impact	No Shared Mobility	Not Required
Scenario B.2.	Low Impact	No Shared Mobility	Not Required
Scenario B.3.	Most Likely Impact	No Shared Mobility	Not Required

Scenario C. New Technology Drives New Behavior & New Ownership Models

This scenario builds on behavioral changes of Scenario B, but also assumes complete change in ownership: It examines a case where all vehicles in operation are SAVs. Multiple reasons could cause shift to shared vehicles, e.g., increased appeal of vehicle sharing as vehicles can drive where they are needed, lower prices due to higher vehicle utilization, or enforcement by cities that ban private cars from certain areas. Table 10 shows the assumptions for scenario C.

Table 10: Scenario C

Scenarios	New Behavior	New Ownership Models	Shared Mobility Policies
Scenario C.1	High Impact	Half Shared Mobility	Not Required
Scenario C.2	High Impact	Half Shared Mobility	Incentives
Scenario C.3	High Impact	Half Shared Mobility	Required
Scenario C.4	Low Impact	Half Shared Mobility	Not Required
Scenario C.5.	Low Impact	Half Shared Mobility	Incentives
Scenario C.6.	Low Impact	Half Shared Mobility	Required
Scenario C.7.	Most Likely Impact	Half Shared Mobility	Not Required
Scenario C.8.	Most Likely Impact	Half Shared Mobility	Incentives
Scenario C.9.	Most Likely Impact	Half Shared Mobility	Required
Scenario C.10.	High Impact	All Shared Mobility	Not Required
Scenario C.11.	High Impact	All Shared Mobility	Incentives
Scenario C.12.	High Impact	All Shared Mobility	Required
Scenario C.13.	Low Impact	All Shared Mobility	Not Required
Scenario C.14.	Low Impact	All Shared Mobility	Incentives
Scenario C.15.	Low Impact	All Shared Mobility	Required
Scenario C.16.	Most Likely Impact	All Shared Mobility	Not Required
Scenario C.17.	Most Likely Impact	All Shared Mobility	Incentives
Scenario C.18.	Most Likely Impact	All Shared Mobility	Required

Passenger Vehicles

The following figure shows the adjusting factors for various scenarios for analyzing the impact of the New behavior of users by emergence of CASE vehicles. Five factors were analyzed to investigate the impact of CASE vehicles on the number of trips by passenger vehicles, including, Efficiency of vehicle operation, attention needed for driving, mobility for those unable to drive, safety of vehicle operation, and empty vehicle mobility. All the five factors include values for pessimistic, optimistic, and most likely scenarios. For example, in the Pessimistic Scenario, for the Efficiency of the vehicle operation parameter, the Number of trips by Cars will increase by 4% as a result of an expected 10% cost savings. In the Optimistic Scenario, the number of trips in the future predicted in the 1st Step would be multiplied by 1.98 to calculate the impact of CAVs New Behavior on the traffic network. Table 11 shows the assumptions for the New Behavior parameter Passenger Vehicles.

Table 11: Assumptions for the New Behavior parameter for Passenger Vehicles

Scenarios	Pessimistic Scenario	Most Likely Impact	Optimistic Scenario
Efficiency of Vehicle Operation	Assume 10% Cost Savings: *0.04*	Assume 30% Cost Savings: *0.1*	Assume 50% Cost Savings: *0.16*
Attention Needed for Driving	Assume 20% reduction in VTTS: *0.05*	Assume 50% reduction in VTTS: *0.15*	Assume 80% reduction in VTTS: *0.25*
Mobility for those Unable to Drive - for Cars	When there is No legislated law; Low CAVs' acceptance rate by people; CAVs in a high Price: *0.05*	When there is incomplete legislated regulation: Medium CAVs' acceptance rate by people; CAVs in average price: *0.15*	When we have complete legislated regulations; High acceptance rate by people and CAVs in low price: *0.25*
Safety of Vehicle Operation for Trucks	*0.04*	*0.08*	*0.12*
Empty Vehicle Mobility for Trucks	When only some of the stores will provide driverless delivery vehicles; People often utilize this type of delivery; No law: *0.04*	When approximately half of stores provide driverless delivery vehicles; People sometimes utilize this type of delivery; Required laws associated with safety, security, & liability of driverless cars are incomplete: *0.12*	When most of stores provide driverless delivery vehicles; People always utilize this type of delivery; Required laws associated with safety, security, & liability of driverless cars are provided: *0.2*
Passenger Vehicles' Count Adjusting Factors	***1.22***	***1.6***	***1.98***

Trucks

The following figure shows the adjusting factors for various scenarios for analyzing the impact of the New behavior of truck users by emergence of CASE vehicles. Five factors were analyzed to investigate the impact of CASE vehicles on the number of trips by trucks, including, Efficiency of vehicle operation, attention needed for driving, truck parking, safety of vehicle operation, and trucks e-commerce. All the five factors include values for pessimistic, optimistic, and most likely scenarios. Table 12 shows the assumptions for the New Behavior parameter Passenger Vehicles. For example, for the Pessimistic Scenario, for Efficiency of vehicle operation parameter, the Number of trips by Trucks will increase by 6%. In the Optimistic Scenario the number of trips by Trucks in the future predicted in the 1st Step would be multiplied by 1.72 to calculate the impact of CAVs New Behavior on the traffic network.

Table 12: Assumptions for the New Behavior parameter for Trucks

Scenarios	Pessimistic Scenario	Most Likely Impact	Optimistic Scenario
Efficiency of Vehicle Operation	When a minority of the Motor Carriers utilize CAV Trucks to advance their business: *0.06*	When approximately half of the Motor Carriers utilize CAV Trucks to advance their business: *0.15*	When a majority of the motor carriers utilize CAV Trucks to advance their businesses: *0.24*
Attention Needed for Driving	Assume 20% reduction in VTTS: *0.05*	Assume 50% reduction in VTTS: *0.1*	Assume 80% reduction in VTTS: *0.15*
Truck Parking	*0.05*	*0.1*	*0.15*
Safety of Vehicle Operation for Trucks	*0.04*	*0.06*	*0.08*
Trucks E-Commerce/ Empty Personal Vehicle Trips to Avoid Parking	*0*	*0.05*	*0.1*
Trucks' Counts Adjusting Factors	***1.2***	***1.46***	***1.72***

Adjusting Factors for New Ownership models (cars) and Shared Mobility Policies

Besides, New Behavior analysis, New Ownership models and Shared Mobility Policies are the two remaining main factors for development of the 22 scenarios of the study. The following figure shows the impact of various combination of the New Ownership models (cars) and Shared Mobility Policies adjustment factors in this study. Table 13 shows the assumptions for the New Policies and Regulations parameter. For example, in the High Shared Mobility-Required Policies Scenario, the number of trips for Passenger Vehicles for any time in the future predicted in the 1st Step Using Machine Learning would be multiplied by 0.2 to present the impact of New Ownership Models on traffic network.

Table 13: Assumptions for the New Policies and Regulations

New Policies & Regulations			
	Policies & Regulations		
	Not Required	**Incentives**	**Required**
New Ownership Models	Pessimistic Scenario (Assume No Requirement or Incentives):	Most Likely Scenario (When there are incentives by the government not to use private ownership):	Optimistic Scenario (When it is required by law to use shared mobility, Potential Penalty for those not following the laws):
No or Low Rate of Shared Mobility	***1***	***1***	***1***
Medium Rate of Shared Mobility	***0.9***	***0.75***	***0.6***
High Rate of Shared Mobility	***0.8***	***0.5***	***0.2***

Mixed Adjusting Factors for All Scenarios

The following figure shows all the scenarios developed in the study with their associated adjusting factors for trucks trips and passenger vehicles trips. Figure 10 shows the mixed adjusting factors for all scenarios. For the scenario 3.11, the number of trips for Passenger Vehicles in the future predicted in the 1st Step would be multiplied by 0.99 to present the impact of New Behavior (number of Trips caused by CAVs) on traffic network and New Ownership Models (Private/ Shared). Also, for the trucks the adjusting factor would be multiplied by 1.72.

Scenarios	New Behavior	New Ownership Models	Shared Mobility Policies	Adj. Factor Trucks	Adj. Factor Trucks
Scenario 1.1.	No Change	No Shared Mobility	Not Required	1	1
Scenario 2.1.	High Impact	No Shared Mobility	Not Required	1.98	1.72
Scenario 2.2.	Low Impact	No Shared Mobility	Not Required	1.22	1.2
Scenario 2.3.	Most Likely Impact	No Shared Mobility	Not Required	1.6	1.46
Scenario 3.1.	High Impact	Half Shared Mobility	Not Required	1.782	1.72
Scenario 3.2.	High Impact	Half Shared Mobility	Incentives	1.485	1.72
Scenario 3.3.	High Impact	Half Shared Mobility	Required	1.188	1.72
Scenario 3.4.	Low Impact	Half Shared Mobility	Not Required	1.098	1.2
Scenario 3.5.	Low Impact	Half Shared Mobility	Incentives	0.915	1.2
Scenario 3.6.	Low Impact	Half Shared Mobility	Required	0.732	1.2
Scenario 3.7.	Most Likely Impact	Half Shared Mobility	Not Required	1.44	1.46
Scenario 3.8.	Most Likely Impact	Half Shared Mobility	Incentives	1.2	1.46
Scenario 3.9.	Most Likely Impact	Half Shared Mobility	Required	0.96	1.46
Scenario 3.10.	High Impact	All Shared Mobility	Not Required	1.584	1.72
Scenario 3.11.	High Impact	All Shared Mobility	Incentives	0.99	1.72
Scenario 3.12.	High Impact	All Shared Mobility	Required	0.396	1.72
Scenario 3.13.	Low Impact	All Shared Mobility	Not Required	0.976	1.2
Scenario 3.14.	Low Impact	All Shared Mobility	Incentives	0.61	1.2
Scenario 3.15.	Low Impact	All Shared Mobility	Required	0.244	1.2
Scenario 3.16.	Most Likely Impact	All Shared Mobility	Not Required	1.28	1.46
Scenario 3.17	Most Likely Impact	All Shared Mobility	Incentives	0.8	1.46
Scenario 3.18	Most Likely Impact	All Shared Mobility	Required	0.32	1.46

Figure 10: Mixed Adjusting Factors for All Scenarios

The full scope and significance of the changes that are to come, what they necessitate, or how they will develop are not known. These forthcoming forces have the potential to change the current traffic network. We may be on the threshold of change as high as any the industry has ever seen. Scenario analysis is a must to process the evaluation of possible future events through the consideration of alternative plausible, though, not equally likely, states of the world. In this section scenarios series for 2021 to 2050 were built to outline the plausible futures compared. So, they could assist in mid- and long-term planning to broaden perspectives and identify the leading factors affecting the traffic network at the system level (accompanied by a sensitivity analysis). To generate the scenario series of this research, and to cover the possible threshold of the future scenarios, three cases namely supportive (a good scenario), most likely, and disruptive scenario were developed. To develop each of the scenario series, CAVs market penetration rate and CAVs travel projection rates, developed scenarios for various New behavior and New ownership models of ACES and CATs era were employed. Regarding the New behavior and New ownership models, the developed scenarios in the previous section were utilized.

About the travel projections of CAVs that plays a crucial role in the development of the scenario-series between 2020 and 2050, this study employed the CAV travel projection rates developed by the study by Litman (2018). The Autonomous Vehicles Travel Projections by Litman is shown in Appendix E. New behavior and new ownership (including the policies' impact) were considered for the development of three main scenario series.

General Scenarios – Productive Scenario

In the productive scenario, both new behavior of customers (about the attractiveness of making trips by CAVs) and new ownership models were considered in a way that is optimistically aligned with higher level of service and less prone to congestion. In the productive scenario users will not change number of trips customers make due to genesis of CAVs drastically. Surely, people will be affected by the automation and connectivity, however, their behavior, and tendency to travel more will not be affected significantly. On the other hand, users will get further from owning the vehicles to sharing the vehicles earlier which is aligned with decreasing the number of trips by vehicles and higher level of service of the traffic network. Additionally, there will be some policies that incentivizes or require customers using shared mobility mode over private ownership of vehicles. In this case, 15 years in the beginning will not have any requirement or incentive, then 11 years of policies which encourage people to use shared mode of traveling more, and finally, 5 years of required shared mobility mode. Figure 11 shows the annual adjusting factors for Productive Scenario.

Year	Travel Market Penetration Cars	Traditional Cars	Travel Market Penetration Trucks	Traditional Trucks	New Behavior (ACE Vehicles)	New Behavior Cars	New Behavior Trucks	New Ownership Models Cars	Shared Mobility Policy Cars	Shared Mobility Adjust. Factor	Adj. Factor Cars	Adj. Factor Trucks
2020	1%	99.00%	6.00%	94.00%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2021	3%	96.98%	8.02%	91.98%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2022	5%	95.05%	9.95%	90.05%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2023	7%	93.12%	11.88%	88.12%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2024	9%	91.20%	13.80%	86.20%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.03	1.03
2025	11%	89.00%	16.00%	84.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.03
2026	13%	87.37%	17.63%	82.37%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.04
2027	15%	85.46%	19.54%	80.46%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.04
2028	16%	83.55%	21.45%	78.55%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.05	1.04
2029	18%	81.64%	23.36%	76.64%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.05	1.05
2030	20%	80.00%	25.00%	75.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.05
2031	22%	77.82%	27.18%	72.82%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.05
2032	24%	75.90%	29.10%	70.90%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.06
2033	26%	73.99%	31.01%	68.99%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.07	1.06
2034	28%	72.06%	32.94%	67.06%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.07	1.07
2035	30%	70.00%	35.00%	65.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.08	1.07
2036	32%	68.19%	36.81%	63.19%	Low Impact	1.22	1.2	Medium Shared Mobility	Not required	0.9	0.97	1.07
2037	34%	66.24%	38.76%	61.24%	Low Impact	1.22	1.2	Medium Shared Mobility	Not required	0.9	0.98	1.08
2038	36%	64.28%	40.72%	59.28%	Low Impact	1.22	1.2	Medium Shared Mobility	Not required	0.9	0.98	1.08
2039	38%	62.31%	42.69%	57.31%	Low Impact	1.22	1.2	Medium Shared Mobility	Not required	0.9	0.98	1.09
2040	40%	60.00%	45.00%	55.00%	Low Impact	1.22	1.2	Medium Shared Mobility	Not required	0.9	0.99	1.09
2041	42%	58.33%	46.67%	53.33%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.15	1.21
2042	44%	56.32%	48.68%	51.32%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.16	1.22
2043	46%	54.29%	50.71%	49.29%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	0.98	1.23
2044	48%	52.25%	52.75%	47.25%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	0.99	1.24
2045	50%	50.00%	55.00%	45.00%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	1.00	1.25
2046	52%	48.09%	56.91%	43.09%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	1.01	1.26
2047	54%	45.99%	59.01%	40.99%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	1.02	1.27
2048	56%	43.86%	61.14%	38.86%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	1.03	1.28
2049	58%	41.71%	63.29%	36.71%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Incentives	0.75	1.03	1.29

Figure 11: Annual adjusting factors for Productive Scenario

General Scenarios – Most Likely Scenario

In the most likely scenario, both new behavior of customers (about the attractiveness of making trips by CAVs) and new ownership models were considered in a way that is moderately aligned with higher level of service. In the productive scenario users will not either change number of trips customers make due to genesis of CAVs drastically or keeping their same behaviors as before. There will only get affected moderately. Moreover, users will get further from owning the vehicles to sharing the vehicles earlier which is aligned with decreasing the number of trips by vehicles and higher level of service of the traffic network. Additionally, there will be some policies that incentivizes or require customers using shared mobility mode over private ownership of vehicles. In this case, 15 years in the beginning will not have any requirement or incentive, then 11 years of policies which encourage people to use shared mode of traveling more, and finally, 5 years of required shared mobility mode. Figure 12 shows the annual adjusting factors for Most Likely Scenario.

Year	Travel Market Penetration Cars	Traditional Cars	Travel Market Penetration Trucks	Traditional Trucks	New Behavior (ACE Vehicles)	New Behavior Cars	New Behavior Trucks	New Ownership Models Cars	Shared Mobility Policy Cars	Shared Mobility Adjust. Factor	Adj. Factor Cars	Adj. Factor Trucks
2020	1%	99.00%	6.00%	94.00%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2021	3%	96.98%	8.02%	91.98%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2022	5%	95.05%	9.95%	90.05%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2023	7%	93.12%	11.88%	88.12%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2024	9%	91.20%	13.80%	86.20%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.03	1.03
2025	11%	89.00%	16.00%	84.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.03
2026	13%	87.37%	17.63%	82.37%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.04
2027	15%	85.46%	19.54%	80.46%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.04
2028	16%	83.55%	21.45%	78.55%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.05	1.04
2029	18%	81.64%	23.36%	76.64%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.05	1.05
2030	20%	80.00%	25.00%	75.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.05
2031	22%	77.82%	27.18%	72.82%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.05
2032	24%	75.90%	29.10%	70.90%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.06
2033	26%	73.99%	31.01%	68.99%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.07	1.06
2034	28%	72.06%	32.94%	67.06%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.07	1.07
2035	30%	70.00%	35.00%	65.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.08	1.07
2036	32%	68.19%	36.81%	63.19%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.22	1.17
2037	34%	66.24%	38.76%	61.24%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.23	1.18
2038	36%	64.28%	40.72%	59.28%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.24	1.19
2039	38%	62.31%	42.69%	57.31%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.26	1.20
2040	40%	60.00%	45.00%	55.00%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.27	1.21
2041	42%	58.33%	46.67%	53.33%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.15	1.21
2042	44%	56.32%	48.68%	51.32%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.16	1.22
2043	46%	54.29%	50.71%	49.29%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.17	1.23
2044	48%	52.25%	52.75%	47.25%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.18	1.24
2045	50%	50.00%	55.00%	45.00%	Most Likely Impact	1.6	1.46	Medium Shared Mobility	Not required	0.9	1.20	1.25
2046	52%	48.09%	56.91%	43.09%	High Impact	1.98	1.72	Medium Shared Mobility	Incentives	0.75	1.17	1.41
2047	54%	45.99%	59.01%	40.99%	High Impact	1.98	1.72	Medium Shared Mobility	Incentives	0.75	1.18	1.42
2048	56%	43.86%	61.14%	38.86%	High Impact	1.98	1.72	Medium Shared Mobility	Incentives	0.75	1.20	1.44
2049	58%	41.71%	63.29%	36.71%	High Impact	1.98	1.72	Medium Shared Mobility	Incentives	0.75	1.22	1.46
2050	61%	39.00%	66.00%	34.00%	High Impact	1.98	1.72	Medium Shared Mobility	Incentives	0.75	1.24	1.48

Figure 12: Annual adjusting factors for Most Likely Scenario

General Scenarios – Disruptive Scenario

In the disruptive scenario, both new behavior of customers and new ownership models were considered in a way that is more prone to experiencing traffic congestion in the traffic network. In the disruptive scenario, users will change the number of trips they make due to genesis of CAVs significantly; their behavior, and tendency to travel more will be affected drastically. Moreover, customers will keep with the private mode over sharing their trips with other customers and will not change their ownership patterns. Additionally, there will not be any policies that incentivizes or require customers using shared mobility mode over private ownership of vehicles. Figure 13 shows the annual adjusting factors for Disruptive Scenario.

Year	Travel Market Penetration Cars	Traditional Cars	Travel Market Penetration Trucks	Traditional Trucks	New Behavior (ACE Vehicles)	New Behavior Cars	New Behavior Trucks	New Ownership Models Cars	Shared Mobility Policy Cars	Shared Mobility Adjust. Factor	Adj. Factor Cars	Adj. Factor Trucks
2020	1%	99.00%	6.00%	94.00%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2021	3%	96.98%	8.02%	91.98%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2022	5%	95.05%	9.95%	90.05%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2023	7%	93.12%	11.88%	88.12%	No Change	1	1	No or Low Shared Mobility	Not required	1	1.00	1.00
2024	9%	91.20%	13.80%	86.20%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.03	1.03
2025	11%	89.00%	16.00%	84.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.03
2026	13%	87.37%	17.63%	82.37%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.04
2027	15%	85.46%	19.54%	80.46%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.04	1.04
2028	16%	83.55%	21.45%	78.55%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.05	1.04
2029	18%	81.64%	23.36%	76.64%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.05	1.05
2030	20%	80.00%	25.00%	75.00%	Low Impact	1.22	1.2	No or Low Shared Mobility	Not required	1	1.06	1.05
2031	22%	77.82%	27.18%	72.82%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.16	1.13
2032	24%	75.90%	29.10%	70.90%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.17	1.13
2033	26%	73.99%	31.01%	68.99%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.19	1.14
2034	28%	72.06%	32.94%	67.06%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.20	1.15
2035	30%	70.00%	35.00%	65.00%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.21	1.16
2036	32%	68.19%	36.81%	63.19%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.22	1.17
2037	34%	66.24%	38.76%	61.24%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.23	1.18
2038	36%	64.28%	40.72%	59.28%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.24	1.19
2039	38%	62.31%	42.69%	57.31%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.26	1.20
2040	40%	60.00%	45.00%	55.00%	Most Likely Impact	1.6	1.46	No or Low Shared Mobility	Not required	1	1.27	1.21
2041	42%	58.33%	46.67%	53.33%	High Impact	1.98	1.72	No or Low Shared Mobility	Not required	1	1.46	1.34
2042	44%	56.32%	48.68%	51.32%	High Impact	1.98	1.72	No or Low Shared Mobility	Not required	1	1.48	1.35
2043	46%	54.29%	50.71%	49.29%	High Impact	1.98	1.72	No or Low Shared Mobility	Not required	1	1.50	1.37
2044	48%	52.25%	52.75%	47.25%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.37	1.38
2045	50%	50.00%	55.00%	45.00%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.39	1.40
2046	52%	48.09%	56.91%	43.09%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.40	1.41
2047	54%	45.99%	59.01%	40.99%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.42	1.42
2048	56%	43.86%	61.14%	38.86%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.44	1.44
2049	58%	41.71%	63.29%	36.71%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.46	1.46
2050	61%	39.00%	66.00%	34.00%	High Impact	1.98	1.72	Medium Shared Mobility	Not required	0.9	1.48	1.48

Figure 13: Annual adjusting factors for Disruptive Scenario

Level of service adjustments by CASE vehicles scenarios

After identifying the adjustment factors for trucks and passenger vehicles on the 22 above-mentioned scenarios, the traffic capacity and level of service calculation should be adjusted. The following steps describe the procedure followed by the study to revise the LOS calculation for each cosite of the study.

1. First, the Neural Network models predicted directional traffic for MADT and MADTT have been used for 2021 to 2045.
2. For any cosite on the interstate highway a 10-mile length of the road and the characteristics had been studied: K factor, Max Speed FFS, and the Number Lanes and Max Service Flow Rate (pc/hr/lane).
3. The study employed the Travel Market Penetration prediction of the CAVs presented by Litman 2018.
4. Based on the traffic prediction data for MADT and MADTT, and the adjustment parameters for the CASE vehicle scenarios, the adjusted traffic flow for directional traffic for passenger

vehicles and trucks were calculated. For any directional adjusted traffic flow, the study considered 3 scenarios, productive, most likely, and disruptive scenarios.

5. By employing the predicted passenger vehicle traffic flow, and the predicted truck traffic flow, the adjusted truck percentage were calculated. Then, based on the truck percentage, the traffic capacity of the road was reduced. Finally, by employing the study by Maurer 2016, the traffic capacity was revised by the impact of Connected and Automated vehicles to increase the capacity. Appendix F shows the Highway Capacity Manual (HCM) values employed in this step.
6. To calculate the passenger vehicle equivalent of trucks vehicles, the number of trucks were multiplied by 1.5. Then, the passenger vehicle Equivalent of all the vehicles for each direction were calculated by MADT unit.
7. To calculate the adjusted LOS, the MADT unit was converted to pc/h/lane by using the K, and FFS of each cosite.
8. Finally, based on the LOS ratio, the LOS of each cosite for any scenario were calculated.

Step 4: Highway construction cost

(Regarding this step the author employed his published study: Mahdavian, A., Shojaei, A., Salem, M., Yuan, J.S. and Oloufa, A.A., 2021b. Data-Driven Predictive Modeling of Highway Construction Cost Items. Journal of Construction Engineering and Management, 147(3), p.04020180.)

The main goal of this step of the study was to forecast the total cost of each type of roadway construction expansion (either 4 or 6 lane-construction or adding lanes to urban or rural roads) for the highway links that experienced overcapacity. Figure 18 represents the pipeline of this step. During preprocessing, data was standardized and divided into training, testing, and validation datasets. Then, the validation and training datasets were fed to a feature selection module that selects the essential features within the data and removes other independent variables. This study examined multiple approaches for both feature selection and linear and non-linear modeling. Through this process, the most appropriate model (for each cost item) was found.

To develop the model, run # 1 was performed and MAPE was used to measure error among the different cost items. Those that had >15% error were deemed failed, and isolated. Independent variables that passed with low MAPE were then moved into the predictor group. This process was subsequently repeated and the application was re-run. This method allows for a larger selection of accurate predictor variables for cost forecasting. The pipeline of this section is presented in Figure 14.

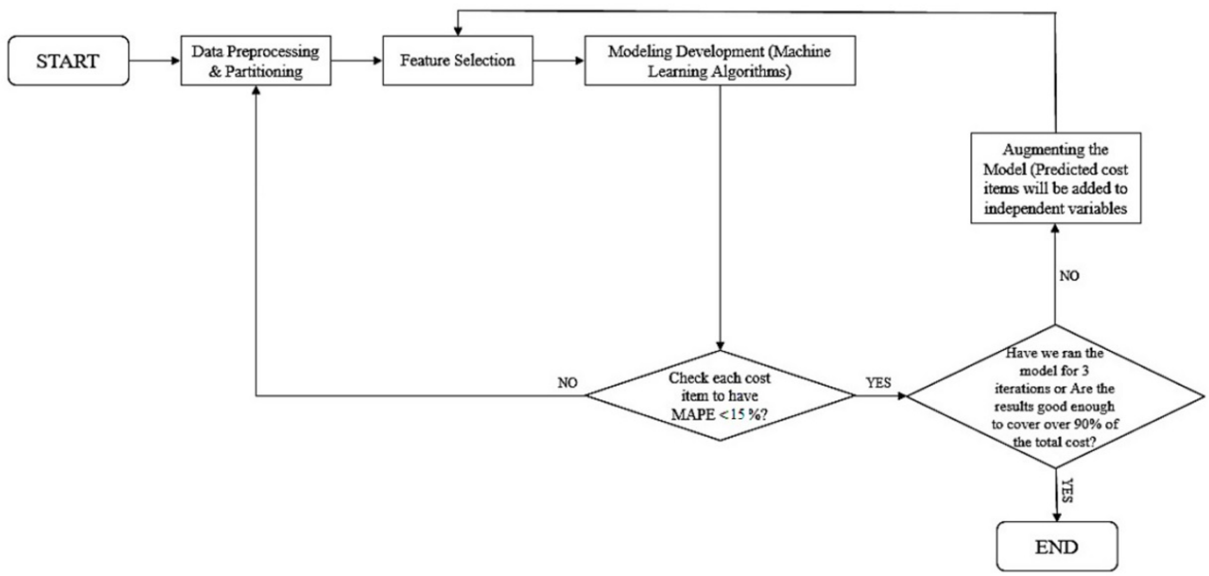


Figure 14: The pipeline of highway construction cost prediction model

A. Data Preprocessing and Partitioning: As before, the preprocessing stage begins with assigning a numerical value to each independent variable. This data was then normalized based on a standard distribution. A standard deviation of 1 and a mean of 0 was selected for regularization. Data was then divided into the groups of test, training, and validation.

Again, as time series data was included, it was important to consider the data continuity. As a result, random data distribution could not be used to maintain the temporal integrity of the data. Instead, a cross-validation expanding window method was used for data assessment, as show in Figure 15. The data used consisted of documented cost item values from 17,121 projects, and was organized based on the year assigned to each split of the training, test, and validation datasets. The first 3 years of data values are used for the training dataset; after which, the following 3 years of data values are used for test validation. Because an expanding window was selected to compare the entire dataset, every phase the training dataset was increased by 3 years. Finally, the testing dataset contained the following 3 years of historical data that accompanied the validation dataset. The mean error was then calculated using the error results for each individual split. The data points used were unique for every fold of validation, training, testing, and cross-validation. To illustrate, in split 4, data from the years 2001-2012 was selected for the training dataset. For that split's testing dataset, information from years 2013-2015 was selected. And finally, data from 2016-2017 was used in the validation dataset. This results in a model that was tested with cost values from real projects performed from 2016-2017. Because separate data points were used for training and testing, the model accuracy reported reflects real construction project cost information. This process was necessary to establish a more robust model, and to avoid creating a randomly accurate, or overfit model.

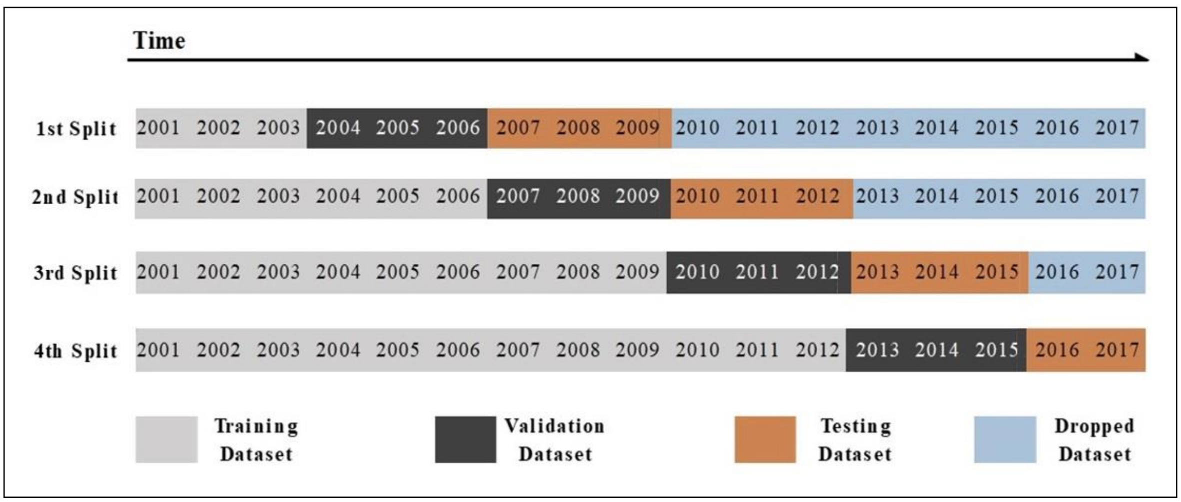


Figure 15: Nested cross-validation; expanding window

All the models used in this study used the validation dataset for evaluation, and the training dataset for training. In addition, a grid search with the validation dataset was performed during parameter optimization, with the purpose of identifying the most optimal model, parameters, and feature selection tool.

B. Feature Selection: Feature selection is the method of selecting the most appropriate predictors and eliminating unnecessary variables from the pool of potential predictors. Depending on the model's structure, feature selection can improve a model's accuracy. This method was carried out by finding the contribution of each variable to the models' precision and then eliminating unnecessary and repetitive variables, while also maintaining the most beneficial ones. Standardization is necessary before feature selection since the independent variables have different magnitudes of order and using them as-is might result in the ones with small magnitudes being overlooked (Mahdavian et al. 2021b). For each parameter set, the cross-validation method discussed earlier served to train, validate, and test the model. In this work, three methods were employed to decide the main features. First, valuable features were chosen via a model (SelectFromModel function from Scikit-learn (2011)). Various modeling techniques capable of implicit feature selection, including Random Forest (RF) Regression, Ridge Regression (Ridge), Bayesian Ridge (BR) Regression, and Decision Tree (DT), were employed in this section (Mahdavian et al. 2021d). The importance threshold considered for the selection parameter of this step changes between 0.25, 0.5, 0.75, 1, 1.25, 1.5, and 1.75. Second, the Recursive Feature Elimination (RFE in Scikit Learn (2011)) was conducted. In this process, the least essential features are eliminated recursively until the most appropriate features are found. The models used to determine the importance of features are the same as the previous step (RFE-RF, RFE-Ridge, RFE-BR, and RFE-DT). In the RFE step, the number of ultimately selected features varies between 1, 3, 5, 10, 20, 30, 40, 50, and 60. Third, a scoring function was used to find the "K" best features in the dataset (SelectKBest in Scikit Learn (2011)). The scoring functions used in this work were ANOVA F-value (FCLASSIF) and Mutual Information (MFCLASSIF). The number of ultimately selected features of this step also fluctuates between 1, 3, 5, 10, 20, 30, 40, 50, and 60. These feature selection approaches were implemented inside a grid search and finally compared to find the best set of parameters (Mahdavian et al. 2021d).

C. Modeling Approaches: Multiple machine learning algorithms were employed in this study, particularly those based on non-linear relationships between variables to forecast the cost items. The models (SelectFromModel function from Scikit-learn (2011)), that were used in this study included Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN), and Neural Network (NN). Moreover, linear regression models, including Linear Regression (Linear), Ridge Regression (Ridge), Bayesian Ridge (BR), Stochastic Gradient Descent (SGD) Regression, and Passive-Aggressive (PA) Regression were evaluated to find the level of improvement of using non-linear models (Mahdavian et al. 2021b). This selection of models allows the user to compare models with different levels of linearity or non-linearity, as well as having control over parametric models.

For the RF and DT algorithms in this research, the model parameter (MP), which is the maximum depth of the trees, varies between 5, 20, 50, 75, 100, and 200. Regarding the K-Nearest Neighbors algorithm employed, the model parameter (Number of neighbors (K)) changes between 1, 3, 5, 7, 10, and 16. Concerning the Neural Network models, the MP, which represents the hidden layer size (number of neurons), varies between 1, 2, and 4 (Mahdavian et al. 2021b). On the other hand, in the linear algorithms, for the Ridge Regression, the MP represents the regularization strength (alpha) and varies between 0.1, 1, 10, 100, 10000 and 1e6; for Bayesian Ridge Regression, the model parameter shows the shape and inverse scale parameters of the prior gamma distribution (alpha_1 and alpha_2) and varies between 0.1, 1, 10, 100, 10000 and1e6. About the Stochastic Gradient Descent Regression, the MP represents the elastic net mixing parameter of L1 and L2 regularization (L1 ratio) and fluctuates between 0, 0.15, 0.3, 0.5, 0.75 and 1. Ultimately, regarding Passive Aggressive Regression, MP shows the maximum step size (regularization C) and changes between 0.1, 1, 10, 100, 10000, and 1e6 (Mahdavian et al. 2021d).

As demonstrated in the feature selection and the modeling approach sections, the developed hyper-parameter optimization includes a wide range of values for the parameters from reasonably low values to reasonably high values, so that it could be applied to various datasets with differing characteristics(Mahdavian et al. 2021d).

CHAPTER FIVE: RESULTS

Step 1: Traffic prediction model – Passenger Vehicles

(Regarding this section, the Author employed the studies reviewed in the article published by author: *Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Yuan, J.S. and Oloufa, A., 2021c. Automated Machine Learning Pipeline for Traffic Count Prediction. Modelling, 2(4), pp.482-513.)*

Figure 16 shows the comparison of the accuracy of different models for the total PVs (total traffic volumes of both directions of the road) on the validation dataset utilizing the grid search of this study. RF, KNN, DT, and NN generated the best performance when they were trained on the training dataset and were tested on the validation dataset. The non-linear models showed better results than linear models.

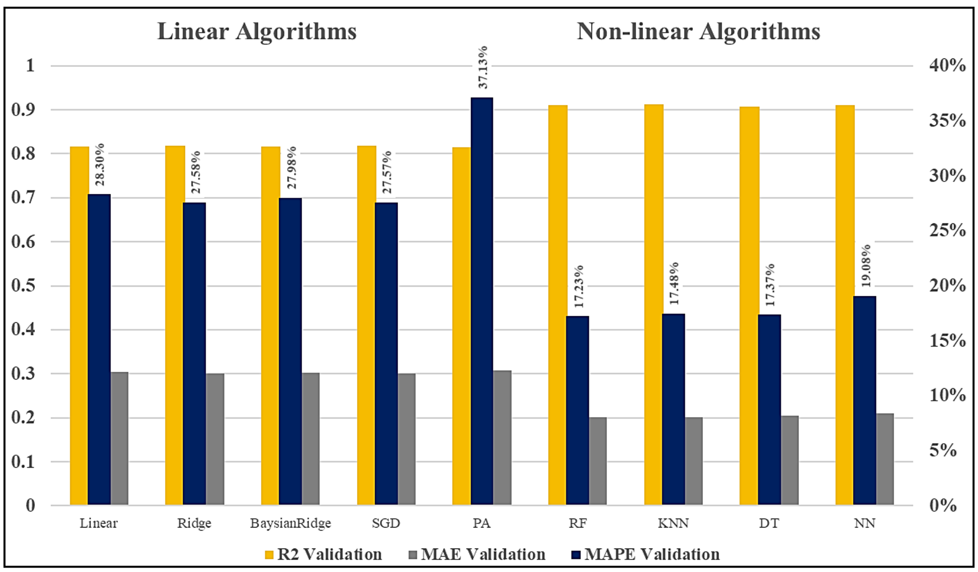


Figure 16: Comparison of different models' best performance on the validation dataset for total cars for the average error of cross validation over four splits

The comparison of the accuracy of different models on the test dataset using the grid search is displayed in Figure 17. It is evident that non-linear models outperformed the linear models. Among non-linear models, RF, KNN, and DT models performed better than NN model. The MAPE error on the test dataset offers a reliable value of 17.46% (Mahdavian et al. 2021c).

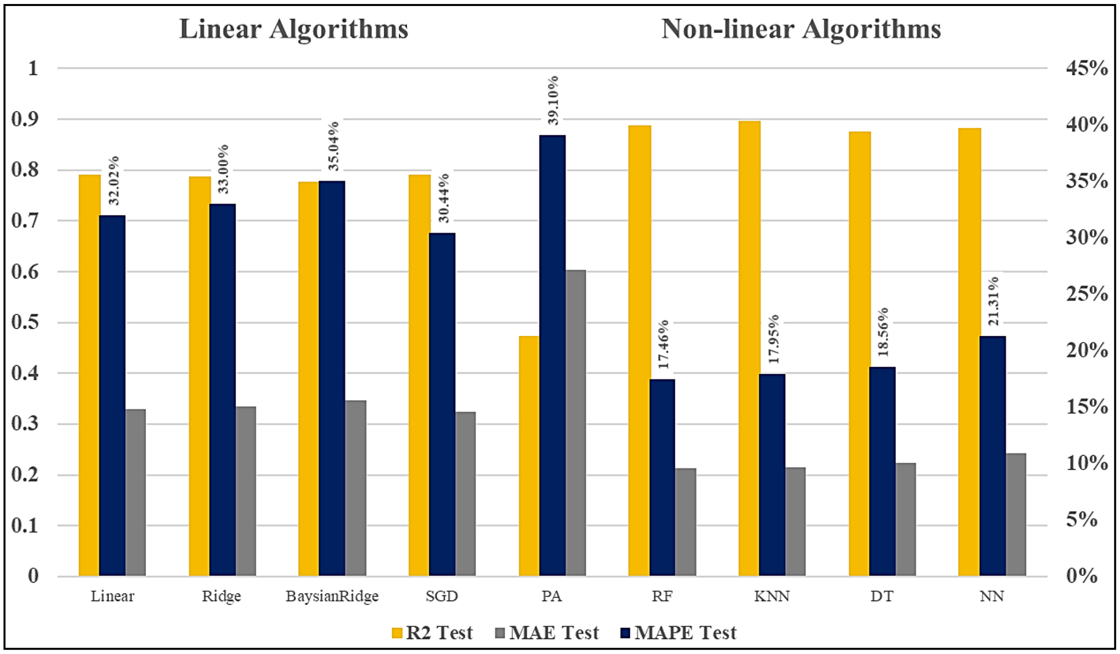


Figure 17: Comparison of different models' best performance on the test dataset for total PVs for the average error of cross validation over four splits

Selected Model of this study for current term (without spatial variables): The RF, KNN, and DT models were the observed to be the highest performing, as highlighted in Figures 19 and 20. Of these models, the KKN model finds the K nearest instances in relation to a reference instance. The model then provides a forecasted output by taking the average of these instances, allowing for interpretation. However, the KNN model is limited by its dependence on the input datasets for predictions, which can produce bias. Another disadvantage is that the KNN model has to search the data each time it makes a prediction and cannot learn; although this does simplify the updating process. In the case of the DT model, dividing features are used to construct a decision tree with the leaves being the regression output (Mahdavian et al. 2021c). The DT model can be used to interpret the results and decision-making process, but because sparse data at the leaves is handled during decision making, the model has the potential to overfit if too many features are used. The RF model is capable of employing an extensive number of decisions trees (~500) on the data used in this study by selecting data groups at random for training. This feature maintains the edges of decisions trees and reduces the possibility of overfitting, making it an appropriate model to use in this study for the purpose of near-term and current prediction. In Figure 18, the outcome of applying the top 10 feature selection approaches to the validation dataset is shown. The grid search process was able to successfully select a set of sufficient training paraments for every feature selection method, and the data can be appropriately modeled with each feature selection method. Of note, the MAPE from the validation dataset for FCLASSIF was 16.98%, the lowest of the feature selection methods tested (Mahdavian et al. 2021c).

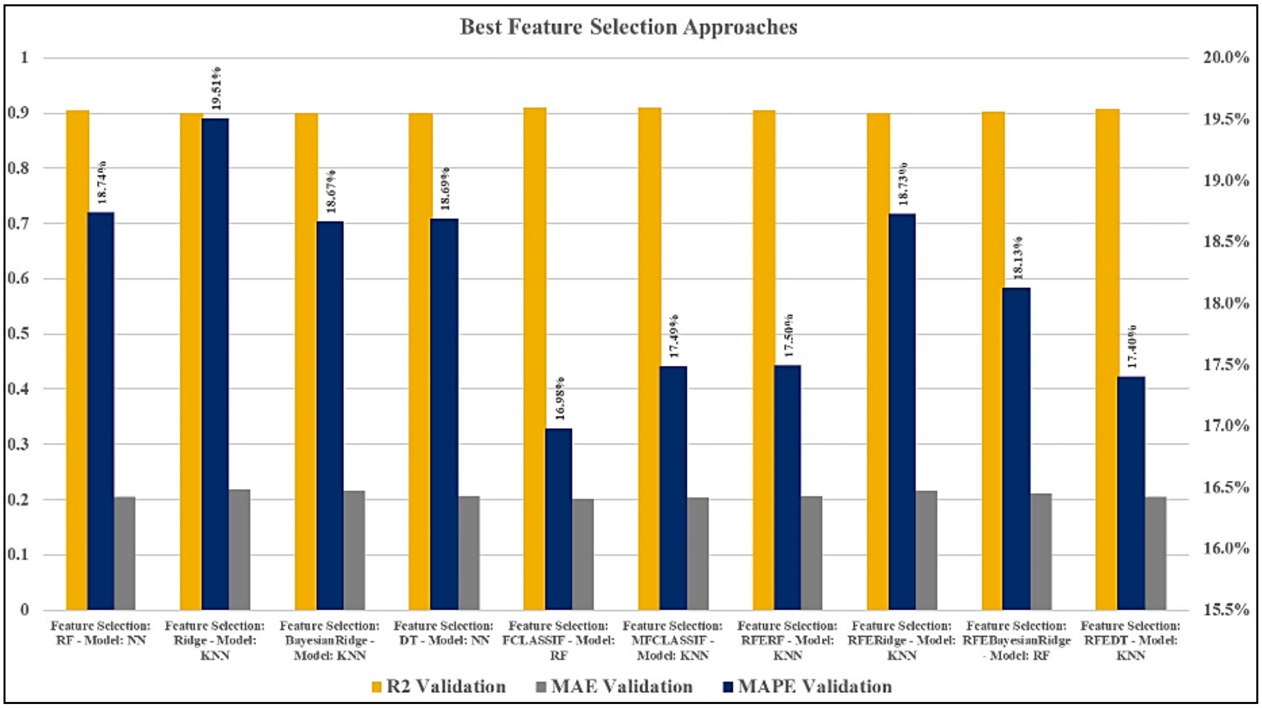


Figure 18: Comparison of feature selection on RF models on validation dataset for total PVs

The comparison of the accuracy of the RF model on the four splits of the performed cross-validation on validation dataset is exhibited in Figure 19. It is apparent that split 4 - covering all the dataset - has a lower MAPE error with 16.35% on the validation dataset (Mahdavian et al. 2021c).

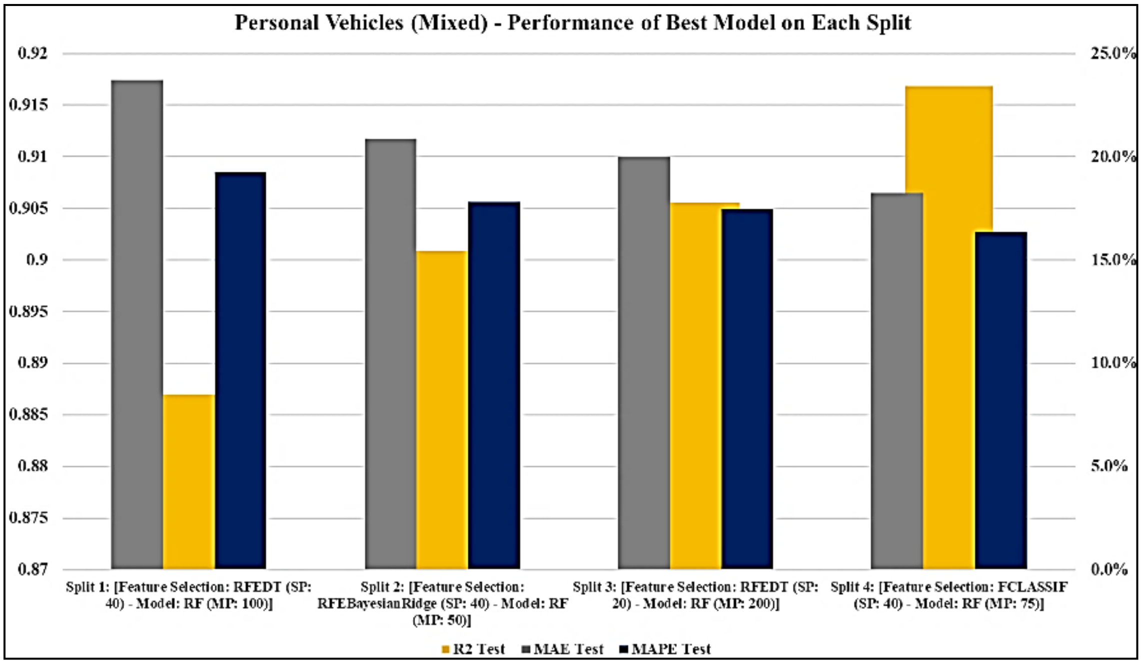


Figure 19: RF model's performance on validation dataset for total PVs

Furthermore, the comparison of the accuracy of the RF model on the four splits of the cross-validation on test dataset is displayed in Figure 20. It is apparent that split 4, has a lower MAPE error with 19.01% on the test dataset.

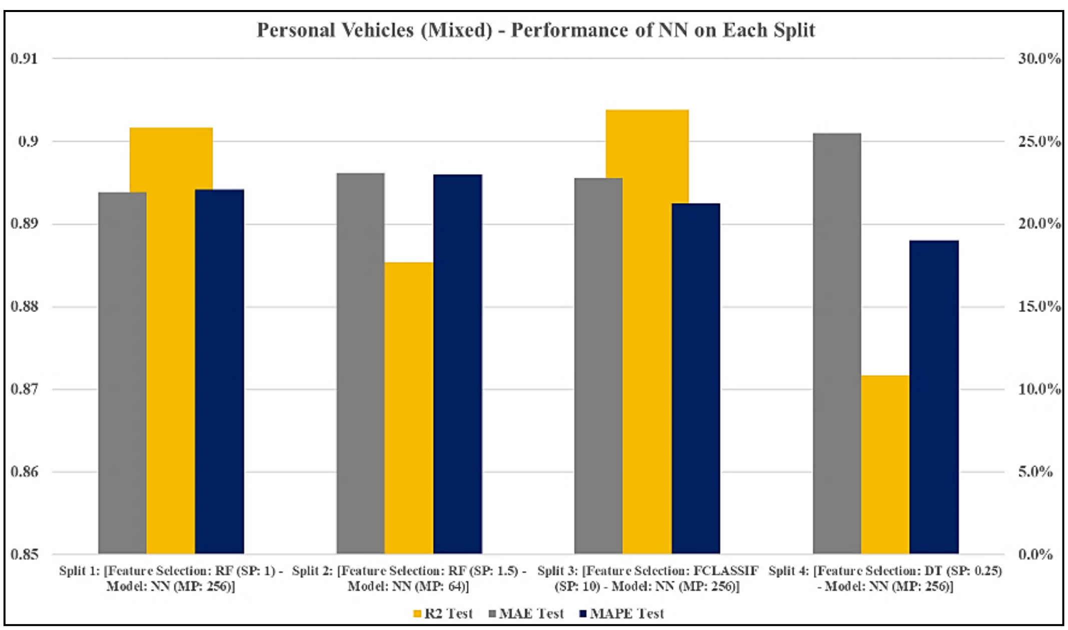


Figure 20: RF model's performance on test dataset for total PVs

Ground truth and the final model's predictions in the validation dataset are presented in Figure 21.

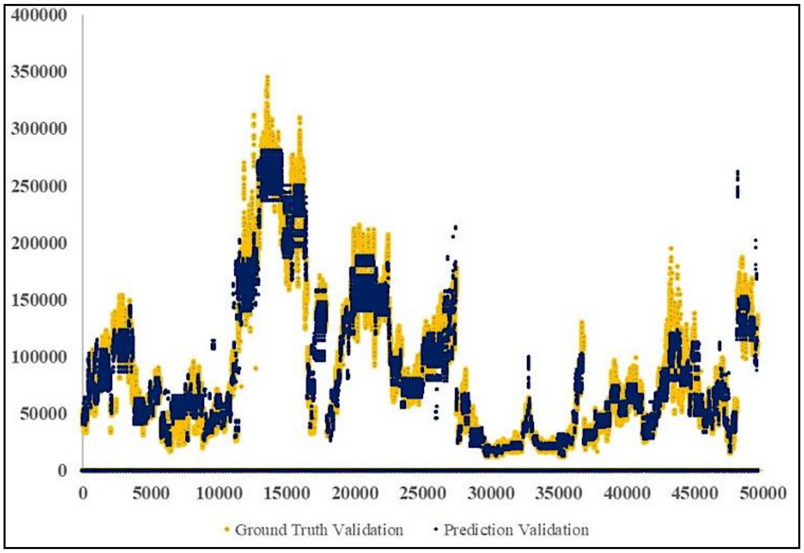


Figure 21: Ground truth prediction of values within the validation dataset employing RF algorithm

Figure 22 also shows the comparison of ground truth and prediction via plotting them against each other. The prediction approximately mirrors the ground truth, and the points are placed around the 45-degree line.

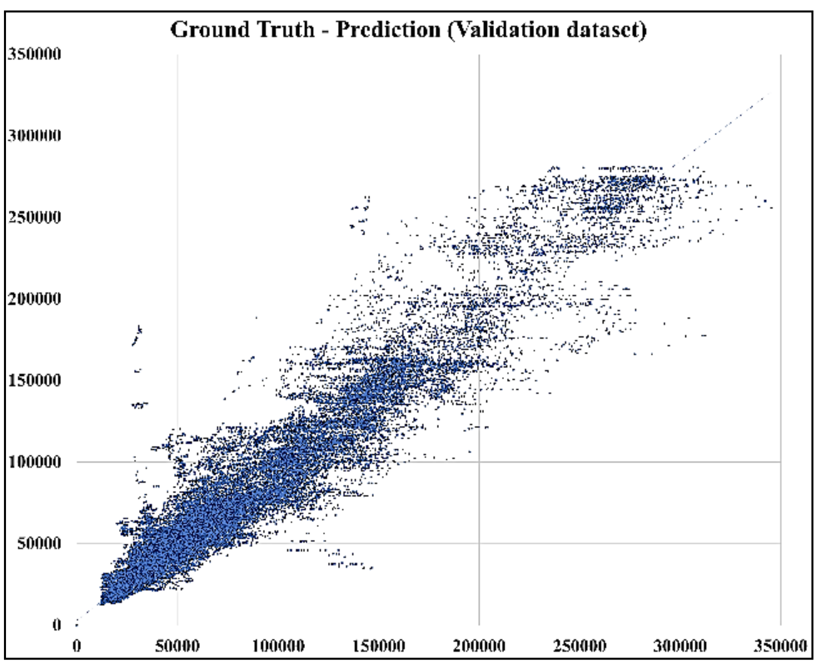


Figure 22: Ground truth prediction of values within the validation dataset employing RF algorithm

Figure 23 depicts the model optimization of the total cars on the split 4 on the validation dataset. The optimum feature selection and modeling approach for this case were found to be *FCLASSIF* and *RF*, respectively. For finding the best selection parameter, the number of features that are ultimately selected is changed between 10 to 40. The same approach is taken for optimizing the *RF* model by alternating the maximum depth of the trees from 5 to 200. The *RF* model, with the depth of 75 trained on 40 selected features, has the lowest MAPE of 17.23% on the validation dataset (Mahdavian et al. 2021d).

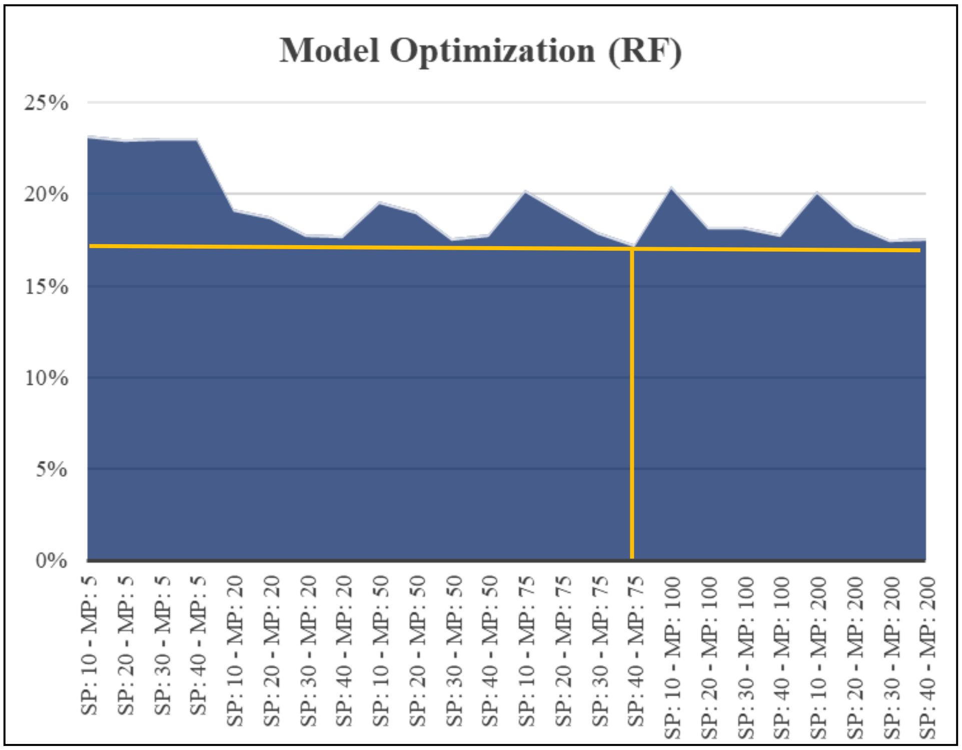


Figure 23: Model optimization for the RF model for total PVs

Figure 24 demonstrates the relative importance of the leading categories of features that were selected as the final set of independent variables from the variable pool. Road characteristics variables, with 67.09% feature importance, ranked first among seven categories of this research. Socioeconomic variables with 30.33% feature importance were ranked second in this research (Mahdavian et al. 2021c).

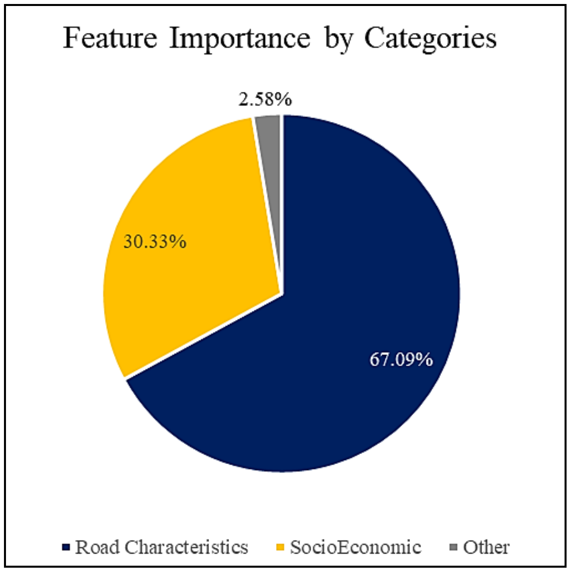


Figure 24: Feature importance categorical of best performing models for PV's RF model (4th split)

Figure 25 shows the top six important features that were contributing to the model's output more than other parameters for total cars. 'Number of Lanes', which represents the capacity of roadway, has the highest impact on the car's prediction model with 61.11% importance. Concerning socioeconomic features, 'length paved roads lane miles' with a 14.24% importance and number of 'Licensed Drivers' with 10.51% are the next important features for the passenger vehicles (PV) prediction model (Mahdavian et al. 2021c).

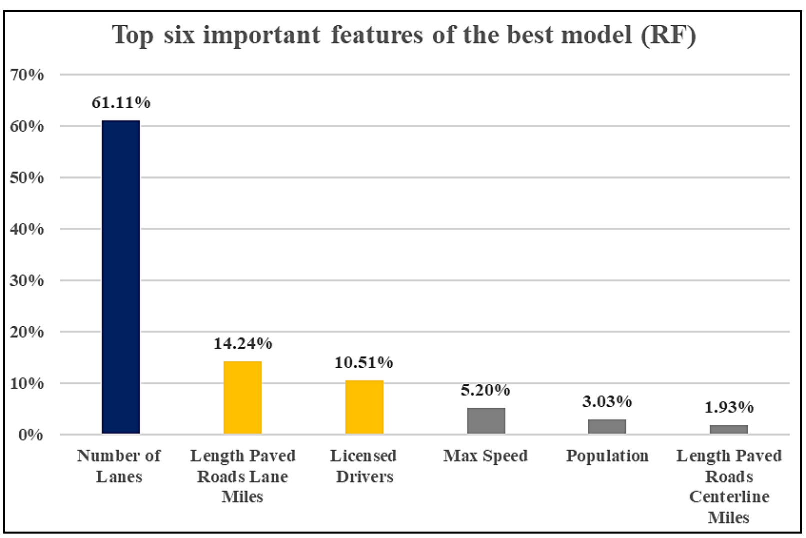


Figure 25: Top six important features of the best performing models for total PVs

Selected Model for long-term PV traffic projections (without spatial variables): One limitation of the RF model is that it is only an estimation based on the given dataset values. A NN algorithm, however, has distinct neuronal layers that are individually capable of non-linear activation function. As a result, this means the BF algorithm is appropriate for near-term and current modeling, but a NN algorithm may be more reliably generalized to long-term projections. Using a NN algorithm, the long-term MADT can be projected because of the model's ability to extrapolate and generate prediction values. During the course of model training, scholastic gradient descent is used to determine ANNs bias and weights. Cross-validation of the implementation of the NN algorithm on the validation dataset from four splits is illustrated in Figure 26. The lowest MAPE error seen was a prediction accuracy of 81% in split 4. This value improved when considered with the accuracy from the additional splits (Mahdavian et al. 2021c).

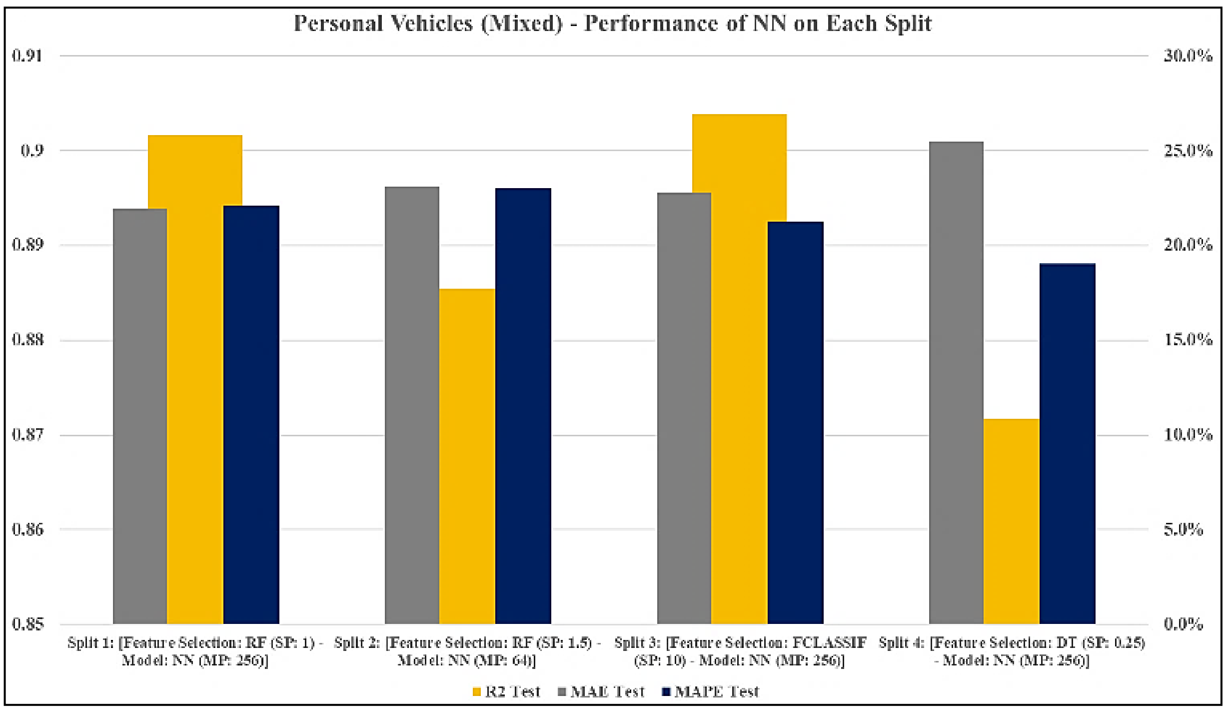


Figure 26: Best model for long-term planning: NN (on validation dataset)

NN models have various parameters that need to be optimized. For finding the best selection parameter, the number of features that are ultimately selected is changed between the importance threshold of 0.25 and 1.75 using a grid search. The same approach is taken for optimizing the NN model by alternating the maximum number of neurons in the hidden layer from 16 to 256. The model optimization of the total PVs on the 4th split on the validation dataset for the neural networks models that are illustrated in Figure 27 showed that the DT feature selection approach with importance threshold of 0.25 and the NN model algorithm with 256 neurons in the hidden layer has the lowest MAPE of 18.29% on the validation dataset. Moreover, the developed NN model has a MAPE of 19.49% on the test dataset on the fourth split (Mahdavian et al. 2021c).

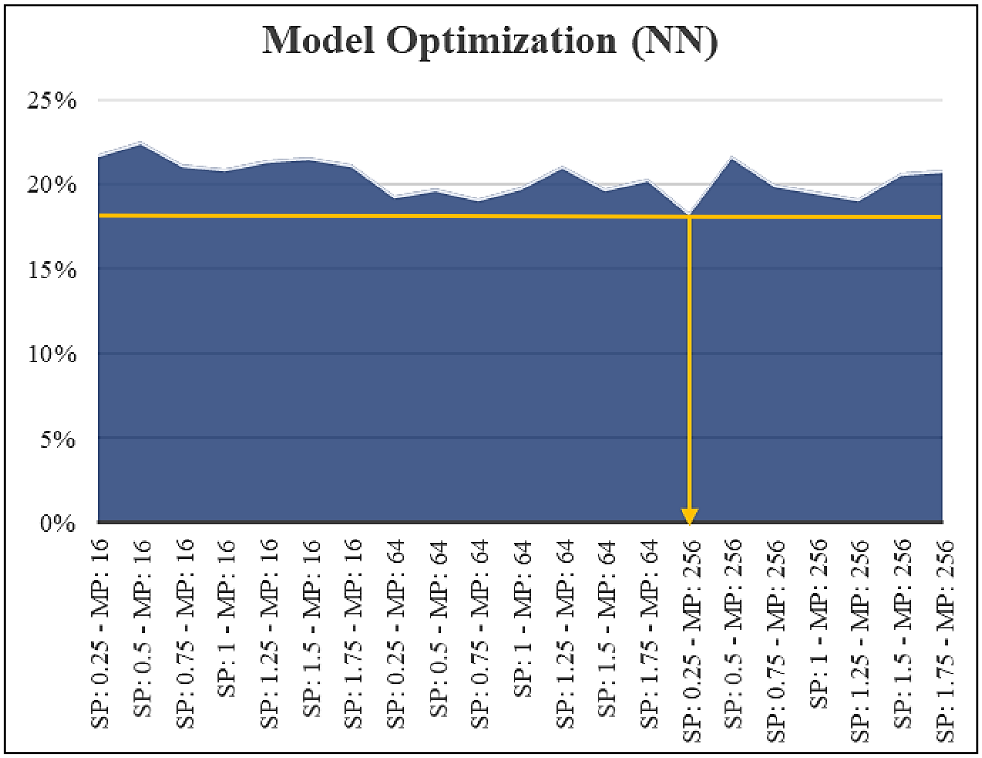


Figure 27: Model optimization for the NN model for total PVs

Spatial Variables: It is vital to examine the influence of spatial variables related to the location of the input data of each cosite (or "site") on the car traffic prediction model. To test the importance of the spatial variables in the car traffic prediction model, this research, added four spatial variables (in table 4) into the prediction model's predictors. Table 14 represents the spatial variables studied in this study among the prior candidate variables used in the developed model in the previous section (Mahdavian et al. 2021c).

Table 14: Spatial candidate variables

Spatial variables	Resource
County Name Interstate ID Cosite ID Euclidean Geometry	Florida Department of Transportation (FDOT)

Comparison of the different models' best performance on the test set showed that non-linear models outperform linear models. However, the MAPE error of the model with spatial candidate variables (added to the previous dataset) showed a better performance compared to the model without spatial variables. The comparison of the models, shown in Table 15, confirms a 4.31% improvement in the accuracy of the MADT by adding the spatial variables (Mahdavian et al. 2021c).

Table 15: RF model performance with and without spatial variables

Models	Label Name	Fold	Selection Approach	Model	R-squared	MAPE Test
Primary model	Total PVs	4	FCLASSIF	RF	0.90	16.35%
Model with spatial variables included	Total PVs	4	RFERF	RF	0.95	12.01%

The comparison of the accuracy of the RF model with spatial variables on the four splits of the cross-validation is shown in Figure 28. It is apparent that split 4, outperforms the other splits of the data. Split 4 has a MAPE error of 12.01% on the test dataset.

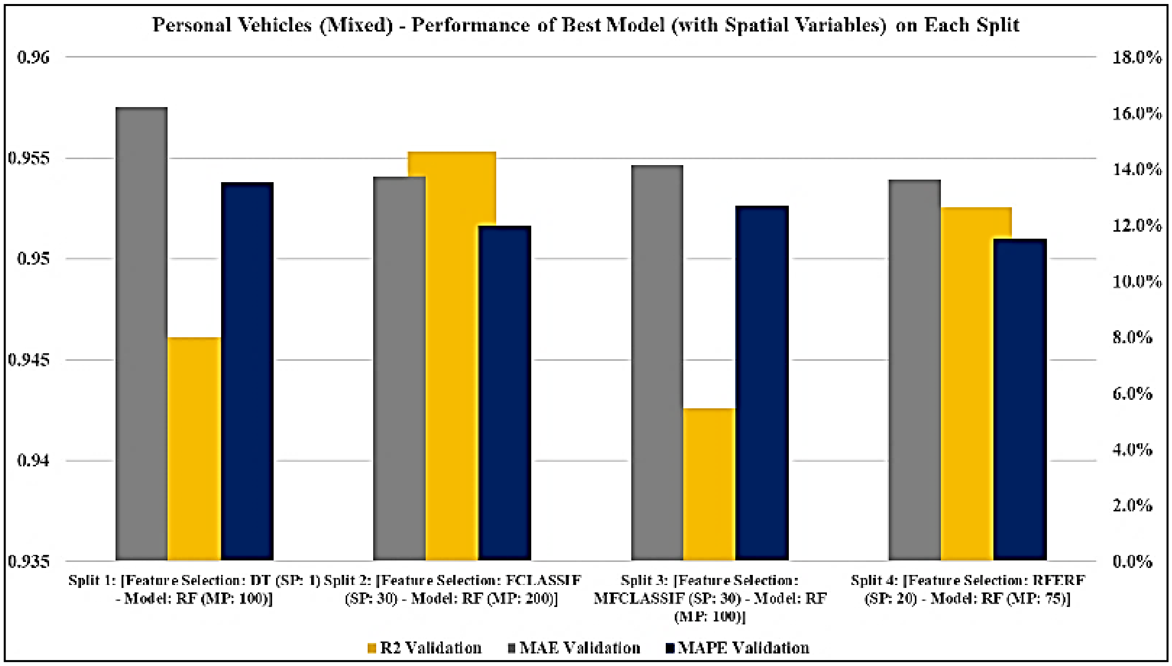


Figure 28: RF model’s (with Spatial variables) performance on test dataset for total PV

Figure 29 depicts the optimum feature selection and modeling approach for this case to be the REFRF and RF, respectively. For finding the best selection parameter, the number of features that are ultimately selected is changed between 10 to 40. The same approach is taken for optimizing the RF model by alternating the maximum depth of the trees from 5 to 200. The RF model, with the depth of 75 trained on 40 selected features, has the lowest MAPE of 12.06% on the validation dataset (Mahdavian et al. 2021d).

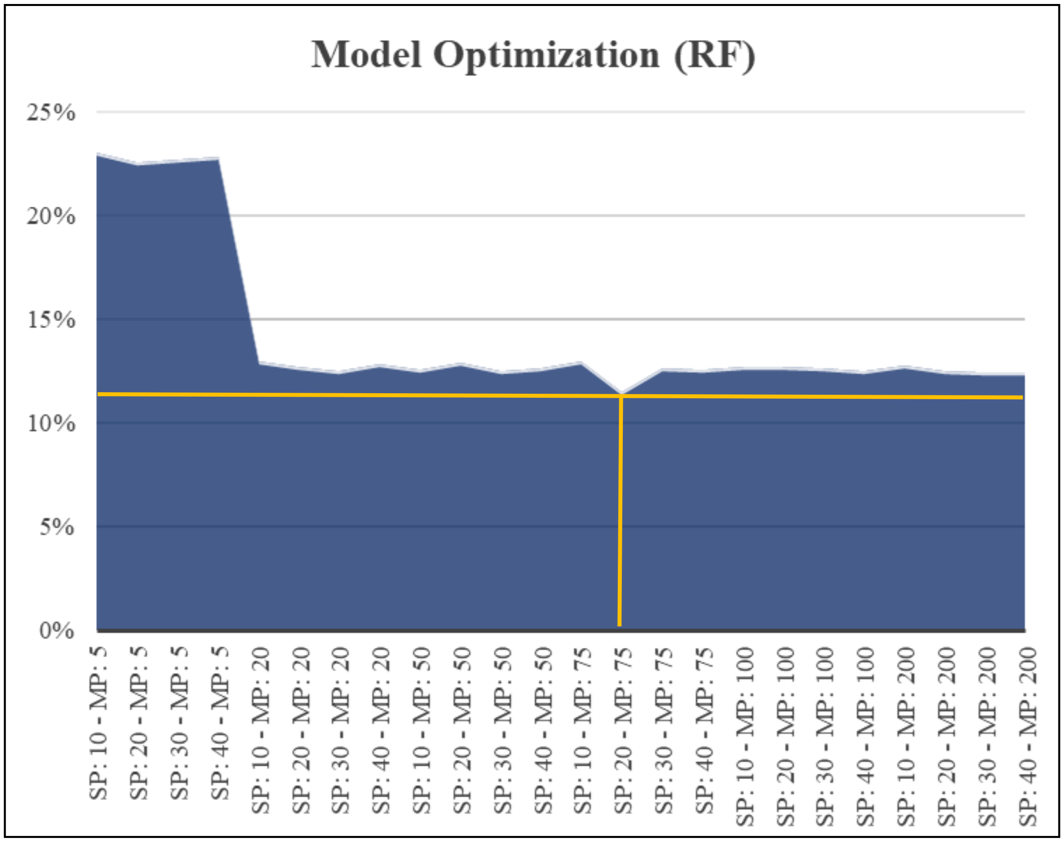


Figure 29: RF Model optimization for total PV (with spatial variables)

Figure 30 shows the categorical feature importance obtained from the best performing models for total PVs (with spatial variables). Road characteristics' category has the most significant impact on the PV traffic prediction model - the same as the previously developed model (without spatial variables) - with a value of 54.78%. Then, the Socioeconomic category, with a value of 22.12%, has the second rank. Ultimately, the Spatial category, with 21.62%, has the third rank.

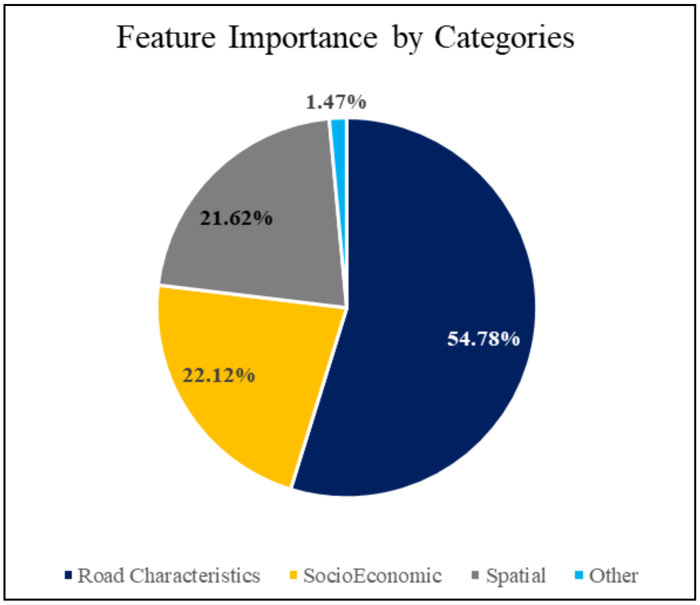


Figure 30: Categorical feature importance derived from best performing models for PVs (model with spatial variables)

Figure 31 shows the top six important features that were contributing to the model's output more than other parameters for total PVs of the model with spatial variables. The "number of lanes" which shows the capacity of the road of the studied location – with 51.95% - had the most important influence on the PV prediction model. Moreover, the "Euclidean geometry", related to the spatial variables. with 14.93% were the second important feature (Mahdavian et al. 2021c).

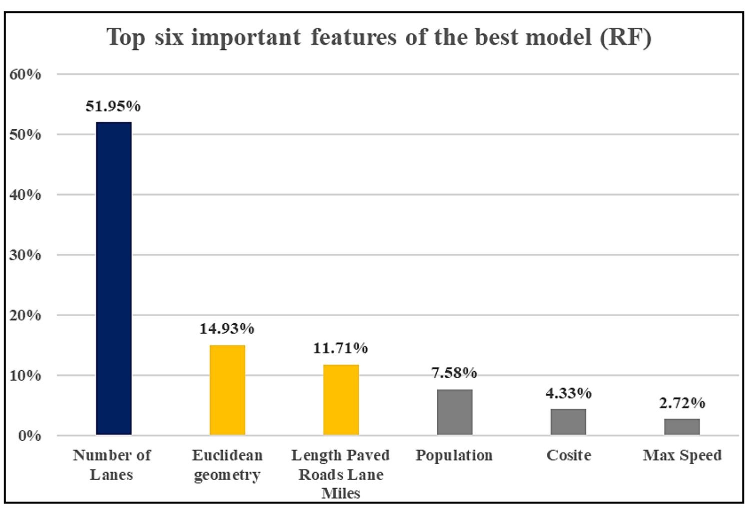


Figure 31: Feature importance derived from best performing models for total PVs (model with spatial variables)

Furthermore, this study developed separate models for each direction (North/Eastbound and South/Westbound) of the traffic flow. The model optimization of the North/Eastbound of the traffic of PVs (with spatial variables) on the 4th split on the validation dataset for the RF models showed that the RFERF feature selection approach with 30 selected features and the RF model algorithm with 75 trees has the lowest MAPE of 12.26% on the validation dataset (Mahdavian et al. 2021c). On the other hand, the model optimization of the South/Westbound of the traffic of PVs (with spatial variables) on the 4th split on the validation dataset for the RF models showed that the RFERF feature selection approach with 20 selected features and the RF model algorithm with 50 trees has the lowest MAPE of 11.61% on the validation dataset.

Selected Model for long-term PV traffic projections (with spatial variables): The comparison of the developed NN models, shown in Table 16, confirms a 2% improvement in the accuracy of the MADT by adding the spatial variables (Mahdavian et al. 2021c).

Table 16: NN models performance with and without spatial variables

Models	**Label Name**	**Fold**	**Selection Approach**	**Model**	**R-squared**	**MAPE Test**
Model without spatial variables	Total PVs	4	DT	NN	0.92	19.49%
Model with spatial variables included	Total PVs	4	RF	NN	0.93	17.48%

The comparison of the accuracy of the NN model with spatial variables on the four splits of the cross-validation is shown in Figure 32. It is apparent that split 4, outperforms the other splits of the data. Split 4 has a MAPE error of 17.48% on the test dataset (Mahdavian et al. 2021d).

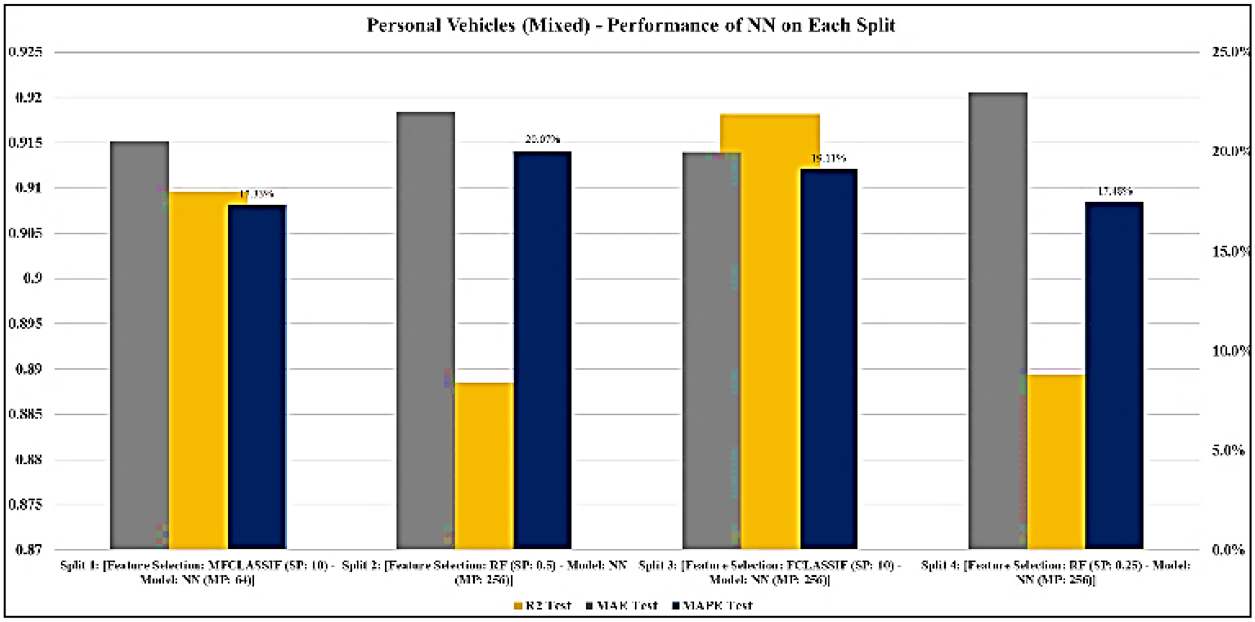


Figure 32: Results from the NN model that incorporates spatial variable on the total PV based on the test dataset

The model optimization of the total PVs (with spatial variables) on the 4th split on the validation dataset for the NN models showed that the RF feature selection approach with importance threshold of 0.25 and the NN model algorithm with 256 neurons in the hidden layer has the lowest MAPE of 16.79% on the validation dataset (Mahdavian et al. 2021c). Figure 33 illustrates the model optimization of the developed NN model with spatial variables.

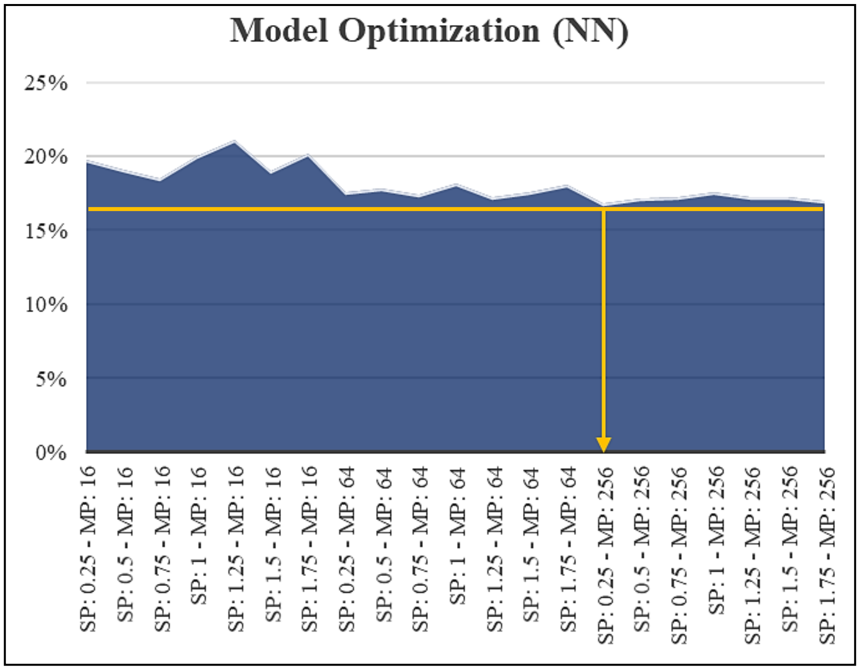


Figure 33: NN Model optimization for total PV (with spatial variables)

The 4th split performed on the validation dataset for model optimization for North/Eastbound for PV traffic was compared for each feature selection approach used for the NN models. The lowest MAPE score of 17.71% was identified in the MFCLASSIF approach that utilized ten selected features and a NN algorithm containing 64 neurons in the hidden layer. In comparison, the lowest MAPE score for NN model optimization on the 4th split of the validation dataset was 16.19% when looking at optimization of the South/Westbound of the traffic of PVs. This value belongs to the RF feature selection approach that utilized an algorithm with 256 neurons in the hidden layer and a value of 0.25 as the importance threshold.

Case Study: To test the validity of the directional NN models developed in this research (spatial variables included), the framework was utilized to forecast directional traffic volumes from 2018-2050. To illustrate the results of the 2018-2050 projection using the direction NN model outlined with the projected independent variables, two different co-sites were chosen from interstate highways I4 and I10 (Mahdavian et al. 2021c).

Case study #1: I4, Orange County, Cosite ID: 750668: Figure 34 shows the total historical and projected PV traffic employing the directional NN model (with spatial variables) developed by the framework of this study. The historical traffic data covers 2001 (beginning month 1) to 2017 (ending month 204) monthly average daily traffic (MADT) of Passenger vehicles. The projected values are for the MADT between 2018 (beginning month 205) to 2050 (ending month 600).

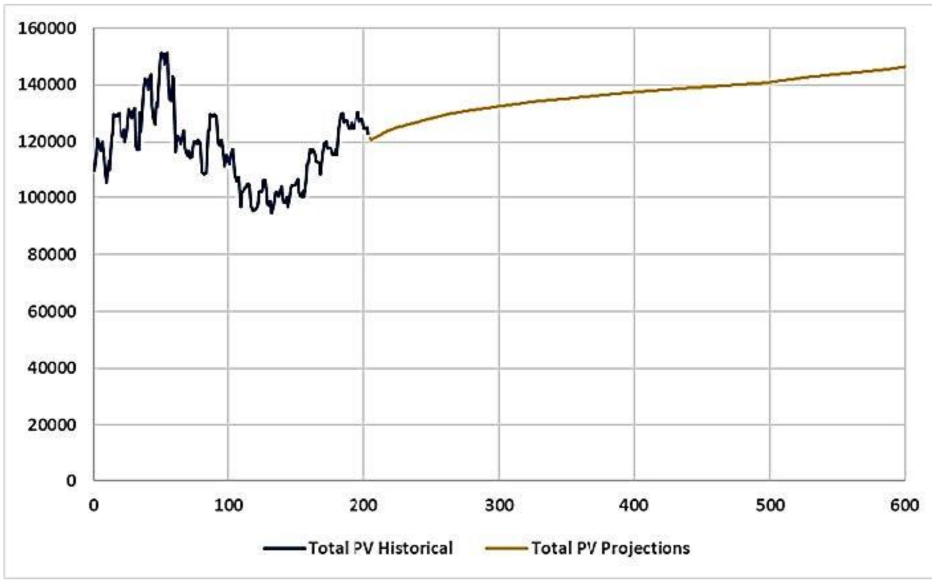


Figure 34: The PV traffic projections of case study #1

Case study #2: I10, Duval County, Cosite ID: 720832: Figure 35 also illustrates the total historical and projected PV traffic employing the directional NN model (with spatial variables) of the case study #2.

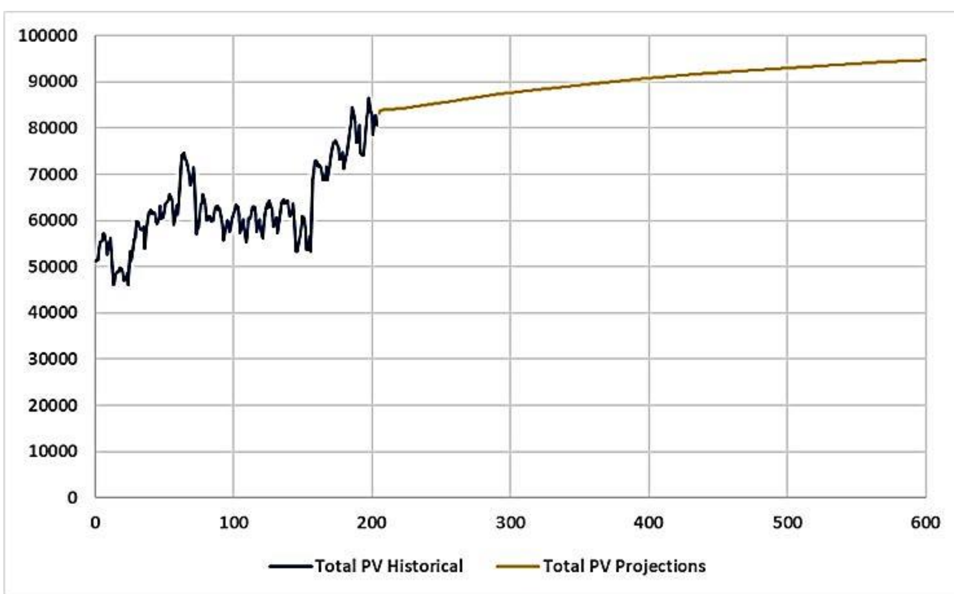


Figure 35: The PV traffic projections of case study #2

Step 2: Traffic prediction model – Trucks

(Regarding the author employed the results of the study: *Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Eluru, N. and Oloufa, A.A., 2021d. A Universal Automated Data-Driven Modeling Framework for Truck Traffic Volume Prediction. IEEE Access, 9, pp.105341-105356.)*

MODEL WITHOUT SPATIAL VARIABLES: Figure 36 illustrates a comparison of the accuracy of various models on the validation dataset using the grid search. RF, KNN, DT, and NN yielded the best performance when they were trained on the training dataset and were tested on the validation dataset. In general, the non-linear models including RF, KNN, DT, and NN, performed better than linear models, including Linear Regression, Ridge Regression, BR, SGD, and PA.

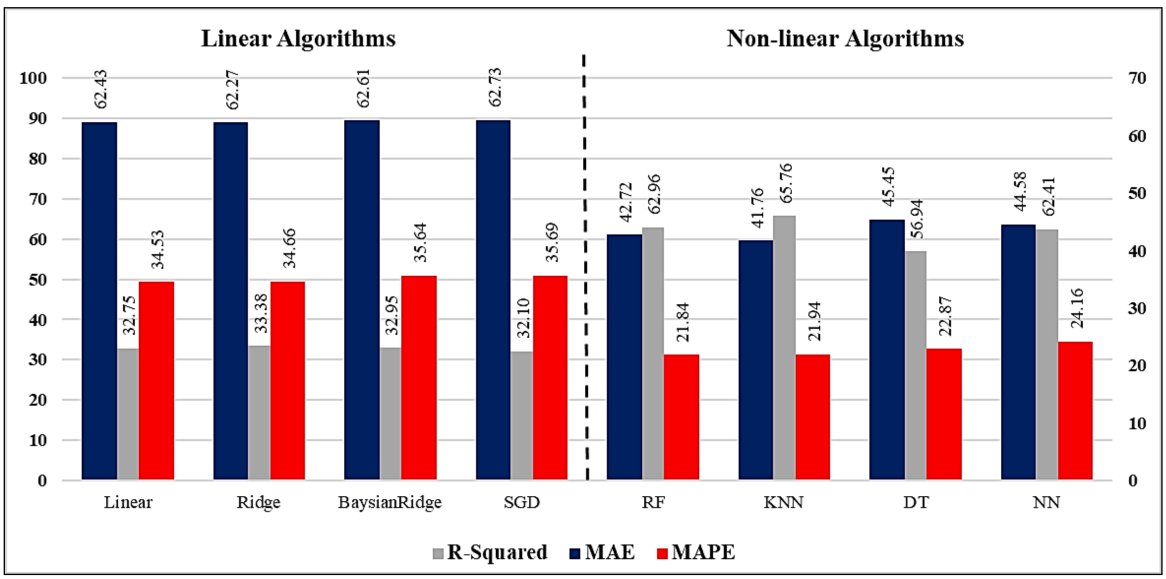


Figure 36: Comparison of different models' best performance on the validation dataset for mixed trucks the average error of cross validation over four splits

A comparison of the accuracy of various models on the test dataset using the grid search is presented in Figure 37. It is evident that non-linear models outperform the linear models overall, and among non-linear models, RF, KNN, and DT model perform better than NN model. The MAPE error (the performance measure used in this study) on test dataset presents a reliable value of about 22.27%.

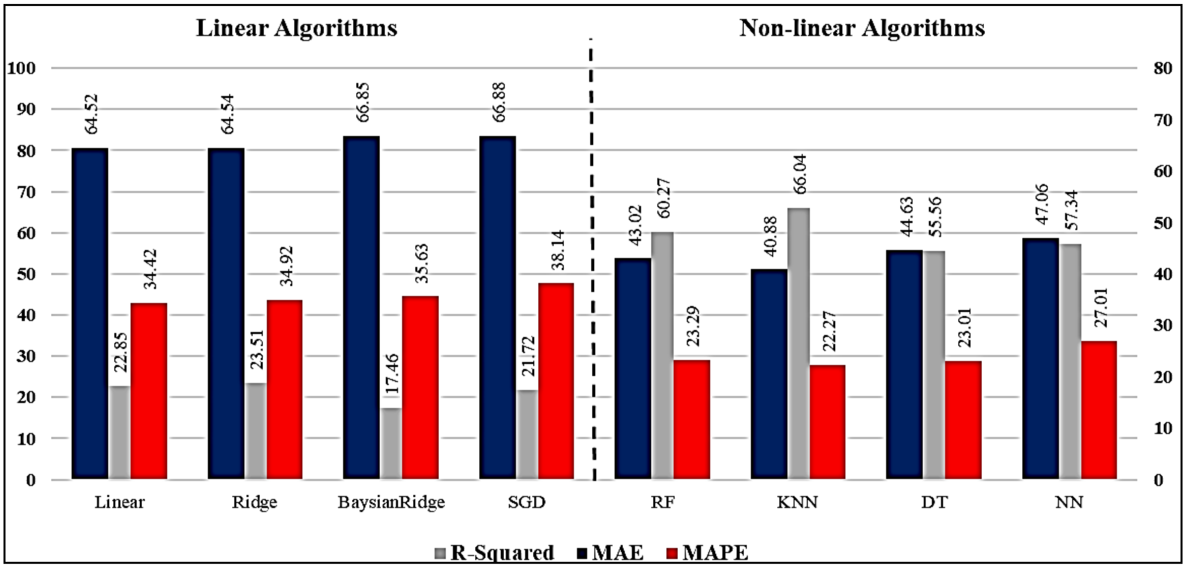


Figure 37: Comparison of different models' best performance on the test dataset for mixed trucks and the average error of cross validation over four splits

The selected model of this study for the current term: As shown in above figures, empirically, RF, KNN, and DT show the best results among the non-linear models. However, theoretically, the KNN model is only capable of predicting the data from the training dataset, which results in biased results. The KNN model finds the K nearest instances to the instance in question and predicts the output by averaging the output of those instances. Through these instances, the model can be interpreted. However, the essential features are not highlighted. Moreover, the model does not learn from data and has to search the data for each prediction. This disadvantage has a silver lining as it makes updating the data and model easier. Concerning DT, this model creates a decision tree based on splitting features. At its leaves is the regression output. The decision-making process and the results are interpretable. However, it can overfit if many features are present since the decision-making handles sparse data at the leaves. However, RF implements many decision trees (500 trees) on the data. It does so by randomly choosing groups of data to train on. Since RF implements many decision trees, it becomes less prone to overfitting while keeping the advantages of decision trees. Thus, the RF model presents an appropriate model, both empirically and theoretically, and was selected for current term prediction in this study (Mahdavian et al. 2021d).

Figure 38 illustrates the result of the four best feature selection approaches utilized in this study on the validation data set. It was found that all four feature selection approaches can provide appropriate modeling of the data, demonstrating the success of the grid search process in finding suitable training parameters for each feature selection method. However, RFE Ridge has the lowest MAPE on the validation dataset among various feature selection approaches (Mahdavian et al. 2021d).

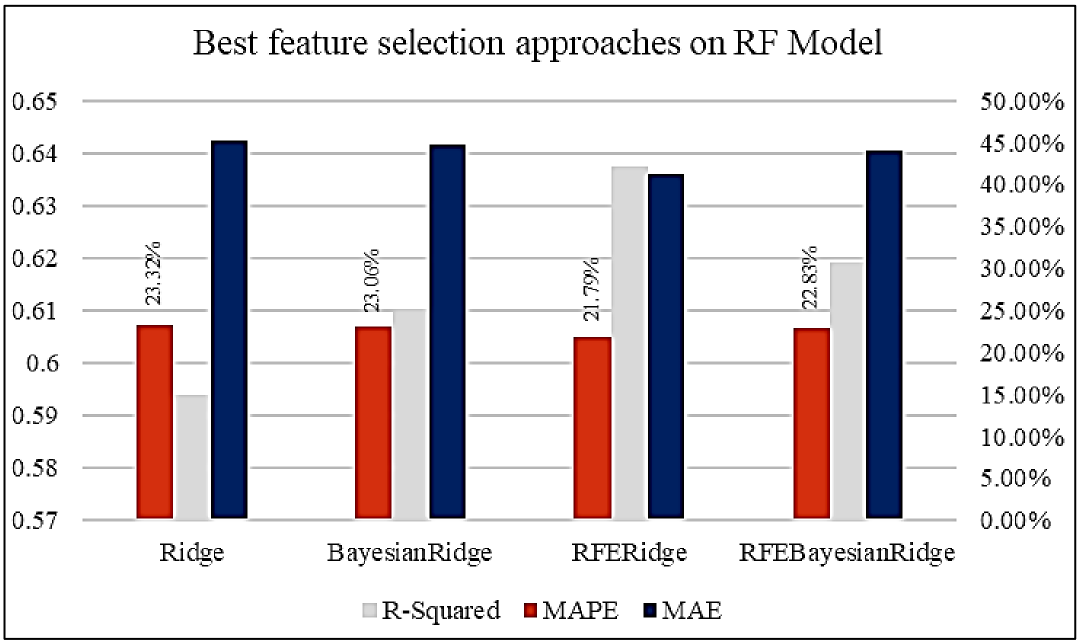


Figure 38: Comparison of the feature selection of RF models on validation dataset for mixed trucks

A comparison of the accuracy of the RF model (selected model for the current and short-term prediction) on the four splits of the dataset is presented in Figure 39. It shows that split 4 (mentioned in Fig. 3), covering all the datasets, would have a lower MAPE error of 18.45% on the validation dataset compared to other splits.

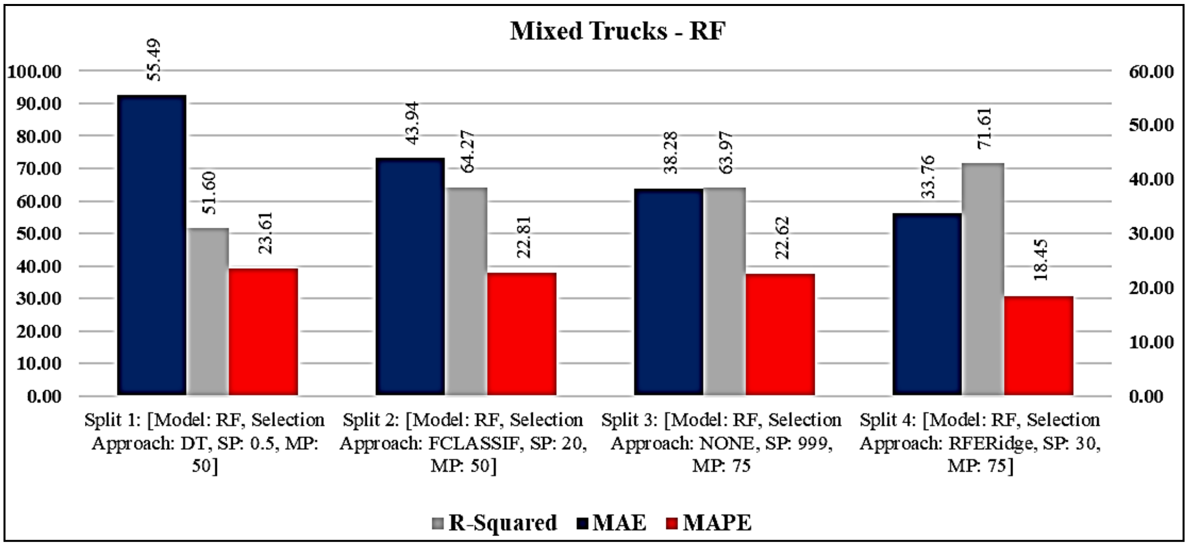


Figure 39: RF model's performance on the validation dataset for mixed trucks

A comparison of the accuracy of the RF algorithm on the four splits of the data is presented in Figure 40. It illustrates that split 4, the split that covers all the dataset has a lower MAPE error (18.24%) on the test dataset, compared to other splits. The MAPE error of split 4 of the RF models on the validation dataset and the test dataset does not differ considerably, which shows that the developed model is robust (Mahdavian et al. 2021d).

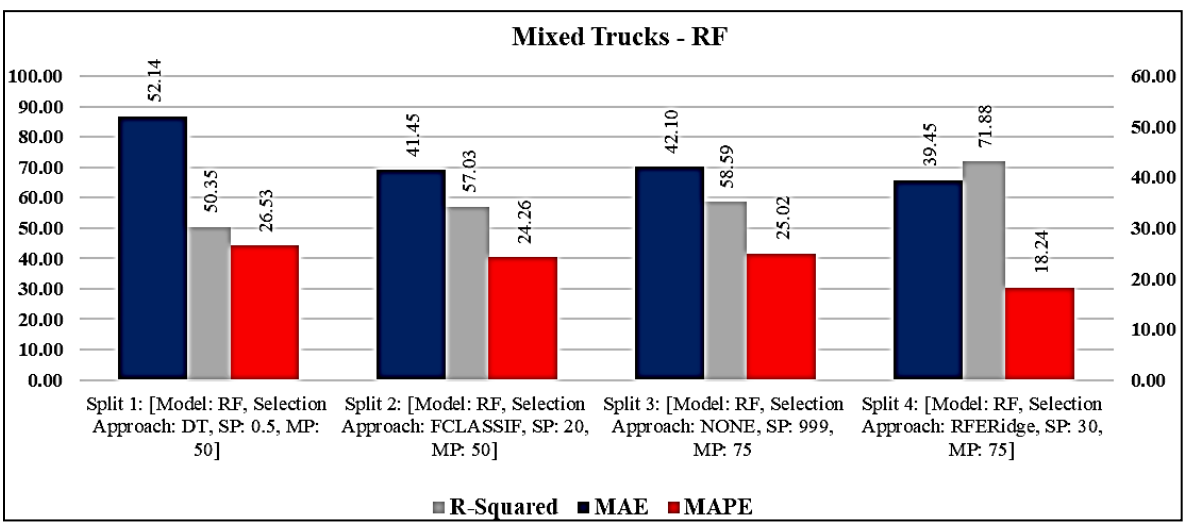


Figure 40: RF model's performance on test dataset for mixed trucks

Ground truth and the final model's predictions in the validation dataset are presented in Figure 41.

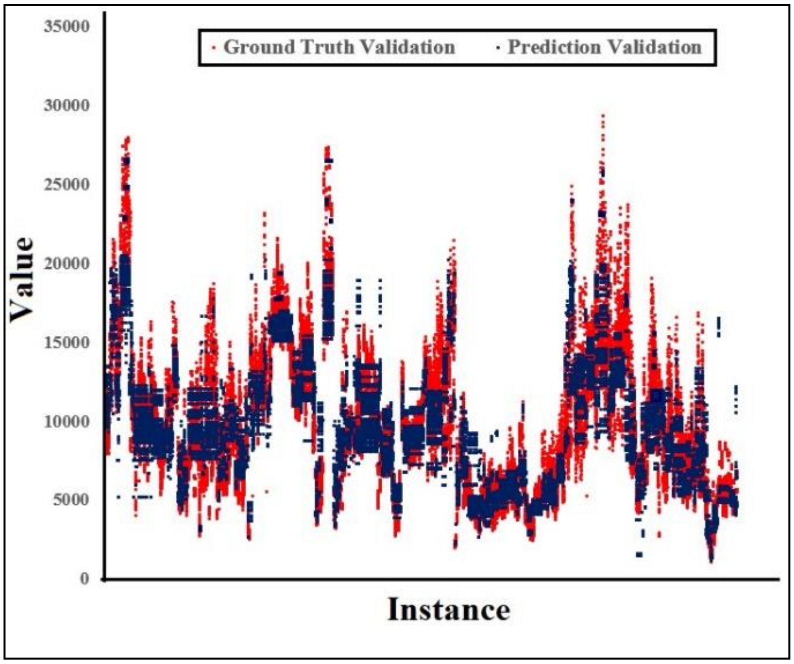


Figure 41: Ground truth prediction of values within the validation dataset using RF algorithm

Figure 42 also shows the comparison of ground truth and prediction via plotting them against each other. The prediction approximately mirrors the ground truth, and the points are placed around the 45-degree line.

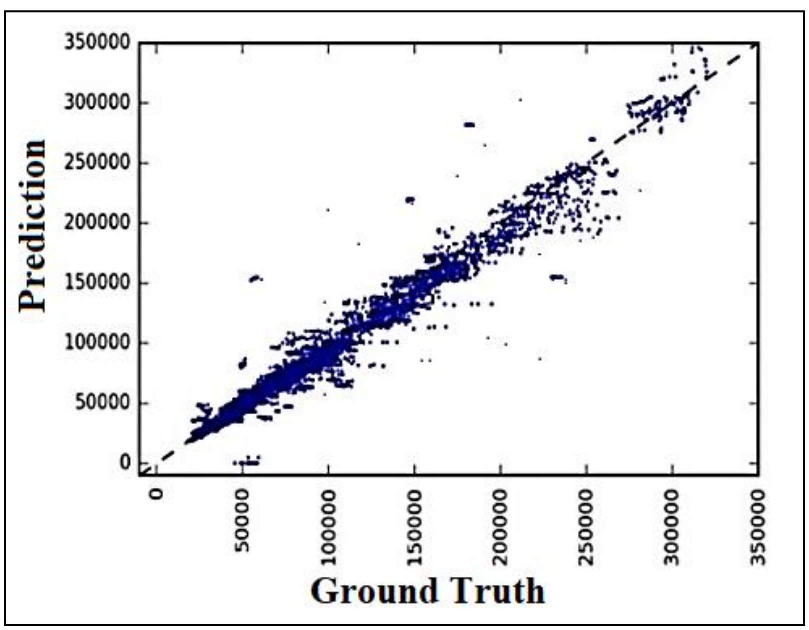


Figure 42: Ground truth prediction of values within the validation dataset using RF algorithm

Figure 43 depicts the model optimization of the mixed trucks on the 4th split on the validation dataset. The optimum feature selection and modeling approach for this case was found to be RFE Ridge and RF, respectively. For finding the best selection parameter, the number of features that are ultimately selected is changed between 10 to 40. The same approach is taken for optimizing the RF model by alternating the maximum depth of the trees from 5 to 200. The RF model, with the depth of 75 trained on 30 selected features, has the lowest MAPE of 18.44% on the validation dataset (Mahdavian et al. 2021d).

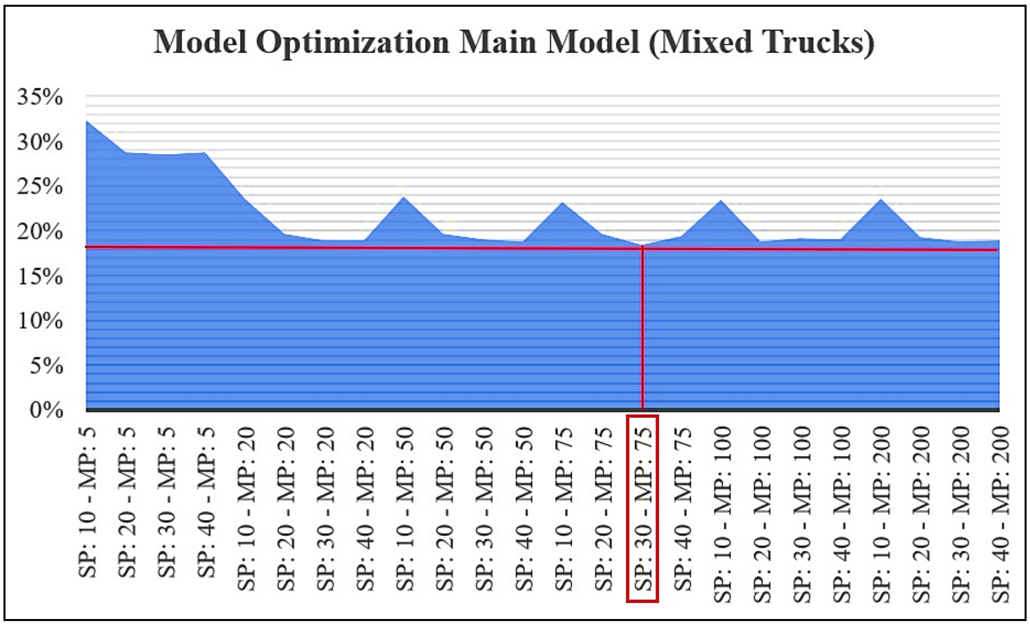


Figure 43: Model optimization for mixed trucks

Figure 44 illustrates the feature categories importance for N/E directional trucks traffic, S/W directional trucks traffic, and mixed trucks. Socioeconomic variables, with 49% feature importance, ranked first among the seven categories of this study. Road characteristics (43% feature importance) and U.S. economy related variables (6% feature importance) were ranked second and third in this study (Mahdavian et al. 2021d).

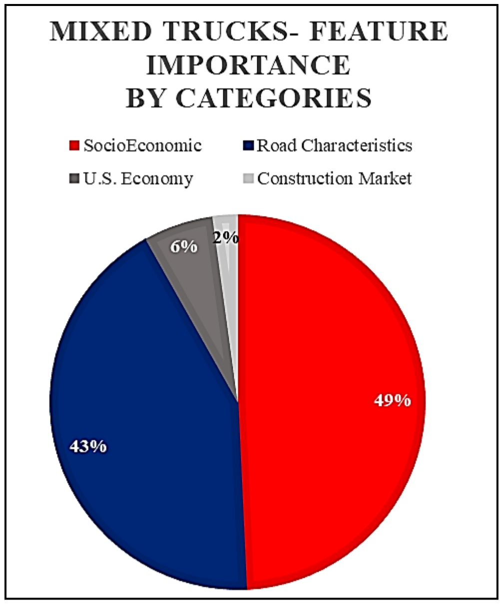


Figure 44: Feature importance for mixed trucks organized by category

Figure 45 illustrates top six important features that were performing better than other parameters for mixed trucks. ‘Number of Lanes’, which depicts the capacity of roadway, has the most important influence on the truck prediction model with a 31% importance. Moreover, ‘length of paved roads centerline miles’ ranked second with a 27% importance. Concerning socioeconomic variables, features such as number of ‘licensed drivers’ and ‘population’ are essential variables for truck prediction model (Mahdavian et al. 2021d).

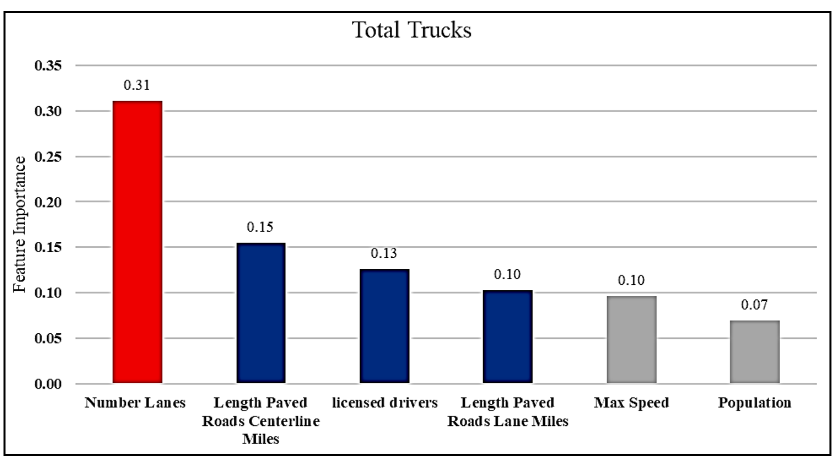


Figure 45: Top six important features of the best performing models for mixed trucks

Selected model for long-term predictions: It is important to note that, the RF model is only capable of interpolating and using the dataset values, which makes the algorithm a suitable option for current and current- term, short-term and mid-term modeling. Concerning the better generalization capabilities of NN, they give an edge to NN models to be used for future projections (long-term studies). The NN algorithm is capable of extrapolating and generating prediction values by changing the hidden layer size to predict the mid- and long-term MADTT. This model is trained by finding the bias and weights of artificial neural network through stochastic gradient descent. It possesses layers of neurons, each of which has a non-linear activation function. Figure 46 shows the four splits' results of cross validation utilized in this study for the NN algorithm; demonstrates that split 3 has a lower MAPE error (with 80% prediction accuracy) and performs better compared with other splits (Mahdavian et al. 2021d).

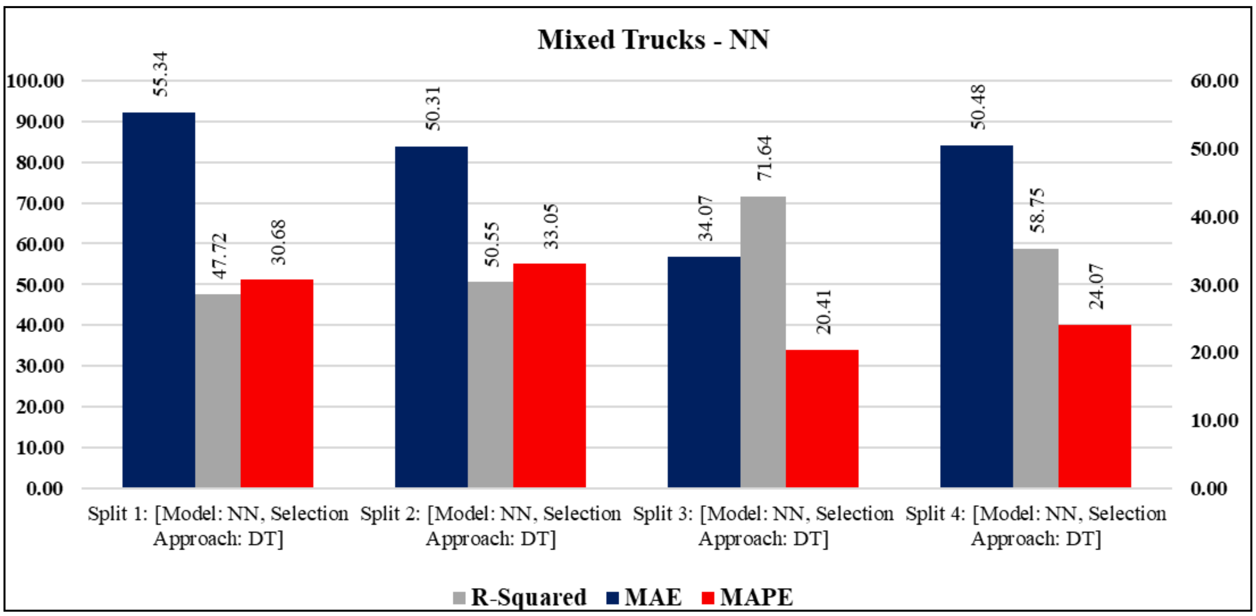


Figure 46: Best Model for mid- and long-term planning: NN

The model optimization of mixed trucks on the 3rd split on the validation dataset for the NN models show that the DT feature selection approach with importance threshold of 0.75. The NN model algorithm with 256 neurons with a hidden layer has the lowest MAPE of 20.41% on the validation dataset. Moreover, the MAPE error on the test dataset is 24.06% which is reasonable (Mahdavian et al. 2021d).

MODEL WITH SPATIAL VARIABLES: Spatial variables: It is essential to consider the impact of spatial variables related to the location of the input data of each site. To test the importance of the spatial variables on the developed truck traffic prediction model, this study added four spatial variables into the prediction model's predictors pool including county name, interstate ID, Site ID, and Location Euclidean Geometry (Mahdavian et al. 2021d).

By comparing the different models' best performance on the test set and the average error of the four splits, non-linear models outperform linear models. However, the MAPE error of the model with spatial candidate variables (added to the previous dataset: all 59 predictors) shows a better performance compared to the model of section 1 (without spatial variables; 55 predictors). The comparison of these models confirms a 4% improvement in the accuracy of the MADTT by adding the spatial variables shown in Table 17 (Mahdavian et al. 2021d).

Table 17: Comparison of the developed RF models on test dataset

Models	**Label Name**	**Fold**	**Selection Approach**	**Model**	**R-squared**	**MAPE Test**
Primary model	Total Trucks	4	RFE Ridge	RF	0.7188	18.23%
Model with spatial variables included	Total Trucks	4	Bayesian Ridge	RF	0.7986	14.53%

Figure 47 illustrates the optimum feature selection and modeling approach for this case were found to be Bayesian Ridge and RF, respectively. For finding the best selection parameter, the number of features that are ultimately selected was changed between the importance threshold of 0.25 and 1.75. The same approach was taken for optimizing the RF model by alternating the maximum depth of the trees from 5 to 200. The RF model, with a depth of 100 trained on selected features with an importance score higher than 1.5, had the lowest MAPE of 12.06% on the validation dataset (Mahdavian et al. 2021d).

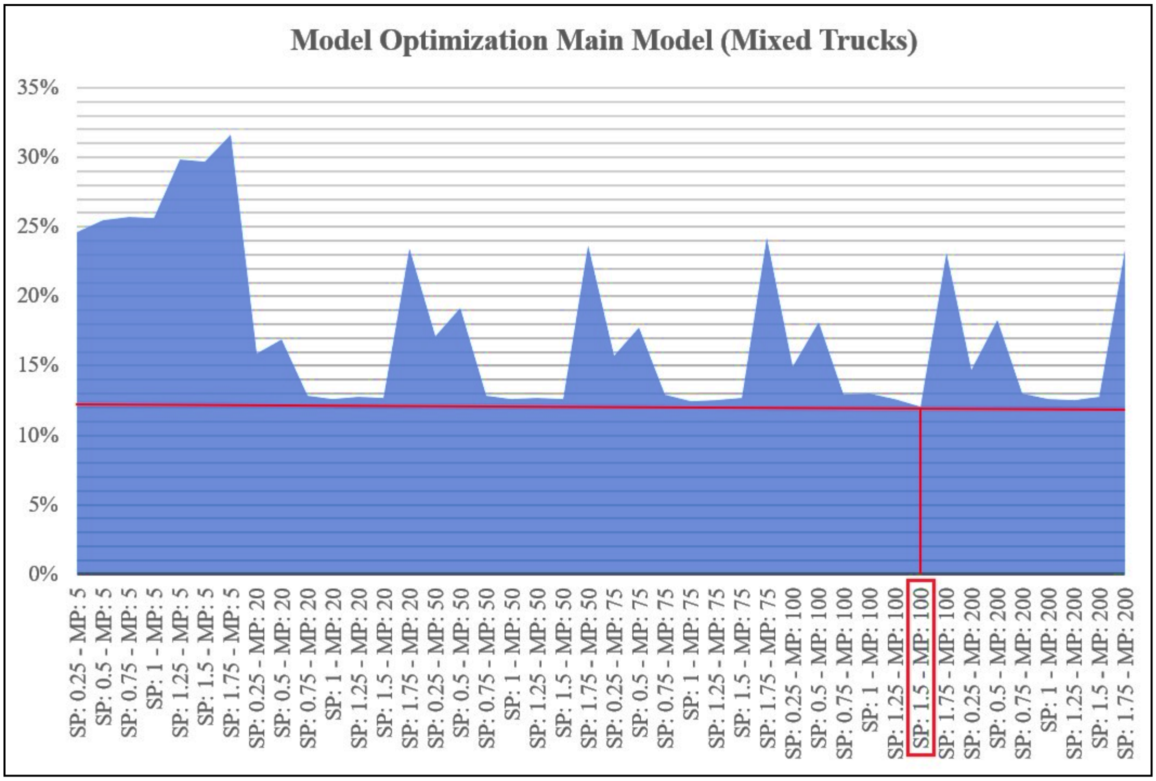


Figure 47: Model optimization for mixed trucks (with spatial variables)

Figure 48 depicts the categorical feature importance derived from the best performing models for mixed trucks. Spatial variables' category had the most significant impact on the truck traffic model with a value of 48%. Road characteristics, with the value of 26%, had the second rank (Mahdavian et al. 2021d).

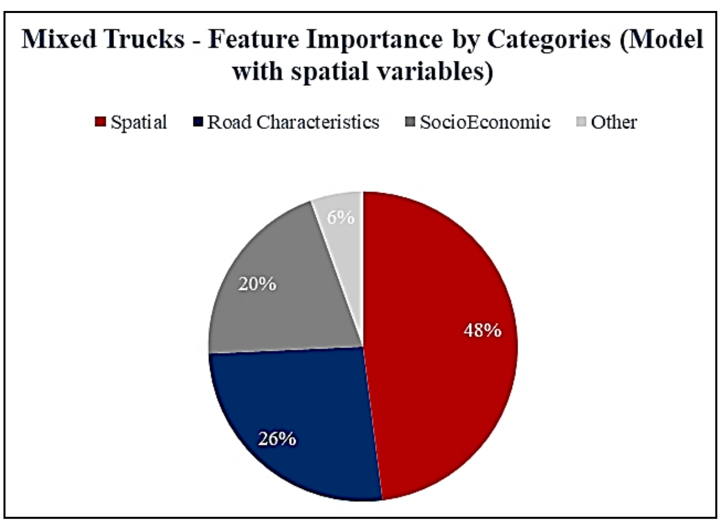


Figure 48: Categorical feature importance derived from best performing models for trucks (model with spatial variables)

Figure 49 depicts the top six important features that are performing better than other parameters for the mixed trucks of the model with spatial variables. The "site" or "co-site", which depicts the ID of the studied location, had the most important influence on the truck prediction model. Moreover, the "number of lanes" shows the second important feature with a 26% importance (Mahdavian et al. 2021d).

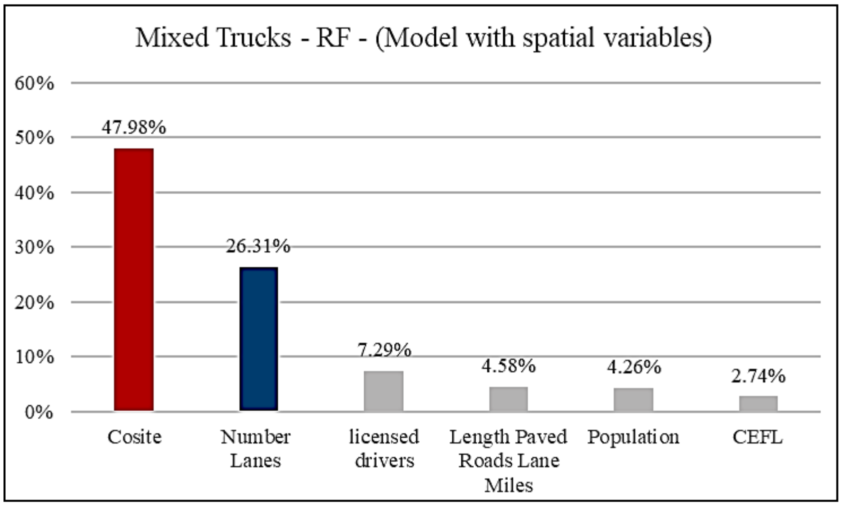


Figure 49: Feature importance derived from best performing models for mixed trucks (model with spatial variables)

Additionally, this study developed separate models for each direction (North/Eastbound and South/Westbound) of the truck traffic flow. The model optimization of the North/Eastbound of truck traffic on the 4th split on the validation dataset for the RF models depicted that the 'RFERF' feature selection approach, with 30 chosen features and the RF model algorithm with 75 trees, has the lowest MAPE of 12.50% on the validation dataset. On the other hand, the model optimization of the South/Westbound of the truck traffic on the 4th split on the validation dataset for the RF models showed that the 'RFE Bayesian Ridge' feature selection approach, with 20 selected features and the RF model algorithm with 50 trees, had the lowest MAPE of 11.96% on the validation dataset (Mahdavian et al. 2021d).

Selected model for long-term truck traffic projections: A comparison of the generated NN models for the framework of this study, shown in Table 18, confirms a 4% improvement in the accuracy of the MADTT by adding the spatial variables.

Table 18: Comparison of the developed NN models on test dataset

Models	Label Name	Fold	Selection Approach	Model	R-squared	MAPE Test
Primary model	Total Trucks	4	DT	NN	0.60	24.06%
Model with spatial variables included	Total Trucks	4	RF	NN	0.72	20.03%

A comparison of the accuracy of the NN model with spatial variables on the four splits of the cross-validation is shown in Figure 50. It is apparent that split 4 outperforms the other splits of the data. Split 4 has a MAPE error of 20.03% on the test dataset (Mahdavian et al. 2021d).

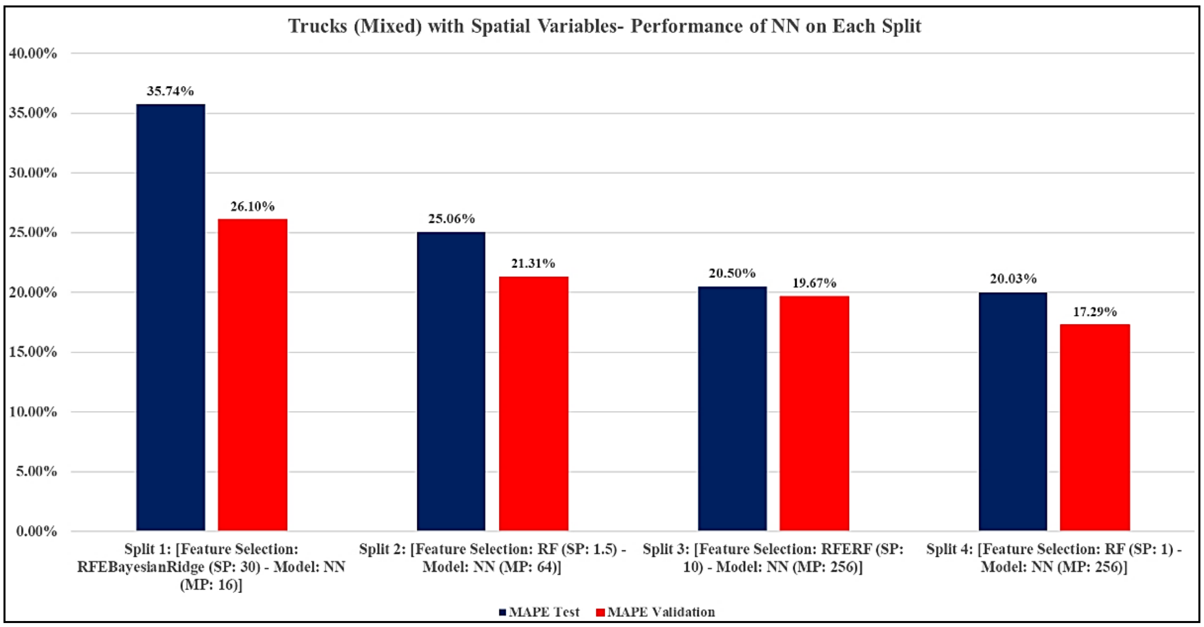


Figure 50: NN model’s (with spatial variables) performance on test dataset for total trucks

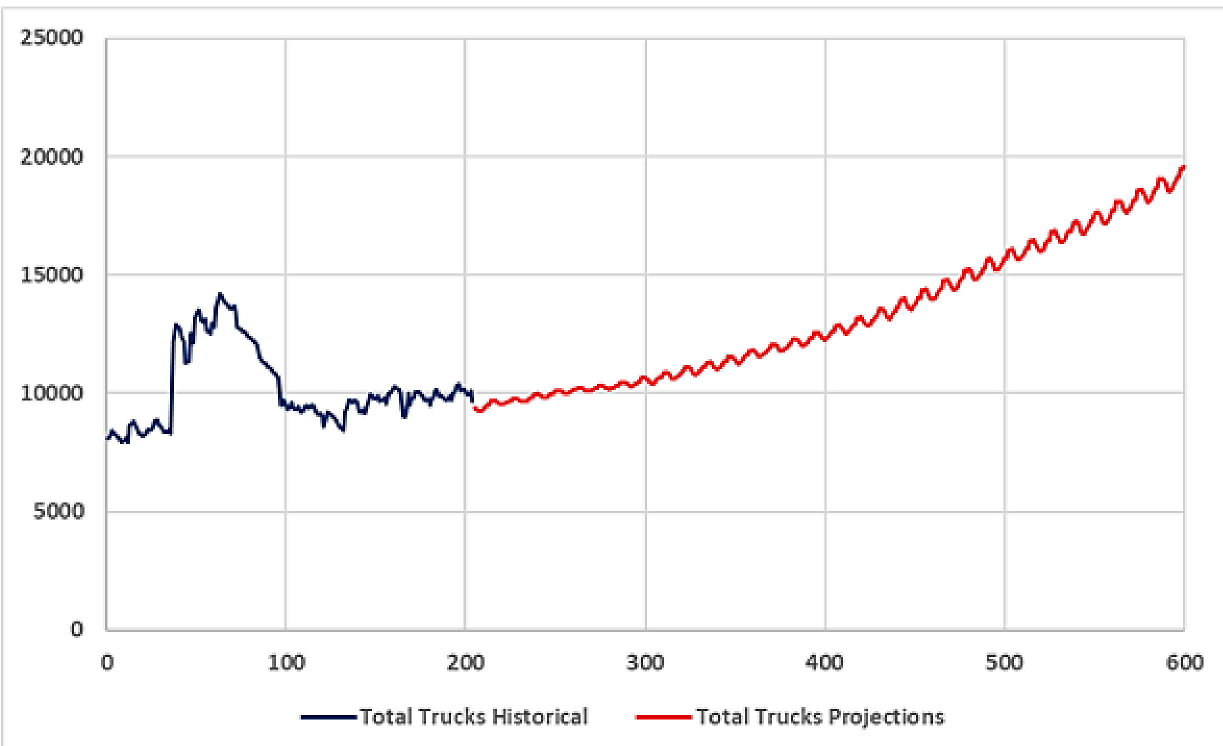
The model optimization of the North/Eastbound of the truck traffic of (with spatial variables) on the 4th split on the validation dataset for the NN models showed that the RFERF feature selection approach, with 10 selected features and the NN model algorithm with 64 neurons in the hidden layer, has the lowest MAPE of 17.77% on the validation dataset. On the other hand, the model optimization of the South/Westbound of the truck traffic (with spatial variables) on the 4th split on the validation dataset for the NN models showed that the RF feature selection approach with importance threshold of 0. 5. The NN model algorithm with 256 neurons in the hidden layer had the lowest MAPE of 17.46% on the validation dataset (Mahdavian et al. 2021d).

Forecast of directional truck traffic volume - case studies (2018 to 2050): In this section, the developed directional NN models (with spatial variables) were deployed to forecast the directional truck volumes for 2018 to 2050. The pool of 59 independent variables in this study contained seven categories including the energy market variables, construction market variables, U.S. economy variables, and socioeconomics variables (excluding population, licensed drivers, length paved road line miles, and centerline miles), where NN was used to predict the future values (Mahdavian et al. 2021d).

A variety of univariate modeling techniques were used to predict the future values of the independent variables to feed the model as an input. Two general types of univariate modeling were used to predict the time-series predictors of this study, namely Auto Regressive Moving Average (ARMA) and Smoothing. The ARMA is the most common classification of models used in forecasting univariate time series. This type of model is represented as an ARMA (p,q), where p is the AR order, and q is the MA order. The order of the AR and MA was chosen via an autocorrelation correlogram function (ACF) and a partial autocorrelation correlogram function (PACF). On the other hand, the Smoothing method includes simple, exponential, double exponential smoothing methods, and Holt-Winters (Linear, Seasonal additive, multiplicative additive). A pool of x independent variables of this study contained seven categories. Including the energy market variables, construction market variables, U.S. economy variables, and seven variables of socioeconomics variables (excluding population, licensed drivers, length paved road line miles and centerline miles) which ARMA and Smoothing methods were employed to predict the future values (Mahdavian et al. 2021d). Regarding two other socioeconomic variables, (population and licensed drivers) the results of the Rayer et al. (2020) were utilized. Furthermore, about the last two socioeconomic variables, the length of paved roads of Florida Highways (length of the paved roads lane miles and length of the paved roads centerline miles) were considered to be fixed during the future years. Ultimately, the road characteristics variables and spatial variables were considered fixed throughout the projection period.

Finally, 2 sites from interstate highways I75 and I4, were selected to show the results for the projection period 2018 to 2050 using the truck directional NN model (with spatial variables) and projected predictors (Mahdavian et al. 2021d).

Case study #1: I4, Orange County, Site ID: 753051: Figure 51 depicts the total, North/Eastbound and South/Westbound historical, and projected truck traffic employing the directional NN model (with spatial variables) developed by this research. The historical traffic data covers 2001 (beginning month 1) to 2017 (ending month 204) monthly average daily truck traffic (MADTT) of passenger vehicles. The projected values are MADTT between 2018 (beginning month 205) to 2050 (ending month 600) (Mahdavian et al. 2021d).



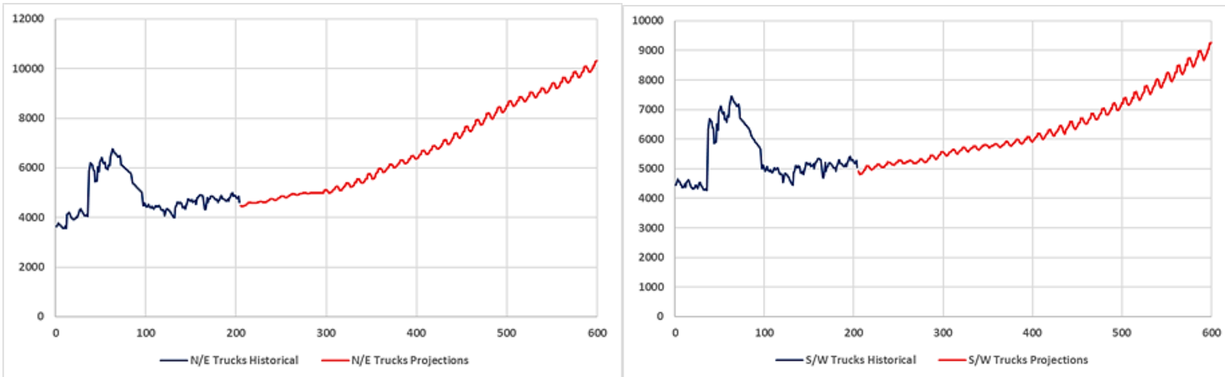
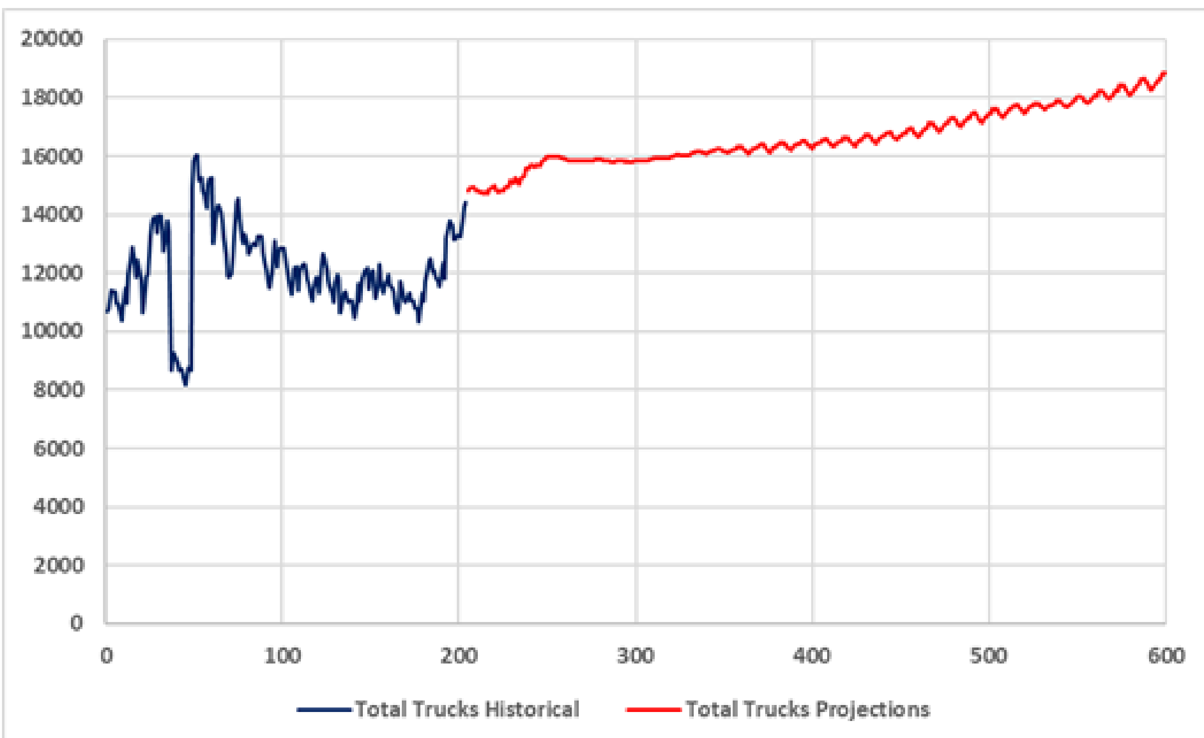


Figure 51: The truck traffic projections of case study #1

Case study #1: I75, Marion County, Site ID: 360437: Figure 52 also shows the total, North/Eastbound and South/Westbound historical and projected truck traffic of site 360437 in Marion County employing the directional NN model (with spatial variables) of the case study #2.



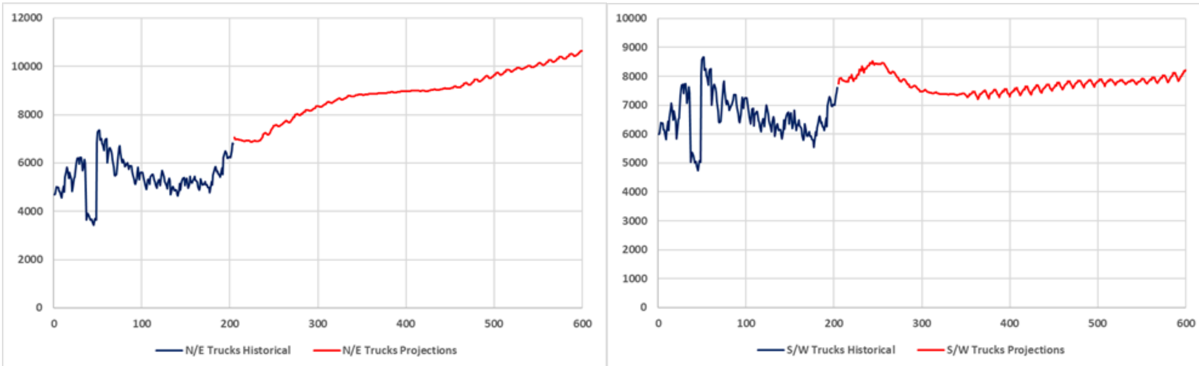


Figure 52: The Truck traffic projections of case study #2

Step 4: Highway construction cost prediction model

(Regarding this section the study published by the author were employed: Mahdavian, A., Shojaei, A., Salem, M., Yuan, J.S. and Oloufa, A.A., 2021b. Data-Driven Predictive Modeling of Highway Construction Cost Items. Journal of Construction Engineering and Management, 147(3), p.04020180.)

To test the feasibility of this approach, the FDOT highway construction cost data between 2001 and 2017 were utilized. These cost items covered about 92.6% of the average total cost of highway construction. Among the fifty cost items (dependent variables) in this study that we collected from the historical data from FDOT, 32 cost items were predicted in stage 1 of the analysis, and 15 cost items were predicted in the second stage, and finally, 3 were not predicted with high accuracy (MAPE below 15%). Figure 53 shows the stage each cost item was predicted. Moreover, the three cost items that were not predicted accurately are depicted (Mahdavian et al. 2021b).

Dependent Variables	Predicted in Stage 1	Predicted in Stage 2	Unable to Predict
MAINTENANCE OF TRAFFIC	✓		
MOBILIZATION	✓		
SEDIMENT BARRIER	✓		
FLOATING TURBIDITY BARRIER	✓		
STAKED TURBIDITY BARRIER- NYL REINF PVC		✓	
SOIL TRACKING PREVENTION DEVICE	✓		
LITTER REMOVAL	✓		
MOWING	✓		
CLEARING & GRUBBING	✓		
REGULAR EXCAVATION		✓	
BORROW EXCAVATION, TRUCK MEASURE			✓
EMBANKMENT		✓	
TYPE B STABILIZATION	✓		
OPTIONAL BASE,BASE GROUP 04		✓	
OPTIONAL BASE,BASE GROUP 09		✓	
MILLING EXIST ASPH PAVT, 1" AVG DEPTH	✓		
MILLING EXIST ASPH PAVT, 4" AVG DEPTH	✓		
SUPERPAVE ASPH CONC, TRAF C,PG76-22,PMA	✓		
SUPERPAVE ASPH CONC, TRAF D,PG76-22,PMA		✓	
ASPH CONC FC,INC BIT,FC-5,PG76-22,PMA		✓	
ASPH CONC FC,TRAFFIC B,FC-9.5,PG 76-22		✓	
CONC CLASS II, ENDWALLS		✓	
INLETS, DT BOT, TYPE D		✓	
INLETS, DT BOT, TYPE E		✓	
INLETS, BARRIER WALL	✓		

Dependent Variables	Predicted in Stage 1	Predicted in Stage 2	Unable to Predict
MANHOLES, J-7			✓
PIPE CULV, OPT MATL, ROUND,24"SD	✓		
PIPE CULV, OPT MATL, ROUND, 24"S/CD	✓		
PIPE CULV, OPT MATL, ROUND, 30"S/CD	✓		
PIPE CULV, OPT MATL, ROUND, 36"S/CD	✓		
PIPE CULV, OPT MATL, ROUND, 42"S/CD		✓	
PIPE CULV, OPT MATL, ROUND, 54"S/CD		✓	
MITERED END SECT, OPTIONAL RD, 24" SD	✓		
MEDIAN CONC BARRIER WALL	✓		
SHLDR CONC BARRIER, RIGID-SHLDR	✓		
CONCRETE DITCH PAVT, NR, 3"	✓		
RUMBLE STRIPS, GROUND-IN, 16" MIN. WIDTH	✓		
FENCING, TYPE B, 5.1-6.0', STANDARD	✓		
PERFORMANCE TURF		✓	
PERFORMANCE TURF, SOD	✓		
SINGLE POST SIGN, F&I GM	✓		
SINGLE POST SIGN, F&I GM, 12-20 SF	✓		
MULTI- POST SIGN, F&I GM, 21-30 SF	✓		
SINGLE POST SIGN, REMOVE	✓		
MULTI- POST SIGN, F&I GM, 31-50 SF	✓		
MULTI- POST SIGN, F&I GM, 51-100 SF	✓		
MULTI- POST SIGN, F&I GM, 101-200 SF	✓		
MULTI- POST SIGN, REMOVE		✓	
RETRO-REFLECTIVE/RAISED PAVEMENT MARKERS	✓		
INITIAL CONTINGENCY AMOUNT (DO NOT BID)			✓

Figure 53: Forecasting of cost items

Figure 54 represents the results of the first stage of running the inputs through the study pipeline on both validation and test dataset. Moreover, the optimized feature selection approach and modeling approach with their selection parameter (SP) and modeling parameter (MP) are depicted in Figure 58. In general, the linear models performed better than the non-linear models. At this stage, we could successfully forecast 32 cost items with more than 85% accuracy. The highlighted cost items in Figure 59 are the ones with higher than 15% forecast error and were chosen to move to the second stage. In the second stage, the cost items that were successfully predicted in the first stage were employed as supplemental inputs (predictors) for the second stage (Mahdavian et al. 2021b).

Stage 1 Results					Validation Dataset		Test Dataset	
Label Name	Feature Selection Approach	Model	SP	MP	R^2	MAPE	R^2	MAPE
MAINTENANCE OF TRAFFIC	RF	Ridge	1	0.1	0.99	1.78%	0.72	8.39%
MOBILIZATION	RF	Linear	1	N/A	0.89	2.60%	0.73	10.01%
SEDIMENT BARRIER	RFERF	PA	20	1	1.00	1.14%	0.84	9.21%
FLOATING TURBIDITY BARRIER	MFCLASSIF	PA	30	1	0.97	3.31%	0.69	6.78%
STAKED TURBIDITY BARRIER- NYL REINF PVC	RFEBaysianRidge	PA	20	1	0.99	5.35%	0.20	15.91%
SOIL TRACKING PREVENTION DEVICE	RFERidge	BaysianRidge	10	0.1	0.99	1.38%	0.69	9.00%
LITTER REMOVAL	RFERF	BaysianRidge	30	1	1.00	1.23%	0.70	8.27%
MOWING	MFCLASSIF	BaysianRidge	20	0.1	0.99	1.25%	0.60	9.18%
CLEARING & GRUBBING	RFEBaysianRidge	BaysianRidge	10	0.1	1.00	1.48%	0.66	9.86%
REGULAR EXCAVATION	RFEBaysianRidge	Ridge	3	1	0.97	3.74%	0.39	16.39%
BORROW EXCAVATION, TRUCK MEASURE	BaysianRidge	Ridge	10	10	0.55	8.20%	0.32	25.30%
EMBANKMENT	RFERidge	PA	5	100	0.99	3.70%	0.55	17.21%
TYPE B STABILIZATION	RFERF	BaysianRidge	50	0.1	1.00	0.28%	0.91	3.00%
OPTIONAL BASE,BASE GROUP 04	BaysianRidge	BaysianRidge	1.75	0.1	0.97	3.20%	0.54	15.03%
OPTIONAL BASE,BASE GROUP 09	MFCLASSIF	BaysianRidge	30	0.1	0.98	1.18%	0.48	16.60%
MILLING EXIST ASPH PAVT, 1" AVG DEPTH	RFERidge	BaysianRidge	5	10000	0.99	0.93%	0.76	6.47%
MILLING EXIST ASPH PAVT, 4" AVG DEPTH	MFCLASSIF	BaysianRidge	40	0.1	1.00	0.78%	0.86	6.60%
SUPERPAVE ASPH CONC, TRAF C, PG76-22,PMA	MFCLASSIF	BaysianRidge	20	1	0.99	0.33%	0.74	3.77%
SUPERPAVE ASPH CONC, TRAF D, PG76-22,PMA	MFCLASSIF	BaysianRidge	20	10	0.99	4.71%	0.43	15.49%
ASPH CONC FC,INC BIT,FC-5,PG76-22,PMA	RF	Linear	1	N/A	0.99	2.79%	0.52	18.99%
ASPH CONC FC,TRAFFIC B,FC-9.5,PG 76-22	RFERidge	NN	1	4	0.98	2.59%	0.49	15.14%
CONC CLASS II, ENDWALLS	MFCLASSIF	BaysianRidge	5	1	0.98	3.30%	0.61	15.89%
INLETS, DT BOT, TYPE D, <10'	RF	BaysianRidge	0.25	100	0.99	3.50%	0.39	15.21%
INLETS, DT BOT, TYPE E, <10'	RFERidge	NN	5	4	0.99	5.83%	0.55	23.20%
INLETS, BARRIER WALL, <=10'	Ridge	BaysianRidge	1.5	0.1	0.97	1.83%	0.71	8.84%

Stage 1 Results					Validation Dataset		Test Dataset	
Label Name	Feature Selection Approach	Model	SP	MP	R^2	MAPE	R^2	MAPE
MANHOLES, J-7, <10'	Ridge	BaysianRidge	1.75	0.1	0.99	4.32%	0.60	17.75%
PIPE CULV, OPT MATL, ROUND,24"SD	BaysianRidge	PA	1	10	0.99	0.60%	0.80	4.21%
PIPE CULV, OPT MATL, ROUND, 24"S/CD	Ridge	PA	0.75	0.1	0.99	2.07%	0.65	11.02%
PIPE CULV, OPT MATL, ROUND, 30"S/CD	RFEDT	BaysianRidge	20	10	0.99	1.41%	0.51	10.81%
PIPE CULV, OPT MATL, ROUND, 36"S/CD	RFERidge	PA	30	10	0.99	1.50%	0.85	6.06%
PIPE CULV, OPT MATL, ROUND, 42"S/CD	RFEDT	Ridge	10	1	0.99	4.29%	0.09	15.56%
PIPE CULV, OPT MATL, ROUND, 54"S/CD	MFCLASSIF	PA	30	10000	0.99	3.84%	0.26	16.20%
MITERED END SECT, OPTIONAL RD, 24" SD	RFERF	BaysianRidge	40	1E+06	1.00	0.40%	0.85	5.85%
MEDIAN CONC BARRIER WALL	MFCLASSIF	BaysianRidge	3	10	0.99	0.70%	0.31	5.47%
SHLDR CONC BARRIER, RIGID-SHLDR	Ridge	BaysianRidge	1.75	1	0.97	2.31%	0.81	14.34%
CONCRETE DITCH PAVT, NR, 3"	Ridge	BaysianRidge	1.75	1	0.99	0.68%	0.55	6.17%
RUMBLE STRIPS, GROUND-IN, 16" MIN. WIDTH	RFEBaysianRidge	BaysianRidge	5	0.1	0.99	0.76%	0.80	4.91%
FENCING, TYPE B, 5.1-6.0', STANDARD	RFERF	BaysianRidge	10	1E+06	0.99	0.48%	0.53	4.00%
PERFORMANCE TURF	RFERF	Linear	10	N/A	0.99	7.11%	0.58	17.99%
PERFORMANCE TURF, SOD	RFEBaysianRidge	BaysianRidge	10	1	0.99	0.59%	0.86	3.85%
SINGLE POST SIGN, F&I GM, <12 SF	DT	BaysianRidge	0.25	1	1.00	0.22%	0.93	2.74%
SINGLE POST SIGN, F&I GM, 12-20 SF	MFCLASSIF	BaysianRidge	3	0.1	1.00	0.55%	0.86	4.89%
MULTI- POST SIGN, F&I GM, 21-30 SF	BaysianRidge	PA	1.75	1E+06	1.00	0.39%	0.90	3.42%
SINGLE POST SIGN, REMOVE	BaysianRidge	Linear	0.75	N/A	0.99	0.68%	0.93	4.44%
MULTI- POST SIGN, F&I GM, 31-50 SF	BaysianRidge	Ridge	1.75	0.1	1.00	0.48%	0.93	4.44%
MULTI- POST SIGN, F&I GM, 51-100 SF	RFEBaysianRidge	Ridge	10	0.1	1.00	0.46%	0.77	6.53%
MULTI- POST SIGN, F&I GM, 101-200 SF	BaysianRidge	Linear	0.5	N/A	0.98	1.12%	0.96	2.85%
MULTI- POST SIGN, REMOVE	RF	Linear	0.25	N/A	1.00	4.45%	0.24	17.16%
RETRO-REFLECTIVE/RAISED PAVEMENT MARKERS	BaysianRidge	BaysianRidge	1.75	1	0.99	0.58%	0.66	2.58%
INITIAL CONTINGENCY AMOUNT, DO NOT BID	RFEBaysianRidge	NN	50	4	0.93	5.61%	0.34	15.40%

Figure 54: Stage 1 results

Figure 55 illustrates the results of the second stage of the modeling process. With the increased pool of dependent variables, we could forecast 15 out of the 18 cost items that initially had higher than the threshold error (15% MAPE on the test dataset). Overall, this processing system resulted in forecasting 47 out of 50 cost items under the study with more than 92% on average accuracy on various highway construction types (Mahdavian et al. 2021b).

Stage 2 Results					Validation Dataset		Test Dataset	
Label Name	**Feature Selection Approach**	**Model**	**SP**	**MP**	**R^2**	**MAPE**	**R^2**	**MAPE**
STAKED TURBIDITY BARRIER- NYL REINF PVC	MFCLASSIF	Linear	50	N/A	1	2.04%	0.56	13.69%
REGULAR EXCAVATION	RF	NN	0.5	4	1	0.89%	0.59	7.51%
BORROW EXCAVATION, TRUCK MEASURE	RF	NN	60	N/A	0.65	5.20%	0.44	18.30%
EMBANKMENT	RFE-Bayesian-Ridge	PA	30	10	1	0.96%	0.75	7.68%
OPTIONAL BASE, BASE GROUP 04	Ridge	Linear	0.75	N/A	1	0.22%	0.88	2.04%
OPTIONAL BASE, BASE GROUP 09	DT	Ridge	1.25	10	0.99	0.68%	0.57	5.92%
SUPERPAVE ASPH CONC, TRAF D, PG76-22, PMA	RFE-Bayesian-Ridge	Bayesian Ridge	40	1	1	0.48%	0.78	8.29%
ASPH CONC FC, INC BIT, FC-5, PG76-22, PMA	RFE-Ridge	SGD	5	1	0.99	0.54%	0.83	2.58%
ASPH CONC FC, TRAFFIC B, FC-9.5, PG 76-22	RFERF	Ridge	5	100	0.99	0.39%	0.3	1.60%
CONC CLASS II, ENDWALLS	MFCLASSIF	PA	30	1	1	0.25%	0.86	2.20%
INLETS, DT BOT, TYPE D, <10'	Ridge	PA	1.75	1E+06	1	0.55%	0.83	3.40%
INLETS, DT BOT, TYPE E, <10'	MFCLASSIF	NN	1	2	1	1.99%	0.76	14.06%
MANHOLES, J-7, <10'	Bayesian-Ridge	Linear	0.5	N/A	0.99	2.88%	0.55	16.81%
PIPE CULV, OPT MATL, ROUND, 42"S/CD	Ridge	Linear	0.25	N/A	1	0.63%	0.86	5.16%
PIPE CULV, OPT MATL, ROUND, 54"S/CD	Bayesian-Ridge	PA	1.25	10	1	0.86%	0.58	11.95%
PERFORMANCE TURF	Bayesian-Ridge	Linear	1	N/A	1	1.65%	0.82	14.21%
MULTI- POST SIGN, REMOVE	Bayesian-Ridge	Linear	0.75	N/A	1	1.32%	0.66	10.20%
INITIAL CONTINGENCY AMOUNT, DO NOT BID	RFE-Ridge	PA	20	1	0.94	4.42%	0.47	16.36%

Figure 55: Stage 2 results

The summary of the result of the developed model is presented in Table 19. It is evident that linear models outperform the non-linear algorithms within the scope of this study. Among 47 predicted cost items in this study, 45 cost items (about 89.6% coverage of the total highway construction cost) were predicted by linear models. Only two cost items were predicted by non-linear algorithms covering about 2.92% of total cost of the highway construction. Within the various linear models examined in this study, Bayesian Ridge performed better for 21 cost items (out of 45 items predicted by linear models) covering about 43.78% of the total cost. Moreover, concerning non-linear models, the NN algorithm was able to predict

“REGULAR EXCAVATION”, and “INLETS, DT BOT, TYPE E, <10'” with higher accuracy compared to the linear models (Mahdavian et al. 2021b).

Table 19: Analysis of results based on different modeling algorithms

Models	# Predicted cost items	Constructing New Urban 6L	Constructing New Urban 4L	Constructing New Rural 6L	Constructing New Rural 4L	Widening 6L to 8L	Widening 4L to 6L	Average
Linear Models	**45**	**92.16%**	**90.97%**	**94.01%**	**93.25%**	**84.72%**	**82.93%**	**89.67%**
Linear	8	18.67%	20.28%	14.10%	13.27%	12.74%	13.23%	15.38%
Ridge	5	14.50%	13.34%	16.46%	13.65%	13.96%	14.68%	14.43%
Bayesian Ridge	21	48.42%	41.85%	43.78%	42.80%	44.30%	41.50%	43.78%
Stochastic Gradient Descent	1	1.92%	1.41%	0.00%	0.08%	6.92%	5.86%	2.70%
Passive Aggressive	10	8.65%	14.09%	19.67%	23.45%	6.80%	7.66%	13.39%
Non-linear Models	**2**	**1.81%**	**1.96%**	**4.26%**	**5.00%**	**2.12%**	**2.39%**	**2.92%**
Neural Network	2	1.81%	1.96%	4.26%	5.00%	2.12%	2.39%	2.92%

The categorical feature importance of various construction types is depicted in Table 20. On average, the construction market category, with 80.32%, had the most significant impact on the highway construction cost prediction model, while the socioeconomic category with 6.4% was second. Additionally, the U.S. Economy had 5.19%, Energy Market had 2.3%, and temporal predictors had 5.85% importance. The Categorical feature importance of all 47 predicted cost items in this study is shown in Appendix B (Mahdavian et al. 2021b).

Table 20: Results of the model on feature importance variables

Categorical Feature Importance	Construction Market	Socioeconomic	Temporal	U.S. Economy	Energy Market
Constructing New Urban 6L	81.26%	7.88%	4.95%	4.20%	1.70%
Constructing New Urban 4L	79.95%	8.51%	5.50%	4.38%	1.66%
Constructing New Rural 6L	79.05%	5.34%	6.84%	5.98%	2.79%
Constructing New Rural 4L	78.68%	5.47%	6.97%	5.76%	3.11%
Widening 6L to 8L	81.74%	5.43%	5.30%	5.26%	2.26%
Widening 4L to 6L	81.23%	5.41%	5.53%	5.53%	2.29%
Average All Construction Types	**80.32%**	**6.34%**	**5.85%**	**5.19%**	**2.30%**

Three critical cost items that had high average percentage impact on the various construction types studied as shown in Table 21 and were selected as a sample for further in-depth analysis. In the previous sections, the reported MAPE on the validation and test datasets were obtained from the average MAPE over all the folds for each cost item. To observe the effect of model parameters on its performance, the results on the fourth split of the data are analyzed. This split (fourth split, consisting of twelve years of training, three years of validation and two years of testing dataset) of the nested cross-validation covers all the datasets and outperformed the other three folds for each cost item (Mahdavian et al. 2021b).

Table 21: Key variables identified from the results of split 4 on model cost items

Cost Item	Average Percentage Impact in All six Methods	Feature Selection Approach	Modeling Approach	Selection Parameter (SP)	Model Parameter (MP)	MAPE (validation dataset, 4th Split)	MAPE (test dataset, 4th Split)
SHLDR CONC BARRIER, RIGID-SHLDR	17.54%	Ridge	Bayesian Ridge	1.75	1	0.59%	12.42 %
SUPERPAVE ASPH CONC,	10.39%	MFCLASSIF	Bayesian Ridge	20	1	0.25%	2.98%

TRAF C, PG76-22						
MAINTENANCE OF TRAFFIC	6.88%	RF	Ridge	1	0.1	1.36%	7.97%

Figure 56 depicts the model optimization of the shoulder concrete barrier, “SHLDR CON BARRIER” on the 4th split of the dataset. The feature selection approach of *Ridge* with a selection parameter of 1.75 and the *Bayesian Ridge* model algorithm with a model parameter of 1 has the lowest MAPE of 0.59% on the validation dataset.

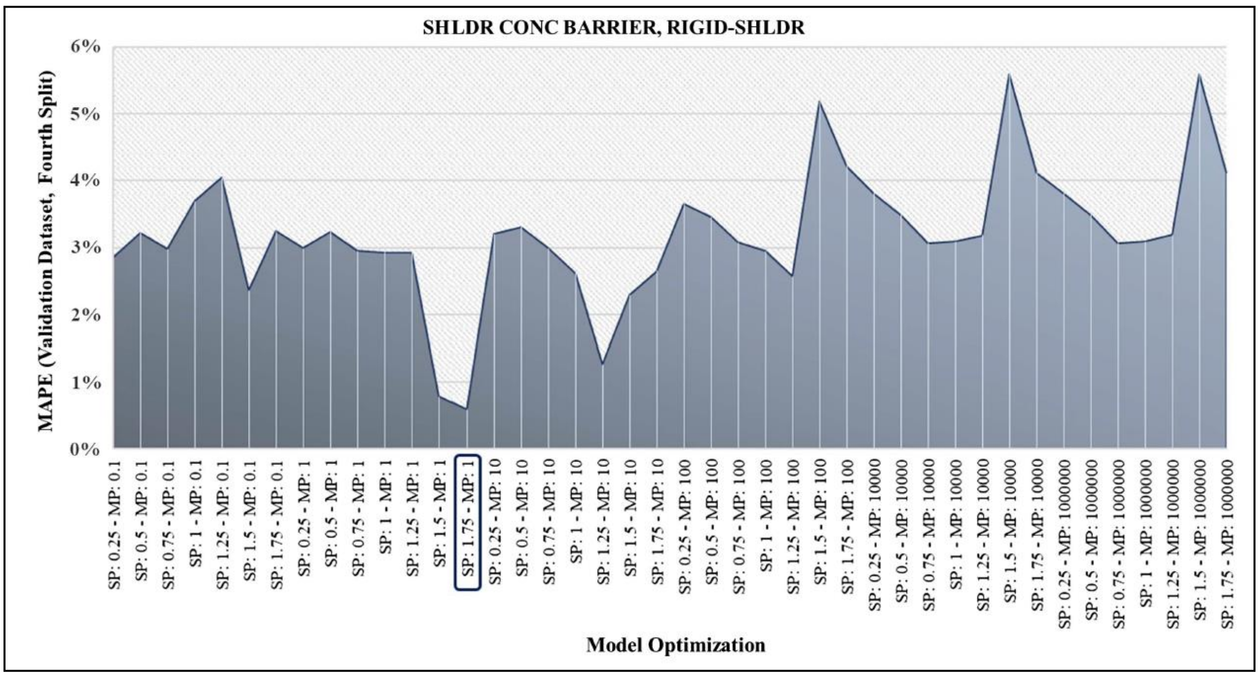


Figure 56: “SHLDR CONC BARRIER” validation vs model optimization results for split 4

Figure 57 shows the categorical and individual feature importance of the “SHLDR CONC BARRIER.” The construction market category had the highest impact with 89.6% importance on this highway construction cost item’s prediction model. Socioeconomic variables with 10% importance had the second rank for this cost item. Moreover, the NHCCI predictor played a significant role in predicting this cost item (Mahdavian et al. 2021b).

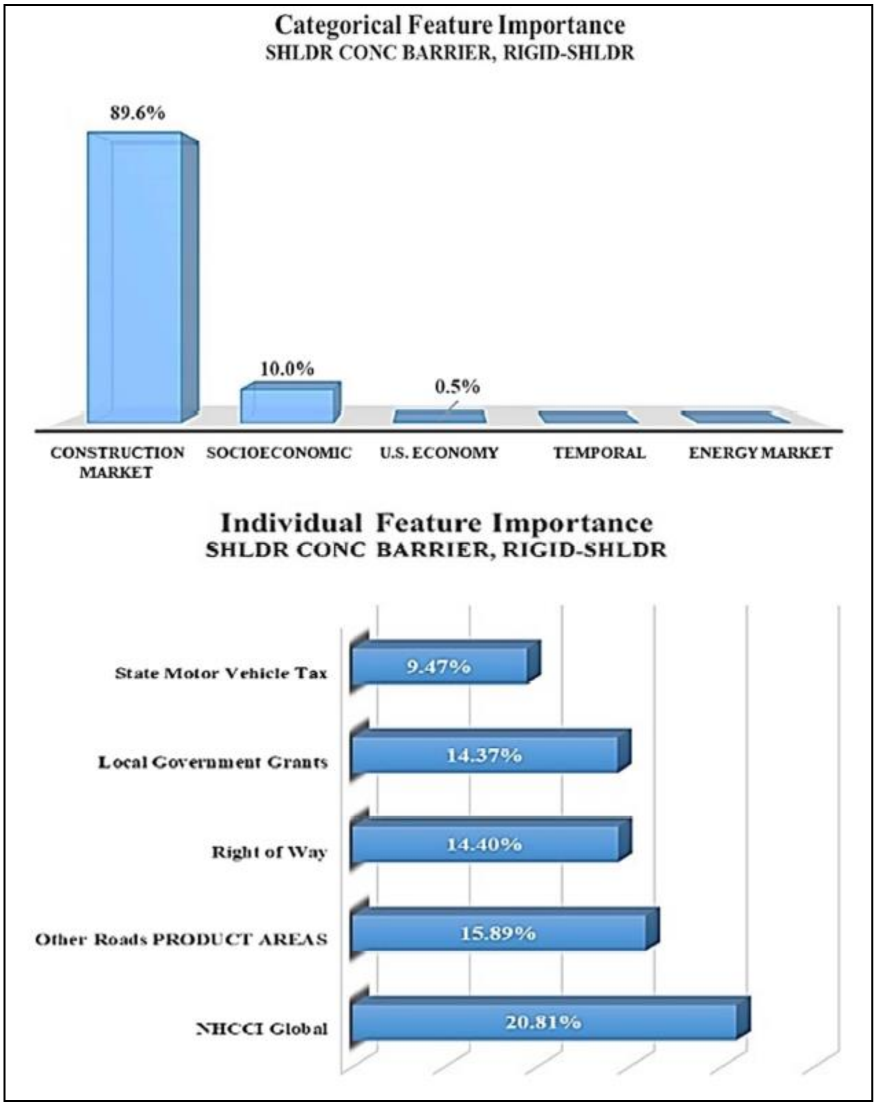


Figure 57: “SHLDR CONC BARRIER” separated based on feature importance category

The following equation shows all the forecasting formula for the “SHLDR CONC BARRIER” cost item:

Cost of “***SHLDR CONC BARRIER, RIGID-SHLDR***” = 0.824025525 × “*NHCCI Global*” + 0.629230173 × “*Other Roads PRODUCT AREAS”* + 0.570224754 × “*Right of Way”* + 0.568821925 × “*Local Government Grants”* + 0.374852392 × “*State Motor Vehicle Tax”* + 0.240822376 × “*Bond Retirement”* + 0.200928502 × “*HHEUS”* + 0.191619513 × “*Other State Funding”* + 0.178818362 × “*AHEPNECUS”* +

0.100279817 × "*State Motor Fuel Tax*" + 0.046363366 × "*NPHUABPFL*" + 0.018570434 × "*DJI*" + 0.014885667 × "*URUS*"

Figure 58 depicts the model optimization of the "ASPH CONC, TRAF C" on the fourth split of the dataset for this cost item. The feature selection approach of *MFCLASSIF* with a selection parameter of 20 and the *Bayesian Ridge* model algorithm with a model parameter of 1 has the lowest MAPE of 1.36% on the validation dataset.

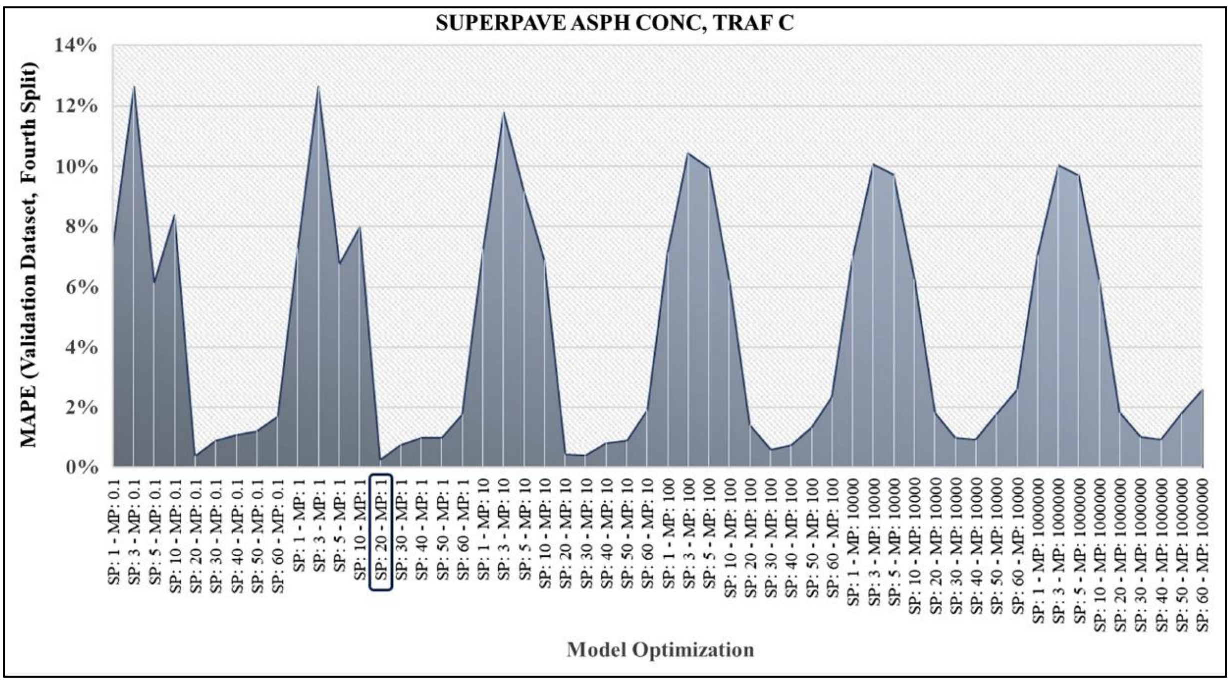


Figure 58: Results for Superpave ASPH CONC, TRAF C. Optimization vs validation, indicated in split 4

Figure 59 depicts the categorical and individual feature importance of the superpave asphalt concrete "Superpave ASPH CONC, TRAF C." The *construction market* had the highest impact, with 89.6% importance on this highway construction cost item's prediction model. *Temporal* variables with 10.9% importance had the second rank for this cost item. *Socioeconomic* variables had the third rank of importance with 5% importance level. Lastly, the *NHCCI* predictor played a key role in predicting this cost item (Mahdavian et al. 2021b).

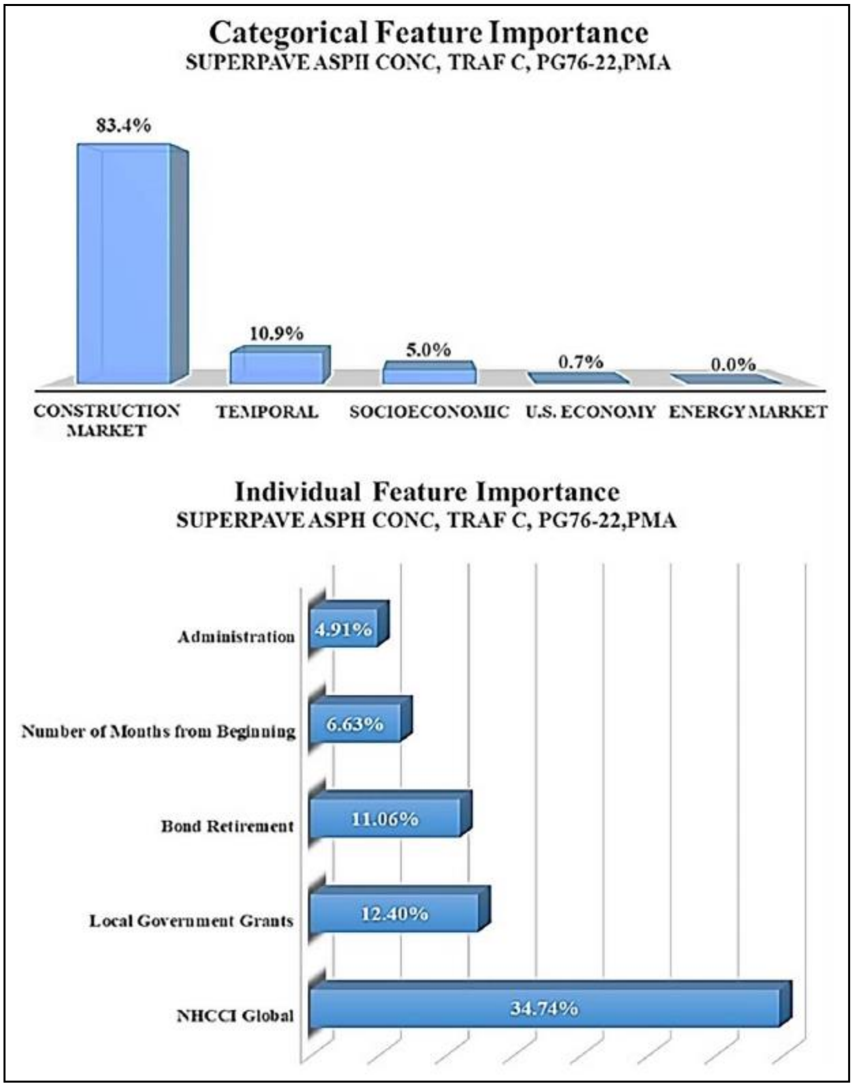


Figure 59: Results for “SUPERPAVE ASPH CONC TRAF C” based on category

The following equation shows all the important predictors and their coefficients on the standardized dataset for the “SUPERPAVE ASPH CONC, TRAF C”:

Cost “***SUPERPAVE ASPH CONC, TRAF C, PG76-22, PMA***” = 0.748396041 × “*NHCCI Global*” + 0.267033067 × “*Local Government Grants*” + 0.23817534 × “*Bond Retirement*” + 0.142771839 × “*Number of Months from Beginning*” + 0.105815124 × “*Administration*” + 0.092030559 × “*YEAR*” + 0.066819567 × “*Interest*” + 0.064595363 × “*State Motor Vehicle Tax*” + 0.062800303 × “*Length Paved Roads Lane Miles*” + 0.06138327 × “*Total Florida State Revenue Sources*” + 0.05549031 × “*Legislative Budget Request Amounts*” + 0.05273566 × “*Capital Expenditures*” + 0.051153537 × “*Total State Highway System (SHS) PRODUCT AREAS*” + 0.044435848 × “*CLFFL*” + 0.031637778 × “*Federal Funding*” + 0.023584501 ×

“*Tolls*” + 0.015849805 × “*Total Florida State DOT Disbursements*” + 0.01339556 × “*Other State Funding*” + 0.010618173 × “*GDP*” + 0.005356619 × “*M2*”

Figure 60 depicts the model optimization of the “MAINTENANCE OF TRAFFIC” on the 4th split of the dataset for this cost item. The feature selection approach of RF with a selection parameter of 1 and the Ridge model algorithm with a model parameter of 0.1 had the lowest MAPE of 0.25% on the validation dataset (Mahdavian et al. 2021b).

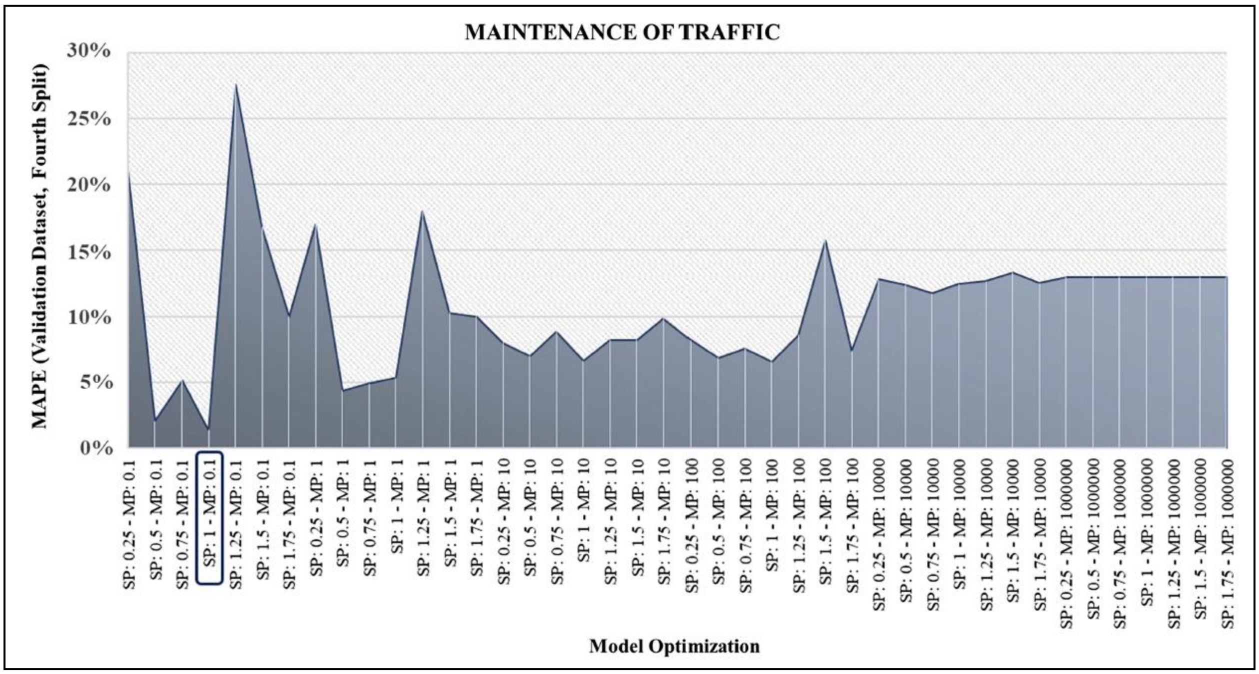


Figure 60: MAINTENANCE OF TRAFFIC results for split 4, validation vs optimization

Figure 61 shows the categorical and individual feature importance of the “MAINTENANCE OF TRAFFIC.” The construction market category of the variables had the highest impact with 89.59% importance on this highway construction cost item’s prediction model. Temporal variables with 8.89% importance had the second rank for this cost item. Additionally, the right of way revenue stream of FDOT predictor played a key role in predicting this cost item (Mahdavian et al. 2021b).

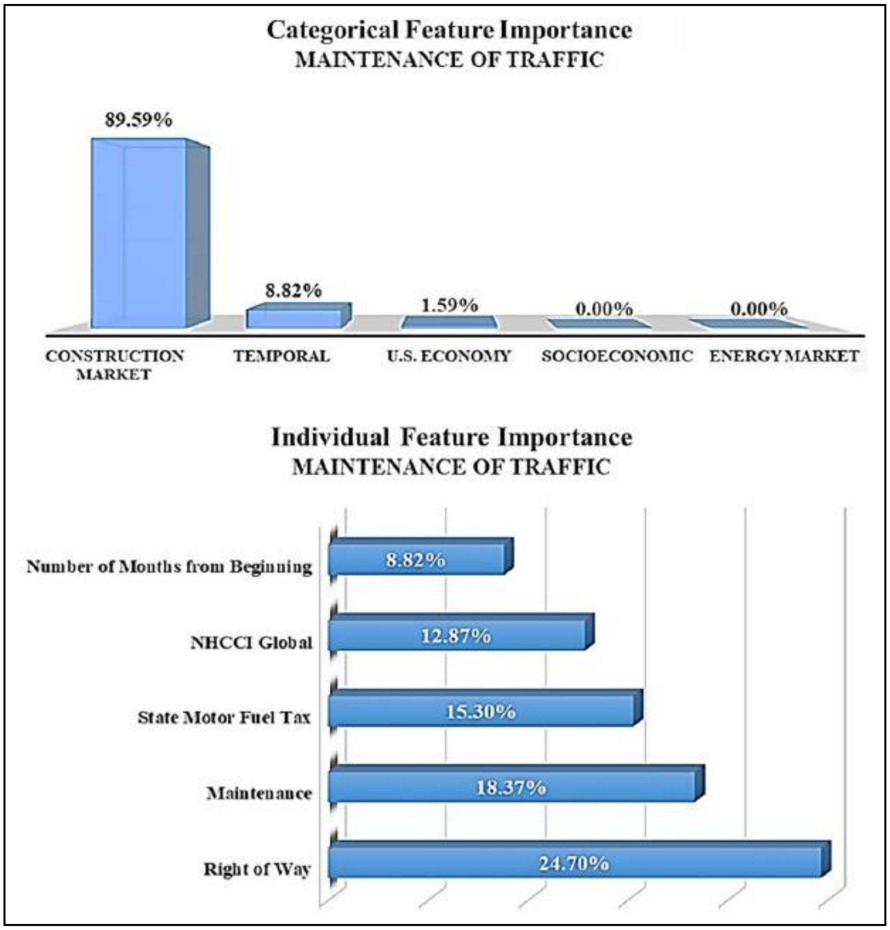


Figure 61: “MAINTENANCE OF TRAFFIC” results presented by category

The following equation shows the all the important predictors and their coefficients on the standardized dataset for the “MAINTENACE OF TRAFFIC”:

Cost “***MAINTENANCE OF TRAFFIC” =*** 1.138962322 ×“*Right of Way*” + 0.847093766 ×“*Maintenance*” + 0.705406042 ×“*State Motor Fuel Tax*” + 0.593492872 “*NHCCI Global*” + 0.406601977 × “*Number of Months from Beginning*” + 0.303016613 ×“*Interest*” + 0.254637769 ×“*Total State Highway System (SHS) PRODUCT AREAS*” + 0.160810353 ×“*CEFL*” + 0.115055866 ×“*Total Florida State Revenue Sources*” + 0.044699378 ×“*BPLRUS*” + 0.028827425 ×“*CANUSER*” + 0.012286083 ×“*AECHCEUS*”

Table 22 summarizes the coverage and accuracy of the results. All of the studied highway construction cost types had more than 90.95% accuracy with a minimum of 85.32% cost coverage and a maximum of 98.27%. As a result, we can argue that the results of the FDOT case study show the viability of this approach. The model was not capable of forecasting the cost item “BORROW EXCAVATION, TRUCK

MEASURE" with an accuracy higher than 85%. This item has a 10.76% weight factor of the total cost of "widening 6 to 8 cost per-mile" and 12.10% of "widening of 4 to 6 cost per-mile", so the coverage of the cost per mile of the models for these two construction types was less than other types (Mahdavian et al. 2021b).

Table 22: Percentage of mile cost covered by the model and the corresponding accuracy

Construction type	Coverage of the total cost per mile of the model	Prediction accuracy
Constructing New Urban 6L	93.97%	90.95%
Constructing New Urban 4L	92.93%	90.99%
Constructing New Rural 6L	98.27%	93.62%
Constructing New Rural 4L	98.25%	93.44%
Widening 6L to 8L	86.84%	93.00%
Widening 4L to 6L	85.32%	93.05%
Average All Construction Types	**92.60%**	**92.51%**

Case Studies – Application of the developed framework

To demonstrate the application of the developed framework this study tested 3 cosites historical information in three different counties in Florida, namely, Marion County, Orange County, and Duval County.

Case study #1: I75, Marion County, Site ID: 360437

The first case study is from the Marion County, interstate highway I75. Table 23 shows the information of the first case study.

Table 23: Case study #1

Interstate	County	Cosite	K	FFS	Number Lanes
I75	Marion	360437	9.6	70	3

For the case study #1, this research assumed that the number of lanes, k, FFS, and Max Service level Rate would be constant. Table 24 shows the predicted traffic flow for the N/E direction and S/W direction for both passenger vehicles and trucks.

Table 24: Cosite Road Characteristics and the Predicted traffic flow for Case study #1

Year	K	FFS	Number Lanes	Max Service Flow Rate (pc/hr/lane)	PC N/E direction	PC S/W direction	Trucks N/E direction	Trucks S/W direction	Baseline V/C
2022	9.6	70	3	**2300**	**30782**	**32450**	**7290**	**8841**	1.22
2023	9.6	70	3	**2300**	**31072**	**32315**	**7419**	**8767**	1.22
2024	9.6	70	3	**2300**	**31248**	**32186**	**7548**	**8539**	1.22
2025	9.6	70	3	**2300**	**31402**	**32063**	**7666**	**8308**	1.22
2026	9.6	70	3	**2300**	**31549**	**31946**	**7786**	**8069**	1.21
2027	9.6	70	3	**2300**	**31688**	**31835**	**7892**	**7901**	1.21
2028	9.6	70	3	**2300**	**31822**	**31720**	**7997**	**7905**	1.22
2029	9.6	70	3	**2300**	**31948**	**31605**	**8115**	**7984**	1.22
2030	9.6	70	3	**2300**	**32069**	**31496**	**8249**	**8071**	1.22
2031	9.6	70	3	**2300**	**32185**	**31392**	**8411**	**8173**	1.23
2032	9.6	70	3	**2300**	**32295**	**31293**	**8570**	**8292**	1.24
2033	9.6	70	3	**2300**	**32400**	**31199**	**8734**	**8417**	1.24
2034	9.6	70	3	**2300**	**32500**	**31110**	**8893**	**8535**	1.25
2035	9.6	70	3	**2300**	**32596**	**31028**	**9048**	**8649**	1.25
2036	9.6	70	3	**2300**	**32688**	**30950**	**9194**	**8738**	1.26
2037	9.6	70	3	**2300**	**32777**	**30875**	**9341**	**8782**	1.26
2038	9.6	70	3	**2300**	**32862**	**30802**	**9478**	**8800**	1.27
2039	9.6	70	3	**2300**	**32944**	**30734**	**9594**	**8822**	1.27
2040	9.6	70	3	**2300**	**33023**	**30670**	**9693**	**8816**	1.27
2041	9.6	70	3	**2300**	**33100**	**30608**	**9801**	**8812**	1.27
2042	9.6	70	3	**2300**	**33175**	**30548**	**9923**	**8843**	1.28
2043	9.6	70	3	**2300**	**33249**	**30489**	**10019**	**8852**	1.28
2044	9.6	70	3	**2300**	**33320**	**30432**	**10109**	**8810**	1.28
2045	9.6	70	3	**2300**	**33391**	**30377**	**10194**	**8745**	1.28
2046	9.6	70	3	**2300**	**33461**	**30322**	**10299**	**8747**	1.28
2047	9.6	70	3	**2300**	**33531**	**30268**	**10414**	**8781**	1.29
2048	9.6	70	3	**2300**	**33601**	**30214**	**10498**	**8762**	1.29
2049	9.6	70	3	**2300**	**33671**	**30160**	**10544**	**8670**	1.29
2050	9.6	70	3	**2300**	**33741**	**30106**	**10609**	**8626**	1.29

Then, the adjusted annual personal vehicles' traffic flow were calculated employing the scenarios developed in the modeling development chapter (chapter four) shown in Table 25.

Table 25: Adjusted annual Personal Vehicles Traffic Flow based on Scenarios for Case study #1

Year	Adjusted Personal Vehicles Traffic Flow based on Scenarios					
	PV N/E direction			PV S/W direction		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	30782	30782	30782	32450	32450	32450
2023	31072	31072	31072	32315	32315	32315
2024	32197	32197	32197	33163	33163	33163
2025	32507	32507	32507	33192	33192	33192
2026	32773	32773	32773	33186	33186	33186
2027	33051	33051	33051	33204	33204	33204
2028	33323	33323	33323	33217	33217	33217
2029	33590	33590	33590	33230	33230	33230
2030	30450	33833	33833	29906	33228	33228
2031	30698	34109	37434	29942	33269	36512
2032	30926	34362	37932	29966	33296	36756
2033	31149	34610	38429	29995	33327	37004
2034	31370	34855	38923	30028	33365	37259
2035	31595	35106	39441	30075	33417	37544
2036	31802	35917	39908	30110	34007	37785
2037	32014	36359	40399	30156	34249	38054
2038	32225	36801	40890	30205	34495	38327
2039	32434	37243	41381	30258	34745	38605
2040	32663	31455	41939	30336	29213	38951
2041	38132	31776	48238	35261	29384	44606
2042	38579	32149	44102	35523	29603	40609
2043	32523	32523	44794	29824	29824	41076
2044	32901	32901	45492	30048	30048	41548
2045	33308	33308	46250	30301	30301	42075
2046	26932	39091	46910	24405	35424	42509
2047	27242	39692	47630	24591	35830	42996
2048	27556	40300	48360	24779	36239	43486
2049	27874	40917	49100	24968	36651	43981
2050	28262	41674	50009	25216	37183	44620

After that, the adjusted annual truck traffic flow were calculated employing the scenarios developed in the modeling development chapter (chapter four) shown in Table 26.

Table 26: Adjusted Truck Traffic Flow based on Scenarios for Case study #1

Year	Adjusted Truck Traffic Flow based on Scenarios					
	Trucks N/E direction			Trucks S/W direction		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	7290	7290	7290	8841	8841	8841
2023	7419	7419	7419	8767	8767	8767
2024	7756	7756	7756	8775	8775	8775
2025	7912	7912	7912	8573	8573	8573
2026	8061	8061	8061	8353	8353	8353
2027	8200	8200	8200	8210	8210	8210
2028	8340	8340	8340	8244	8244	8244
2029	8495	8495	8495	8357	8357	8357
2030	8662	8662	8662	8474	8474	8474
2031	8869	8869	9463	8617	8617	9195
2032	9068	9068	9717	8775	8775	9402
2033	9276	9276	9981	8939	8939	9618
2034	9479	9479	10241	9098	9098	9829
2035	9682	9682	10505	9255	9255	10042
2036	9871	10751	10751	9382	10218	10218
2037	10065	11006	11006	9463	10348	10348
2038	10250	11254	11254	9516	10448	10448
2039	10413	11478	11478	9575	10554	10554
2040	10566	11700	11700	9609	10640	10640
2041	11905	11905	13094	10704	10704	11773
2042	12145	12145	13401	10824	10824	11943
2043	12357	12357	13678	10917	10917	12084
2044	12562	12562	13949	10948	10948	12157
2045	12773	12773	14231	10957	10957	12208
2046	12994	14518	14518	11036	12330	12330
2047	13240	14838	14838	11164	12512	12512
2048	13451	15120	15120	11226	12619	12619
2049	13614	15349	15349	11195	12622	12622
2050	13829	15650	15650	11245	12725	12725

After that, the adjusted annual truck percentage were calculated shown in Table 27.

Table 27: Adjusted Truck Percentage based on Scenarios for Case study #1

Year	**Adjusted Truck Percentage based on Scenarios**					
	N/E direction			**S/W direction**		
	Productive	**Most Likely**	**Disruptive**	**Productive**	**Most Likely**	**Disruptive**
2022	0.19	0.19	0.19	0.21	0.21	0.21
2023	0.19	0.19	0.19	0.21	0.21	0.21
2024	0.19	0.19	0.19	0.21	0.21	0.21
2025	0.20	0.20	0.20	0.21	0.21	0.21
2026	0.20	0.20	0.20	0.20	0.20	0.20
2027	0.20	0.20	0.20	0.20	0.20	0.20
2028	0.20	0.20	0.20	0.20	0.20	0.20
2029	0.20	0.20	0.20	0.20	0.20	0.20
2030	0.22	0.20	0.20	0.22	0.20	0.20
2031	0.22	0.21	0.20	0.22	0.21	0.20
2032	0.23	0.21	0.20	0.23	0.21	0.20
2033	0.23	0.21	0.21	0.23	0.21	0.21
2034	0.23	0.21	0.21	0.23	0.21	0.21
2035	0.23	0.22	0.21	0.24	0.22	0.21
2036	0.24	0.23	0.21	0.24	0.23	0.21
2037	0.24	0.23	0.21	0.24	0.23	0.21
2038	0.24	0.23	0.22	0.24	0.23	0.21
2039	0.24	0.24	0.22	0.24	0.23	0.21
2040	0.24	0.27	0.22	0.24	0.27	0.21
2041	0.24	0.27	0.21	0.23	0.27	0.21
2042	0.24	0.27	0.23	0.23	0.27	0.23
2043	0.28	0.28	0.23	0.27	0.27	0.23
2044	0.28	0.28	0.23	0.27	0.27	0.23
2045	0.28	0.28	0.24	0.27	0.27	0.22
2046	0.33	0.27	0.24	0.31	0.26	0.22
2047	0.33	0.27	0.24	0.31	0.26	0.23
2048	0.33	0.27	0.24	0.31	0.26	0.22
2049	0.33	0.27	0.24	0.31	0.26	0.22
2050	0.33	0.27	0.24	0.31	0.25	0.22

Then, the adjusted annual capacity (pc/h/lane) was calculated considering the impact of truck share on the traffic network shown in Table 28.

Table 28: Adjusted Traffic Capacity by Truck Share for Case study #1

Year	**Adjusted Traffic Capacity by Truck Share**					
	N/E direction (pc/h/lane)			**S/W direction (pc/h/lane)**		
	Productive	**Most Likely**	**Disruptive**	**Productive**	**Most Likely**	**Disruptive**
2022	2139	2139	2139	2089	2089	2089
2023	2139	2139	2139	2089	2089	2089
2024	2139	2139	2139	2089	2089	2089
2025	2139	2139	2139	2089	2089	2089
2026	2139	2139	2139	2089	2089	2089
2027	2139	2139	2139	2139	2139	2139
2028	2089	2089	2089	2139	2139	2139
2029	2089	2089	2089	2089	2089	2089
2030	2089	2089	2089	2089	2089	2089
2031	2089	2089	2089	2089	2089	2089
2032	2089	2089	2089	2089	2089	2089
2033	2089	2089	2089	2089	2089	2089
2034	2089	2089	2089	2089	2089	2089
2035	2089	2089	2089	2089	2089	2089
2036	2089	2089	2089	2089	2089	2089
2037	2089	2089	2089	2089	2089	2089
2038	2089	2089	2089	2089	2089	2089
2039	2089	2089	2089	2089	2089	2089
2040	2089	2045	2089	2089	2045	2089
2041	2089	2045	2089	2089	2045	2089
2042	2089	2045	2089	2089	2045	2089
2043	2045	2045	2089	2045	2045	2089
2044	2045	2045	2089	2045	2045	2089
2045	2045	2045	2089	2045	2045	2089
2046	2000	2045	2089	2000	2045	2089
2047	2000	2045	2089	2000	2045	2089
2048	2000	2045	2089	2000	2045	2089
2049	2000	2045	2089	2000	2045	2089
2050	2000	2045	2089	2000	2045	2089

Then, the adjusted annual capacity (pc/h/lane) was finally revised considering the impact of the CASE vehicles on the traffic network presented in Table 29.

Table 29: Final Adjusted Traffic Capacity for Case study #1

Year	**Final Adjusted Traffic Capacity (Considering both Scenarios and Truck Share Impact)**					
	N/E direction pc/h/lane			**S/W direction pc/h/lane**		
	Productive	**Most Likely**	**Disruptive**	**Productive**	**Most Likely**	**Disruptive**
2022	2179	2179	2179	2128	2128	2128
2023	2194	2194	2194	2143	2143	2143
2024	2209	2209	2209	2158	2158	2158
2025	2225	2225	2225	2173	2173	2173
2026	2241	2241	2241	2189	2189	2189
2027	2258	2258	2258	2258	2258	2258
2028	2214	2214	2214	2267	2267	2267
2029	2231	2231	2231	2231	2231	2231
2030	2249	2249	2249	2249	2249	2249
2031	2267	2267	2267	2267	2267	2267
2032	2286	2286	2286	2286	2286	2286
2033	2305	2305	2305	2305	2305	2305
2034	2325	2325	2325	2325	2325	2325
2035	2345	2345	2345	2345	2345	2345
2036	2366	2366	2366	2366	2366	2366
2037	2398	2398	2398	2398	2398	2398
2038	2419	2419	2419	2419	2419	2419
2039	2431	2431	2431	2431	2431	2431
2040	2454	2401	2454	2454	2401	2454
2041	2477	2424	2477	2477	2424	2477
2042	2501	2447	2501	2501	2447	2501
2043	2471	2471	2525	2471	2471	2525
2044	2484	2484	2539	2484	2484	2539
2045	2520	2520	2575	2520	2520	2575
2046	2489	2545	2601	2489	2545	2601
2047	2514	2571	2627	2514	2571	2627
2048	2540	2597	2654	2540	2597	2654
2049	2566	2623	2681	2566	2623	2681
2050	2630	2689	2748	2630	2689	2748

Then, the total passenger vehicle (pv) equivalent of the truck trips were calculated in Table 30.

Table 30: Passenger Vehicle Equivalent of Trucks for Case study #1

Year	Passenger Vehicle Equivalent of Trucks					
	N/E direction MADT			S/W direction MADT		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	10935	10935	10935	13261	13261	13261
2023	11129	11129	11129	13151	13151	13151
2024	11634	11634	11634	13163	13163	13163
2025	11868	11868	11868	12860	12860	12860
2026	12092	12092	12092	12530	12530	12530
2027	12300	12300	12300	12315	12315	12315
2028	12510	12510	12510	12367	12367	12367
2029	12742	12742	12742	12536	12536	12536
2030	12993	12993	12993	12711	12711	12711
2031	13303	13303	14195	12926	12926	13792
2032	13603	13603	14575	13162	13162	14103
2033	13914	13914	14971	13408	13408	14426
2034	14219	14219	15361	13646	13646	14743
2035	14522	14522	15757	13882	13882	15062
2036	14807	16127	16127	14072	15327	15327
2037	15097	16509	16509	14194	15522	15522
2038	15375	16881	16881	14274	15671	15671
2039	15619	17216	17216	14362	15831	15831
2040	15848	17550	17550	14413	15961	15961
2041	17857	17857	19641	16056	16056	17660
2042	18217	18217	20101	16236	16236	17915
2043	18535	18535	20516	16375	16375	18126
2044	18843	18843	20923	16422	16422	18235
2045	19160	19160	21346	16436	16436	18311
2046	19492	21777	21777	16555	18496	18496
2047	19861	22257	22257	16747	18768	18768
2048	20176	22680	22680	16839	18928	18928
2049	20421	23023	23023	16792	18932	18932
2050	20744	23475	23475	16867	19087	19087

Then, the total predicted passenger vehicle (pv) trips and the pv equivalent of the truck trips were added to each other shown in Table 31.

Table 31: Passenger Vehicles Equivalent of Trucks and PVs All together Case study #1

Year	Passenger Vehicles Equivalent of Trucks and PVs All together					
	N/E direction MADT			S/W direction MADT		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	41718	41718	41718	45711	45711	45711
2023	42200	42200	42200	45466	45466	45466
2024	43831	43831	43831	46326	46326	46326
2025	44375	44375	44375	46052	46052	46052
2026	44864	44864	44864	45715	45715	45715
2027	45351	45351	45351	45519	45519	45519
2028	45833	45833	45833	45584	45584	45584
2029	46332	46332	46332	45766	45766	45766
2030	43442	46826	46826	42617	45940	45940
2031	44001	47412	51628	42868	46195	50304
2032	44528	47965	52508	43129	46458	50859
2033	45064	48525	53400	43403	46736	51431
2034	45588	49074	54284	43675	47011	52002
2035	46118	49628	55199	43957	47299	52606
2036	46608	52043	56034	44183	49333	53112
2037	47112	52868	56908	44351	49771	53576
2038	47600	53681	57770	44480	50166	53999
2039	48053	54460	58598	44621	50576	54436
2040	48512	49004	59489	44749	45174	54912
2041	55989	49633	67879	51317	45440	62266
2042	56796	50366	64203	51759	45838	58524
2043	51058	51058	65310	46199	46199	59202
2044	51744	51744	66416	46471	46471	59784
2045	52467	52467	67596	46737	46737	60386
2046	46423	60869	68687	40960	53920	61005
2047	47103	61949	69888	41338	54597	61763
2048	47733	62980	71040	41618	55166	62414
2049	48295	63940	72123	41760	55583	62913
2050	49006	65149	73483	42083	56271	63707

Then, the total passenger vehicle (pv) trips unit was converted from MADT to pc/h/lane presented in Table 32.

Table 32: Final Traffic Flow (pc/h/lane) for Case study #1

Year	Final Traffic Flow (pc/h/lane)					
	N/E direction (pc/h/lane)			S/W direction (pc/h/lane)		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	1335	1335	1335	1463	1463	1463
2023	1350	1350	1350	1455	1455	1455
2024	1403	1403	1403	1482	1482	1482
2025	1420	1420	1420	1474	1474	1474
2026	1436	1436	1436	1463	1463	1463
2027	1451	1451	1451	1457	1457	1457
2028	1467	1467	1467	1459	1459	1459
2029	1483	1483	1483	1465	1465	1465
2030	1390	1498	1498	1364	1470	1470
2031	1408	1517	1652	1372	1478	1610
2032	1425	1535	1680	1380	1487	1627
2033	1442	1553	1709	1389	1496	1646
2034	1459	1570	1737	1398	1504	1664
2035	1476	1588	1766	1407	1514	1683
2036	1491	1665	1793	1414	1579	1700
2037	1508	1692	1821	1419	1593	1714
2038	1523	1718	1849	1423	1605	1728
2039	1538	1743	1875	1428	1618	1742
2040	1552	1568	1904	1432	1446	1757
2041	1792	1588	2172	1642	1454	1993
2042	1817	1612	2054	1656	1467	1873
2043	1634	1634	2090	1478	1478	1894
2044	1656	1656	2125	1487	1487	1913
2045	1679	1679	2163	1496	1496	1932
2046	1486	1948	2198	1311	1725	1952
2047	1507	1982	2236	1323	1747	1976
2048	1527	2015	2273	1332	1765	1997
2049	1545	2046	2308	1336	1779	2013
2050	1568	2085	2351	1347	1801	2039

Then, the final V/C Ratio for case study #1 presented in Table 33. The cells highlighted in green have the B or C grade of the level of service (desired by this study) for the traffic network. by considering the information presented in table 33, the users could change the number of lanes to find the V/C ratio for each scenario for each year.

Table 33: Final V/C Ratio for Case study #1

Year	Final V/C Ratio					
	N/E direction V/C Ratio			S/W direction V/C Ratio		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	0.61	0.61	0.61	0.69	0.69	0.69
2023	0.62	0.62	0.62	0.68	0.68	0.68
2024	0.63	0.63	0.63	0.69	0.69	0.69
2025	0.64	0.64	0.64	0.68	0.68	0.68
2026	0.64	0.64	0.64	0.67	0.67	0.67
2027	0.64	0.64	0.64	0.64	0.64	0.64
2028	0.66	0.66	0.66	0.64	0.64	0.64
2029	0.66	0.66	0.66	0.66	0.66	0.66
2030	0.62	0.67	0.67	0.61	0.65	0.65
2031	0.62	0.67	0.73	0.61	0.65	0.71
2032	0.62	0.67	0.74	0.60	0.65	0.71
2033	0.63	0.67	0.74	0.60	0.65	0.71
2034	0.63	0.68	0.75	0.60	0.65	0.72
2035	0.63	0.68	0.75	0.60	0.65	0.72
2036	0.63	0.70	0.76	0.60	0.67	0.72
2037	0.63	0.71	0.76	0.59	0.66	0.72
2038	0.63	0.71	0.76	0.59	0.66	0.71
2039	0.63	0.72	0.77	0.59	0.67	0.72
2040	0.63	0.65	0.78	0.58	0.60	0.72
2041	0.72	0.66	0.88	0.66	0.60	0.80
2042	0.73	0.66	0.82	0.66	0.60	0.75
2043	0.66	0.66	0.83	0.60	0.60	0.75
2044	0.67	0.67	0.84	0.60	0.60	0.75
2045	0.67	0.67	0.84	0.59	0.59	0.75
2046	0.60	0.77	0.85	0.53	0.68	0.75
2047	0.60	0.77	0.85	0.53	0.68	0.75
2048	0.60	0.78	0.86	0.52	0.68	0.75
2049	0.60	0.78	0.86	0.52	0.68	0.75
2050	0.60	0.78	0.86	0.51	0.67	0.74

Ultimately, year 2039 traffic flow was selected to be compared with the highway expansion scenario. Table 30 shows the widening of the highway in the cosite under the study from 6L to 8L, could enhance the level of service from 0.72 in Most Likely scenario for N/E direction to the final V/C Ratio for case study #1 presented in Table 29. The cells highlighted in green have the B or C grade of the level of service (desired by this study) for the traffic network. by considering the information presented in table 34, the users could change the number of lanes to find the V/C ratio for each scenario for each year.

Table 34: Highway Expansion Impact on V/C Ratio for Case study #1

Construction Type	Year	N/E direction V/C Ratio			S/W direction V/C Ratio		
		Productive	**Most Likely**	**Disruptive**	**Productive**	**Most Likely**	**Disruptive**
No Construction	**2039**	0.63	0.72	0.77	0.59	0.67	0.72
Widening 6L to 8L	**2039**	0.47	0.54	0.58	0.44	0.50	0.54

By employing the highway construction cost prediction model, the final cost per mile of widening the highway from 6L to 8L in 2039 would be $18491113.81. Moreover, this study considers a highway link of 10 mile for each cosite. Furthermore, the final highway construction cost for the case study 1 would be $184’911’138.1.

Case study #2: I4, Orange County, Cosite ID: 750668

The second case study is from the Orange County, interstate highway I4. Table 35 shows the information of the first case study.

Table 35: Case study #2

Interstate	County	Cosite	K	FFS	Number Lanes
I4	Orange	750668	8.53	65	3

Table 36 shows the predicted traffic flow for the N/E direction and S/W direction for both passenger vehicles and trucks for the case study #2.

Table 36: Cosite Road Characteristics and the Predicted traffic flow for Case study #2

Year	**K**	**FFS**	**Number Lanes**	**Max Service Flow Rate (pc/hr/lane)**	**PV N/E direction**	**PV S/W direction**	**Trucks N/E direction**	**Trucks S/W direction**	**Baseline V/C**
2022	8.53	65	3	**2300**	**48679**	**61797**	**2698**	**3488**	1.48
2023	8.53	65	3	**2300**	**48105**	**62749**	**2792**	**3432**	1.49
2024	8.53	65	3	**2300**	**47563**	**63560**	**2921**	**3409**	1.49
2025	8.53	65	3	**2300**	**47072**	**63992**	**3048**	**3348**	1.49
2026	8.53	65	3	**2300**	**46724**	**64350**	**3199**	**3336**	1.49
2027	8.53	65	3	**2300**	**46653**	**64585**	**3348**	**3330**	1.50
2028	8.53	65	3	**2300**	**46621**	**64775**	**3530**	**3422**	1.51
2029	8.53	65	3	**2300**	**46591**	**64967**	**3710**	**3527**	1.51
2030	8.53	65	3	**2300**	**46562**	**65093**	**3892**	**3647**	1.52
2031	8.53	65	3	**2300**	**46534**	**65199**	**4085**	**3784**	1.53
2032	8.53	65	3	**2300**	**46508**	**65308**	**4274**	**3909**	1.53
2033	8.53	65	3	**2300**	**46482**	**65302**	**4452**	**4047**	1.54
2034	8.53	65	3	**2300**	**46497**	**65271**	**4602**	**4147**	1.54
2035	8.53	65	3	**2300**	**46728**	**65241**	**4764**	**4284**	1.55
2036	8.53	65	3	**2300**	**47007**	**65212**	**4904**	**4416**	1.56
2037	8.53	65	3	**2300**	**47329**	**65183**	**5027**	**4538**	1.57
2038	8.53	65	3	**2300**	**47649**	**65155**	**5164**	**4648**	1.58
2039	8.53	65	3	**2300**	**47967**	**65127**	**5320**	**4792**	1.59
2040	8.53	65	3	**2300**	**48285**	**65099**	**5462**	**4900**	1.59
2041	8.53	65	3	**2300**	**48591**	**65072**	**5616**	**5026**	1.60
2042	8.53	65	3	**2300**	**48801**	**65062**	**5795**	**5213**	1.61
2043	8.53	65	3	**2300**	**48994**	**65055**	**5957**	**5378**	1.62
2044	8.53	65	3	**2300**	**49193**	**65048**	**6107**	**5496**	1.63
2045	8.53	65	3	**2300**	**49397**	**65044**	**6252**	**5574**	1.63
2046	8.53	65	3	**2300**	**49609**	**65074**	**6427**	**5726**	1.64
2047	8.53	65	3	**2300**	**49848**	**65095**	**6614**	**5919**	1.65
2048	8.53	65	3	**2300**	**50155**	**65084**	**6755**	**6035**	1.66
2049	8.53	65	3	**2300**	**50481**	**65058**	**6860**	**6093**	1.67
2050	8.53	65	3	**2300**	**50824**	**65064**	**6998**	**6211**	1.68

Then, the adjusted annual personal passenger vehicles equivalent (of Trucks and Passenger Vehicles All together) were calculated and is shown in Table 37.

Table 37: Passenger Vehicles Equivalent for Case study #2

Year	Passenger Vehicles Equivalent (of Trucks and Passenger Vehicles All together)					
	N/E direction MADT			S/W direction MADT		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	52726	52726	52726	67029	67029	67029
2023	52294	52294	52294	67897	67897	67897
2024	53510	53510	53510	70745	70745	70745
2025	53448	53448	53448	71427	71427	71427
2026	53504	53504	53504	72028	72028	72028
2027	53878	53878	53878	72553	72553	72553
2028	54343	54343	54343	73185	73185	73185
2029	54811	54811	54811	73845	73845	73845
2030	50340	55252	55252	67549	74417	74417
2031	50846	55778	61017	68173	75083	82218
2032	51320	56268	61895	68745	75694	83358
2033	51780	56746	62762	69230	76206	84392
2034	52238	57224	63636	69632	76632	85334
2035	52939	57971	64836	70114	77140	86402
2036	53631	60252	65991	70556	79400	87361
2037	54353	61386	67220	71001	80327	88361
2038	55102	62557	68486	71432	81243	89350
2039	55887	63775	69800	71921	82227	90407
2040	56689	55880	71210	72401	70878	91547
2041	66209	56880	82068	84121	71627	104904
2042	67387	57929	76612	85228	72619	97050
2043	58945	58945	78204	73584	73584	98657
2044	59955	59955	79802	74474	74474	100186
2045	61024	61024	81511	75357	75357	101764
2046	52093	71547	83138	63213	88131	103336
2047	53114	73144	84946	64175	89707	105118
2048	54115	74749	86780	64975	91099	106711
2049	55077	76324	88593	65659	92363	108175
2050	56253	78257	90811	66643	94105	110177

Then, the total passenger vehicle (pv) trips unit was converted from MADT to pc/h/lane presented in Table 38.

Table 38: Passenger Vehicles Equivalent for Case study #2

Year	Final Traffic Flow					
	Passenger Vehicles Equivalent (of Trucks and Passenger Vehicles ALL) pc/h/lane					
	N/E direction pc/h/lane			S/W direction pc/h/lane		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	1499	1499	1499	1906	1906	1906
2023	1487	1487	1487	1931	1931	1931
2024	1521	1521	1521	2012	2012	2012
2025	1520	1520	1520	2031	2031	2031
2026	1521	1521	1521	2048	2048	2048
2027	1532	1532	1532	2063	2063	2063
2028	1545	1545	1545	2081	2081	2081
2029	1558	1558	1558	2100	2100	2100
2030	1431	1571	1571	1921	2116	2116
2031	1446	1586	1735	1938	2135	2338
2032	1459	1600	1760	1955	2152	2370
2033	1472	1613	1785	1968	2167	2400
2034	1485	1627	1809	1980	2179	2426
2035	1505	1648	1844	1994	2193	2457
2036	1525	1713	1876	2006	2258	2484
2037	1545	1745	1911	2019	2284	2512
2038	1567	1779	1947	2031	2310	2541
2039	1589	1813	1985	2045	2338	2571
2040	1612	1589	2025	2059	2015	2603
2041	1883	1617	2333	2392	2037	2983
2042	1916	1647	2178	2423	2065	2759
2043	1676	1676	2224	2092	2092	2805
2044	1705	1705	2269	2118	2118	2849
2045	1735	1735	2318	2143	2143	2893
2046	1481	2034	2364	1797	2506	2938
2047	1510	2080	2415	1825	2551	2989
2048	1539	2125	2467	1847	2590	3034
2049	1566	2170	2519	1867	2626	3076
2050	1599	2225	2582	1895	2676	3133

Then, the final V/C Ratio for case study #2 presented in Table 39. The cells highlighted in green have the B or C grade of the level of service (LOS desired by this study) for the traffic network. By considering the information presented in table 38, the users could change the number of lanes to find the V/C ratio for each scenario for each year.

Table 39: Final Adjusted Level of V/C Ratio for Case study #2

Year	Final Adjusted Level of Service Ratio					
	N/E direction V/C Ratio			S/W direction V/C Ratio		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	0.66	0.66	0.66	0.83	0.83	0.83
2023	0.65	0.65	0.65	0.84	0.84	0.84
2024	0.66	0.66	0.66	0.87	0.87	0.87
2025	0.65	0.65	0.65	0.85	0.85	0.85
2026	0.65	0.65	0.65	0.85	0.85	0.85
2027	0.65	0.65	0.65	0.85	0.85	0.85
2028	0.65	0.65	0.65	0.85	0.85	0.85
2029	0.65	0.65	0.65	0.88	0.88	0.88
2030	0.59	0.65	0.65	0.79	0.88	0.88
2031	0.59	0.65	0.71	0.80	0.88	0.96
2032	0.59	0.65	0.72	0.80	0.88	0.97
2033	0.59	0.65	0.72	0.79	0.87	0.97
2034	0.59	0.65	0.72	0.79	0.87	0.97
2035	0.61	0.65	0.73	0.79	0.87	0.98
2036	0.62	0.67	0.74	0.79	0.89	0.98
2037	0.62	0.69	0.74	0.78	0.89	0.98
2038	0.62	0.70	0.75	0.78	0.89	0.98
2039	0.62	0.71	0.76	0.78	0.90	0.98
2040	0.63	0.62	0.77	0.78	0.76	0.99
2041	0.73	0.62	0.88	0.90	0.77	1.12
2042	0.73	0.63	0.83	0.90	0.77	1.03
2043	0.63	0.63	0.84	0.77	0.77	1.03
2044	0.64	0.64	0.85	0.78	0.78	1.04
2045	0.64	0.64	0.86	0.77	0.77	1.05
2046	0.56	0.75	0.87	0.66	0.90	1.05
2047	0.56	0.76	0.88	0.66	0.90	1.06
2048	0.57	0.76	0.89	0.66	0.93	1.06
2049	0.57	0.77	0.90	0.66	0.93	1.07
2050	0.57	0.77	0.90	0.66	0.93	1.06

Ultimately, year 2031 traffic flow was selected to be compared with the highway expansion scenario. Table 40 shows the widening of the highway in the cosite under the study from 6L to 8L, could enhance the level of service from 0.71 to 0.53 in disruptive scenario for N/E direction.

Table 40: Highway Expansion Impact on V/C Ratio for Case study #2

Construction	Year	N/E direction V/C Ratio			S/W direction V/C Ratio		
		Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
No Construction	2031	0.59	0.65	0.71	0.80	0.88	0.96
Widening 6L to 8L	2031	0.45	0.49	0.53	0.60	0.66	0.72

By employing the highway construction cost prediction model, the final cost per mile of widening the highway from 6L to 8L in 2031 would be \$14’726’056.11. Moreover, this study considers a highway link of 10 mile for each cosite. Furthermore, the final highway construction cost for the case study 1 would be \$147’260’561.1.

Case study #3: I10, Duval County, Cosite ID: 720832

The third case study is from the Duval County, interstate highway I10. Table 41 shows the information of the first case study.

Table 41: Case study #3

Interstate	County	Cosite	K	FFS	Number Lanes
I10	Duval	720832	7.96	50	4

Table 42 shows the predicted traffic flow for the N/E direction and S/W direction for both passenger vehicles and trucks for the case study #3.

Table 42: Cosite Road Characteristics and the Predicted traffic flow for Case study #3

Year	K	FFS	Number Lanes	Max Service Flow Rate (pc/hr/lane)	PV N/E direction	PV S/W direction	Trucks N/E direction	Trucks S/W direction	Baseline V/C
2022	7.96	50	4	**2300**	**74250**	**78654**	**4019**	**5601**	1.45
2023	7.96	50	4	**2300**	**74893**	**79429**	**4024**	**5704**	1.46
2024	7.96	50	4	**2300**	**75615**	**80266**	**4061**	**5739**	1.48
2025	7.96	50	4	**2300**	**76642**	**81165**	**4159**	**5749**	1.49
2026	7.96	50	4	**2300**	**77692**	**82047**	**4273**	**5782**	1.51
2027	7.96	50	4	**2300**	**78686**	**82815**	**4377**	**5817**	1.53
2028	7.96	50	4	**2300**	**79627**	**83415**	**4523**	**5872**	1.55
2029	7.96	50	4	**2300**	**80522**	**83973**	**4679**	**5860**	1.56
2030	7.96	50	4	**2300**	**81373**	**84507**	**4837**	**5824**	1.57
2031	7.96	50	4	**2300**	**82185**	**85017**	**5010**	**5790**	1.59
2032	7.96	50	4	**2300**	**82963**	**85505**	**5178**	**5790**	1.60
2033	7.96	50	4	**2300**	**83710**	**85984**	**5355**	**5804**	1.61
2034	7.96	50	4	**2300**	**84431**	**86462**	**5542**	**5798**	1.63
2035	7.96	50	4	**2300**	**85131**	**86943**	**5723**	**5810**	1.64
2036	7.96	50	4	**2300**	**85814**	**87415**	**5877**	**5854**	1.65
2037	7.96	50	4	**2300**	**86483**	**87861**	**6033**	**5908**	1.66
2038	7.96	50	4	**2300**	**87144**	**88100**	**6183**	**5963**	1.67
2039	7.96	50	4	**2300**	**87801**	**88254**	**6346**	**6050**	1.68
2040	7.96	50	4	**2300**	**88234**	**88408**	**6496**	**6125**	1.69
2041	7.96	50	4	**2300**	**88406**	**88563**	**6658**	**6228**	1.70
2042	7.96	50	4	**2300**	**88581**	**88719**	**6841**	**6405**	1.71
2043	7.96	50	4	**2300**	**88759**	**88879**	**7010**	**6560**	1.71
2044	7.96	50	4	**2300**	**88941**	**89037**	**7158**	**6672**	1.72
2045	7.96	50	4	**2300**	**89162**	**89155**	**7291**	**6753**	1.73
2046	7.96	50	4	**2300**	**89460**	**89269**	**7455**	**6914**	1.73
2047	7.96	50	4	**2300**	**89773**	**89388**	**7644**	**7129**	1.74
2048	7.96	50	4	**2300**	**90100**	**89510**	**7821**	**7318**	1.75
2049	7.96	50	4	**2300**	**90442**	**89622**	**7975**	**7472**	1.76
2050	7.96	50	4	**2300**	**90801**	**89737**	**8180**	**7691**	1.77

Then, the adjusted annual personal passenger vehicles equivalent (of Trucks and Passenger Vehicles All together) were calculated and is shown in Table 43.

Table 43: Passenger Vehicles Equivalent for Case study #3

Year	Passenger Vehicles Equivalent (of Trucks and Passenger Vehicles ALL)					
	N/E direction MADT			S/W direction MADT		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	80278	80278	80278	87055	87055	87055
2023	80929	80929	80929	87985	87985	87985
2024	84171	84171	84171	91550	91550	91550
2025	85778	85778	85778	92921	92921	92921
2026	87341	87341	87341	94208	94208	94208
2027	88891	88891	88891	95443	95443	95443
2028	90462	90462	90462	96538	96538	96538
2029	92007	92007	92007	97489	97489	97489
2030	84883	93467	93467	89412	98328	98328
2031	86312	95022	104042	90247	99257	108652
2032	87665	96492	106252	91071	100169	110279
2033	89010	97952	108466	91912	101097	111932
2034	90356	99411	110691	92724	101997	113564
2035	91703	100871	112975	93599	102963	115319
2036	92952	104598	115075	94473	106318	116990
2037	94222	106597	117257	95366	107905	118734
2038	95485	108602	119445	96065	109280	120242
2039	96774	110648	121677	96738	110629	121715
2040	97894	95804	123819	97458	95297	123367
2041	113974	97000	142180	113373	96369	141548
2042	115567	98399	131613	114927	97732	130914
2043	99790	99790	133933	99075	99075	133174
2044	101163	101163	136247	100352	100352	135372
2045	102643	102643	138766	101624	101624	137629
2046	86113	120277	141179	84935	118910	139767
2047	87514	122605	143859	86218	121048	142210
2048	88923	124960	146573	87472	123166	144638
2049	90318	127319	149300	88666	125225	147007
2050	92051	130250	152679	90203	127853	150020

Then, the total passenger vehicle (pv) trips unit was converted from MADT to pc/h/lane presented in Table 44.

Table 44: Final Traffic Flow for Case study #3

Year	**Final Traffic Flow**					
	Passenger vehicles equivalent (of trucks and passenger vehicles all) pc/h/lane					
	N/E direction pc/h/lane			**S/W direction pc/h/lane**		
	Productive	**Most Likely**	**Disruptive**	**Productive**	**Most Likely**	**Disruptive**
2022	1598	1598	1598	1732	1732	1732
2023	1610	1610	1610	1751	1751	1751
2024	1675	1675	1675	1822	1822	1822
2025	1707	1707	1707	1849	1849	1849
2026	1738	1738	1738	1875	1875	1875
2027	1769	1769	1769	1899	1899	1899
2028	1800	1800	1800	1921	1921	1921
2029	1831	1831	1831	1940	1940	1940
2030	1689	1860	1860	1779	1957	1957
2031	1718	1891	2070	1796	1975	2162
2032	1745	1920	2114	1812	1993	2195
2033	1771	1949	2158	1829	2012	2227
2034	1798	1978	2203	1845	2030	2260
2035	1825	2007	2248	1863	2049	2295
2036	1850	2082	2290	1880	2116	2328
2037	1875	2121	2333	1898	2147	2363
2038	1900	2161	2377	1912	2175	2393
2039	1926	2202	2421	1925	2202	2422
2040	1948	1907	2464	1939	1896	2455
2041	2268	1930	2829	2256	1918	2817
2042	2300	1958	2619	2287	1945	2605
2043	1986	1986	2665	1972	1972	2650
2044	2013	2013	2711	1997	1997	2694
2045	2043	2043	2761	2022	2022	2739
2046	1714	2394	2809	1690	2366	2781
2047	1742	2440	2863	1716	2409	2830
2048	1770	2487	2917	1741	2451	2878
2049	1797	2534	2971	1764	2492	2925
2050	1832	2592	3038	1795	2544	2985

Then, the final V/C Ratio for case study #3 presented in Table 45. As shown in table all the scenarios would have D or E level of service.

Table 45: Final Adjusted V/C Ratio for Case study #3

Year	Final Adjusted V/C Ratio					
	N/E direction V/C Ratio			S/W direction V/C Ratio		
	Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
2022	0.70	0.70	0.70	0.76	0.76	0.76
2023	0.70	0.70	0.70	0.76	0.76	0.76
2024	0.72	0.72	0.72	0.79	0.79	0.79
2025	0.73	0.73	0.73	0.79	0.79	0.79
2026	0.74	0.74	0.74	0.80	0.80	0.80
2027	0.75	0.75	0.75	0.80	0.80	0.80
2028	0.76	0.76	0.76	0.81	0.81	0.81
2029	0.76	0.76	0.76	0.81	0.81	0.81
2030	0.70	0.77	0.77	0.74	0.81	0.81
2031	0.71	0.78	0.85	0.74	0.81	0.89
2032	0.71	0.78	0.86	0.74	0.81	0.89
2033	0.72	0.79	0.87	0.74	0.81	0.90
2034	0.72	0.79	0.88	0.74	0.81	0.90
2035	0.72	0.80	0.89	0.74	0.81	0.91
2036	0.73	0.82	0.90	0.74	0.83	0.92
2037	0.73	0.82	0.91	0.74	0.83	0.92
2038	0.73	0.83	0.91	0.74	0.84	0.92
2039	0.74	0.84	0.93	0.74	0.84	0.93
2040	0.74	0.72	0.93	0.74	0.72	0.93
2041	0.85	0.73	1.06	0.85	0.72	1.06
2042	0.86	0.73	0.97	0.85	0.72	0.97
2043	0.73	0.73	0.98	0.73	0.73	0.98
2044	0.74	0.74	0.99	0.73	0.73	0.99
2045	0.74	0.74	1.00	0.73	0.73	0.99
2046	0.63	0.86	1.01	0.62	0.85	1.00
2047	0.63	0.86	1.01	0.62	0.85	1.00
2048	0.64	0.87	1.02	0.63	0.86	1.01
2049	0.64	0.88	1.03	0.63	0.87	1.02
2050	0.64	0.88	1.03	0.62	0.86	1.01

Ultimately, year 2026 traffic flow was selected to be compared with the highway expansion scenario. Table 30 shows the widening of the highway in the cosite under the study from 8L to 10L, could enhance the level of service and the V/C ratio from 0.8 to 0.53 in all scenarios for S/W direction to the final V/C Ratio for case study #3 presented in Table 46.

Table 46: Highway Expansion Impact on V/C Ratio for Case study #3

Construction	Year	N/E direction V/C Ratio			S/W direction V/C Ratio		
		Productive	Most Likely	Disruptive	Productive	Most Likely	Disruptive
No Construction	2026	0.74	0.74	0.74	0.80	0.80	0.80
Widening 8L to 10L	2026	0.49	0.49	0.49	0.53	0.53	0.53

By employing the highway construction cost prediction model, the final cost per mile of widening the highway from 6L to 8L in 2039 would be $12436945.91. Moreover, this study considers a highway link of 10 mile for each cosite. Furthermore, the final highway construction cost for the case study 1 would be $124’369’459.1.

CHAPTER SIX: DISCUSSION

Chapter 5 presented the results of the four steps of the framework of the study that were tested on the Florida department of transportation historical data. This section, discussions, review the findings of the various steps of the framework on the test data, discusses the outcomes, and stakes some claims.

Step 1: Traffic prediction model – Passenger Vehicles

(Regarding this section the author employed his published study: Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Yuan, J.S. and Oloufa, A., 2021c. Automated Machine Learning Pipeline for Traffic Count Prediction. Modelling, 2(4), pp.482-513.)

The Current State of Practice at FDOT (Mahdavian et al. 2021c): Florida Statewide Model (FLSWM) is a comprehensive travel demand model that was developed using the traditional four-step modeling approach. The purpose of the statewide model is to forecast the demand changes from 2020 to 2045. In this model, the primary data source is the 2010 (origin-destination) OD Survey in Florida, which was collected at the census block level. Traffic counts collected from the onsite detectors from 2001 to 2015 were employed for validation and calibration purposes of the approach. Gravity models, combined with discrete choice models, such as multinomial logistic regression, were utilized in the trip distribution step to determine the destination choice of travelers. Similarly, discrete choice methods were used for the modal split in two parts: First, long-distance mode choice; second, auto occupancy/short choice mode choice. For the first part of the modal split, a nested logit model transferred from the Virginia DOT TDM was used. In contrast, for the second part, a hybrid transit abstraction methodology was transferred from the California statewide TDM. Freight transportation forecasting was performed via a separate module named FreightSIM. Finally, in the highway assignment procedure, seven vehicle classes were assigned in the statewide model via a multi-class user equilibrium methodology. Model outputs were also evaluated via cost-benefit analysis. The overall accuracies of the model were found to be reasonable. With the recent updates to FLSWM made in January 2020, some limitations can be listed as: (1) The model calibration, and validation processes rely on annual historical data, thus monthly, or daily changes are not captured, (2) although, many socio-economic parameters were utilized, some of the essential global economic factors were not considered, (3) linear or non-linear machine learning algorithms are not considered.

As demonstrated, the proposed framework shows a high degree of prediction accuracy. It can be readily used as a complementary tool in analyzing existing models of traffic volume prediction. Based on the results presented in this study, non-linear models showed an advantage over linear models, as evident by the apparent difference in performance seen on the traffic dataset used. In contrast to the studies that have shown that linear regression models utilizing roadway characteristics and socioeconomic factors can predict AADT with a reasonable level of errors, this study has shown that, even by using a broader category of predictors, linear models are not capable of predicting the traffic counts with reasonable accuracy in this case. On the other hand, this study confirms the results of the study by Liu and Wu that the RF algorithm is capable of traffic flow prediction with high accuracy due to its robustness and practicality (though only in short term). Additionally, the developed RF and NN models by the framework of this study have shown a better accuracy compared with the TDM model developed by Wang et al. with a 52% MAPE. The NN model developed in this study with a MAPE of 17.48% has higher accuracy than the developed ANN model Fu and Kelly (2017) with a MAPE of 28.58%. Finally, the result of this study is conforming with the results of the studies by Ratrouta and Gazdera and Chen et al., that NN models have shown better accuracy than the linear regression method for predicting daily traffic (Mahdavian et al. 2021c).

The results of the research showed that RF algorithm outperformed the other employed non-linear algorithms on the test set to predict the current pattern of the passenger vehicle traffic on the highways. The generalization capacities of RF give it an edge for current MADT projections. The developed RF model (with spatial variables) on the test dataset of the study showed the ability to forecast the MADT with 88% accuracy. Road characteristics' category has the most significant impact on the PV traffic prediction model - the same as the previously developed model (without spatial variables) - with a value of 54.78%. Then, the Socioeconomic category, with a value of 22.12%, has the second rank. Ultimately, the Spatial category, with 21.62%, has the third rank. Regarding the critical features of the RF model (with spatial variables), the “road characteristics” played a key role with 54.78% importance, and second, “socioeconomic variables” with 22.12% importance, had a notable role in the PV volume prediction model. Thirdly, Spatial category with 21.62% importance level ranked third. The “number of lanes” which shows the capacity of the road of the studied location – with 51.95% - had the most important influence on the PV prediction model. Moreover, the “Euclidean geometry”, related to the spatial variables. with 14.93% were the second important feature. Notably, the “number of lanes” with 51.95%, and the “Euclidean geometry” with 14.93% are the leading variables affecting the PV traffic volumes. The results showed that the NN model outperforms other linear and non-linear algorithms for the long- term prediction with an 81% prediction accuracy. Adding the spatially related variables to the developed model of this study resulted in an increase in the accuracy of the model to 83% (Mahdavian et al. 2021c).

Step 2: Traffic prediction model – Trucks

(Regarding this section the author employed his published study: Mahdavian, A., Shojaei, A., Salem, M., Laman, H., Eluru, N. and Oloufa, A.A., 2021d. A Universal Automated Data-Driven Modeling Framework for Truck Traffic Volume Prediction. IEEE Access, 9, pp.105341-105356.)

THE CURRENT STATE OF PRACTICE AT FLORIDA DEPARTMENT OF TRANSPORT (FDOT) (Mahdavian et al. 2021d): With the latest updates made in January 2020, the Florida Statewide Model (FLSWM) for travel demand forecasting is a traditional four-step model with a freight demand modeling component named FreightSIM. In the four-step model developed using the Citilabs Cube Voyager and Avenue software platform, trips are generated from the 2010 origin–destination (OD) survey conducted in Florida at the census block level, and traffic counts from 2001 to 2015 are used for validation and calibration at the transportation analysis zone (TAZ) level. Trip distribution is performed with the use of gravity models combined with multinomial logit models for destination choice. To forecast truck traffic, the analysis modules used in the FreightSIM model include sound synthesis, supplier firm selection, distribution channels, shipment size and frequency, modes and transfers, and freight trip assignment, that is integrated into the overall highway assignment as truck traffic. Additionally, the input/output database from the U.S. Bureau of Economics, port tonnage information, employment data from County Business

Patterns (CBP), and freight flow from the freight analysis framework version 4 (FAF4) are utilized in the calibration and validation of the FreightSIM model. FAF is a national framework developed by the Bureau of Statistics and Federal Highway Administration (FHWA) to provide a comprehensive understanding of U.S. freight movements and forecast both optimistic and pessimistic growth scenarios from 2020 through 2045. In the Florida Department of Transportation (FDOT) model, some socioeconomic variables and freight-related economic variables, along with the 2010 Florida OD survey, were employed to predict future traffic counts. The truck counts prediction model for use on state highways developed in this study may assist transportation planners and decision-makers to insert highly accurate traffic counts into their four-step or activity-based models. In doing so, they can increase the robustness of predictions and quantify more accurate truck traffic in order to assist near-, mid-, and long-term planning solutions (Mahdavian et al. 2021d).

This study generated and optimized a framework containing feature selection via a three-step approach to assist the training of models with high accuracy. With its high prediction accuracy, the proposed methodology presents a promising complementary tool to be utilized in the calibration and validation of existing truck volume prediction models. In contrast to Lu et al., which demonstrated that both linear and compound growth models fit truck traffic growth trends well, this study has shown that linear models are not able to predict the MADTT accurately. Additionally, this study confirms the results of studies by Polson et al., Oswald et al., Rilett and Park, and Liu and Wu, which claimed that the superior capability of nonparametric models to capture temporal-spatial relationships and non-linear patterns offer more accurate truck traffic forecasting compared to parametric models (Mahdavian et al. 2021d).

By analyzing the results on the test and validation dataset, it can be concluded that non-linear models outperform linear models. This is evident in the notable gap between the performances of linear models on the truck dataset versus those of the non-linear models. Overall, four models, namely DT, RF, NN, and KNN, were evaluated. The generalization capabilities of RF give it an edge for current and near-term

MADTT projections. Meanwhile, the RF algorithm results produced on the test dataset of the study demonstrate the models' ability to predict the MADTT with 82% accuracy. However, by adding spatial-related variables (county, interstate, site ID, and Euclidean geometry of each site) the accuracy of the model improved to 86%, illustrating the importance of considering location-related features for truck traffic prediction models. Regarding the important features of the RF model with spatial variables, the "spatial variables" category ranked first with 48% importance, followed by "road characteristics," with 26% importance. Both have a significant role in the truck counts prediction model. Furthermore, the developed NN model with spatial variables for long-term predictions shows the capability of the model to predict the MADTT, with 80% accuracy (Mahdavian et al. 2021d).

Step 3: CASE vehicles impact on traffic network

Regarding this section the author employed his published publications: *Mahdavian, A. Shojaei, A., Oloufa, A. 2019a. Service Level Evaluation of Florida's Highways Considering the Impact of Autonomous Vehicles. Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC). And: Mahdavian, A., A. Shojaei, and A. Oloufa. 2019b. Assessing the long-and mid-term effects of connected and automated vehicles on highways' traffic flow and capacity. International Conference on Sustainable Infrastructure 2019: Leading Resilient Communities through the 21st Century. Reston, VA: American Society of Civil Engineers. And also: Mahdavian, A., Shojaei, A., Mccormick, S., Papandreou, T., Eluru, N. and Oloufa, A.A., 2021a. Drivers and Barriers to Implementation of Connected, Automated, Shared, and Electric Vehicles: An Agenda for Future Research. IEEE Access, 9, pp.22195-22213.)*

In this modern age, the push towards clean energy, smart cities, a sharing economy, and global urbanization, all fuel the impetus for new, innovative technological development. While the application of CATs, smart roads, and CAVs seemed theoretical a few years ago, they are becoming increasingly common. This type of travel-based technology can be used to help improve the everyday life's of millions, through safer roads, improved travel experience, and shorter delivery times. In 2050, more than 66% of the population are expected to live in urban areas around the world. Today, these areas already contain 55% of the population. This means these limited areas are expected to grow by 2.5 billion individuals. This massive increase in population means the existing cities and infrastructure will be pushed to their maximum capacity, necessitating improvements. Technological advances in travel could help facilitate these improvements, but changes must first be made. For example, at the moment, the benefits (higher traffic capacity) that could be obtained by using CASE vehicles is not expected to come to pass due to low rates of market penetration. More precisely, Van Arem et al. suggested that if market penetration is less than 40%, these enhancements to traffic capacity will not occur.

The current state of the CASE movement however remains tentative, with much of the automotive industry moving away from that direction. This change had been fueled by a better understanding of what CASE implementation would look like, and the types of automation that will be offered and the relevant timeline. Networking by the automotive industry, including multiple mergers, partnerships, and consolidations, have been attempted with the goal of reaching critical market penetration of CASE technology. Despite this, the contribution by agencies on a federal level has remained lower, with most investments coming from private parties. Unfortunately, this means investors that focus more on specific, narrow categories of for-use cases. It is clear level 5 automation or autonomous vehicles is still, very far away.

Of the more recent improvements made to advance autonomous feel operations, some progress has been achieved. More and more desire for forms of driverless human transport is growing, including robo-taxis, robo-delivery, and robo-trucks. This type of autonomy goods transport can be put into 4 categories; resource roads, streets, highways, and controlled environments. Some examples of this automated goods movement in the case of B2B delivery includes Waymo’s partnership with UPS, Walmart and Loblaws partnership with GATIK, Nurus work with both Fry’s Food, CVS, and Kroger, and finally Einrides partnership with Coca-Cola, Lidl, and Oatly. Of the category controlled environments, the market is smaller and mostly includes logistic yards and industrial use. Little investment has been made by larger OEMs. For resource roads, which include unpaved roads and remote areas, some companies like FPInnovations use truck automation for their timber hauling. Lastly, the highway categories include solo driverless vehicles and platooning vehicles. Multiple startups and established companies have entered into both categories. For solo driverless vehicles, these include Utobon, Waymo, tusimple, Aurora, Ainride, Ike, Kodiak, embake, pony.ai, Navistar Volva, Daimler, plus.ai, Traton, and Tesla. These companies how to use dock-to-dock and ramp-to-ramp automated trips. For platooning, these companies include Volvo, Traton Group, and Daimler; in addition to the start-ups Locomation, Robotic Research, and Peloton.

Understandably, there are still many other barriers in place regarding travel automation technology including; user attitude, software safety, software Verification and validation (V&V), CAV regulation, and others, that have continued to develop in the last 10 years. Some of these must be addressed sooner than others if the adoption of CASE vehicles is to occur in a more seamless manner. There are also final regulatory based polices that need to be put in place. But ultimately, the user attitude regarding CASE vehicles has to change. In order to improve the current transportation network planning process related to CASE vehicles, risk assessment of internal impacts (effects the user) and external impacts (others) needs to be considered. Negative internal risks can include additional risks like user crashes, reduced privacy or security, and higher vehicle costs. Negative external risks meanwhile related to concerns about social equity, decreased security, decreased employment, and higher traffic concerns and infrastructure costs. There is also an optimism bias about CAV that can impeded the benefits of different types of management strategies and transport improvements.

In the following section, factors related to safety concerns, the emergence of an e-commerce based delivery system, and the addition of new traffic categories for people will be discussed in a step by step process.

New categories: Regarding new traffic categories for PV and their effects on traffic flow; CAVs are expected to increase the appeal and number of vehicle trips.

Safety: CAVs are expected to increase safety, which will impact both traffic flow, and traffic capacity. While some safety benefits have been considered, some research suggests the risks of CAV technology has not been efficiently explored (Koopman and Wagner 2017). Currently these risks reduce the appeal of CAV based travel. The benefits however, are implied to be fewer traffic accidents, reducing congestion and nonrecurrent related delays. Some literature reports suggest these types of traffic accidents cause 25% of the traffic congestion seen on the road. A CAV can easily navigate a majority of these accident situations, but it has been challenging thus far to design a reliable CAV system for every possible outcome (Campbell et al. 2010). CAVs themselves may cause more accidents, for the reasons outlined below:

1. Hardware and software: Vehicle accidents are unavoidable 100%, so AV's need to appropriately recognize and response to objects in their field. False interpretations could be made based on the location of objects and the size and conformity. The highly complex electronic systems used by AVs can be effected by even small failures like a distorted signal or false sensor, leading to catastrophic consequences. Some drivers are expected to cancel automated driving in these situations and take manual control, as suggested by Farhadi et al. (2009). This can further complicate matters as human perception is more easily impaired on the highway than AV perception.

2. Increased risk-taking: As discussed by Millard-Ball (2016), an over-reliance on technology can lead users to feel safer and thus engage in higher risk behavior. This is known as risk compensation or offsetting behavior. Ackerman (2017) stated that in users view CAVs as safe, that may take higher risks and show decreased seatbelt use.

3. Platooning risks: In order to achieve the advantages of automated technology (lower emissions and traffic congestion) platooning must be used. This can increase the number of human drivers in the platoon, increasing risk and crash severity.

4. Increased total vehicle travel: As highlighted by Trommer et al. (2016), making CAV's more convenient and comfortable may also lead to more VMT and overall crashes. It is expected AV's may have

trouble with the detection, communication, and accommodation of bicyclists, motorcycles, and pedestrians, and this can also increase accidents.

5. Lower investment in conventional safety strategies: Research by Lawson (2018) has implied that AV's could lead to less resources devoted to improving driver safety. Advocates claim the net safety increases of AVs will be 90%, but this is unlikely to occur if the further risks created by AV crashes are not considered. A study by Sivak and Schoettle (2015) found that compared to the average driver, AVs were no safer per-mile traveled, and the number of crashes can actually increase with self-driven or human-driven vehicles mix. While some like Groves and Kalra (2017) have stated the benefits of AV use are worth it if even a 10% reduction in crash rates occurs; but their study indicates as technology progresses, these net safety gains decrease.

E-Commerce: As the transport system in the U.S. evolves, new forms of transportation and delivery systems arise. With E-commerce delivery, CAVs and other technology can be brought into the consumer and freight industries. These connected vehicles, along with improved data collection and sharing methods, have made it possible to increase delivery efficiency. However, these innovations are limited by the actual roadway space on highways, which has not expanded at the same rate. Using connected zero occupant vehicles (ZOVs) can also lower traffic capacity themselves during the time they spend searching for parking or finding customers. As such, special consideration should be given to ZOVs in particular when planning for the traffic increases related to E-commerce.

Despite these potential setbacks, most researchers overall agree that CAV use will lead to greater roadway capacity. However, this expanded capacity will not occur if planners do not proceed appropriately. As mentioned previously for example, if market penetration remains low, the positive effects of CAV use cannot happen. Based on a study by Markridis et al. (2018), this scenario occurs because lower rates of CAV market penetration would lead to underutilization of the existing CAVs because there are a limited number of network vehicles to communicate with to establish travel patterns. And, as mentioned by Van Arem et al. (2012), > 40% market penetration rates are needed to alter roadway capacity. Other researchers have come to the same conclusion. For example, Hartmann et al. (2017) stated that no obvious improvements to roadway capacity are expected at low market rates. If these higher rates are to be achieved, key factors to consider will be user acceptance, CAV regulations, and the technology required. Only through appropriately accounting for these factors will market penetration rates increase in a reliable manner.

In terms of the technology needed for additional AV use, the role of advanced driver assistance systems (ADAS) cannot be understated. It has been found that users who are tech-savvy are more likely to embrace this type of technology and become SAV users (Bansal et al. 2016). Currently, 88% of existing ADAS users are content with its performance (Here et al. 2017). This high positivity rating suggests ADAS could help bridge the trust gap for other users by presenting ADAS as an example of automated driving success. By building off of these features, the steps towards full vehicle automation can then be taken. Because of this, its essential to maintain the current path of successful ADAS technology. As ADAS implementation advances, its positive effects are expected to trickle down.

Step 4: Highway construction cost prediction model

(Regarding this section the study published by the author were employed: Mahdavian, A., Shojaei, A., Salem, M., Yuan, J.S. and Oloufa, A.A., 2021b. Data-Driven Predictive Modeling of Highway Construction Cost Items. Journal of Construction Engineering and Management, 147(3), p.04020180.)

During the course of this study, a workflow was devised that utilizes machine learning for the accurate prediction of future highway construction costs. To reiterate, the work performed included data preprocessing, feature selection, model reaction, optimization of the relevant parameters, and finally model evaluation. These steps were selected in order to automate the prediction process and streamline the workflow for users. In contrast to previous studies, this research looked at highway construction cost on a monthly level. This monthly, as opposed to yearly approach, increased model accuracy by adding additional data points. The model designed was then testing using 5 categories of predictor variables: energy market, socioeconomic, construction market, U.S. economy, and temporal variables. In total, 69 independent variables were used, and the data was obtained from FDOT historical data from 2001-2017.

From the 60 cost items (dependent variables) covering 100% of the total cost of 6 highway expansion types (constructing and widening), 10 cost items' monthly historical data were not available (about 7.4% of the total cost). 32 cost items were predicted in stage 1 of the analysis, 15 cost items were predicted in the second stage, and finally, 3 were not predicted with high accuracy (MAPE below 15%). The model developed in this study covers 92.6% (on average) of the highway total cost per mile; 89.68% of which were predicted with linear models, while 2.92% utilized non-linear algorithms. The highway prediction accuracy model developed in this study forecasted the FDOT highway cost with 92.51% accuracy (on average among different types). The results of the study show that the construction market category of the variables with 80.32% had the highest impact on the highway construction cost forecast, while the socio-economic category with 6.4% was second. Additionally, the U.S. Economy had a 5.19% impact, energy market had 2.3%, and ultimately, temporal predictors had 5.85%.

General framework

A literature review indicated that to a minor degree, there has been some consideration paid to less-quantifiable consequences, such as behavioral changes, impacts on attitudes about changes to land-use, public transit, and the impact on regional planning. Articles that give a more holistic approach to the impact of the emerging technologies on the traffic network are limited. About the traffic count models, and highway construction cost models the majority of modeling studies encompass one or two linear or nonlinear algorithms. In these studies, the success of one model over another was inconsistent and varied depending on the specific case study being discussed, and the results could not be directly utilized beyond the case study under review. These findings suggest that traffic forecasting or highway construction cost forecasting is dependent on the interplay between local and global variables, which may be either linear or non-linear based on multiple factors such as location, project type, and the level of analysis. This complication can be overcome by using a universal framework for traffic volume forecasting that is more generalized, in order to optimize the process and the final outcome based on specific input data characteristics.

This research strived to recognize some of the consequences of CASE vehicles at the system level, by first developing a highly accurate traffic flow prediction model considering the impact of CASE vehicles, and second, generating a highly accurate highway expansion cost-prediction model to enhance traffic capacity. By employing the above-mentioned steps, the model could predict the cost of the expansion of the network link that would be affected by CASE vehicles and compare the cost to the alternative solutions cost and take the best measure.

To that end, the analysis performed in this study was all-inclusive of the reviewed methods regarding feature selection and modeling approach. A broad dataset of the discussed variables were utilized to confirm that new users could efficiently make use of the generated framework. By following the proposed method, regardless of the location, type, or scope of the project involved, users can input their data to identify the traffic links that may face overcapacity and to investigate the factors related to the results in a more automated way than previously explored. This provides advantages over existing models that utilize assumptions and methodologies specific to a certain case study. Moreover, the proposed framework increases the number of predictors involved to allow for more accurate forecasting; and automating the methodology reduces the time and expertise required to forecast the complexities of the traffic network, highway construction cost, and in a broader aspect, the impact of the CASE vehicles on the traffic network in a mid- and long-term.

Application of the framework

To overcome the above-mentioned issues, several solutions including smart solutions, fleet conversion, shared mobility, and highway expansion.

HIGHWAY CONSTRUCTION: Civil infrastructures are an integration of engineered systems and individuals in an ecological context. It is crucial to consider the resilience of these complex systems during their design, operation, and maintenance to ensure efficient operation. The disruption of infrastructure services can cause notable social and economic losses. Because infrastructure is crucial to public health, human safety, quality of life, trade, industry, and economic productivity, the disruption of infrastructure services can have severe economic consequences and destructive influences on health and the operability of the areas that they serve. It is essential to plan for traditional roadway expansions and provide the required capacity that is expected. Therefore, traditional solutions must be considered as well.

SMART TRANSPORTATION: In the modern world, physical objects in industrial, mobile, and domestic settings are no longer isolated systems; they are increasingly being transformed into networked Internet-enabled devices. These devices can communicate with each other and the cloud. This new intelligent technology is called the Internet of Things (IoT). Companies are creating new types of innovative services and applications in various sectors, including construction (smart transportation and smart homes), manufacturing, utilities, and health care by leveraging the benefits of these intelligent connected systems. This remarkable innovation has the potential to transform previously standalone systems into integrated networks that leverage larger computer capabilities and data analytics to enhance efficiency and productivity.

Smart cities will be the epicenter of IoT utilization and use cases, including smart transportation. Initially, the use case will be vertical (sector-specific). As time passes and a larger number of industries use the new technology, cities will become horizontal IoT platforms, where individual use cases can be fluidly interconnected to maximize efficiency and productivity. In this way, citizens will experience ease of use of IoT platforms, which is directly correlated with quality of life. Specialists in both academia and industry acknowledge smart cities as the ideal solution for approaching the impending challenges. These challenges include population growth, radical urbanization, deterioration of energy sources, and environmental pollution. Mobility is the essence of cities and is crucial for urban life.

Intelligent mobility is a system for considering how to connect places, people, and goods across all transport modes (McKinsey & Company 2016). The intelligence of infrastructure is a vital element in developing a smart city. If the infrastructure is connected and integrated correctly, a city can optimize resources, monitor public security, and provide effective maintenance. Many of the benefits provided by

CAVs will be enhanced through connectivity between the vehicles and broader infrastructure (McKinsey & Company 2016). Wireless connectivity networks inside urban areas will enable vehicles to communicate with traffic management systems in real time. In addition, sharing information such as signal phasing, timing, and live traffic conditions are additional benefits of connectivity networks. With this information, CAVs will be able to optimize their speed and navigate to minimize journey times and overall congestion. Finally, it should be noted that a strong bridge must be built between policies, strategies, and stakeholders' involvement and empowerment to create a strong alignment in the urban system for continuous sustainability and the ability of multiple human resources to achieve peak performance. The enablers of smart transportation are presented in Figure 7.

FLEET CONVERSION: It is predicted that a low market penetration rate of CAVs will not lead to the expected benefits. A variation of purpose-built CAVs may take over city streets long before private cars appear on the market. It has also been noted that commercial fleet turnover will accelerate the CAV transition (Transportation Energy Data Book, Oak Ridge National Labs). Taxis and commercial and government vehicles are an appropriate starting point for increasing market penetration, familiarizing people with CAV technologies, building bridges of trust in safety aspects, and, more importantly, encouraging the culture of shared mobility transport. Commercial and government vehicles have a significant presence on city streets, composing more than 25% of traffic. USDOT (2015) has reported the number of vehicles in use as follows – government: 3,150,000, business: 3,025,000, police: 212,000, unassigned: 2,709,000, utilities: 815,000, and rental: 2,738,000. However, it should be noted that the process of replacing and upgrading these vehicles occurs on different timelines. Commercial and government fleets are automated at different rates. Commercial vehicles in the United States average approximately 26,000 miles annually and are replaced every 3 or 4 years. In comparison, the average private car in the United States is more than 10 years old.

SHARED MOBILITY: To reach the desired outcomes discussed, it is essential to develop methods to reduce the attractiveness of traveling by CAVs. These methods should increase the attractiveness of public transit, discourage urban sprawl, limit the amount of driving that people are allowed to do, or a combination of the above. Simply because a new technology proposes benefits on paper does not imply that consumers will ultimately adopt it. Ingo Wolf (Free University of Berlin) surveyed drivers concerning their reluctance to forfeit control to an automated system for various tasks. They reported that most respondents were not eager to forfeit control to an AV for steering or complete control. It is important to bear in mind that many of the benefits of a CAV can be leveraged by using lower cost per mile shared mobility. This is particularly true for something as inherent to the United States' individual and collective mindfulness as the automobile. Most citizens consider owning and driving a car a rite of passage and a representation of freedom and prestige strengthened by decades of advertising. In addition, at least in the United States, consumers may dispute the erosion of the American dream. All else being equal, there may be more rapid uptake in countries with a less established automobile culture. Moreover, the high dependence on private vehicles in the United States has a large impact. This dependence increases private vehicle occupancy rates and also has a negative environmental, economic, and social impact on transportation. This finding highlights the importance of urban structures to secure the future of public transportation in the United States. It should be kept in mind that all the measures proposed up to now are primary insights. Applicants should not assume that ownership will become obsolete; individuals will still wish to buy CAVs.

There is no debate about the importance of smart transportation methods, fleet conversion to CAVs, and improving the shared mobility culture to enhance the level of service of the highways. So that, the framework developed by this study, has the capability to forecast the construction cost of the expansion of the highway affected by the CASE vehicles. Individuals could employ the predicted cost and compare it to other potential options, including, smart mobility, shared mobility, and fleet conversion. Furthermore, they could invest the limited resources in the best option.

CHAPTER SEVEN: CONCLUSION

Considering the external and internal forces affecting the transportation network, the demand for solutions to the United States' traffic gridlock dilemma becomes more severe each year. The risks associated with the various forces threatening the efficiency of the transportation network must be meticulously examined. Otherwise, congestion can have undesirable effects on the quality of the life of citizens in terms of the possibility of decreased human productivity, reduced driver health, quality of life, increase in stress, and increased fatigue.

A literature review indicated that to a minor degree, there has been some consideration paid to less-quantifiable consequences, such as behavioral changes, impacts on attitudes about changes to land-use, public transit, and the impact on regional planning. Articles that give a more holistic approach to the impact of the emerging technologies on the traffic network are limited. About the traffic count models, and highway construction cost models the majority of modeling studies encompass one or two linear or nonlinear algorithms. In these studies, the success of one model over another was inconsistent and varied depending on the specific case study being discussed, and the results could not be directly utilized beyond the case study under review. This research strived to recognize some of the consequences of CASE vehicles at the system level, by first developing a highly accurate traffic flow prediction model considering the impact of CASE vehicles, and second, generating a highly accurate highway expansion cost-prediction model to enhance traffic capacity. By employing the above-mentioned steps, the model could predict the cost of the expansion of the network link that would be affected by CASE vehicles and compare the cost to the alternative solutions cost and take the best measure.

In this study, a data-driven methodology was employed to identify the top features and modeling approach. This enabled the inclusion of all available linear and non-linear models and the independent variables and parameters involved in feature selection, in addition to modeling approach selection. The resulting framework is more comprehensive and can be utilized by new users. By following this framework, a user may automatically identify the feature selection methods, algorithms, and set of features best suited to their unique project and dataset. This is possible because the framework developed in this model not only incorporates the approaches previously highlighted in the literature but also contains improvements and enhancements to create a more complex model, based on the number of employed features and the feature selection methods employed in an automated fashion.

The framework of this study was validated using historical traffic data and historical highway construction cost data. The historical traffic data was gathered from 259 traffic sites, spanning the course of 17 years of the Florida department of transportation. This study also employed 17 years of the historical cost data of 17,121 projects of various size in Florida to demonstrate the application of the model and the level of accuracy. The selection features and models used were chosen through a data-driven method in order to prevent bias, and the results indicate which features may be classified with high importance in the process of traffic volume and highway construction cost prediction models based on this dataset. Accordingly, the framework developed in this study is not only more comprehensive than a stand-alone case study-based approach, but it can be used for more accurate generalization.

Range of applicability

The main application of the developed framework of this study is that, for any input data, regardless of location, project type and size, it has the capability to forecast the construction cost of the expansion of the highway affected by the CASE vehicles. Individuals could employ the predicted cost and compare it to other potential options, including, smart mobility, shared mobility, and fleet conversion. Furthermore, they could invest the limited resources in the best option. Also, this framework can help planners to obtain the state roadways impacted by CASE vehicles, to assist with long-term planning solutions such as roadway expansions by calculating the level of service to find the critical links needing investment for expanding the road, including adding lanes or constructing new roads or new bridges, developing plans for pavement designs, prediction and planning for future trips, environmental impact analysis, and the examination of highway investment policies. Transportation planners would be able to plan for the critical links on the U.S. roads suffering overcapacity issues and examine the optimized solutions enhancing the traffic network well in advance. The results of this research could also be used to attract private sector partnerships to foster economic development and improve safety and mobility. This would be accomplished by developing a suitable request for proposals and decent incentives accurately and on time by utilizing the proposed robust cost forecasting method. As a result, the quality of life of citizens could be increased by reducing traffic congestion, enhancing air quality, and decreasing the number of crashes.

Limitations

Small sample size is one of the primary limitations of this research (259 cosites and 17 years of historical PV traffic counts), and roadway construction cost data (50 costs available of 60 and only 17 years of historical cost data we had access to) and the data level (using monthly level historical traffic data – it could potentially be better to use weekly, daily, or even hourly data).

Future work and Recommendations

Generalization could be achieved in the modeling of this study, although more research on the extreme multitude of factors in each case should be done to further improve modeling approaches like deep learning models. To increase model accuracy the next step would be the inclusion environmental, energy, and political trends as available predictors within the given variables. Managed and express lane data would also be a inclusion as their effects on traffic congestion have been of some note as of late, and their addition adds another possible solution. Other possible solutions include truck platooning and more importantly the consequences of managed truck lanes on truck traffic density along commuter highways. The classification of trucks (medium vs heavy duty) and loaded vs unloaded vehicle mass in motion data could be a valuable addition. It is important to further examine the results of individual contractor's management style on cost.

APPENDIX A: INDEPENDENT VARIABLES FOR STEP 1 AND 2

#	Candidate variable	Acronyms	Scope	Source
A1. Socioeconomic candidate variables				
#	**Candidate variable**	**Acronyms**	**Scope**	**Source**
1	Population		FL Counties	U.S. Bureau of Census
2	Number of Licensed Drivers		FL Counties	FL Department of Highway Safety and Motor Vehicles
3	Length Paved Roads (Centerline Miles)		FL Counties	Florida Department of Transportation
4	Length Paved Roads (Line Miles)		FL Counties	Florida Department of Transportation
5	Number of Household Estimates	HHEUS	FL Counties	U.S. Bureau of Census
6	Civilian Labor Force	CLFFL	FL State	U.S. Bureau of Labor Statistics
7	All Employees	AEFL	FL State	U.S. Bureau of Labor Statistics
8	Unemployment Rate	URUS	U.S.	U.S. Bureau of Labor Statistics
9	Change in Labor Market Conditions Index	CLMCIUS	U.S.	U.S. Bureau of Labor Statistics
10	Average Hourly Earnings Labor Employees: Construction	AHEPNECUS	U.S.	U.S. Bureau of Labor Statistics
11	Average Weekly Hours of All Employees Construction	AWHAECFL	FL State	U.S. Bureau of Labor Statistics
A2. Economy candidate variables				
#	**Candidate variable**	**Acronyms**	**Scope**	**Source**
1	Gross Domestic Products	GDP	U.S.	U.S. Bureau of Economic Analysis
2	Industrial Production	IP	U.S.	Federal Reserve System
3	Inflation Rate	IRUS	U.S.	World Bank
4	Consumer Price Index FL	CPIFL	FL State	U.S. Bureau of Labor Statistics
5	CPI for Urban Consumers: New vehicles	CPIAUCNV	U.S.	U.S. Bureau of Labor Statistics
6	CPI for All Urban Consumers: Used cars and trucks	CPIAUCUCT	U.S.	U.S. Bureau of Labor Statistics
7	Price Pressures Measure	PPMUS	U.S.	U.S. Bureau of Labor Statistics
8	Bank Prime Loan Rate	BPLRUS	U.S.	Federal Reserve System
9	30-Year Conventional Mortgage Rate	30YCMR	U.S.	Federal Reserve System
10	Leading Index for U.S.	LIUS	U.S.	Federal Reserve Bank
11	Leading Index for Florida	LIFL	FL State	Federal Reserve Bank
12	Producer Price Index for Commodities	PPIACO	U.S.	Federal Reserve Bank
13	Effective Federal Funds Rate	EDDRUS	U.S.	Federal Reserve Bank
14	M1	M1	U.S.	Federal Reserve Bank

Figure 62A: INDEPENDENT VARIABLES FOR PASSENGER VEHICLES

A2. Economy candidate variables				
#	**Candidate variable**	**Acronyms**	**Scope**	**Source**
15	M2	M2	U.S.	Federal Reserve Bank
16	Gold Prices	GP	U.S.	Yahoo Finance
17	Silver Prices	SP	U.S.	Yahoo Finance
18	Durable Goods Orders	DGOUS	U.S.	Yahoo Finance
19	Dow Jones Index Adj Close	DJI	U.S.	Yahoo Finance
20	S&P 500 Index	S&P500	U.S.	Yahoo Finance
21	St. Louis Fed Financial Stress Index	StLFFSI	U.S.	Yahoo Finance
22	Wilshire 5000 Total Market Full Cap	W5000TMFCI	U.S.	Yahoo Finance
23	NASDAQ Composite Index, Index	NASDAQ	U.S.	Yahoo Finance
24	Canada / U.S. Foreign Exchange Rate	CANUSER	U.S.	Yahoo Finance
25	China / U.S. Foreign Exchange Rate	CHUSER	U.S.	Yahoo Finance
26	Mexico / U.S. Foreign Exchange Rate	MEXUSER	U.S.	Yahoo Finance
27	U.S. / Euro Foreign Exchange Rate	USEUER	U.S.	Yahoo Finance
A3. Construction market candidate variables				
#	**Candidate variable**	**Acronyms**	**Scope**	**Source**
1	New Private Housing Units (Building Permits)	NPHUABPFL	FL State	U.S. Bureau of Census
2	Construction Spending Nonresidential	CSNUS	U.S.	U.S. Census Burea
3	Construction Spending Highway	TCSHSUS	U.S.	U.S. Census Burea
4	Construction Employees FL	CEFL	FL State	U.S. Bureau of Labor Statistics
5	Construction Employees U.S.	AECHCEUS	U.S.	U.S. Bureau of Labor Statistics
A4. Energy market candidate variables				
1	Electricity Price	ELECFL	FL State	U.S. Energy Information Administratio
2	Crude Oil Price	COP	U.S.	
3	Natural Gas Prices	NGP	U.S.	
4	Gas Price FL	GASPFL	FL State	
Road characteristics candidate variables				
1	Max Speed	Cosite		Florida Department of Transportation
2	Number Lanes			
3	Toll Road			

Figure 63A: INDEPENDENT VARIABLES FOR PASSENGER VEHICLES

APPENDIX B: INDEPENDENT VARIABLES FOR STEP 4

A1. Socioeconomic candidate variables				
#	Candidate variable	Acronyms	Scope	Source
1	Length Paved Roads (Centerline Miles)	LPRCMC	County	Florida Department of Transportation
2	Length Paved Roads (Line Miles)	LPRLMC	County	Florida Department of Transportation
3	Number of Household Estimates	HHEUS	County	U.S. Bureau of Census
4	Civilian Labor Force FL	CLFFL	Florida	U.S. Bureau of Labor Statistics
5	All Employees FL	AEFL	Florida	U.S. Bureau of Labor Statistics
6	Unemployment Rate	URUS	U.S.	U.S. Bureau of Labor Statistics
7	Change in Labor Market Conditions Index	CLMCIUS	U.S.	U.S. Bureau of Labor Statistics
8	Average Hourly Earnings Labor Employees: Construction	AHEPNECUS	U.S.	U.S. Bureau of Labor Statistics
9	Average Weekly Hours of All Employees Construction	AWHAECFL	Florida	U.S. Bureau of Labor Statistics
A2. Economy candidate variables				
#	Candidate variable	Acronyms	Scope	Source
1	Gross Domestic Products	GDP	U.S.	U.S. Bureau of Economic Analysis
2	Industrial Production	IP	U.S.	Federal Reserve System
3	Inflation Rate	IRUS	U.S.	World Bank
4	Consumer Price Index FL	CPIFL	Florida	U.S. Bureau of Labor Statistics
5	CPI for Urban Consumers: New vehicles	CPIAUCNV	U.S.	U.S. Bureau of Labor Statistics
6	CPI for All Urban Consumers: Used cars and trucks	CPIAUCUCT	U.S.	U.S. Bureau of Labor Statistics
7	Price Pressures Measure	PPMUS	U.S.	U.S. Bureau of Labor Statistics
8	Bank Prime Loan Rate	BPLRUS	U.S.	Federal Reserve System
9	30-Year Conventional Mortgage Rate	30YCMR	U.S.	Federal Reserve System
10	Leading Index for U.S.	LIUS	U.S.	Federal Reserve Bank
11	Leading Index for Florida	LIFL	Florida	Federal Reserve Bank
12	Producer Price Index for Commodities	PPIACO	U.S.	Federal Reserve Bank
13	Effective Federal Funds Rate	EDDRUS	U.S.	Federal Reserve Bank
14	M1	M1	U.S.	Federal Reserve Bank
15	M2	M2	U.S.	Federal Reserve Bank
16	Gold Prices	GP	U.S.	Yahoo Finance
17	Silver Prices	SP	U.S.	Yahoo Finance
18	Durable Goods Orders	DGOUS	U.S.	Yahoo Finance
19	Dow Jones Index Adj Close	DJI	U.S.	Yahoo Finance
20	S&P 500 Index	S&P500	U.S.	Yahoo Finance
21	St. Louis Fed Financial Stress Index	StLFFSI	U.S.	Yahoo Finance
22	Wilshire 5000 Total Market Full Cap	W5000TMFCI	U.S.	Yahoo Finance
23	NASDAQ Composite Index, Index	NASDAQ	U.S.	Yahoo Finance
24	Canada / U.S. Foreign Exchange Rate	CANUSER	U.S.	Yahoo Finance
25	China / U.S. Foreign Exchange Rate	CHUSER	U.S.	Yahoo Finance
26	Mexico / U.S. Foreign Exchange Rate	MEXUSER	U.S.	Yahoo Finance
27	U.S. / Euro Foreign Exchange Rate	USEUER	U.S.	Yahoo Finance
28	Total Vehicle Sales U.S.	TSVUS	U.S.	Yahoo Finance

Figure 64B: INDEPENDENT VARIABLES FOR HIGHWAY CONSTRUCTION MODEL

A3. Construction market candidate variables				
#	Candidate variable	Acronyms	Scope	Source
1	New Private Housing Units (Building Permits)	NPHUABPFL	Florida	U.S. Bureau of Census
2	Construction Spending Nonresidential	CSNUS	U.S.	U.S. Census Burea
3	Construction Spending Highway	TCSHSUS	U.S.	U.S. Census Burea
4	Construction Employees	CEFL	Florida	U.S. Bureau of Labor Statistics
5	Construction Employees	AECHCEUS	U.S.	U.S. Bureau of Labor Statistics
6	NHCCI Global	NHCCI	U.S.	U.S. Bureau of Labor Statistics
7	Capital Expenditures	CEXFL	Florida	Florida State DOT Disbursements
8	DOT Disbursements: Maintenance	FDOTDM	Florida	Florida State DOT Disbursements
9	Administration Disbursements	ADFL	Florida	Florida State DOT Disbursements
10	Interest	IFL	Florida	Florida State DOT Disbursements
11	Bond Retirement	BRFL	Florida	Florida State DOT Disbursements
12	Local Government Grants	LGGFL	Florida	Florida State DOT Disbursements
13	Total Florida State DOT Disbursements	TFSDDFL	Florida	Florida State DOT Disbursements
14	Federal Funding	FFFL	Florida	Florida State Revenue Sources
15	State Motor Fuel Tax	SMFTFL	Florida	Florida State Revenue Sources
16	State Motor Vehicle Tax	SMVTFL	Florida	Florida State Revenue Sources
17	Tolls Income	TIFL	Florida	Florida State Revenue Sources
18	Other State Funding	OSFFL	Florida	Florida State Revenue Sources
19	Local Funding	LFFL	Florida	Florida State Revenue Sources
20	Total Florida State Revenue Sources	TFSRSFL	Florida	Florida State Revenue Sources
21	Right of Way	ROWFL	Florida	Florida Department of Transportation
22	Total State Highway System (SHS) PRODUCT AREAS	TSHSFL	Florida	Florida Department of Transportation
23	State Highway System (SHS) PRODUCT AREAS	SHSPAFL	Florida	Florida Department of Transportation
24	Other Roads PRODUCT AREAS	ORPAFL	Florida	Florida Department of Transportation
25	Legislative Budget Request	LBRAGFL	Florida	Florida Department of Transportation
A4. Energy market candidate variables				
1	Electricity Price	ELECFL	Florida	U.S. Energy Information Administration
2	Crude Oil Price	COP	U.S.	U.S. Energy Information Administration
3	Natural Gas Prices	NGP	U.S.	U.S. Energy Information Administration
4	Gas Price FL	GASPFL	Florida	U.S. Energy Information Administration

A5. Temporal candidate variables	
1	Number of Months from Beginning
2	Month
3	YEAR

Figure 65B: INDEPENDENT VARIABLES FOR HIGHWAY CONSTRUCTION MODEL

APPENDIX C: CATEGORICAL FEATURE IMPORTANCE FOR STEP 4

Cost item	Construction market (%)	Energy market (%)	Socioeconomic (%)	US economy (%)	Temporal (%)
MAINTENANCE OF TRAFFIC	89.59	0.00	0.00	1.59	8.82
MOBILIZATION	80.35	6.12	5.51	4.87	3.15
SEDIMENT BARRIER	59.51	0.00	7.10	26.38	7.01
FLOATING TURBIDITY BARRIER	69.18	0.00	15.73	12.63	2.47
STAKED TURBIDITY BARRIER-NYL REINF PVC	68.98	0.00	0.04	0.00	30.99
SOIL TRACKING PREVENTION DEVICE	92.64	0.00	5.91	1.45	0.00
LITTER REMOVAL	69.92	0.00	10.96	15.94	3.18
MOWING	82.63	0.00	6.33	8.67	2.37
CLEARING & GRUBBING	59.57	19.81	2.25	0.00	18.37
REGULAR EXCAVATION	80.54	0.00	9.65	8.96	0.85
EMBANKMENT	75.68	2.73	8.02	3.87	9.72
TYPE B STABILIZATION	73.51	0.32	11.97	14.10	0.09
OPTIONAL BASE, BASE GROUP 04	95.41	0.00	0.00	0.00	4.59
OPTIONAL BASE, BASE GROUP 09	75.59	0.00	2.77	21.64	0.00
MILLING EXIST ASPH PAVT, 1" AVG DEPTH	100.00	0.00	0.00	0.00	0.00
MILLING EXIST ASPH PAVT, 4" AVG DEPTH	82.54	0.00	6.63	7.92	2.90
SUPERPAVE ASPH CONC, TRAF C, PG76-22	83.38	0.00	4.98	0.74	10.90
SUPERPAVE ASPH CONC, TRAF D, PG76-22	81.21	2.66	7.11	3.10	5.92
ASPH CONC FC, INC BIT, FC-5, PG76-22, PMA	73.01	0.00	2.12	1.43	0.00
ASPH CONC FC, TRAFFIC B, FC-9.5, PG 76-22	62.53	0.00	0.00	17.80	1.95
CONC CLASS II, ENDWALLS	79.43	0.04	10.64	6.13	3.77
INLETS, DT BOT, TYPE D, <10′	73.98	5.98	8.19	8.25	3.61
INLETS, DT BOT, TYPE E, <10′	100.00	0.00	0.00	0.00	0.00
INLETS, BARRIER WALL, <= 10′	87.33	0.00	8.89	3.78	0.00
PIPE CULV, OPT MATL, ROUND,24"SD	61.02	0.00	18.41	18.27	2.30
PIPE CULV, OPT MATL, ROUND, 24"S/CD	56.17	0.00	19.99	18.41	5.44
PIPE CULV, OPT MATL, ROUND, 30"S/CD	75.43	0.70	16.13	7.46	0.29
PIPE CULV, OPT MATL, ROUND, 36"S/CD	52.93	1.22	22.37	17.59	5.89
PIPE CULV, OPT MATL, ROUND, 42"S/CD	76.78	0.00	2.54	0.00	20.68
PIPE CULV, OPT MATL, ROUND, 54"S/CD	79.22	2.20	7.13	2.37	9.09
MITERED END SECT, OPTIONAL RD, 24" SD	67.51	1.50	8.99	20.02	1.97
MEDIAN CONC BARRIER WALL	69.31	0.00	30.69	0.00	0.00
SHLDR CONC BARRIER, RIGID-SHLDR	89.56	0.00	9.97	0.47	0.00
CONCRETE DITCH PAVT, NR, 3"	99.70	0.00	0.00	0.30	0.00
RUMBLE STRIPS, GROUND-IN, 16" MIN. WIDTH	100.00	0.00	0.00	0.00	0.00
FENCING, TYPE B, 5.1-6.0', STANDARD	85.31	0.00	2.98	11.71	0.00
PERFORMANCE TURF	72.27	0.00	0.00	0.00	27.73
PERFORMANCE TURF, SOD	80.35	14.83	3.25	1.57	0.00
SINGLE POST SIGN, F&I GM, <12 SF	94.86	0.00	0.00	5.14	0.00
SINGLE POST SIGN, F&I GM, 12-20 SF	70.74	0.00	0.00	0.00	29.26
MULTIPOST SIGN, F&I GM, 21-30 SF	73.36	0.00	10.28	16.37	0.00
SINGLE POST SIGN, REMOVE	92.60	0.00	0.00	0.00	7.40
MULTIPOST SIGN, F&I GM, 31-50 SF	87.26	0.00	0.00	3.03	9.71
MULTIPOST SIGN, F&I GM, 51-100 SF	93.29	6.71	0.00	0.00	0.00
MULTIPOST SIGN, F&I GM, 101-200 SF	100.00	0.00	0.00	0.00	0.00
MULTIPOST SIGN, REMOVE	83.31	0.00	0.00	0.00	16.69
RETRO-REFLECTIVE/RAISED PAVEMENT MARKERS	45.28	0.00	23.00	7.51	24.20

Figure 66C: CATEGORICAL FEATURE IMPORTANCE RESULTS FOR COST ITEMS

APPENDIX D: AUTONOMOUS VEHICLE TRAVEL PROJECTION

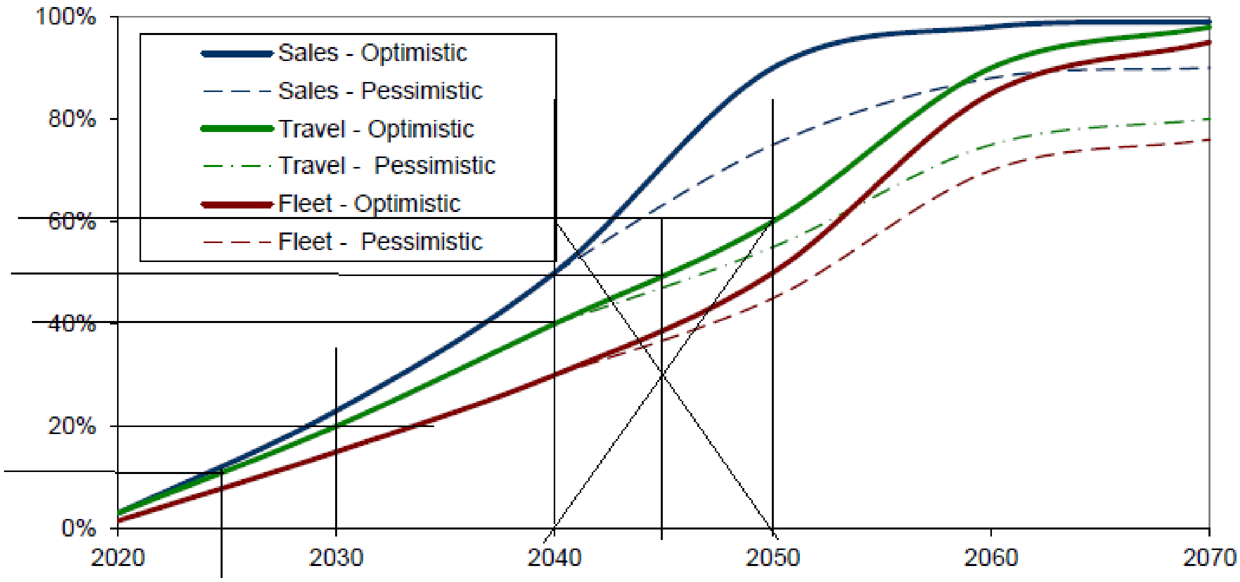


Figure 67D: AUTONOMOUS VEHICLE TRAVEL PROJECTION BY LITMAN (2018)

APPENDIX E: TRAFFIC CAPACITY AND LOS CALCULATIONS

FFS = 120 km/h or 75 mi/h (Rural Freeway)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	36.7
Min Speed (mi/h)	75	75	71.6	63	60
Max v/c	0.35	0.55	0.77	0.92	1
Max service flow rate (pc/h/ln)	840	1320	1840	2200	2300

FFS = 70 mi/h / 4 lane freeway (2 each) (Urban Freeway)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	36.7
Min Speed (mi/h)	70	70	68.5	63	60
Max v/c	0.318	0.509	0.747	0.916	1
Max service flow rate (pc/h/ln)	700	1120	1644	2015	2200

FFS = 70 mi/h / 6 or 8 lane freeway (3 or 4 each)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	36.7
Min Speed (mi/h)	70	70	68.5	63	60
Max v/c	0.304	0.487	0.715	0.876	1
Max service flow rate (pc/h/ln)	700	1120	1644	2015	2300

FFS = 65 mi/h / 4 lane freeway (2 each)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	39.3
Min Speed (mi/h)	65	65	64.5	61	56
Max v/c	0.295	0.473	0.704	0.887	1
Max service flow rate (pc/h/ln)	650	1040	1548	1952	2200

FFS = 65 mi/h / 6 or 8 lane freeway (3 or 4 each)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	43.4
Min Speed (mi/h)	65	65	64.5	61	53
Max v/c	0.283	0.457	0.673	0.849	1
Max service flow rate (pc/h/ln)	650	1040	1548	1952	2300

FFS = 60 mi/h / 4 lane freeway (2 each)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	41.5
Min Speed (mi/h)	60	60	60	57	53
Max v/c	0.272	0.436	0.655	0.829	1
Max service flow rate (pc/h/ln)	600	960	1440	1824	2200

FFS = 60 mi/h / 6 or 8 lane freeway (3 or 4 each)					
Criteria	A	B	C	D	E
Max Density	10	16	24	32	46
Min Speed (mi/h)	60	60	60	57	50
Max v/c	0.261	0.412	0.626	0.793	1
Max service flow rate (pc/h/ln)	600	960	1440	1824	2300

Figure 68E: TRAFFIC CAPACITY AND LOS CALCULATIONS (HCM)

APPENDIX F: FDOT PROJECT DETAILS COMPOSITE REPORT

FDOT Long Range Estimating System - Production					
R4: Project Details Composite Report					
By Version					
Project: WDUI68-U-25-BB					**Letting Date:** 01/2099
Description: Widen 6 Lane Urban Interstate with Closed Median to 8 Lanes (Outside); Mill & Resurface Existing; 10' Shoulders Outside					
District: 09	**County:** 99 DISTRICT/STATE WIDE				
Project Manager: Cost-Per-Mile Model					
Version 15-P Project Grand Total					**$10,417,796.23**
Description: July 2020 Updates					
Pay Items					
Pay Item	Description	Total Quantity	Unit	Weighted Avg. Unit Price	Total Amount
102-1	MAINTENANCE OF TRAFFIC	10.00			$852,450.39
101-1	MOBILIZATION	10.00			$937,695.43
104-10-3	SEDIMENT BARRIER	12,144.00	LF	$1.70	$20,644.80
104-11	FLOATING TURBIDITY BARRIER	100.00	LF	$10.00	$1,000.00
104-12	STAKED TURBIDITY BARRIER- NYL REINF PVC	100.00	LF	$5.00	$500.00
104-15	SOIL TRACKING PREVENTION DEVICE	1.00	EA	$2,500.00	$2,500.00
107-1	LITTER REMOVAL	3.40	AC	$20.00	$68.00
107-2	MOWING	3.40	AC	$34.00	$115.60
110-1-1	CLEARING & GRUBBING	15.53	AC	$18,000.00	$279,540.00
120-1	REGULAR EXCAVATION	4,840.00	CY	$6.50	$31,460.00
120-2-2	BORROW EXCAVATION, TRUCK MEASURE	17,498.31	CY	$17.00	$297,471.27
160-4	TYPE B STABILIZATION	25,813.33	SY	$3.80	$98,090.65
285-704	OPTIONAL BASE,BASE GROUP 04	12,120.53	SY	$13.00	$157,566.89
285-709	OPTIONAL BASE,BASE GROUP 09	14,467.20	SY	$19.00	$274,876.80
327-70-1	MILLING EXIST ASPH PAVT, 1" AVG DEPTH	11,733.33	SY	$2.60	$30,506.66
327-70-7	MILLING EXIST ASPH PAVT, 4" AVG DEPTH	42,240.00	SY	$3.80	$160,512.00
334-1-53	SUPERPAVE ASPH CONC, TRAF C, PG76-22	1,936.00	TN	$100.00	$193,600.00
334-1-54	SUPERPAVE ASPH CONC, TRAF D, PG76-22	12,003.20	TN	$109.00	$1,308,348.80
337-7-25	ASPH CONC FC,INC BIT,FC-5,PG76-22	2,314.76	TN	$140.00	$324,066.40
425-1-541	INLETS, DT BOT, TYPE D,	1.00	EA	$4,100.00	$4,100.00
425-1-921	INLETS, ADJACENT BARRIER, <=10'	30.00	EA	$5,200.00	$156,000.00
425-2-71	MANHOLES, J-7,	1.00	EA	$8,200.00	$8,200.00
430-174-142	PIPE CULV, OPT MATL, ROUND,42"SD	504.00	LF	$200.00	$100,800.00

Figure 69F: FDOT PROJECT DETAILS COMPOSITE REPORT

FDOT Long Range Estimating System - Production					
R4: Project Details Composite Report					
By Version					
Project: WDUI68-U-25-BB					**Letting Date:** 01/2099
Description: Widen 6 Lane Urban Interstate with Closed Median to 8 Lanes (Outside); Mill & Resurface Existing; 10' Shoulders Outside					
District: 09	**County:** 99 DISTRICT/STATE WIDE				
Project Manager: Cost-Per-Mile Model					
Version 15-P Project Grand Total					**$10,417,796.23**
Description: July 2020 Updates					
430-174-154	PIPE CULV, OPT MATL, ROUND,54"SD	360.00	LF	$440.00	$158,400.00
430-175-130	PIPE CULV, OPT MATL, ROUND, 30"S/CD	5,280.00	LF	$110.00	$580,800.00
430-175-142	PIPE CULV, OPT MATL, ROUND, 42"S/CD	56.00	LF	$160.00	$8,960.00
430-175-154	PIPE CULV, OPT MATL, ROUND, 54"S/CD	200.00	LF	$260.00	$52,000.00
430-530-100	STRAIGHT CONC ENDW 30", SINGLE, 0 ROUND	8.00	EA	$5,973.03	$47,784.24
430-542-100	STRAIGHT CONC ENDW 42", SINGLE, 0 ROUND	4.00	EA	$9,100.00	$36,400.00
430-554-100	STRAIGHT CONC ENDW 54", SINGLE, 0 ROUND	2.00	EA	$17,000.00	$34,000.00
521-72-40	SHLDR CONC BARRIER,38" OR 44" HEIGHT	10,560.00	LF	$280.00	$2,956,800.00
546-72-1	GROUND-IN RUMBLE STRIPS, 16"	2.00	GM	$1,600.00	$3,200.00
550-10-220	FENCING, TYPE B, 5.1-6.0', STANDARD	11,160.00	LF	$20.00	$223,200.00
550-60-234	FENCE GATE,TYP B,SLIDE/CANT,18.1-20'OPEN	1.00	EA	$4,200.00	$4,200.00
570-1-2	PERFORMANCE TURF, SOD	33,513.00	SY	$2.60	$87,133.80
700-1-11	SINGLE POST SIGN, F&I GM,	2.00	AS	$340.00	$680.00
700-1-12	SINGLE POST SIGN, F&I GM, 12-20 SF	24.00	AS	$1,200.00	$28,800.00
700-1-50	SINGLE POST SIGN, RELOCATE	2.00	AS	$220.00	$440.00
700-1-60	SINGLE POST SIGN, REMOVE	24.00	AS	$30.00	$720.00
700-2-14	MULTI- POST SIGN, F&I GM, 31-50 SF	2.00	AS	$4,500.00	$9,000.00
700-2-60	MULTI- POST SIGN, REMOVE	2.00	AS	$750.00	$1,500.00
700-4-113	OH STATIC SIGN STR, F&I, C 31-40 FT	1.00	EA	$79,000.00	$79,000.00
700-4-126	OH STATIC SIGN STR, F&I, S 101-150 FT	1.00	EA	$182,000.00	$182,000.00
700-4-610	OH STATIC SIGN STR, REMOVE, CANT	1.00	EA	$5,000.00	$5,000.00
700-4-620	OH STATIC SIGN STR, REMOVE, SPAN	1.00	EA	$11,000.00	$11,000.00
706-1-1	RAISED PAVMT MARK, TYPE B W/O FINAL SURF	945.00	EA	$4.40	$4,158.00

Figure 70F: FDOT PROJECT DETAILS COMPOSITE REPORT

FDOT Long Range Estimating System - Production					
R4: Project Details Composite Report					
By Version					
Project: WDUI68-U-25-BB					**Letting Date:** 01/2099
Description: Widen 6 Lane Urban Interstate with Closed Median to 8 Lanes (Outside); Mill & Resurface Existing; 10' Shoulders Outside					
District: 09	**County:** 99 DISTRICT/STATE WIDE				
Project Manager: Cost-Per-Mile Model					
Version 15-P Project Grand Total					**$10,417,796.23**
Description: July 2020 Updates					
710-11-101	PAINTED PAVT MARK,STD,WHITE,SOLID,6"	8.00	GM	$900.00	$7,200.00
710-11-131	PAINTED PAVT MARK,STD,WHITE,SKIP, 6"	12.00	GM	$430.00	$5,160.00
711-15-101	THERMOPLASTIC, STD-OP, WHITE, SOLID, 6"	4.00	GM	$4,500.00	$18,000.00
711-15-131	THERMOPLASTIC, STD-OP, WHITE, SKIP, 6"	6.00	GM	$1,500.00	$9,000.00
999-25	INITIAL CONTINGENCY AMOUNT (DO NOT BID)	1.00	LS	$103,146.50	$103,146.50
LIGHT-RURAL	RURAL LIGHT POLES - 52 AT $10,000.00	1.00	LS	$520,000.00	$520,000.00
Project Unknowns			0.00	%	$0.00
Design/Build			0.00	%	$0.00
Version 15-P Project Grand Total					**$10,417,796.23**

Figure 71F: FDOT PROJECT DETAILS COMPOSITE REPORT

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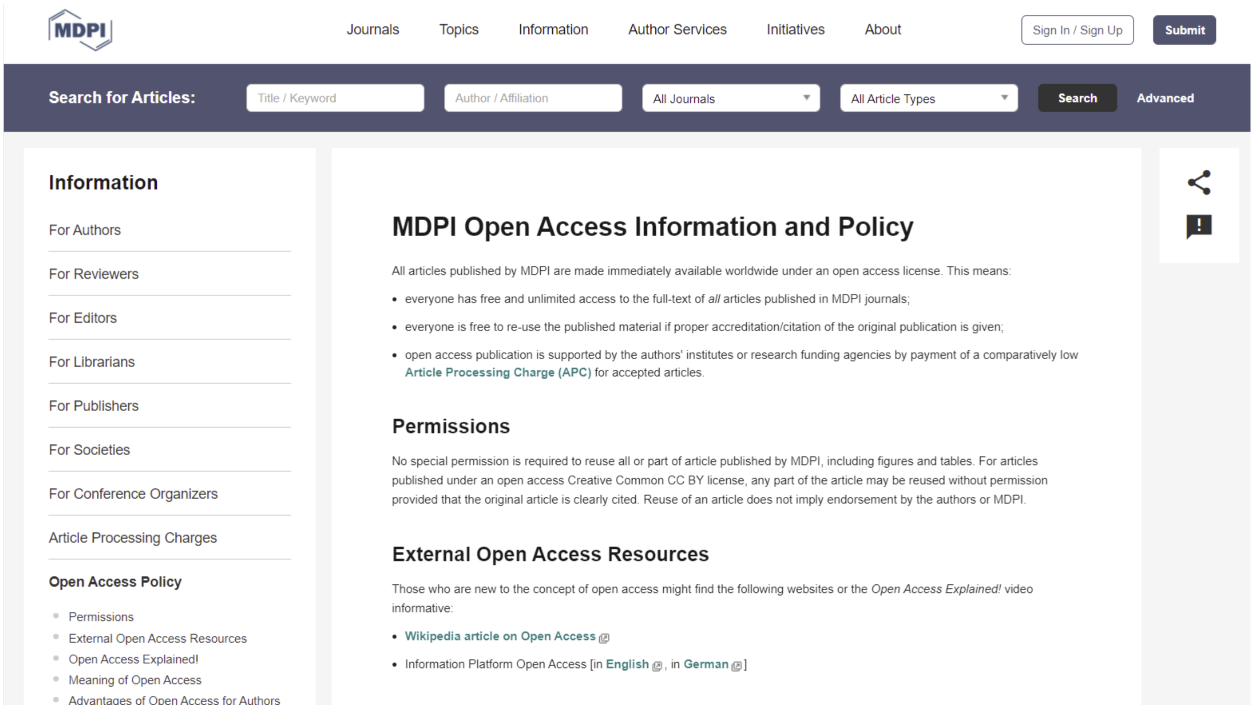
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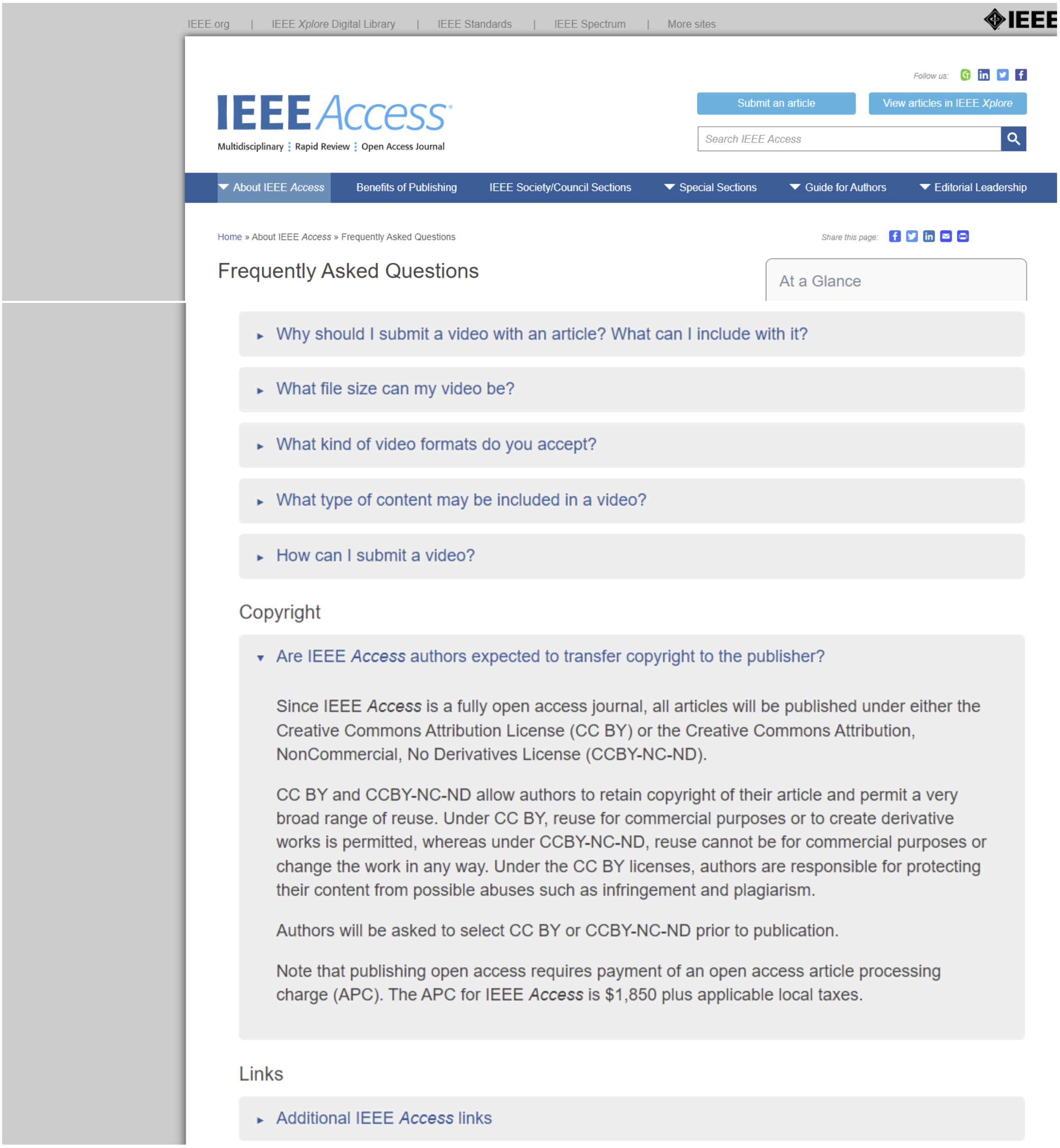

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