A MULTI-CONTEXTUAL APPROACH TO MODELING THE IMPACT OF CRITICAL HIGHWAY WORK ZONES IN LARGE URBAN CORRIDORS

A Dissertation

by

JUNSEO BAE

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Kunhee Choi
Co-Chair of Committee,	Liliana O. Beltrán
Committee Members,	José L. Fernández-Solís
	Yoonsuck Choe
Head of Department,	Robert Warden

May 2017

Major Subject: Architecture

ABSTRACT

Accurate Construction Work Zone (CWZ) impact assessments of unprecedented travel inconvenience to the general public are required for all federally-funded highway infrastructure improvement projects. These assessments are critical, but they are also very difficult to perform. Most existing prediction approaches are project-specific, short-term, and univariate, thus incapable of benchmarking the potential traffic impact of CWZs for highway construction projects.

This study fills these gaps by creating a big-data-based decision-support framework and testing if it can reliably predict the potential impact of a CWZ under arbitrary lane closure scenarios. This study proposes a big-data-based decision-support analytical framework, “Multi-contextual learning for the Impact of Critical Urban highway work Zones” (MICUZ). MICUZ is unique as it models the impact of CWZ operations through a multi-contextual quantitative method utilizing sensored big transportation data.

MICUZ was developed through a three-phase modeling process. First, robustness of the collected sensored data was examined through a Wheeler’s repeatability and reproducibility analysis, for the purpose of verifying the homogeneity of the variability of traffic flow data. The analysis results led to a notable conclusion that the proposed framework is feasible due to the relative simplicity and periodicity of highway traffic profiles. Second, a machine-learning algorithm using a Feedforward Neural Networks (FNN) technique was applied to model the multi-contextual aspects of

long-term traffic flow predictions. The validation study showed that the proposed multi-contextual FNN yields an accurate prediction rate of traffic flow rates and truck percentages. Third, employing these predicted traffic parameters, a curve-fitting modeling technique was implemented to quantify the impact of what-if lane closures on the overall traffic flow. The robustness of the proposed curve-fitting models was then scientifically verified and validated by measuring forecast accuracy.

The results of this study convey the fact that MICUZ would recognize how stereotypical regional traffic patterns react to existing CWZs and lane closure tactics, and quantify the probable but reliable travel time delays at CWZs in heavily trafficked urban cores. The proposed framework provides a rigorous theoretical basis for comparatively analyzing what-if construction scenarios, enabling engineers and planners to choose the most efficient transportation management plans much more quickly and accurately.

DEDICATION

To my mentor and role model,

Dr. Kunhee (KC) Choi

and also to my beloved family

who made all of this possible with their endless love, support, and patience

ACKNOWLEDGEMENTS

I would like to express the deepest appreciation to my committee chair, Dr. Kunhee Choi, who gave me the right direction, sincere advice, and encouragement at every single moment, while helping me overcome many of the challenges I faced in this journey. My deep gratitude is extended to my co-chair of the committee, Dr. Liliana O. Beltrán, who gave me valuable advice and encouragement throughout my doctoral study. I also would like to sincerely thank my committee members: Dr. José L. Fernández-Solís and Dr. Yoonsuck Choe for their insightful comments and support that improved the dissertation, while widening my research from various perspectives.

Besides the committee, I would like to truly thank Professor Joe Horlen, who provided me invaluable opportunities that will strengthen my future career. I would like to give my appreciation to Dr. Hyun Woo Lee of the University of Washington, who supported me with many opportunities so that I could continue to grow professionally. I would like to extend my appreciation to Dr. Kenneth Joh of the Metropolitan Washington Council of Governments (MWCOG), who encouraged me to successfully complete my doctoral study. My sincere thanks also goes to Dr. Tongbin Teresa Qu, who enabled me to understand and know about essential and crucial concepts of traffic modeling and simulation. I am also thankful to my friends, colleagues, and the department faculty and staff for making my time at Texas A&M University a great experience.

Finally, I am indebted and will be forever grateful to my beloved family for their tireless support that strongly motivates me to pursue my dreams and achieve goals.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Associate Professor Kunhee Choi of the Department of Construction Science (Chair), Associate Professor Liliana O. Beltrán of the Department of Architecture (Co-Chair), Associate Professor José L. Fernández-Solís of the Department of Construction Science (Member) and Professor Yoonsuck Choe of the Department of Computer Science and Engineering (Member).

All work for the dissertation was completed independently by the student.

Funding Sources

There are no outside funding contributions to acknowledge related to the research and compilation of this document.

NOMENCLATURE

AADT	Annual Average Daily Traffic
AIAG	Automotive Industry Action Group
ANN	Artificial Neural Networks
ARIMA	Auto-Regressive Integrated Moving Average
ARRA	American Recovery and Reinvestment Act
BFGS	Broyden-Fletcher-Goldfarb-Shanno
BP	Back Propagation
BPR	Bureau of Public Roads
Caltrans	California Department of Transportation
CBD	Central Business District
CG	Conjugate Gradient
CWZ	Construction Work Zone
EMP	Evaluating the Measurement Process
FAST	Fixing America's Surface Transportation Act
FHWA	Federal Highway Administration
FNN	Feedforward Neural Networks
HAM	Historical Average Method
HCM	Highway Capacity Manual
HG	Honest Gauge repeatability and reproducibility
ITS	Intelligent Transportation System

KNN	k-Nearest Neighbor
MAP-21	Moving Ahead for Progress in the 21st Century Act
MICUZ	Multi-contextual learning for the Impact of Critical Urban highway work Zones
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSA	Measurement System Analysis
NOAA	National Oceanic and Atmospheric Administration
PeMS	Performance Measurement System
QCLCD	Quality Controlled Local Climatological Data
RBF	Radial Basis Function
R&R	Repeatability and Reproducibility
STA	State Transportation Agency
SVM	Support Vector Machine
TMP	Transportation Management Plan
TTI	Travel Time Index
VDF	Volume-Delay Function

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

Page

1. INTRODUCTION

1.1 Highway Infrastructure: Where We Are

Most state highways in the United States were constructed in the 1950s as prompted by the Federal Aid Highway Act of 1956. The main intent was to provide about 41,000 miles of national interstate and defense highways (Weingroff 1996). However, the majority of the transportation infrastructure has become obsolete because they were designed to sustain for 20-year serviceability (Bayraktar and Hastak 2009; Choi and Bae 2015; Choi et al. 2016; Choi et al. 2010; Choi et al. 2016; Federal Highway Administration 2002; Napolitan and Zegras 2008). Figure 1 illustrates the current state of practice in maintaining transportation infrastructure by state (Ingraham 2015).

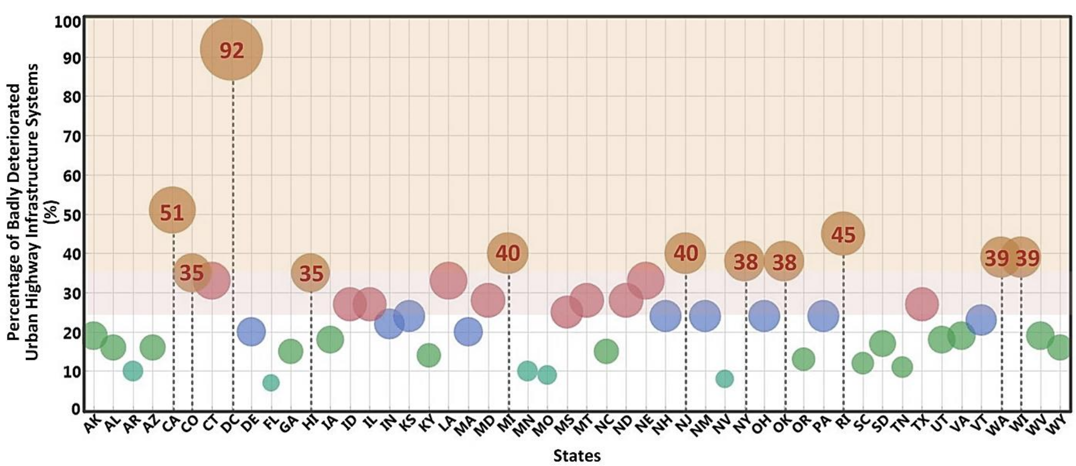


Figure 1 Percentages of deteriorated major urban roadways in the United States

To address this emergent issue that is tied closely to the health of national economy, state highway agencies are under ever-increasing pressure to rebuild the aging infrastructure systems across the state. The American Recovery and Reinvestment Act (ARRA) of 2009 was enacted to promote the restoration and repair of deteriorating highway systems as well as to spark up the economic growth of the nation (Choi et al. 2016; Conley and Dupor 2011). The ARRA Act allocated $27.5 billion for highway infrastructure improvement projects under the Federal Highway Administration (FHWA) (Conley and Dupor 2011; Orndoff and Papkov 2011). Recently, transportation agencies, daily commuters, and business sectors are facing an immediate need for massive highway infrastructure rebuilding, as promoted by the 2015 Fixing America's Surface Transportation (FAST) Act funding plans worth $305 billion for extensive transportation infrastructure rehabilitation projects (Federal Highway Administration 2016).

In spite of the economic stimulus, rehabilitating the deteriorated infrastructure systems is still challenging because it can cause costly traffic delays and disruptions to the traveling public and surrounding communities during construction. Meanwhile, these issues often impede the timely delivery of these types of projects (Choi and Bae 2015; Choi et al. 2016). Accelerating project delivery and reducing the level of motorist's inconvenience during lane closure in and between CWZs have been identified as some of key challenges that State Transportation Agencies (STAs) and the traveling public face, throughout the Moving Ahead for Progress in the 21st Century Act (MAP-21) (Choi et al. 2016; Federal Highway Administration 2014).

1.2 Traffic Impacts of Highway Construction

Traffic congestion is regarded as one of the most critical problems facing transportation agencies and the general public especially in large metropolitan areas in the United States (Nam and Drew 1998). According to the Texas A&M Transportation Institute's annual mobility report, in 2011 alone traffic congestion cost urban Americans an additional 5.5 billion hours of travel time and 2.9 billion gallons of fuel; together, this brings the congestion cost to $121 billion or $818 for each automobile commuter in the 498 urban areas in the United States (Texas A&M Transportation Institute 2012).

Highway traffic congestion can be classified into two groups: recurrent and non-recurrent. Recurrent congestion is caused by high traffic volume and thus is predictable. Conversely, non-recurrent congestion is affected by incidents on the highway such as vehicle accidents, stalled vehicles, spills and debris on the road, inclement weather, and work zones (Chung 2011; Hou et al. 2015). Especially, National Cooperative Highway Research Program (NCHRP) Report 726 by Shane et al. (2012) indicates that road construction and maintenance activities form a remarkable portion of traffic congestion, approximately 10% of the total congestion on highways and 24% of non-recurrent congestion (Abdelmohsen and El-Rayes 2016). The FHWA reported that traffic congestion due to road maintenance and construction can be translated into annual fuel loss more than 310 million gallons in 2014 (Federal Highway Administration 2014).

1.3 Motivating Case of Research: Work Zone Rule

Construction Work Zones (CWZs) are imperative when rehabilitating aging highway infrastructure networks. A CWZ occurs within an existing highway system wherever maintenance, rehabilitation, and/or reconstruction work is conducted. During construction, traffic and highway work exist in close proximity to one another (Karim and Adeli 2003). Traffic has both spatial and temporal features, which means that traffic on a road is affected by traffic on nearby roadways; moreover, traffic on a road has a significant relationship with previous flows at the same location (Dell'Acqua et al. 2015).

In this regard, a CWZ causes spatial and temporal restrictions on a highway by negatively impacting the normal flow of traffic (Karim and Adeli 2003). Therefore, they have become one of the leading causes of traffic congestion in heavily trafficked urban areas and caused significant inconvenience to the traveling public and affected communities (Bayraktar and Hastak 2009; Jiang and Adeli 2004; Karim and Adeli 2003; Zhu et al. 2009). Negative impacts of highway infrastructure improvement include increased travel times, queue delays, reductions in highway capacity, potential increases in accident rates, and higher levels of dissatisfaction in and between construction work zones (Karim and Adeli 2003; Zhu et al. 2009). Specifically, highway infrastructure improvement projects conducted in heavily trafficked urban areas frequently cause severe traffic congestion (Zhu et al. 2009), resulting in the average driver losing 67 hours and burning 32 extra gallons of fuel each year (Hasley 2013).

Given these significant economic impact, there is a pressing need to improve safety and mobility in and between CWZs. To meet with this need, updates to the work zone regulations at "23 Code of Federal Regulations (CFR) 630 Subpart J" were made by the FHWA in 2004, which is named the "Rule on Work Zone Safety and Mobility" (Choi and Bae 2015; Choi and Kwak 2012; Scriba 2006). Key terms in this rule are defined as follows (Legal Information Institute 2004):

- "Work zone" is an area of highways where construction, maintenance, or utility work activities are occurred;
- "Safety" represents any potential exposure to hazards for highway workers and users of highway facilities. Specifically, "work zone safety" refers to minimizing these potential hazards near work zone areas and at the work zone area interfacing with traffic. The number of crashes or criticality of crashes at a particular location or along a segment of highway can be used as means of measurement; and
- "Mobility" in relation to work zones aims to efficiently move road users through or around work zones, with only a minimum delay as compared to baseline travel under normal conditions. The most commonly used performance measures for evaluating mobility encompass delay, speed, queue length, and travel time.

The updated rule was designed to 1) address several issues of CWZs such as increasing traffic volumes and congestion, little growth in roadway capacity, concerns about safety, and disruptions to the public, 2) develop and implement the effective management strategies to reduce safety and mobility impacts, and 3) develop feasible provisions to control the both current and future CWZ issues (Scriba 2006). In pursuit of these goals, all state and local governments receiving federal-aid funding have been mandated to comply with the provisions of the rule since October 2007 (Federal Highway Administration 2007).

Among these specific objectives, a key focus of this rule is enforcing STAs and thus assisting in developing and implementing a sounder Transportation Management Plan (TMP) for each project. A TMP lays out how a set of well-coordinated transportation management strategies should be applied to manage CWZ impacts in order to improve safety and mobility during construction (Federal Highway Administration 2006; Federal Highway Administration 2015). The FHWA has identified three key components for a systematic TMP (Federal Highway Administration 2006; Federal Highway Administration 2015):

1) A CWZ impact assessment through traffic pattern analysis and quantification of traffic impacts at the work zone;
2) Guiding ideas regarding how work zone impacts can be managed; and
3) Public outreach strategies to effectively and efficiently inform the public about the planned project.

2. PROBLEMS AND RESEARCH SETTING

2.1 Problems and Research Questions

For a successful TMP, impact assessments of CWZ are essential, but they are also very difficult to perform. The completion of impact assessments of CWZs may be facilitated if critical traffic measurements such as traffic flow and travel time can be benchmarked from previous projects with similar characteristics. However, it is very challenging to benchmark traffic patterns and accurately quantify the potential traffic impact of CWZs for planned future highway infrastructure improvement projects, due to the increasing complexity of urban highway networks on multi-contextual aspects.

A common issue of existing methods to perform CWZ impact analysis is how to obtain accurate estimates of traffic parameters and their patterns effectively and efficiently. Accurate estimates of traffic flow are very essential and crucial to conduct the mandated CWZ traffic impact analysis. Flow is defined as "*the hourly distribution of vehicles (for each of the 24 hours in a day) passing through the roadway in a single direction and under normal operating conditions*" (Federal Highway Administration 2011). In current state of practice, actual traffic flow measurements are often required, and accurate results need a considerable time investment since these figures are unknown. Although many research efforts have been made to overcome this difficulty, most existing traffic flow prediction approaches are project-specific, short-term, and univariate, thus incapable of benchmarking the potential traffic impact of CWZs for planned future highway infrastructure improvement projects.

In addition, accurate estimates of travel time play a pivotal role in assessing the level of motorist's inconvenience during lane closure in and between CWZs. Accurate information about expected travel time during construction is essential for the traveling public to make better-informed decisions about their trips and find optimal alternate routes when necessary. However, most existing models cannot reveal the travel time variability before and during construction accurately, due to a lack of the capability to estimate the difference between recurrent traffic congestion under normal traffic flow conditions and traffic flow congestion caused by the presence of a CWZ.

Unfortunately, there are still gaps in the existing body of knowledge, and this has prevented researchers from studying traffic prediction algorithms; little is known about the application of big sensored data, as well as exploring effective prediction approaches that can cover the multi-contextual complexity inherent in this issue. The following are key questions to identify gaps in current knowledge and establish the primary objective of this study:

- What methods can leverage the simplicity and periodicity of traffic profiles on large urban highways?
- Which prediction techniques are the most effective and accurate specifically for predicting the potential long-term traffic flow for incorporation into CWZ impact analysis?
- How effectively can traffic prediction techniques and multi-contextual characteristics be intermingled into modeling the impact of CWZs?

- How to create a numerical model that can quantify the probable but reliable impact of CWZs under arbitrary lane closure scenarios on travelers at the construction zone, undertaking a parametric functional form that has the strength in practical applications?

2.2 Gaps in Current Knowledge

Knowledge gaps emerged from the extensive review of previous studies on the subjects of 1) traffic flow prediction techniques for incorporation into CWZ impact analysis (Sections 2.2.1 and 2.2.2), 2) existing methods to perform CWZ impact analysis (Section 2.2.3), and 3) validating the robustness of collected large volumes of traffic sensor readings (Section 2.2.4).

2.2.1 Traffic Flow Prediction for Incorporation into Work Zone Analysis

The FHWA underlines that knowing precisely about unknown potential traffic flow is needed to determine whether a facility will be forced to operate either above or below its capacity (Federal Highway Administration 2014). However, most existing traffic measurement and information systems focus on providing historical and real-time data with no capability of predicting future long-term traffic flow, particularly for lane closure impacts. For example, as one of the most widely used traffic measurement systems, GPS-based traffic information collected from many individual travelers would cause inaccuracy due to limited user participation (that is also changeable) as well as inherent imprecision of the current GPS devices (Bhat et al. 2004; Vovsha and Bradley 2006).

To address this issue, previous research efforts to predict traffic flows were made through univariate and multivariate time series analyses. As the most representative univariate model, Auto-Regressive Integrated Moving Average (ARIMA) models tend to focus on means, omitting the extreme values (Kamarianakis and Prastacos 2003). Therefore, ARIMA cannot capture sudden changes in traffic flow caused by any incidents or work zones (Pan et al. 2012). Even though ARIMA models would shorten computational time, these hold a critical issue to obtain accurate and reliable results because they do not respond to any change in traffic flow caused by incidents or CWZs. On the other hand, multivariate approaches such as space-time ARIMA models can represent the spatial characteristics of the roadway network and temporal evolution of traffic flow in other locations in the network (Kamarianakis and Prastacos 2003). Although multivariate models improve the accuracy, the both time series analyses assume linear correlation structures. In other words, the nonlinearity of traffic flow by its nature cannot appear through time series models.

In an effort to unlock the increasing nonlinear complexity of traffic flow, many studies have endeavored to find solutions to this problem and consequently have reported that Machine Learning (ML) approaches are effective and efficient not only for analyzing large quantities of traffic data but also for predicting traffic patterns and recommending alternatives. ML is a technique for processing data and exhibiting inferences by applying lessons learned from a training dataset (Portugal et al. 2016;

Simovici 2015). Many studies have explored ML approaches to developing a series of traffic flow prediction models, such as artificial neural networks, support vector machine, k-nearest neighbor algorithms.

However, throughout the thorough review of previous studies, it was found that there is still very little known about the capability of existing models whether they can predict traffic flow for incorporation into the mandated CWZ traffic analysis. Traffic flow prediction can be classified into two different temporal scales: short-term and long-term. Short-term traffic flow predictions include15, 30, 45 and 60 minutes advanced forecasts, which are needed for real-time traffic control and management (Habtemichael and Cetin 2016; Hou et al. 2015). In other words, short-term traffic flow prediction serves as a fundamental input and is a crucial aspect of being successful in advanced traffic management system (Zhang et al. 2014). Most of these studies have focused on short-term traffic flow prediction (Abdi et al. 2012; Abdi et al. 2013; Abouaissa et al. 2016; Barros et al. 2015; Bing et al. 2015; Cai et al. 2016; Chen and Chen 2007; Dia 2001; Dougherty and Cobbett 1997; Habtemichael and Cetin 2016; Hamed et al. 1995; Hong et al. 2015; Hu et al. 2016; Innamaa 2000; Jiang et al. 2016; Jiang et al. 2013; Kim and Hobeika 1993; Lee and Fambro 1999; Lin et al. 2013; Ma et al. 2015; Pan et al. 2013; Pan et al. 2015; Shahsavari and Abbeel 2015; Smith and Demetsky 1994; Tan et al. 2016; Vlahogianni et al. 2005; Wei and Liu 2013; Xu et al. 2013; Zhang and Ye 2008; Zhang et al. 2014).

In contrast, long-term traffic flow predictions concentrate on predictions on levels of hours, days, months, and even years for the unit of time. Long-term traffic flow prediction is typically appropriate for CWZ scheduling applications because planning CWZs utilizes traffic flows during different times of a specific day as input to help STAs schedule traffic operation plans and construction progress timely, while minimizing the negative impactful times during lane closures (Hou et al. 2015; Jiang et al. 2013; Yu et al. 2015). Throughout an extensive literature review, it was found that only a very limited number of studies used ML approaches to predict long-term traffic flow under normal conditions (Çetiner et al. 2010; Choi and Bae 2015) or future traffic flows in urban work zones (Hou et al. 2015). In a nutshell, the literature search concludes that most previous ML studies to date were focused on predicting "short-term" traffic flow under a normal condition, and therefore, knowledge about learning the long-term impact of urban highway work zones is largely missing.

2.2.2 Multi-Contextual Complexity of Construction Work Zones

Despite a sizeable body of research, little scientific work has been done on holistic approaches to obtaining the most realistic and reliable traffic flow patterns. Many of the existing methods predict traffic flow at a single section considering temporal dimensions solely, thereby ignoring the spatial or other characteristics of the road network. In other words, these methods employed the univariate approach and assume that the variable of interest is affected by a single factor (Dell'Acqua et al. 2015).

On the other hand, the multivariate approach assumes that multiple factors affect the prediction variable; this assumption produces more accurate and reliable forecasts (Dell'Acqua et al. 2015). However, a limited number of studies have explored multivariate approaches to the prediction of traffic flow, due to the increasing multi-contextual complexity of roadway networks. For example, Roh et al. (2015) reported that previous studies proved that highway traffic variations (i.e., reduction in traffic volume and changes in traffic patterns) are affected by weather conditions along with spatial characteristics of roadway network (Datla et al. 2013; Keay and Simmonds 2005; Maze et al. 2006). Nevertheless, there are limitations of previous studies because spatial or temporal features of traffic flow did not appear through these studies.

In summary, existing approaches are inadequate with regards to predicting traffic flow within a distinct set of clusters, because they fail to incorporate the unique characteristics of a particular spatial cluster into the prediction model. These exclusive characteristics should be construed as multiple contexts such as spatial, temporal, weather, socio-demographic, and highway facility function conditions. In this regard, there remains a significant gap in current knowledge regarding how model the multi-contextual aspects of long-term traffic flow predictions.

2.2.3 Existing Methods to Conduct Work Zone Delay Analysis

Most State Transportation Agencies (STAs) currently use the methodology in the Highway Capacity Manual (HCM) in order to analyze CWZ traffic impacts (Federal Highway Administration 2014; Vadakpat et al. 2000). The HCM lists the most widely used macroscopic deterministic model for use in predicting whether a facility will be forced to operate either above or below its capacity (Federal Highway Administration 2014). A number of HCM-based work zone impact analysis tools have been widely used, such as spreadsheets, Queue and User Cost Evaluation of Work Zones (QUEWZ), DELAY Enhanced 1.2, IntelliZone, QuickZone, and Construction Analysis for Pavement Rehabilitation Strategies (CA4PRS). Most of these tools (i.e., spreadsheets, QUEWZ, DELAY Enhanced 1.2, and IntelliZone) are very simple to use but complex with regards to determining adjustment factors, which often results in the overestimation of traffic impacts (Abdel-Rahim et al. 2010). QuickZone, developed by the FHWA, incorporates various factors affecting delays at work zones and therefore provides comprehensive and detailed outputs (Abdel-Rahim et al. 2010). However, it also requires a huge amount of detailed input information about the roadway network. CA4PRS quantifies a CWZ impact on the traveling public on the aspect of time spent in queue (Lee and Choi 2006). CA4PRS's traffic module can be operated by either a manual input of 24-hour traffic flow data or updates through the California Department of Transportation (Caltrans) the freeway Performance Measurement System (PeMS). PeMS converts freeway sensor data into intuitive tables and graphs that show historical and real-time traffic patterns on highways in California (Caltrans 2012). Its scope, however, is limited to the collection and analysis of historical and real-time data; it has no capability to predict traffic flow (Demiryurek et al. 2010). These simple macroscopic input-output traffic analysis methods have a critical limitation to benchmark traffic impact patterns because they cannot maintain historical datasets and learn from them in making better-informed decisions (Karim and Adeli 2003). In addition, an input-output analysis assumes that planners and engineers are aware of the impact of work zones on highway capacity reduction due to the planned construction (Karim and Adeli 2003).

As a different approach to quantifying the impact of CWZs, most traffic simulators developed in recent decades adopt microscopic simulation models (Ben-Akiva et al. 1998; Hourdakis et al. 2003; Kamarianakis and Prastacos 2005). Microscopic simulation models such as VISSIM and CORSIM utilize a differential equation for single vehicle motion, along with various boundary conditions (Abdel-Rahim et al. 2010; Ghosh-Dastidar and Adeli 2006). The microsimulations employ dynamic route assignment algorithms that can test various alternatives (Abdel-Rahim et al. 2010). However, questions are remained regarding effectiveness and efficiency of their ability to address various real-world situations. Instead of using real-world traffic data, they are dependent upon the start time at a source node, using simplistic models with synthetic datasets to represent the temporal aspect of the road network.

2.2.4 Traffic Data Measurements: Are They Repeatable and Reproducible?

In an effort to achieve the most representative traffic pattern within a particular cluster that includes a number of sensors, it is important to identify effective and efficient validation methods to test whether traffic data obtained from multiple sensor readings can be repeatable and reproducible on a certain temporal scale; this is necessary for the projection of a particular single cluster's characteristics. Several studies have reported that Repeatability and Reproducibility (R&R) analyses can be employed as a means of determining the most accurate and precise measurement systems (AIAG 2010; Joubert and Meintjes 2015). However, to the best of this author's knowledge after an extensive literature review, little is known about R&R studies for transportation applications. The only one conducted in the last decade studied R&R for transportation industry applications. Joubert and Meintjes (2015) determined the R&R of GPS data for freight activity chains. Each GPS dataset had unique characteristics, so the process required corresponding processing and validation techniques to extract vehicle behaviors, even though GPS data processing was automated through advanced algorithms.

A key fundamental aspect of R&R analysis is determining the number of samples and repeat readings (MoreSteam 2015). Larger numbers of parts and repeat readings provide results with higher confidence levels (MoreSteam 2015). Sensored big transportation data used in this study address spatiotemporally large variations along with each different sensor locations at different temporal scales (i.e., hour, day, week, and season), which means that R&R analysis is appropriate to validate the robustness of traffic sensored big data on the aspect of the periodicty. However, there is a lack of research on testing the robustness of collected data to investigate the precision of traffic sensored data; this information is necessary for the management and validation of archived traffic data that must occur before a traffic data analysis can be conducted.

2.3 Research Objectives

Accurate work zone impact assessments of unprecedented travel inconvenience to the general public are required for all federally-funded highway infrastructure improvement projects. These assessments are critical, but they are also very difficult to perform for projects located in large urban areas with relatively dense roadway networks. Most existing prediction approaches are project-specific, short-term, and univariate, thus incapable of benchmarking the potential traffic impact of CWZs for highway rehabilitation projects.

This study fills these gaps by creating a big-data-based decision-support framework and testing if it can reliably predict the potential impact of a CWZ under arbitrary lane closure scenarios. This study proposes a big-data-based decision-support analytical framework, “Multi-contextual learning for the Impact of Critical Urban highway work Zones (MICUZ).” MICUZ is unique as it models the impact of what-if work zone operations through a multi-contextual quantitative method utilizing sensored big transportation data. Following describes the proposed MICUZ framework, followed by key sub-objectives of this study.

2.3.1 The Proposed MICUZ Framework

The significant impact of using large volumes of real-world traffic data on the prediction performance was identified by the previous studies. If the number of loop detectors is large enough the prediction performance of model can be improved by capturing the relationship between time slots and traffic data in different locations (i.e., spatiotemporal relationship) (Kamarianakis and Prastacos 2003; Pan et al. 2012). In addition to using sensored big transportation data, to make a significant leap forward in impact assessments of CWZs, MICUZ incorporates multi-contextual aspects into predicting long-term traffic flow and quantifying the potential traffic impact of CWZs, while mirroring various real-world situations.

MICUZ specifically focuses on modeling and predicting the traffic impact of nighttime CWZs on the aspect of travel time delays to assess the level of motorist's inconvenience caused by the presence of a CWZ in heavily trafficked large urban corridors. To define large urban corridors, MICUZ addresses critical highways in large urban cores where the Annual Average Daily Traffic (AADT) volume is over 250,000 (Federal Highway Administration 2015). AADT is simply represents how busy highways, drawn as the total volume of vehicle traffic. In large urban corridors, various construction alternatives in the conventional nighttime closures have been widely used because nighttime construction can improve daytime mobility, allowing road users to avoid traffic congestion during peak hours (Al-Kaisy and Hall 2003; Shane et al. 2012). On the other hand, nighttime construction often decreases work zone capacity due to reduced attention from travelers (Al-Kaisy and Hall 2003).

As depicted in Figure 2, the proposed MICUZ framework was developed through a three-phase modeling process: 1) robustness check of collected sensored data; 2) multi-contextual learning modeling using an Artificial Neural Network (ANN) technique; and 3) curve-fitting modeling. Three phases of each are identified as specific sub-objectives of this study, and described in the following sections (Sections 2.3.2 to 2.3.4).

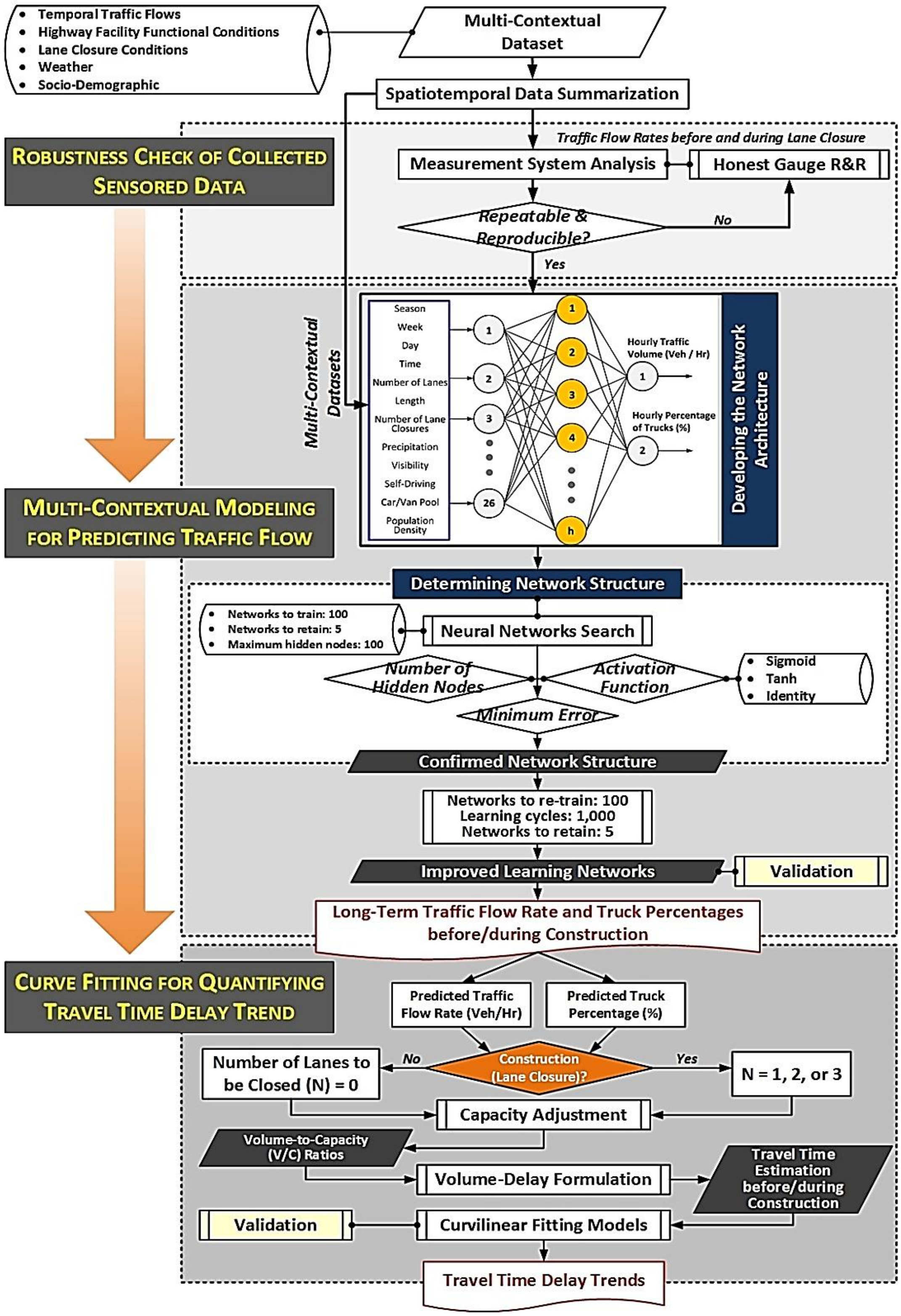


Figure 2 The proposed MICUZ framework

2.3.2 Phase I: Robustness Check of Collected Sensored Data

The objective of Phase I is to test whether traffic flows extracted from archived multiple sensor readings can be repeatable and reproducible, thereby validating the robustness of the collected multi-sensored data whether they can represent the temporal traffic flow within a distinct set of spatial clusters (i.e., different sensor locations on different (or same) highways adjacent to a large urban core).

- Hypothesis: The unique temporal periodicity (i.e., a single temporal traffic flow trend) is represented by numerous traffic flow data collected from multiple sensors that are placed in different locations within a large urban core.
- Research approach: In the proposed MICUZ framework, Wheeler's Honest Gauge repeatability and reproducibility (HG) analysis is conducted to test the robustness of historical traffic data collected from multiple sensor readings.
- Significance: This research phase is the first of its kind that is undertaken for testing the repeatability and reproducibility of measurements of numerous traffic sensor readings. This approach will lay groundwork for efficiently and effectively classifying various temporal traffic flows into a distinct spatial regional cluster, as a pre-process for numerous traffic analyses.

2.3.3 Phase II: Multi-Contextual Learning Modeling via Neural Networks

Phase II aims to develop a multi-contextual predictive model that determines the stereotypical patterns of traffic flow. Specifically, the proposed network model predicts traffic flow rates (veh/hr) and truck percentages (%) under prevailing traffic conditions as well as under lane closures, along with the multi-contextual characteristics.

- Hypothesis: There is a strong correlation between long-term traffic flows before/during construction and multi-contextual characteristics such as weather conditions (visibility and precipitation), highway facility functional information (number of lanes, lane width, shoulder, and number of lanes to be closed), and socio-demographic conditions (population density adjacent to the traffic flow analysis zone and percentages of primary commute modes on highways such as self-driving and car/vanpooling).
- Research approach: The MICUZ framework develops a multi-contextual learning model and tests the validity of its use of ANN whether it can robustly predict long-term traffic flow rates and truck percentages before and during construction simultaneously, within a distinct set of urban highway clusters. When considering multi-contextual characteristics that include several types of continuous, ordinal, and categorical datasets, ANNs take advantage over other ML techniques because it can be feasibly applied to any system and is capable of inherently modeling highly nonlinear systems.
- Deliverables: The most effective architecture and learning structure for ANN are achieved, specifically centering to improved long-term traffic flow prediction on critical urban highway systems. Predicted values obtained from the proposed model encompass the potential long-term traffic flow rates and truck percentages within the corresponding traffic flow. The predicted traffic flow rates are then

incorporated into the proposed curve-fitting models directly, while the predicted truck percentages are used for the capacity adjustment to develop the proposed curve-fitting models (Phase III).

- Significance: The proposed multi-contextual learning model yield an accurate prediction rate of long-term traffic flow, which proves that the proposed model would be repeatable and verifiable to other traffic region.

2.3.4 Phase III: Modeling the Potential Work Zone Travel Time Delay Impact

The objective of Phase III is to model, quantify, and validate the potential impact that CWZs have on travelers on the aspect of travel time delays. To achieve this goal, this phase adopted a curve-fitting technique that specifically aims to quantify travel time delay trends under what-if lane closure schemes for the nighttime construction.

- Hypothesis: The proposed curve-fitting models bolster trend approximation of CWZ delay impacts at the boundaries of critical highway work zones.
- Research Approach: MICUZ creates curve-fitting formulations by transforming the exisiting volume-delay function and blending the predicted long-term traffic flow rates and truck percentages obtained from the multi-contextual learning networks (Phase II) with what-if lane closure schemes.
- Deliverables: The proposed curve-fitting models produce travel time delay trends under prevailing traffic conditions as well as under a number of what-if lane closure schemes for weekday and weekend nighttime construction in heavily trafficked urbanized downtown areas, which would be practically used.

- Significance: The proposed curve-fitting models overcome the drawbacks of the existing volume-delay function, capturing the travel time variability under prevailing traffic conditions and aribitrary lane closure scenarios. The end results quantify the probable but reliable travel time delays to assess the level of motorist's inconvenience caused by the presence of a CWZ in heavily trafficked large urban cores.

2.4 Research Methodology

In pursuit of the end goal of this study, MICUZ utilizes large volumes of real-world traffic sensored data along with the corresponding multi-contextual characteristics, specifically aimed at deepening knowledge in improving the accuracy and reliability of work zone travel time delay impacts. The discussed objectives were achieved through a solid eight-stage methodology:

1. A total of 17,518 traffic sensor readings on Interstate highways (I-10 East and I-110 South) adjacent to the Central Business District (CBD) in the City of Los Angeles (LA), California were extracted from the PeMS database. Hourly traffic volumes that include the percentage of trucks within the corresponding traffic flow are collected during the whole year in 2014 (0:00 am on January 1 to 11:59 pm on December 31, 2014).
2. Multi-contextual datasets were gathered in order to improve the accuracy of prediction of the proposed network learning model, including highway facility functional information, weather conditions, and socio-demographic

characteristics. Highway facility functional variables were collected from the PeMS to capture the impact of the existing highway capacity condition on the traffic flow variation under normal condition as well as lane closures. The weather conditions including the historical datasets of daily precipitation and visibility in 2014 were collected from the Quality Controlled Local Climatological Data (QCLCD) database provided by National Oceanic and Atmospheric Administration (NOAA). As socio-demographic characteristics, Population density in the Census areas adjacent to the traffic flow analysis zone was collected from Census Tracts of California. In addition, percentages of primary commute modes on the highways, such as self-driving and car/vanpooling, were collected from the LA Department of City Planning.

3. To test whether traffic flows extracted from archived multiple sensor readings can be repeatable and reproducible, a two-stage R&R study on the collected historical traffic flow sensor readings was conducted through Wheeler's Honest Gauge R&R (HG) method: the R&R of the collected traffic flow measurements 1) before lane closure and 2) during lane closure.
4. Based on the validated robustness of multiple sensored data, a multi-contextual learning model was developed adopting an artificial neural network technique to predict long-term traffic flow rates and truck percentages within the corresponding traffic flow, by incorporating the multi-contextual characteristics. To develop the proposed learning model, a five-stage modeling process was implemented within Phase II of MICUZ modeling framework: 1) developing the

architecture of ANN; 2) identifying the critical components affecting the learning performance of the model; 3) determining the learning structure of the proposed model; 4) developing the multi-contextual learning model; and 5) evaluating the learning performance of the proposed model. In detail, the proposed model was designed with three layers based on the MLP feedforward neural networks. The learning structure of the proposed model was then determined to control the most critical components affecting the performance of neural networks, such as training algorithm, activation functions, and the optimal number of hidden nodes in the hidden layer. In order to improve the accuracy and reliability of the model, the confirmed learning structure network was re-trained, thereby achieving the improved multi-contextual learning model. The learning performance of training, cross-validation, and test sets was then statistically validated by comparing actual values with predicted values.

5. As the pre-process for modeling the impact of potential work zone delays, the adjusted capacities of highway facilities before and during construction were computed through a procedure in the Highway Capacity Manual; this process incorporated the predicted truck percentages obtained from the proposed multi-contextual learning model as one of a number of adjustment factors.
6. Potential travel times before and during lane closure were estimated by creating stereotypical traffic volume-capacity ratio patterns that incorporate the predicted long-term traffic flow rates and the corresponding truck percentages.

7. In an effort to quantify the percentile travel time delay trend before and during construction, curve-fitting models were developed through the third-order polynomial equations.
8. The robustness of the proposed curve-fitting models was scientifically verified and validated by measuring the forecast accuracy through Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE).

2.5 Research Assumptions and Limitations

This research was performed according to the following assumptions:

- This study assumes that any incident with a higher level of uncertainty would not occur.
- This study uses unidirectional traffic sensor readings, which capture the traffic flow toward the study region. The other directions are assumed to have a traffic profile symmetric with the studied directions.
- It is assumed that annual temporal weather conditions at the studied spatial zone are identical.

The following are limitations of this study:

- The focal point of this research is confined to highway systems, and the scope of the highway network examined is limited to mainlines in multilane (3, 4, and 5 lanes in one direction having 12 ft. of each lane width plus shoulders) highways (and therefore excludes ramps, intersections, and HOV lanes) where the traffic flow is significantly simpler and more predictable than arterials in a local road network.

- This study is limited to nighttime construction. Nighttime construction is a dominant construction window on highways in urbanized downtown areas with CBDs, which is intended to minimize inconvenience to the traveling public during the daytime.
- This study is limited to quantifying the potential CWZ impact on the aspect of travel time delays, which means that queue length and road user cost are excluded from the scope of analysis.
- Work zone travel time delay trend achieved from this study is confined to nighttime construction (9:00 pm-6:00 am during weekdays and 8:00 pm-11:59 pm on Sundays) in a large urban core, such as the CBD.
- Regarding open lane conditions, this study is limited to lane drops only, and excluded the median crossover.
- Though it is one of the critical weather conditions affecting traffic conditions, snowfall was excluded due to the climatic characteristics of the study region.

2.6 Contributions

The proposed MICUZ framework is unique as it models the impact of what-if CWZ operations from a quantitative perspective using high-confidence real-world multi-contextual big data. Based on the proposed multi-contextual approach through ANN and curve-fitting, MICUZ is able to learn and generalize from a training data set of certain critical urban highway systems, and apply this knowledge to other highway systems with similar characteristics but where sensor data are not available.

Phase I of MICUZ is the first of its kind that is undertaken for testing temporal and spatial periodicity present among traffic flow measurements of multiple traffic sensors through a measurement system analysis. The results will allow for more efficient management of measured sensor data through an assessment of its repeatability and reproducibility. The proposed multi-contextual learning model (Phase II) is expected to provide a solid foundation for the accurate and reliable prediction of long-term traffic flows before and during construction, which will serve as a baseline for incorporation into CWZ impact analyses encompassing travel time delay, queue length, and road user cost. In additions, through the proposed curve fitting models (Phase III), MICUZ has a potential to generalize travel time delay trends under normal traffic conditions and a number of what-if lane closure schemes for nighttime construction that is the most popular construction alternative in urban cores.

This study conveys a notable conclusion that travelers' inconvenience can be assessed into a set of distinct signature modeling patterns. The proposed MICUZ framework provides a rigorous theoretical basis for comparatively analyzing what-if construction scenarios, enabling engineers and planners to choose the most efficient transportation management plans much quickly and accurately. This study will assist STAs and the general traveling public in understanding potential traffic flow issues attributable to construction in heavily trafficked large urban cores (i.e., downtown areas with CBDs), while improving mobility in and between CWZs and positively affecting regional development. Moreover, the proposed multi-contextual models will also help state transportation agencies quantify the reasonable rate of traffic demand reduction under various alternative lane closure scenarios in advance, while providing the traveling public both pre-trip planning and en-route guidance during construction.

3. LITERATURE REVIEW

This section reviews previous studies on CWZ traffic analysis and traffic flow prediction techniques as key to successful implementation of CWZ impact assessments. A review of pertinent literature was intended to extract existing knowledge about work zone traffic impact analysis, focusing on traditional empirical studies on work zones and traffic flow dynamics (Section 3.1). Three key areas for the literature review related to traffic flow prediction modeling approaches were then identified. Section 3.2 focused on the three approaches such as 1) univariate, 2) multivariate, and 3) ML approaches to traffic flow predictions. Among the studied ML approaches, previous studies on ANN approaches were reviewed deeply to gain insight into traffic flow prediction modeling, as the most appropriate learning technique for the proposed MICUZ framework (Section 3.3).

3.1 Construction Work Zone Traffic Analysis

Overall, previous efforts on conducting construction work zone traffic impact analysis can be divided into two research areas: 1) traditional empirical studies and 2) applications of traffic flow dynamics at microscopic and macroscopic levels.

3.1.1 Traditional Empirical Studies on Work Zones

Many previous research efforts on CWZ traffic analysis were made to identify and model work zone impacts on aspects of traffic flow, work zone capacity, and traffic congestion. Dudek and Richards (1981) developed a chart showing the cumulative distribution of work zone capacity and delay by analyzing 37 work zone sites in Texas. Krammes and Lopez (1994) presented a single base work zone capacity by analyzing 33 different work zone configurations. The authors highlighted that the work zone capacity could be adjusted to reflect the intensity of work, percentage of trucks, and the existence of ramps upstream of the work zone. Dixon et al. (1996) analyzed 24 work zone data to capture work zone capacity on urban and rural highways. The authors underlined that work zone capacity is critically affected by the intensity of work, locational characteristics of urban and rural areas, and the level of darkness. Ullman (1996) studied about natural diversion on traffic conditions upstream of work zone lane closures on urban highways in Texas, which represents that the existence of work zone forces road users to choose alternate routes when the highway has continuous frontage roads. Cottrell (2001) developed an empirical model of queueing delay through a linear regression analysis that utilized 161 highway queuing observations. The developed model aimed to quantify the statistical relationship between traffic flow and capacity variables and queue delay. However, this linear regression model has drawbacks in its applicability to work zone traffic conditions because it represents recurrent congestion under prevailing traffic flow conditions. As the most widely used guideline, the HCM currently provides the current state of practice in traffic analyses by summarizing the previous empirical studies over the past 30 years (Transportation Research Board 2010).

It is obvious that previous empirical studies laid a groundwork for analyzing CWZ traffic impacts. However, they are very limited to particular projects, thereby often leading to unmatched findings of the study. For example, Dixon and Hummer (1996) reported that work zone capacity was about 10 percent higher than the capacity shown in the HCM, by analyzing work zones during 1994 and 1995 in North Carolina. On the other hand, Al-Kaisy and Hall (2003) found that work zone capacity of six long-term work zone sites was lower than the HCM base capacity. In this regard, the results and main findings of these empirical studies are not applicable to other various scenarios of work zones all the time.

3.1.2 Traffic Flow Dynamics: Microscopic Versus Macroscopic Models

For the assessment of CWZ impact incurred by the presence of lane closures being performed to rehabilitate again highway networks, two primary techniques are widely used such as microscopic and macroscopic modeling techniques (Adeli and Ghosh-Dastidar 2004). A microscopic model utilizes a differential equation for a single vehicle in the traffic flow (Adeli and Ghosh-Dastidar 2004). The microscopic model deals with acceleration as the control variable affected by the inter-vehicular density (Bando et al. 1995; Chandler et al. 1958; Kachroo and Özbay 2012). Most of the traffic simulators developed in the recent decade adopt microscopic models, such as VISSIM and CORSIM (Ben-Akiva et al. 1998; Hourdakis et al. 2003; Kamarianakis and Prastacos 2005). The microsimulations employ dynamic route assignment algorithms that can test various alternatives (Abdel-Rahim et al. 2010). These microscopic models can provide detailed analyses. However, they cannot capture global descriptions of the traffic flow rate, density, and velocity and often are restricted to synthetic or simplified data (Van Lint et al. 2002). The accuracy of these models relies heavily on the accuracy of social, environmental, and behavioral data that critically affect the traffic flow.

On the other hand, a macroscopic model controls the traffic flow as a continuum, which means that traffic flow changes over space and time constantly (Nam and Drew 1998). The macroscopic model is based on a differential equation of continuity that consists of traffic flow measured in vehicles per hour, speed in miles (or kilometers) per hour, and density measured in vehicles per mile (or kilometer) (Adeli and Ghosh-Dastidar 2004; May 1990). Two different principal analyses have been used to develop macroscopic models: 1) shock wave analysis (also known as kinematic wave theory or Lighthill-Whitham-Richards (LWR) model) and 2) queueing analysis (also called queuing theory or simple input-output model). A pioneering concept in analyzing traffic flow at bottlenecks was introduced by Lighthill and Whitham (1955), which assumes traffic flow as a compressive fluid flow. This idea was strengthened by adding the concept of shock waves on highways proposed by Richards (1956), resulting in the so-called LWR model or kinematic wave theory (Mazaré et al. 2011). This theory presents traffic is supposed to behave like a fluid, and its kinematic waves are generated from each vehicle. When demand exceeds capacity at a bottleneck, these waves interact with each other, called shock waves (Vadakpat et al. 2000). A shock wave is defined as a boundary condition in the time-space domain, which shows a discontinuity in the flow-density condition (Nam and Drew 1998). A shock wave analysis traces shock waves in time and space in order to determine which flow regions are queued or uncongested (Karim and Adeli 2003). In other words, this analysis presents traffic queues through traffic density changes in the time-space domain. The central premise of this analysis is the relationship between flow and density is known throughout roadways (Nam and Drew 1998; Vadakpat et al. 2000). A shock wave analysis assumes a single deterministic flow-density relationship over the whole time-space domain, which is simple to use. However, in general, density is considered as a traffic parameter that is difficult to measure directly (Nam and Drew 1998). In addition, the single deterministic flow-density relationship maintains over the entire length of the studied road segment, which is also identical over the studied time duration. Therefore, the wave model has its limited applications because it cannot consider the multi-contextual complexity of work zones when modeling the traffic impact of CWZs.

Alternatively, queuing analysis uses a cumulative queuing diagram to determine traffic queues at a particular time based on the difference between the cumulative arrivals and the cumulative departures at a bottleneck, without considering the space dimension (Zhu and Ahmad 2008). Queuing analysis can be either deterministic or stochastic. However, stochastic queuing analysis requires the information of traffic distribution that is often too difficult to obtain from the real-world condition (Karim and Adeli 2003). In this regard, most STAs currently adopt the procedures described in the HCM, which is based on the deterministic queueing analysis at macroscopic level for the prediction of whether a facility can be forced to operate either above or below its capacity (Federal Highway Administration 2014; Vadakpat et al. 2000). A deterministic macroscopic queuing model is based on the principle of conservation of traffic flow, which represents that the number of vehicles entering a segment during a particular time period must be equal the number of vehicles exiting the segment during the same time period under the identical roadway condition (Karim and Adeli 2003).

Many previous research efforts were made to help conduct CWZ impact analysis, using a number of tools based on deterministic queuing theory at the macroscopic level: spreadsheets, QUEWZ, QuickZone, and CA4PRS. As a traditional way, the spreadsheet-based tool estimates work zone delay and queue lengths by integrating the deterministic queuing theory explained in the HCM with analytical equations (Abdel-Rahim et al. 2010). A number of previous studies utilized the QUEWZ that is a DOS-based analysis tool developed by the Texas A&M Transportation Institute, specifically aiming at predicting congestion and the corresponding road user costs in work zone (Abdel-Rahim et al. 2010; Copeland 1998; Karim and Adeli 2003; Krammes et al. 1987; Memmott and Dudek 1984; Sadegh et al. 1988). However, these tools are commonly very simple to use, but complicated to determine adjustment factors, which often result in overestimating traffic impacts (Abdel-Rahim et al. 2010). Especially, QUEWZ is operated based on the conservation of traffic flow principle and follows empirical speed-flow-density relationships, missing the work zone layouts.

Alternatively, the FHWA developed a Microsoft Excel-based software application called QuickZone in order to predict the average queue lengths and travel times in work zones (Abdel-Rahim et al. 2010; Adeli and Ghosh-Dastidar 2004; Federal Highway Administration 2015; Karim and Adeli 2003). QuickZone has the capability of incorporating various factors that affect delays at work zones, thereby providing comprehensive and detailed outputs (Abdel-Rahim et al. 2010). It utilizes the difference between traffic demand at hourly and daily levels and highway capacity to estimate queuing and travel times, incorporating the seasonal demand factors. Then, it compares travel time before and during construction to identify the additional travel time or delay due to work zones. However, it requires a huge amount of input information about detailed roadway network. In addition, QuickZone does not model traffic flow under lane closure, dealing with it indirectly in the form of the capacity reduction in work zones.

CA4PRS developed by the University of California Pavement Research Center through the UC Berkeley Institute of Transportation Studies is also one of the most widely used software application, specifically aiming at supporting the integrated analysis of rehabilitation project alternatives in terms of cost, time, and traffic impacts (Federal Highway Administration 2015; Lee and Ibbs 2005). CA4PRS's traffic module quantifies the CWZ impacts on aspects of time spent in queue and road user cost (Lee et al. 2008). One of the powerful features of this module is that it can be integrated with the macroscopic or microscopic traffic models to quantify CWZ traffic impacts (Lee and Ibbs 2005). CA4PRS's traffic module can be operated by either a manual input of 24-hour traffic flow data or updates through the Caltrans PeMS. A manual input of traffic flow for every single analysis is labor-intensive and time-consuming. In spite of its capability of integrating with the Caltrans PeMS, as stated previously, the scope of PeMS is limited to collection and analysis of historical and real-time data with no capability of predicting long-term traffic flow (Demiryurek et al. 2010). The major limitation of these conventional macroscopic models is that they are too simplistic to create accurate traffic impacts of highway construction work zones, especially roadway segments upstream of work zones affected by lane closure. In addition, macroscopic models assume that planners and engineers are aware of the impact of work zones on the aspect of highway capacity reduction due to the planned construction (Karim and Adeli 2003).

3.2 Modeling Approaches to Traffic Flow Prediction

Despite many previous research efforts, most existing approaches to traffic flow prediction are often univariate, assumed as linear structures, and focused on short-term. These previous studies cannot therefore provide a guidance for benchmarking the potential traffic impact of CWZs. To address this issue, a comprehensive review of literature on the subject of traffic flow prediction modeling approaches was conducted, thereby identifying pros and cons of existing modeling approaches and determining the most appropriate method for the proposed multi-contextual modeling. Traffic flow prediction modeling methods were classified into three different approaches: 1) univariate modeling; 2) multivariate modeling; and 3) machine learning approaches.

3.2.1 Univariate Modeling Approaches

In univariate models, historical traffic flow data obtained from a specific location are utilized to model and predict the future traffic flow on the same location (Kamarianakis and Prastacos 2003). Univariate approaches to traffic flow prediction are mainly presented by Historical Average Methods (HAMs) and time series models.

HAMs use the cyclic feature of traffic flow, by simply employing the average values of past traffic volumes to predict future traffic flow (Chang et al. 2011). These methods have been applied to the urban traffic control system and traveler information systems (Jeffery et al. 1987; Kamarianakis and Prastacos 2003; Kaysi et al. 1993; Stephanedes et al. 1981). Even though these methods would shorten computational time, these methods hold a critical issue to obtain accurate and reliable results as they do not respond to any change in traffic flow, such as incidents and work zones.

A majority of time series models is presented by Auto-Regressive Integrated Moving Average (ARIMA) models (Ahmed and Cook 1979; Hamed et al. 1995; Kim and Hobeika 1993; Lee and Fambro 1999; Williams et al. 1998; Yao and Cao 2006). ARIMA models were emerged by merging the concepts of Auto Regression (AR) and Moving Average (MA) models, which is also known as the Box-Jenkins model (Oh et al. 2015). In an effort to predict traffic flow based on stochastic traffic mechanism, Ahmed and Cook (1979) and Levin and Tsao (1980) introduced the ARIMA models. Comparing with HAMs, it was found that the ARIMA has better performance (Smith and Demetsky 1997). However, a number of researchers reported the limitations of ARIMA models as they tend to focus on means, omitting the extreme values. Therefore, they cannot capture rapid changes in traffic flow caused by any incidents or work zones (Davis et al. 1990). Kamarianakis and Prastacos (2003) underlined that numerous loop detectors' data cause excessive computational time when predicting traffic flow through ARIMA, which is difficult to reflect the real-world urban roadways.

Functional limitations of existing HAMs and ARIMA models for predicting traffic flow were comprehensively reported by Pan et al. (2012). They underscored that HAMs cannot react to traffic dynamics affected by any traffic events (e.g., road construction, social events, and accidents), while ARIMA has no capability to control sudden changes in traffic flow. Also, it was found that ARIMA models are not accurate in long-term traffic flow because they rely on the very recent data (Pan et al. 2012).

3.2.2 Multivariate Modeling Approaches

Unlike univariate models, multivariate models can represent traffic flow in numerous locations (Kamarianakis and Prastacos 2003). Kamarianakis and Prastacos (2003) underscored that multivariate models could represent the spatial characteristics of the roadway network and temporal evolution of traffic flow in other locations in the network. Multivariate models are created through the state-space formulation. A state-space model extends a univariate time series model to multivariate conditions. State-space models were introduced by Okutani and Stephanedes (1984), in an effort to predict traffic diversion in urban freeway entrance ramps. Kamarianakis and Prastacos (2005) proposed the space-time ARIMA model that attempts to represent the spatiotemporal evolution of traffic flow in urban roadways. Statthopoulos and Karlaftis (2003) highlighted that multivariate state-space models improved the accuracy of prediction, compared to univariate ARIMA models.

As a parametric statistical technique, a Kalman filter is the most widely used technique to obtain a solution for the state-space formulation (Chang et al. 2011; Oh et al. 2015; Okutani and Stephanedes 1984; Whittaker et al. 1997). This technique continuously updates the selected state variables through time series approaches, by assuming certain relationships between state vectors and discrete time period, and between observation vectors and the corresponding observation equations (Kalman 1960; Oh et al. 2015). Utilizing Markov transition matrix, a selected state vector is generated through the past and current observations along with an optimal state vector (Kalman 1960). However, Kalman filters based on the Markov process has limitations for use in efficiently and effectively predicting future traffic flow. The Markov process encompasses hidden mechanisms, lacking the dependence on functional mechanisms (Oh et al. 2015). In addition, the first-order Markov chains with stationary transition probability have no capability to deal with inconsistent and disproportionate natures of traffic flow.

3.2.3 Machine Learning Approaches

Due to the nonlinear characteristic of traffic flow by its nature, researchers have paid much attention to nonparametric methods that do not undertake any particular functional form to represent the relationship between the dependent and independent variables. Nonparametric methods attempt to detect historical data that are similar to the prediction one and utilize the average of the detected datasets to forecast future (Lin et al. 2013; Lv et al. 2015). As nonparametric methods, ML techniques aim to achieve definitive information from large sets of data for pattern recognition, classification, and prediction by unlocking the complexity of nonlinearity (Arciszewski et al. 1994; Effati et al. 2015; Jain et al. 1996; Kargah-Ostadi 2014), which has become widely used since 1990s (Portugal et al. 2016).

ML algorithms are generally classified into three kinds of learning: 1) supervised; 2) unsupervised; and 3) reinforcement learning (Portugal et al. 2016). Supervised learning starts with a training phase using labeled data having the expected output. The learning algorithm is then implemented having unlabeled input data and generating output, which is available for using with unknown data to validate the accuracy of the predictive responses (Ekedebe et al. 2015). Unsupervised learning algorithms are appropriate for discovering hidden patterns by employing unlabeled data, such as clustering and k-means. Reinforcement learning algorithms that learn from the mistakes aim to improve rewards of future outputs by receiving feedback from the corresponding real-world outputs.

Most widely-used supervised ML algorithms for traffic flow prediction include Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Artificial Neural Networks (ANN) algorithms. Some researchers applied the SVM algorithm to short-term traffic flow prediction because it has good generalization ability based on statistical learning theory (Chang et al. 2011; Cong et al. 2016; Gu et al. 2015; Su et al. 2007; Tang et al. 2013; Wei and Liu 2013; Yu and Lam 2014). In addition, KNN algorithm also has been widely used in traffic flow pattern searching studies, because of its simple process of training data and estimating parameters (Cai et al. 2016; Dell'Acqua et al. 2015; Hong et al. 2015; Zheng and Su 2014). However, these algorithms have several drawbacks in practical application. SVMs tend to make decisions difficult in choosing the kernel and the size of training and testing sets, while not providing a parametric functional form for the reasonable interpretation (Chang et al. 2011; Karamizadeh et al. 2014; Yu and Lam 2014), while nonparametric regression such as KNN is computationally expensive to find the nearest neighbors if the dataset is large (Chang et al. 2011).

Among various ML algorithms, ANN approaches have been proven to provide potentially plausible prediction models with the good accuracy for many transportation applications and have been explored extensively over the decades (Abdi and Moshiri 2015; Kumar et al. 2015; Liu et al. 2016; Pamuła 2011; Sommer et al. 2015). Especially, a large number of studies have been deployed in an effort to predict traffic flow using ANNs (Chen and Chen 2007; Dougherty and Cobbett 1997; Innamaa 2000; Kumar et al. 2015; Ledoux 1997; Li and Liu 2014; Lingras and Mountford 2001; Pan et al. 2015; Shahsavari and Abbeel 2015; Smith and Demetsky 1994; Sommer et al. 2015; Tiefeng 2010; Zhang 2000; Zhu et al. 2014). An extensive systematic review of literature in this specific ML approach to predicting traffic flow is undertaken in the following section (Section 3.3).

In summary, as depicted by Figure 3, most of the previous studies using the most widely used ML techniques such as SVM, KNN, and ANNs over the past fifteen years have been centered on predicting the generic short-term traffic flow under the normal condition, which are not suitable for scheduling construction work zone applications. All the previous studies using the selected ML approaches focused on predicting normal traffic conditions over the last decade, without work zone conditions. As shown in Figure 3, ANNs have been the most commonly used ML approaches to traffic flow prediction, compared to KNN and SVM. Specifically, previous research efforts prove that the ANNs has a relatively high potential to be suited for the long-term traffic flow prediction. In other words, there remains questionable about the suitability of long-term traffic flow prediction through the other learning approaches.

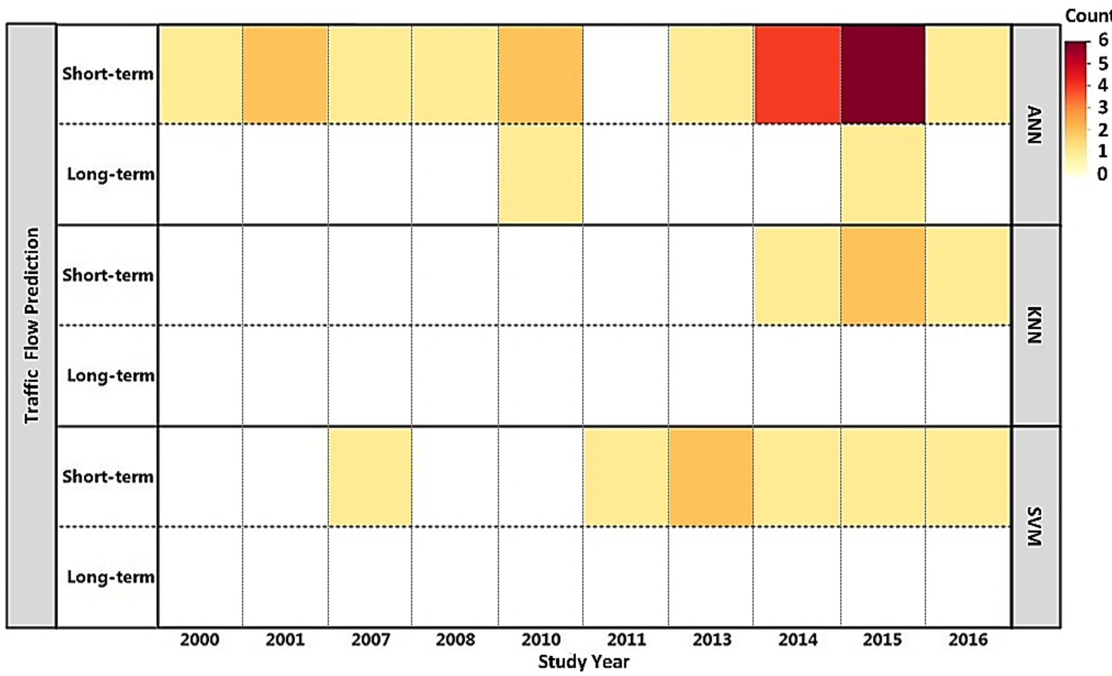


Figure 3 A summary of studied machine learning approaches to traffic flow prediction (2000-2016)

3.3 Traffic Flow Prediction Using Artificial Neural Networks

In spite of common drawbacks of long training time and complex internal structure in ANNs (Chang et al. 2011; Sommer et al. 2015), there are main reasons why a large amount of studies have paid much attention to ANNs among several ML approaches. First, ANNs have the capability of controlling multi-dimensional data and do not require assumption checking regarding data (Ma et al. 2015). Second, the structure of an ANN is robust to achieve reliable prediction performance by changing its structure and internal information that pass through the network during the training phase, thereby being applied feasibly to any system (Rizwan et al. 2016; Sheela and Deepa 2013; Sommer et al. 2015). Last, ANNs are capable of inherently modeling highly nonlinear systems (Gevrey et al. 2003; Rizwan et al. 2016; Sheela and Deepa 2013; Sommer et al. 2015).

With these strength of ANN learning approaches, many studies over the last decade have been used ANN approaches to transportation applications, specifically aiming at improving the accuracy and efficiency of traffic flow prediction. In detail, many of previous studies applied Multi-Layer Perception (MLP) networks for traffic flow prediction. Innamaa (2000) employed an MLP network to predict short-term traffic flow 15 minutes ahead of the observed data. The proposed network used the combination of activation functions including a hyperbolic tangent for the hidden layer and a linear function for the output layer, in order to improve the accuracy of the network model. Although the performance of the proposed model was accurate by having a small mean squared errors, mean relative errors, and mean errors, the authors pointed out that a small amount of data (i.e., one-month period) and the number of observations during peak period should be greater in order to make the model learn and predict the potential short-term flow better.

Dia (2001) proposed an object oriented neural network for short-term traffic prediction, which lays a solid groundwork for modeling complex interactions, by mixing rules of supervised and unsupervised learning algorithms in the same network model or incorporating a recurrent processing factor into a hidden layer of Feedforward Neural Networks (FNN). Jin and Sun (2008) introduced the multi-task learning NN through FNN for traffic flow prediction from the historical dataset. The multi-task learning in this study represents more than one predicted output values, which is different from single task learning that has the only one single main predicted flow output. The proposed model was developed using a sigmoid function for the activation function and trained by Levenberg-Marquardt algorithm considering its efficiency and precision. The authors underlined that single task learning tends to fail to attach important information resources, while the proposed multi-task learning can improve the generalization of the network and have higher accuracy of the prediction. Çetiner et al. (2010) employed a three-layered ANN to predict traffic flow in a metropolitan city in Turkey, Istanbul, by using temporal traffic input data during one year, 2006. To achieve the best performance of the network, the network was trained and tested by changing the network structure and cases of input variables related to temporal characteristics. The prediction was performed based on either 5-minutes interval traffic data or 1-hour data through two different network models. The authors concluded that hourly prediction is recommended because of the accuracy of prediction in the study area, Istanbul.

Passow et al. (2013) tested the suitability of four distinct ANN techniques to predict traffic flow conditions in the city of Leicester, UK, which include feed-forward backpropagation, cascade-forward back propagation, radial basis, and generalized regression ANNs. To achieve the accuracy of the prediction, hours of the day, days of the week, and a number of weather conditions (i.e., temperature, cloud coverage, air pressure, rain, wind speed, and direction) were taken into the network. The authors highlighted that the feed-forward backpropagation led to the best results, closely followed by the cascade-forward backpropagation. To predict short-term traffic flow, Cao and Han (2014) applied a back propagation neural network that is a multilayer FNN training with the error back propagation algorithm. The proposed model trained and predicted traffic flow at the same time of different days and sequent time of the same day in a Chinese urban arterial. The authors concluded that the error was small, and thus the proposed network can predict the short-term flow well.

Dai et al. (2015) investigated the unique characteristics of traffic patterns in holidays within Zhejiang province in Shanghai freeway in China, both spatially and temporally. An ANN model using an MLP network was then applied to predict the traffic flow in the future 5 minutes, which led to the good accuracy of the traffic flow prediction in holidays. Kumar et al. (2015) investigated whether ANN is effective to predict short-term traffic prediction. An MLP network, also known as FNN was used to predict 5-minute ahead traffic volumes of four-lane non-urban highway in India. For generating the network, a set of 480 data records were used, including the day of the week, time of day, classified traffic volume (e.g., car, van, bus, truck, and so on), the corresponding average speed of vehicles and density of vehicles. The authors underlined that FNN could predict vehicle count accurately even if vehicle types and their corresponding speeds were controlled separately. However, key issues behind this study lie in the use of a limited number of input parameters and time period. Specifically, weather condition, seasonal variation, and congestion were not taken into consideration.

In addition, the study data collected during only off-peak hours would cause practical and technical limitations. Liu et al. (2016) compared four training algorithms (Gradient Descent (GD), Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Fletcher-Reeves conjugate gradient (CGF)) in an MLP ANN model to test the accuracy and efficiency of short-term traffic flow prediction. The results represented that the models trained by LM, BR, and CGF had similar performance on the aspect of the prediction accuracy, while these three outperformed GD-based MLP model. In terms of the computation efficiency, BR-based MLP network model held the best performance. The authors concluded that the BR-based MLP network model is the most appropriate for prediction short-term traffic flow.

Other studies employed the RBF neural network that is the other type of the FNN. Chen and Chen (2007) explored an ensemble learning approach that combines Radial Basis Function (RBF) network predictors with the bagging method in order to improve the predictability of unstable procedures of existing RBF networks. As one of the most popular ensemble methods, bagging stands for Bootstrap Aggregation and attempts to decrease the variance of prediction by producing additional training data from the original dataset. The authors employed the proposed network to predict short-term traffic flow at a certain location of the Loop 3 freeway in Beijing, China. Zhu et al. (2014) proposed a new method based on RBF networks to predict short-term traffic flow at the adjacent intersections.

To summarize the review of previous studies on ANN approaches to traffic flow prediction in a nutshell, there is a still knowledge gap in achieving accurate and reliable prediction of long-term traffic flow before and during construction. In addition, there still remains a significant gap in existing body of knowledge whether they can capture the potential stereotypical long-term traffic flow within a distinct set of clusters, while covering the multi-contextual complexity that affects traffic flows before and during construction.

3.4 Summary of Literature Review

It was found throughout an extensive literature review that existing methods and processes for the implementation of work zone impact analysis and traffic flow prediction still have critical limitations. For the betterment of construction work zone traffic analysis, many previous research efforts have been made through empirical studies. However, empirical studies are very project-specific, thereby lacking the capability to develop generalized computational models for successful TMPs.

To overcome this deficiency, microscopic and macroscopic modeling approaches to traffic flow dynamics have been mainly used to analyze CWZ impacts, by estimating queue lengths and travel delay. Throughout the pertinent literature review, it was revealed that microscopic models could not represent global descriptions of traffic characteristics and often are restricted to simplified data that cannot be applicable to various real-world situations. In addition, macroscopic traffic flow models based on the kinematic wave theory and queuing theory are too simplistic to create accurate traffic impacts of highway construction work zones, especially roadway segments upstream of work zones affected by lane closure.

A common issue of existing CWZ impact analysis methods was identified that they require accurate estimates of traffic flow. Despite many previous research efforts, most existing approaches to traffic flow prediction are often univariate, assumed as linear structures, and focused on short-term. These previous studies cannot therefore provide a guidance for benchmarking the potential traffic impact of CWZs.

To address this issue, a comprehensive overview of three different traffic flow prediction modeling approaches was conducted. As the most representative univariate model, ARIMA models tend to focus on means, omitting the extreme values. In turn, they cannot control rapid changes in traffic flow. Although multivariate models improve the accuracy of prediction compared to univariate models, the both univariate and multivariate time series analyses assume linear correlation structures, which means that they have limitations to effectively address the nonlinearity of traffic flow.

Due to the nonlinearity of traffic flow by itself, ML approaches have been widely used to predict traffic flow, utilizing SVM, KNN, and ANN over the past fifteen years. Comparing with SVM and KNN, many studies over the last decade adopted ANN approaches to transportation applications, specifically aiming at improving the accuracy and efficiency of traffic flow prediction. However, most of these ML approaches focused on generic short-term traffic prediction under normal traffic flow conditions, meaning that these are inappropriate for incorporation into scheduling CWZ applications. Therefore, there is a still knowledge gap in achieving accurate and reliable prediction of long-term traffic flow. In addition, there still remains a significant gap in existing body of knowledge whether they can accurately capture the potential stereotypical long-term traffic flow within a distinct set of clusters, by integrating the multi-contextual complexity in and around work zones.

4. MULTI-CONTEXTUAL DATA COLLECTION AND SUMMARIZATION

In an effort to benchmark long-term traffic flow in heavily trafficked critical urban highway networks, Annual Average Daily Traffic (AADT) values served as a baseline for addressing highly congested urban areas where the AADT volumes are over 250,000 (Federal Highway Administration 2015). Among various urban sets of heavy AADT clusters that were examined, the City of Los Angeles (LA) in the state of California was chosen for this study because LA has been named the city with the worst traffic in the United States (CBS Los Angeles 2016; Chew 2016). A national transportation research group named by TRIP estimated that the average driver in urban areas in LA loses 61 hours a year due to traffic congestion, which can be translated into the form of $2,485 of additional vehicle operating costs due to congestion annually (TRIP 2014). In this regard, the learned knowledge through the case of LA would be applied to other critical urban highway systems with similar characteristics but where sensor data are not available.

Within a city or county limit, it was found that the overall traffic flow follows different patterns along with types of spatial regions (e.g., downtown, residential, and attraction areas) because the traffic flow is significantly affected by the spatial characteristics (Demiryurek et al. 2009). Among several spatial regions, in general, the Central Business District (CBD) is characterized by a key urban structure type and commercial land use (i.e., retail and service business). CBDs commonly appear through large cities and is home to numerous economic activities (Stewart et al. 2016;

Taubenböck et al. 2013). Nilsson and Smirnov (2016) pointed out that these economic activities are significantly affected by changes in the transportation system, such as the potential capacity expansion and the proximity of transportation infrastructure.

In this study, as the traffic flow analysis zone, Interstate highways adjacent to the CBD, simply known as "Downtown LA," were selected for this study. In detail, highway directions toward the CBD including I-10 East and I-110 South were served as the traffic flow analysis network. When considering that the CBD is a common significant urban structure in major cities, the potential traffic impact of CWZs in a large urban core would be appropriately benchmarked by the CBD in LA. As a part of the LA metropolitan area, Downtown LA ranks the first on the list of congested regions in the United States (CBS Los Angeles 2016). Therefore, the traffic analysis zone chosen for this study is expected to be applicable for analyzing the potential traffic impact in other large urban cores.

Figure 4 shows the hierarchical outline of the data collection for this study as follows:

1) A traffic flow analysis zone was selected, which is highways adjacent to the CBD.
2) Traffic sensored data in the traffic analysis zone were achieved from the Caltrans PeMS during the whole year in 2014.
3) Multi-contextual datasets such as highway facility, weather, and socio-demographic contexts were collected from the PeMS, National Oceanic and

Atmospheric Administration, U.S. Census Track, and the City of LA, respectively.

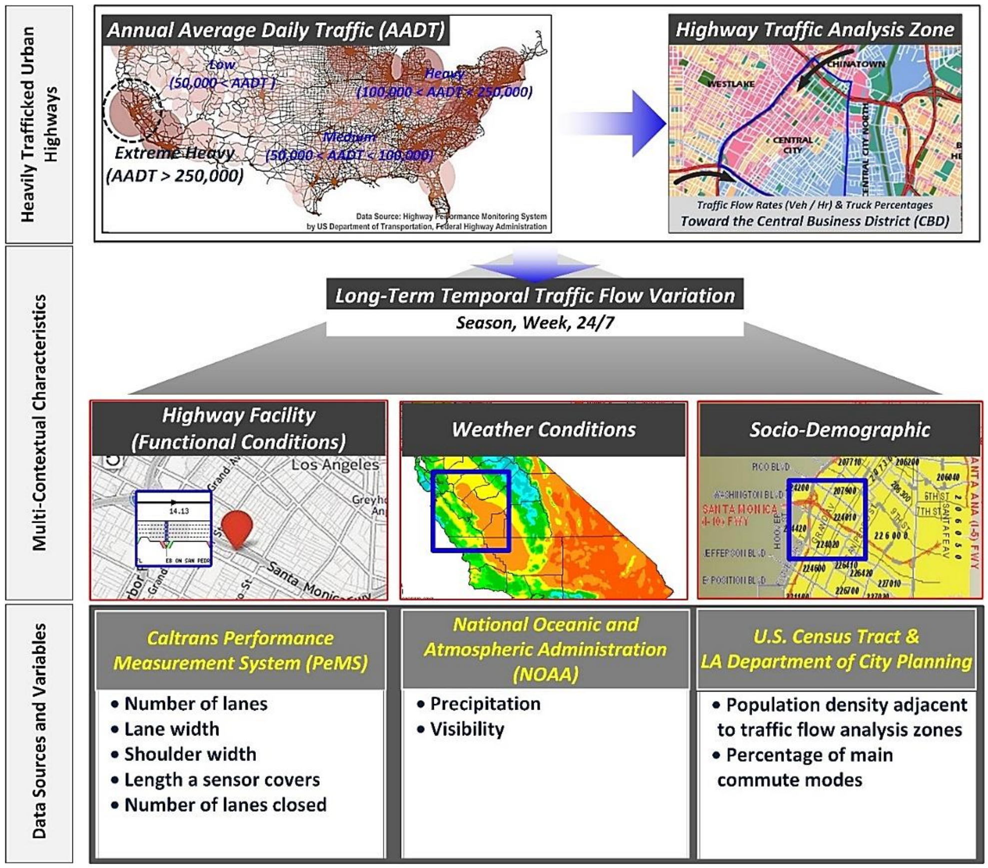


Figure 4 Multi-contextual data collection

4.1 Traffic Data Collection and Summarization

Traffic flow data near the CBD in LA were collected from the Caltrans PeMS database. PeMS collects traffic data every 30 seconds from over 15,000 individual loop detectors that are placed in freeway systems across the state of California (Chen et al. 2001; Lv et al. 2015). The collected traffic data are then aggregated at a 5-minute interval for each detector (Caltrans 2012; Lv et al. 2015).

In this study, a total of 17,518 traffic sensor readings on Interstate highways (I-10 East and I-110 South) adjacent to the CBD were extracted from the PeMS database. Hourly traffic volumes that include the corresponding percentage of trucks are collected during the whole year in 2014 (0:00 am on January 1 to 11:59 pm on December 31, 2014). These two key traffic parameters of hourly traffic volumes and truck percentages were served as target prediction values in the proposed network model, which can contribute to conduct the mandated work zone traffic analysis through the demand-capacity model described in the Highway Capacity Manual (Transportation Research Board 2010). Especially, demand is defined as the 24-hour hourly distribution of vehicles passing through the work zone in a single direction under normal operating conditions, which are unknown and thus require reliable potential traffic flow at the work zone site (Federal Highway Administration 2011). In addition, capacity is defined as the maximum possible traffic service flow (Transportation Research Board 2010), and percentage of trucks is one of the most critical determinants of the capacity adjustment during construction.

Figure 5 shows a summary of temporal granularity of the traffic flow data projected by 24-hour traffic flow on every day in a week per season, while a total of 10 American holidays were separated from the regular day of the week. First, 24-hr traffic flow datasets obtained from each sensor were collected. At the second level, the granularity of temporal summaries was increased by providing a set of traffic flow with each one representing a unique day in a week, which consist of a total of 8 categories of days of the week and a total of 3 categories of week levels including weekdays, weekends, and holidays. At the third level, the temporal granularity was increased by seasonal information, which is classified into four seasons: 1) Spring (March-May); 2) Summer (June-August); 3) Fall (September-November); and 4) Winter (December-February). Based on such a hierarchy, the summarized traffic flow datasets were classified into different long-term temporal scales.

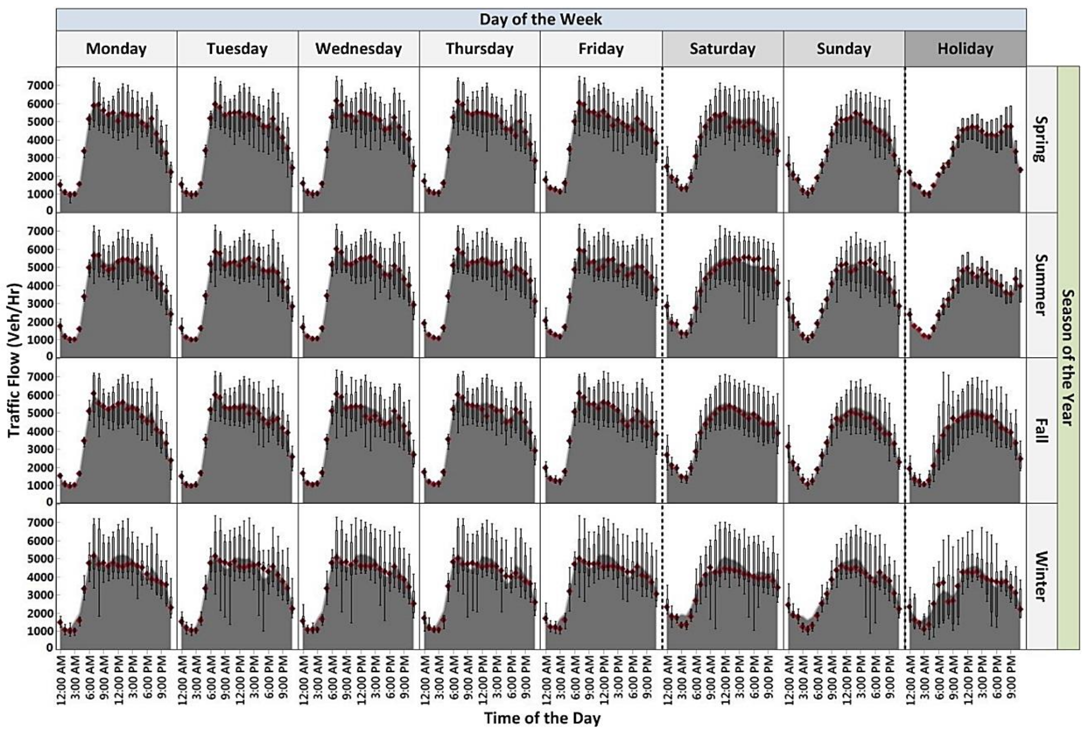


Figure 5 A summary of temporal granularity of the traffic flow data

As shown in Figure 5, the filled areas representing traffic flows are generated by the corresponding mean values. The other graphical components present box-and-whisker plots of the traffic flow data at the long-term traffic scales. The ends of the whiskers show the lowest and highest flow data within 1.5 interquartile range of the lower and upper quartiles to effectively isolate outliers (Choi et al. 2016). The boxplots also indicate that all the temporally classified traffic data had large gaps of interquartile ranges, caused by the generalized long-term temporal scales obtained from multiple sensor readings. Therefore, there remains questionable about the quality of traffic data whether this generalized profile of long-term temporal traffic flow toward the CBD can be repeatable and reproducible in an effort to apply for other similar cases. This issue was resolved through the gauge repeatability and reproducibility study in Section 5.2.

4.2 Multi-Contextual Characteristics

In addition to the temporal context frame as seen in Figure 4, other multi-contextual datasets were collected in order to improve the accuracy of prediction of the proposed network learning model: 1) highway facility functional information; 2) weather conditions; and 3) socio-demographic characteristics.

4.2.1 Highway Facility Functional Information

Highway facility functional variables were collected from the PeMS to capture the impact of the existing highway capacity condition on the traffic flow variation under normal condition as well as the potential traffic flow under lane closures. In this study, as stated previously through Section 2.5, the location-based highway facility functional information is limited to mainlines in multilane (3, 4, and 5 lanes in one direction having 12 ft. of each lane width). Finally, the highway facility functional context included the number of lanes, the road length covered by each sensor, and the number of lane closures due to construction.

4.2.2 Weather Conditions

As stated previously, previous studies using statistical approaches have reported that changes in traffic flow are affected by weather conditions along with spatial characteristics of roadway network (Datla et al. 2013; Keay and Simmonds 2005; Maze et al. 2006). To capture traffic flow variations affected by weather conditions and improve the accuracy of prediction, precipitation and visibility data were incorporated into the MICUZ framework. The historical datasets of daily precipitation and visibility in 2014 were collected from the Quality Controlled Local Climatological Data (QCLCD) database provided by National Oceanic and Atmospheric Administration (NOAA). Figure 6 shows a summary of weather conditions at the daily temporal scale. Snowfalls were excluded due to the climatic characteristics of the study region.

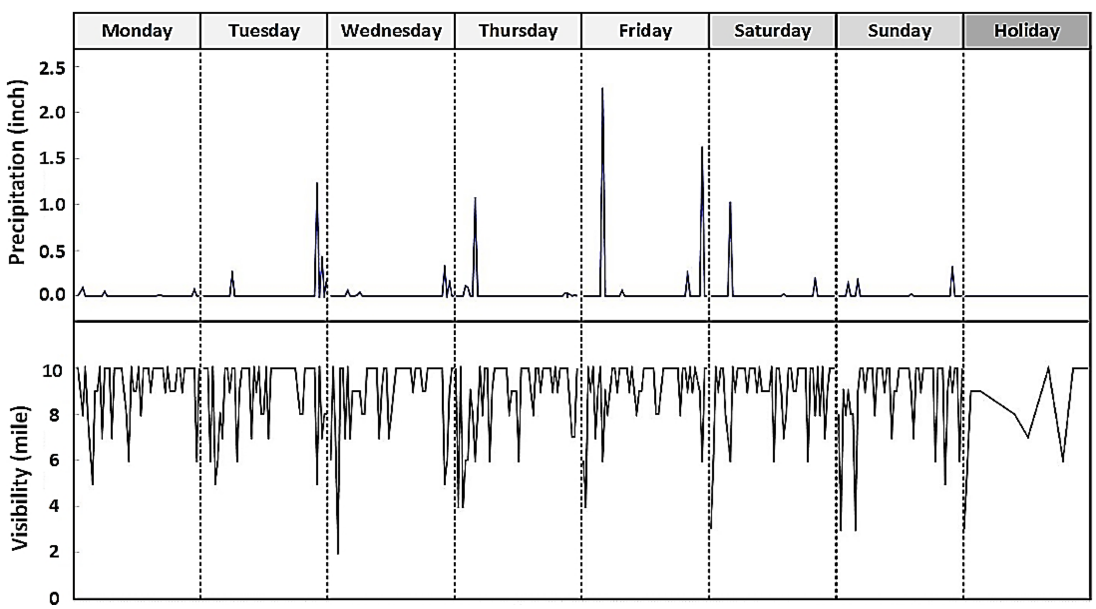


Figure 6 Weather conditions at the daily temporal scale

4.2.3 Socio-Demographic Characteristics

To improve accuracy, the MICUZ framework employs the context of socio-demographic characteristics, including the population density near traffic flow analysis zones and primary commute modes on highways. When considering the unique characteristics of CBDs, other factors such as household size, household income, and public transit mode were excluded, which might be effective to predict the future traffic flow around residential areas. Population density in the Census areas adjacent to the traffic flow analysis zone was collected from Census Tracts of California (State of California 2016). In addition, percentages of primary commute modes on the highways, such as self-driving and car/vanpooling, were collected from the LA Department of City Planning (City of Los Angeles 2016). The both quantity data were originally provided by the U.S. Census Bureau.

4.3 Descriptive Statistics of Multi-Contextual Datasets

Table 1 shows descriptive statistics of multi-contextual variables used in the proposed multi-contextual learning model (Phase II), which consists of a total of 2 prediction target variables and 26 input variables that are classified into the aforementioned four different multi-contextual frames. As seen in Table 1, multi-contextual frames include several types of continuous, ordinal, and categorical variables, which represents that the multi-contextual frames are shown as a highly nonlinear and complex system. Therefore, a ML algorithm using an ANN technique is expected to be the most appropriate to develop the proposed learning model through Phase II of the MICUZ framework, compared to other ML algorithms such as SVM and KNN.

Table 1 Descriptive Statistics of Multi-Contextual Variables

Context	Variable	Unit	Type	Min.	Max.	Mean	Standard Deviation
Prediction Target	Traffic flow rate	veh/hr	Continuous	495	7,523	4,032.3 9	1773.47
	Percentage of trucks	%	Continuous	0	23.55	1.571	1.493
Temporal	Season	-*	Categorical	-			
	Week	-**	Categorical	-			
	Day	-***	Categorical	-			
	Time	am/pm	Continuous	0:00	23:59	-	-
Highway	Number of lanes	EA	Ordinal	3	5	-	-
	Length	mile	Continuous	0.65	1.08	0.866	0.215
	Number of lanes closed	EA	Ordinal	0	4	-	-
	Lane closure filter	-****	Categorical	-			
Weather	Precipitation	inch	Continuous	0	2.24	0.028	0.178
	Visibility	mile	Continuous	2	10	8.996	1.543
Socio-Demographic	Population density	ppl/sqmi	Continuous	12,427	16,494	14,545	2,033.53
	Self-Driving	%	Continuous	25.3	57.1	41.854	15.8
	Car/vanpool ing	%	Continuous	5.8	10.9	8.245	2.55

*: Spring, Summer, Fall, and Winter
**: Weekdays, Weekends, and Holidays
***: Monday-Sunday, and Holiday
****: Yes or No

5. PHASE I: ROBUSTNESS CHECK OF COLLECTED SENSORED DATA

The main objective of this research phase aims to test whether traffic flows extracted from archived multiple sensor data can be repeatable and reproducible and be thus applicable to spatiotemporally similar characteristics of roadway networks. Existing traffic data management systems obtain numerous traffic data from multiple sensor readings, which would result in biased results when identifying the unique characteristics of traffic data within a distinct set of clusters. Specifically, Interstate highways adjacent to the CBD in the City of LA consist of multiple traffic sensor readings so that it is difficult to capture the most representative periodicity of traffic data representing the CBD. Therefore, there is a pressing need to adopt an appropriate validation technique to extract the informative data that can spatiotemporally represent the unique characteristics of a distinct set of traffic analysis zones, such as heavily trafficked urban highways adjacent to the CBD in major cities.

As a preparation for developing the proposed network learning model that predicts long-term traffic flow before and during construction, this study performed the Repeatability and Reproducibility (R&R) study on the collected historical traffic flow sensor readings through Wheeler's Honest Gauge R&R (HG) Method. A two-stage R&R study was conducted to determine the R&R of the collected traffic flow measurements before lane closure (Stage I) and to validate the R&R of historical traffic flow measurements during lane closure (Stage II).

5.1 Background of Measurement System Analysis

Variations of data in measurement systems always occur due to measuring devices, operators, or the nature of measured parts (Burdick et al. 2003; Joubert and Meintjes 2015), which often cause the systematic error (i.e., bias) in a measurement (Smith et al. 2007). Hoffa and Laux (2007) stated that the Automotive Industry Action Group (AIAG) provides one of the widely used standard methods of assessing the measurement precision error defines a measurement system as "*a collection of instruments or gauges, standards, operations, methods, fixtures, software, personnel, environment, and assumptions used to quantify a unit of measure or the complete process used to obtain measurements* (AIAG 2002)."

To scientifically validate the use of data in various measurement systems while overcoming certain limitations, a Measurement System Analysis (MSA) plays a vital role in determining the accuracy and precision of measurement systems. MSA qualifies a measurement system for use by quantifying systematic errors through the examination of multiple sources of variation in a process (Awad et al. 2009; Hoffa and Laux 2007; Larsen 2003).

The precision of measurements can be translated into two key parameters: repeatability and reproducibility. Repeatability is the variation caused by the measurement system, which is determined by comparing the measurement results in the same part under the same condition more than once (Awad et al. 2009; Erdmann et al. 2009; Joubert and Meintjes 2015; MoreSteam 2015; Zanobini et al. 2016). Reproducibility is the variation caused by the measurement system or the variation observed when different operators measure the same part under the same condition (Awad et al. 2009; Erdmann et al. 2009; Joubert and Meintjes 2015; MoreSteam 2015; Zanobini et al. 2016). In order to determine how much of the process variability would be observed due to the variability of the measurement system, a study known as the Gauge Repeatability and Reproducibility (R&R) has been widely used (Zanobini et al. 2016).

5.1.1 Methods of Repeatability and Reproducibility Studies

Three methods of Gauge R&R studies have been widely used: 1) AIAG's Average and Range (A&R) method; 2) the Analysis of Variance (ANOVA) method; and 3) Wheeler's Honest Gauge R&R method (Joubert and Meintjes 2015).

The A&R method estimates the R&R, part-to-part contributions of the precision error, and the total measurement precision error, by analyzing the data through average and range charts (Stamm 2013). The ANOVA method of R&R analysis performs the R&R study by selecting multiple parts of a system and measuring a feature with multiple measuring devices several times. When it comes to these two methods described in the MSA manual by the AIAG, some of the previous studies pointed out that the ANOVA approach outperforms the A&R method (Antony et al. 1999; Burdick et al. 2003; Kazerouni 2009). The A&R has the tendency to underestimate the reproducibility of part interactions (Antony et al. 1999), whereas the ANOVA of R&R studies can calculate the confidence intervals of the R&R study (Burdick et al. 2003). To tackle these results, Osma (2011) compared the A&R method and the ANOVA method using a total of 90 measurements. The results represented that the A&R achieved the measurement system acceptable, while the ANOVA led to the unacceptable system by showing that the residuals were not normally distributed. Therefore, the author concluded that the ANOVA approach to the R&R study is not valid. Some researchers criticized the AIAG's methods, by pointing out that the AIAG's methods rely on the precision-to-tolerance ratio and produce the error of the calculation of the part-to-part variation that results in the weak acceptability (Ermer 2006; Knowles et al. 2000).

As the third method, Wheeler's HG method also comes from the criticism of the AIAG methods (Joubert and Meintjes 2015; Stamm 2013). In detail, Wheeler (2006) pointed out the traditional AIAG method controls standard deviations incorrectly. Wheeler (2006) introduced an alternative method of determining the precision of measurement systems, called the EMP (Evaluating the Measurement Process) methods. The HG method is an EMP version of a traditional Gauge R&R study, which differs from the AIAG's methods on the aspect of the measurement precision error sum to the total amount of variation and the criteria for assessing the R&R (Wheeler 2006). Stamm (2013) compared these three methods and underlined that A&R and HG methods are well fitted into determining the R&R in measurement systems that have low to medium criticality, whereas the ANOVA is suited to measurement systems that are highly critical (Joubert and Meintjes 2015). Joubert and Meintjes (2015) pointed out that the R&R study approaches to transportation applications can be categorized into low to medium criticality, which means that the A&R or HG method is appropriate. Table 2 shows mathematical formulation of the repeatability and reproducibility of measurement systems through the A&R and HG methods:

Table 2 Calculation Methods of the Repeatability and Reproducibility

	A&R Method	HG Method
Repeatability (R1) (%)	$(\frac{\bar{R}}{d})/TV \times 100$	$(\frac{\bar{R}}{d})^2/(TV)^2 \times 100$
Reproducibility (R2) (%)	$\sqrt{\frac{(R_o)^2}{d_o} - (\frac{o}{n \cdot o \cdot p} \times \frac{\bar{R}}{d})} \Big/ TV \times 100$	$(\sqrt{\frac{(R_o)^2}{d_o} - (\frac{o}{n \cdot o \cdot p} \times \frac{\bar{R}}{d})})^2 \Big/ (TV)^2 \times 100$
Combined R1&R2 (%)	$\sqrt{R1^2 + R2^2}/TV \times 100$	$(R1^2 + R2^2)/(TV)^2 \times 100$

Where

$\bar{R}$: Average range of all the collected data;

d: Bias correction factor;

R_o: The range of operator averages;

d_o: Bias correction factor for estimating variances for the number of operators;

n: The number of measurements taken on each part;

o: The number of operators;

p: The number of measured parts; and

TV: Total variation.

The total variation (TV) of the both methods shown in Table 2 is calculated by the following equation (Equation (1)):

$$\text{Total Variation (TV)} = \sqrt{R1^2 + R2^2 + PV^2} \quad (1)$$

Where PV represents the part variation that can be calculated by Equation (2):

$$\text{Part Variation (PV)} = \frac{R_p}{d_p} \quad (2)$$

Where R_p is the range of part averages and d_p is the bias correction factor for estimating variances for the number of parts.

5.1.2 Assessing the Repeatability and Reproducibility of Measurement Systems

As the guideline on acceptability of measurement systems, the AIAG offers the following guidance of criteria index (AIAG 2010; Joubert and Meintjes 2015):

- If R&R < 10%, then the Measurement System (MS) is acceptable;
- If 10% < R&R < 30%, then the MS may be acceptable; and
- If R&R > 30%, then the MS needs improvement.

Wheeler's method of determining the acceptability is based on the class of monitor. Specifically, a key of interpreting the test results lies on its four-class process monitoring approach based on the ratio of combined R&R to the total variation (Wheeler

2006). The following are the class monitors that were categorized by the attenuation of process signals:

- First class: less than 10% of attenuation of process signals;
- Second class: 10-30% of attenuation of process signals;
- Third class: 30-55% of attenuation of process signals; and
- Fourth class: over 55% of attenuation of process signals.

5.2 Repeatability and Reproducibility Analysis of Collected Sensored Data

The robustness of collected sensored data was analyzed through a two-stage Repeatability and Reproducibility (R&R) study on traffic flow measurements 1) before lane closure (Stage I) and 2) during lane closure (Stage II).

5.2.1 Stage I: Traffic Flow Before Lane Closure

As the very beginning stage of the HG method, the average and range charts of hourly traffic flow was generated. The average chart shows the average measurement for each operator and the combination of a number of parts in a measurement system, which serves as the baseline for making a decision whether it is needed to detect measurable part-to-part variation (SAS Institute 2007).

Figure 7 shows the average measurements of traffic flow on a daily basis as an operator role and 24-hr temporal part combination within each operator. This average chart presents that the variability in the mean of hourly traffic flow is outside of upper and lower control limits, which needs to discover measurable part-to-part variation. The both control limits are based on the most common principle of three standard deviations (i.e.,$\mu \pm 3\sigma$).

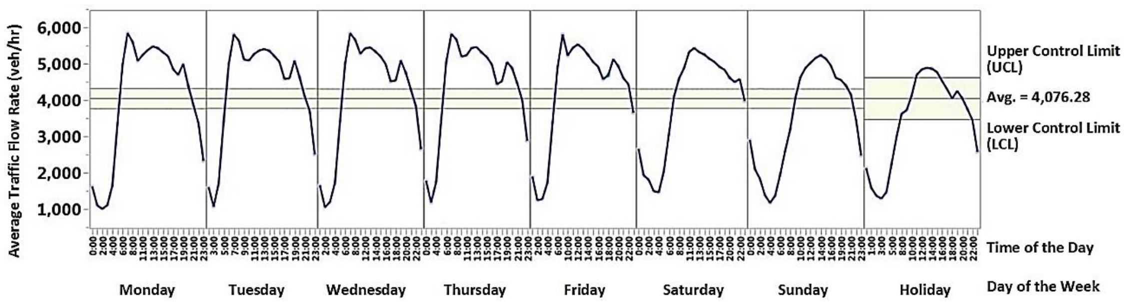


Figure 7 24/7 traffic flow measurement before construction

Figure 8 indicates the range chart showing the variability for each operator and the combination of 24-hr temporal parts. This chart represents that the collected multiple traffic flow sensor readings adjacent to the CBD followed the same measuring method and were consistent spatiotemporally, including the homogeneity of errors (i.e., similar variation).

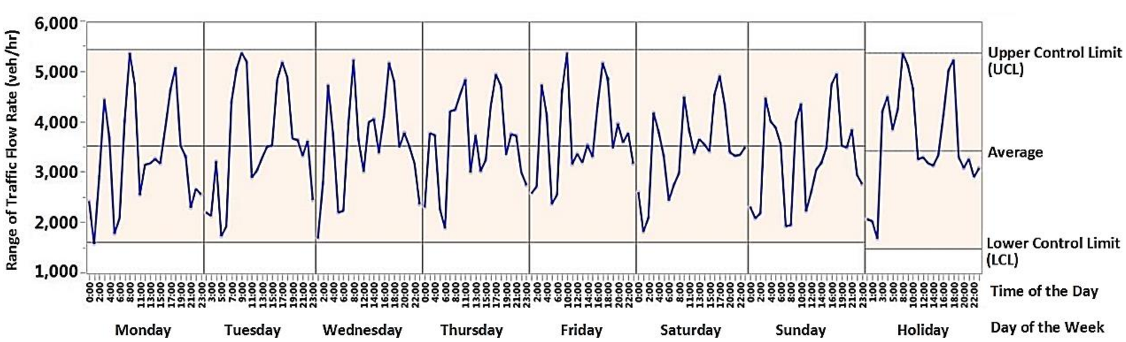


Figure 8 24/7 traffic flow fluctuation before construction

Table 3 shows the R&R study results of traffic flow measurements. Repeatability is determined by comparing the measurement results in the same time (hourly scale). Repeatability of traffic flow measurements led to 26.7% of total variation, which represents that the temporally classified traffic flow measurements are marginally acceptable. Meanwhile, reproducibility is the variation caused when different daily temporal scale measures the identical hourly scale. Reproducibility held 2% of total variation, which is less than 10% and is thus acceptable. The combined proportions (26.7 + 2 = 28.7%) caused the marginal acceptance of the repeatability and reproducibility of the traffic flow measurements.

Table 3 Gauge R&R Results of Traffic Flow Measurements

	Gauge R & R		
	Repeatability	**Reproducibility**	**Combined**
Proportions (%) of Total Variation	26.7	2	28.7

The result of determining the acceptability of the temporally classified traffic flow measurements was obtained from Wheeler's HG method. Bias impact was incorporated into calculating the intraclass correlation, which represents the amount how much the bias factors affect the measurement system and reduce the potential intraclass correlation. As seen in Table 4, 16.89% of attenuation of process signal indicates the second class classification meaning that the strength of the process signal would be weakened by 16.89%. The bias factors had 1.53% of the impact on the intraclass correlation, which represents that the intraclass correlation coefficient would be improved by 1.53% if the bias factors are eliminated.

Table 4 Four-Class Classification Monitor Results of Traffic Flow Measurements

Bias Impact	**Intraclass Correlation***	**Attenuation of Process Signal**	**Classification**	
			Current*	Potential**
0.0153	0.6907	0.1689	Second Class	Second Class

*: with bias
**: with no bias

5.2.2 Stage II: Traffic Flow During Lane Closure

Stage II R&R study aims to validate the repeatability and reproducibility of the collected historical traffic flow under lane closures due to construction, which can serve as the baseline of work zone traffic flow scenarios in the proposed network learning model by having scientifically validated traffic data near the CBD. Stage II analysis was conducted by the same procedure of stage I analysis.

Figure 9 shows the average measurements of traffic flow for work zones at weekly temporal scale as an operator role and nighttime part combination within each operator. This average chart presents that the variability in the mean of hourly traffic flow during weekday and weekend nighttime construction is outside of upper and lower control limits, which needs to identify measurable part-to-part variation.

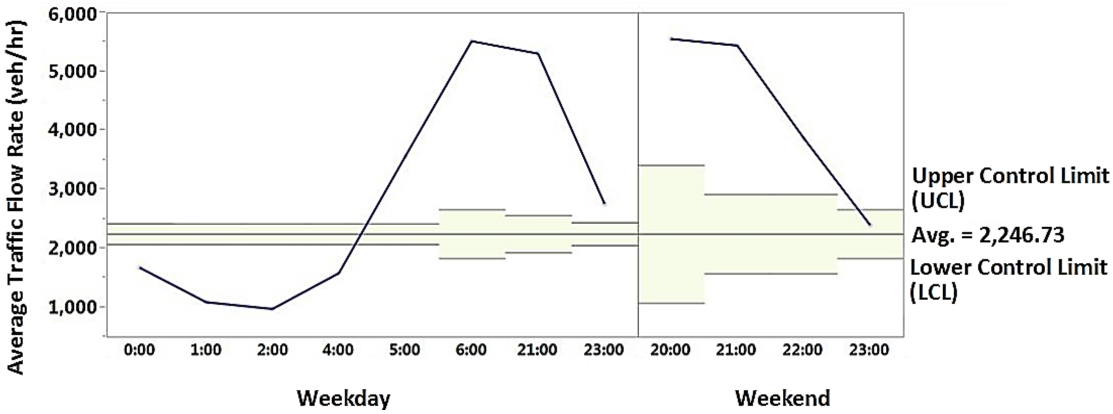


Figure 9 Traffic flow measurement during nighttime construction

Figure 10 indicates the range chart showing the variability for each operator and the combination of 24-hr temporal parts. This chart represents that the multiple traffic flow sensor readings during construction near the CBD include homogeneity of errors spatiotemporally.

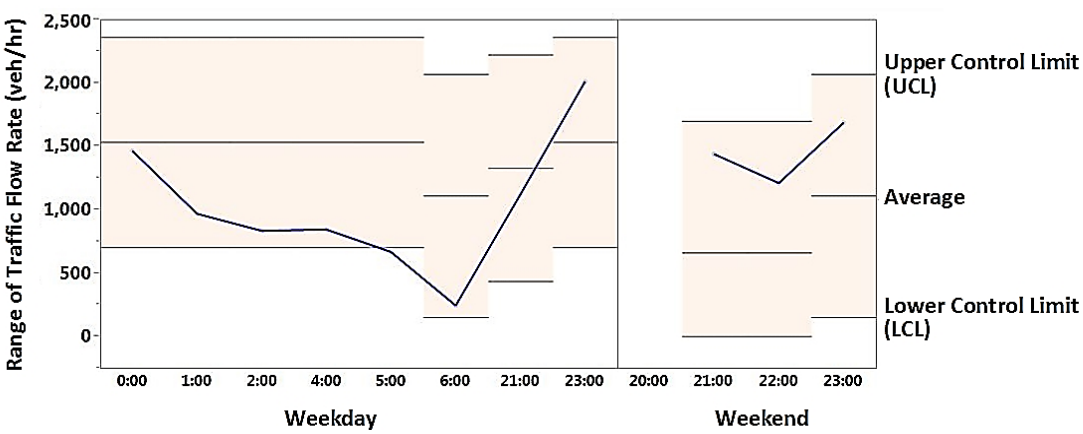


Figure 10 Traffic flow fluctuation during nighttime construction

Table 5 shows the R&R study results of traffic flow measurements. Repeatability is determined by comparing the measurement results in the same time (hourly scale). Repeatability of traffic flow measurements led to 2.4% of total variation, which represents that the work zone traffic flow measurements are highly acceptable. Meanwhile, reproducibility is the variation caused when different weekly temporal scales measure the identical hourly scale. Reproducibility had very little measurement variation by having zero percent of the total variation, which is also acceptable. The combined proportions (2.4 + 0 = 2.4%) caused the clear acceptance of the repeatability and reproducibility of the traffic flow measurements during the nighttime construction at the weekly temporal scale.

Table 5 Gauge R&R Results of Traffic Flow Measurements During Construction

	Gauge R & R		
	Repeatability	**Reproducibility**	**Combined**
Proportions (%) of Total Variation	2.4	0	2.4

In detail, as seen in Table 6, 1.22% of attenuation of process signal specifies the first class classification meaning that the strength of the process signal would be weakened by 1.22%. The bias factors had no impact on the intraclass correlation.

Table 6 Four-Class Classification Monitor Results of Traffic Flow Measurements During Construction

Bias Impact	**Intraclass Correlation***	**Attenuation of Process Signal**	**Classification**	
			Current*	Potential**
0	0.9758	0.0122	First Class	First Class

*: with bias
**: with no bias

5.3 Summary of Phase I

Multiple traffic sensor readings within a spatiotemporally distinct set of clusters, such as highway traffic flow variations adjacent to the CBD at a specific time on a specific day, would result in biased results when predicting the potential traffic flow under similar conditions. To address this issue, this research phase attempted to test whether multiple traffic sensor readings on traffic flows can be applicable to spatiotemporally similar characteristics of roadway networks. To achieve this goal, this study adopted Wheeler's HG method to determine the repeatability and reproducibility of temporally classified traffic flow measurements before construction (Stage I) and those of nighttime work zone traffic flow (Stage II). As the results, Table 7 provides a summary of two-stage R&R studies.

Table 7 A Summary of Two-Stage Repeatability and Reproducibility Studies

Measurements	**Components of Measurement System**		**Results**	
	Parts	Operators	Wheeler's Honest Gauge R&R Monitor	Combined R&R (%)
Stage I: Traffic flow before lane closure	24-hr temporal distribution	Daily temporal scales	Second Class	28.7
Stage II: Traffic flow during lane closure	Nighttime construction time period	Weekly temporal scale	First Class	2.4

For the both Stage I and II analyses, hourly temporal distribution served as the parts of the measurement system. The overall 24-hr time period was used in stage I analysis, while nighttime construction hours were served as the part considering the historical work zone traffic data. As the role of an operator that includes several parts, the daily temporal scale was used in stage I analysis to take a closer look at the repeatability and reproducibility of traffic flow variation. On the other hand, instead of the daily temporal scale, the weekly temporal scale was considered as the operator of nighttime work zone traffic flow measurements because the difference between weekday and weekend traffic flow was investigated through the normal traffic flow measurement analysis (Stage I). The results confirmed that the both Stage I and II analyses were scientifically validated by meeting with the R&R criteria and the class classification monitors developed by Wheeler, by resulting in the second class monitoring classification for Stage I analysis and the first class for Stage II analysis.

To summarize the confirmed results, it is noteworthy that traffic flow measurements during lane closure were relatively simpler and periodical within the urbanized downtown area. The analysis results can be translated into work zone characteristics. In general, work zones are relatively small areas, and certain restrictions are often applied to work zone traffic such as no lane changing, lowered speed limit, highway patrols' enforced traffic control, and so on. In this regard, work zone traffic flow data in urban downtown areas can appear more repeatable and reproducible than those under normal traffic flow conditions.

6. PHASE II: MULTI-CONTEXTUAL LEARNING MODELING VIA ANN

Throughout the previous section, the collected historical traffic data were scientifically validated on aspects of the repeatability and reproducibility at temporal scales. Especially, the historical traffic flow during lane closure revealed that highway construction projects were implemented employing the nighttime construction, considering the urban characteristics of the CBD. Based on the validated collected sensored data extracted from multiple sensor readings adjacent to the CBD in LA, California, this research phase aims to predict long-term traffic flow on the aspect of hourly traffic flow rates and the corresponding percentages of trucks. To achieve this goal, this research phase is intended to develop a multi-contextual learning model via artificial neural networks. The predicted outcomes will be then incorporated into the proposed curve fitting models specifically aiming at predicting the impact of CWZs in terms of travel time delay quantification throughout Section 7.

6.1 Background of Artificial Neural Networks

6.1.1 The Origin of Artificial Neural Networks

ANNs govern a simplified functioning of a biological neural system and attempt to simulate the network through advanced data management (Grant 2014; Kumar et al. 2015; Sommer et al. 2015). McCulloch and Pitts (1943) started with the concept of a single perceptron that is a single artificial neuron, currently also referred to as a node in

ANNs. ANNs as standard mathematical models were developed by Fausett (1994), based on the following assumptions:

- Numerous single neurons generate information processing;
- Neurons pass signals through connection links;
- Each connection link has a relevant weight by multiplying by the signal transmitted; and
- An activation function that is usually nonlinear is applied by each single neuron to its net input that is the sum of weighted input signals to determine the final output signal.

Fausett (1994) concluded that a neural network could be characterized by 1) its pattern of connection between neurons (i.e., its architecture); 2) its method how to determine the weights on the connection (i.e., its training or learning algorithm); and 3) its type of activation function.

6.1.2 Basic Structure of Artificial Neural Networks

A basic ANN topology can be drawn as a basic connection among perceptrons with the most simplistic network, as depicted in Figure 11 (Grant 2014; Kumar et al. 2015; Sommer et al. 2015). Any ANN must have each input and output layer and would one or more hidden layers to set a connection between input and output layers. A single (or multiple) hidden layer(s) include one or more hidden neurons that are connected to the neurons of the successive layer. As shown in Figure 11, an input is given to the corresponding input neurons (x_1 to x_n), which pass each of them to the next layer (i.e., output layer in this simple structure). The output layer then returns the final result.

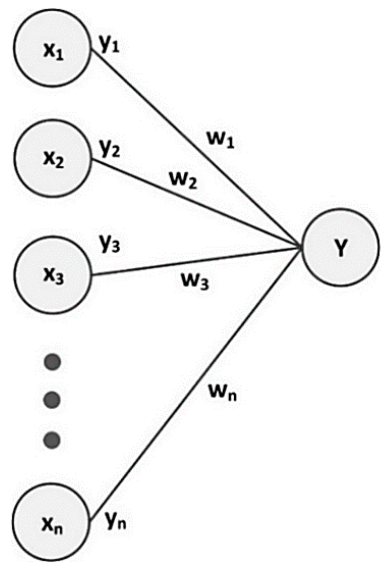


Figure 11 A basic ANN topology

Missing in the figure are bias neurons that are added to each input. The bias is commonly represented by a weight being multiplied by a constant input value. Specifically, the input value of perceptron *Y* is based on the weighted sum of the outputs of all neurons of the previous layer, as shown in Equation (3):

$$\sum_{i=1}^{n}(y_i \times w_i) \tag{3}$$

Where n is the number of connection of neurons, y_i is the i^{th} output value, w_i is the corresponding weight of the connection between two neurons.

The output of perceptron, Y, is then calculated by the selected activation function, f, shown in Equation (4) that highlights that the performance of ANN significantly depends on the connection weights and activation functions (Sommer et al. 2015).

$$Y = f\left(\sum_{i=1}^{n} y_i \times w_i\right) \tag{4}$$

6.2 Feedforward Neural Networks

The most widely used ANN model in traffic flow prediction is the Feedforward Neural Networks (FNN) that are specifically modeled by Multi-Layer Perception (MLP) or Radial Basis Function (RBF) (Karlaftis and Vlahogianni 2011; Kumar et al. 2015; Zhu et al. 2014). The MLP neural network is defined as an ANN having at least three layers of neurons that are interconnected: 1) an input layer; 2) one or more hidden layer(s); and 3) an output layer. During the learning process in an MLP network, all inputs are mapped on the corresponding outputs, which represents the supervised learning. In the MLP network, the hidden layer typically uses the sigmoid or the hyperbolic tangent function. The difference between the actual and the prediction outputs serves as a baseline to adjust the weights of neurons iteratively, thereby minimizing the total error over all input-output pairs (Abdi and Moshiri 2015).

As the other type of the FNN, the RBF neural network is also a supervised learning technique. However, the RBF network is different from the MLP network on aspects of its structure and the use of activation functions. The RBF network consists of a single hidden layer within the common three-layer network structure. In the RBF network structure, unlike the MLP, the input layer includes neurons with a linear function. The hidden layer employs a Gaussian function. Finally, the output layer produces the response of the network (Abdi and Moshiri 2015). The RBF take an advantage over the MLP because it is simpler than the MLP. The RBF acts as the local approximation networks, and their outputs are affected by specified hidden neurons in certain corresponding local values.

Although the MLP has more complex structure requiring iterative training, which might be slow for a large number of hidden nodes and datasets, many previous studies underlined that the MLP networks are compact and yield better learning outcomes, compared to other types of networks (Bissacot et al. 2016; Ilonen et al. 2003; Santos et al. 2013; Yu et al. 2011). A key reason is that the MLP networks work for large scale problems, and their outputs are determined by all the neurons in the networks (Ilonen et al. 2003; Santos et al. 2013; Yu et al. 2011).

6.3 Development of Multi-Contextual Feedforward Neural Networks

The proposed multi-contextual learning model encompasses a five-stage modeling process of the proposed learning model: 1) developing the network architecture; 2) determining the learning structure; 3) identifying the critical factors affecting the learning performance; 4) developing a multi-contextual learning model; and 5) evaluating the learning performance of the proposed model.

6.3.1 Stage I: Developing the Network Architecture

Stage I aims to create an architecture of the proposed network learning model based on the Multi-Layer Perceptron (MLP) network. As an MLP network, the proposed network is designed with three layers of neurons that are interconnected: 1) an input layer; 2) one hidden layer; and 3) an output layer. Figure 12 presents the architecture of the multi-contextual feedforward neural networks to predict long-term traffic flow and the corresponding truck percentage within a specific hourly traffic volume at a specific time on a specific day in a specific season, before and during construction.

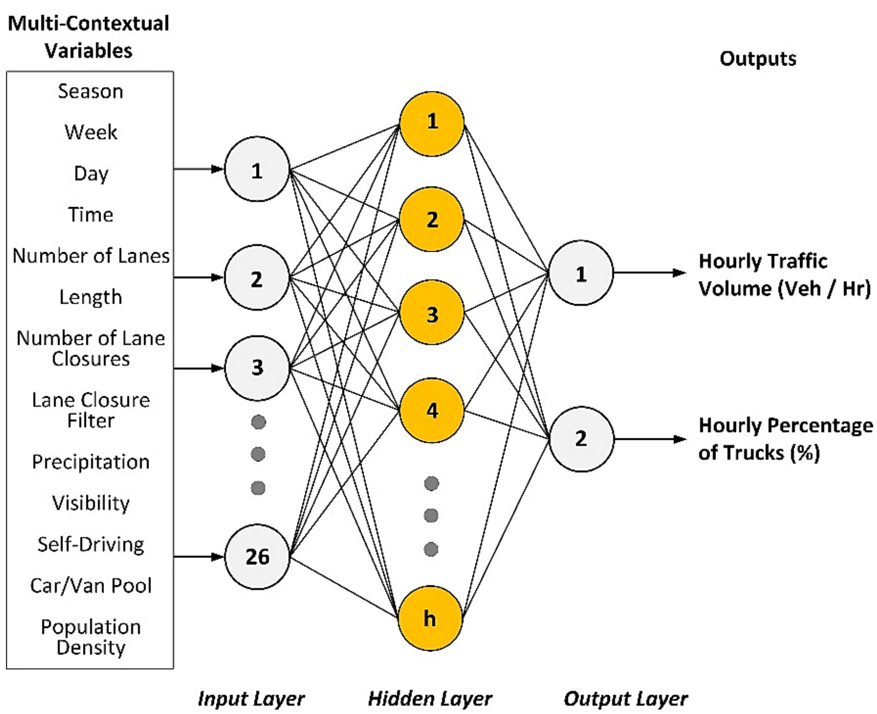


Figure 12 Architecture of the proposed multi-contextual learning model

As stated previously through Section 4.2, multi-contextual variables used in the proposed network learning model consist of a total of 26 input variables and 2 prediction target variables (outputs), which includes a total of 17,518 supervised data samples. All the multi-contextual variables (inputs) are mapped on the corresponding outputs, which represents the proposed learning model centers on the supervised learning of artificial neural networks.

6.3.2 Stage II: Identifying Critical Components of the Networks

The performance of neural networks is significantly affected by the connection weights and activation functions (Sommer et al. 2015). The connection weights are unknown parameters that can be estimated by a training algorithm (Vijayalakshmi and Sugumar 2016). In addition, activation functions are mathematical formulas, specifically aiming at deciding the output of processing nodes. An activation function plays a vital role in transforming inputs into the network (Kumar 2016). In detail, activation function for hidden nodes is needed to incorporate the nonlinearity into the networks.

For the betterment of determining the learning structure, critical components of the MLP networks were identified through previous studies: 1) activation functions, 2) training algorithms, and 3) the number of hidden nodes.

6.3.2.1 Activation Functions

Activation functions attempt to determine the output of processing nodes, by transforming inputs in the network (Kumar 2016). There are most commonly used activation functions in the MLP network: 1) the identity (i.e., linear) function, 2) the (logistic) sigmoid function, and 3) the hyperbolic tangent (*tanh*) function (Kumar 2016; Sommer et al. 2015).

With the identity function, the activation level is passed directly as the output of the processing neurons, without transforming the input (Bissacot et al. 2016). The sigmoid function is an *S*-shaped curve having the range (0, 1), while the hyperbolic tangent function is a symmetric *S*-shaped function that has the output range (-1, +1) (Bissacot et al. 2016; Kumar 2016; Sommer et al. 2015). The following are the mathematical forms of the aforementioned activation functions (Equations (5), (6), and (7)):

- The identity function

$$\mathrm{f(x)} = x \tag{5}$$

- The sigmoid function

$$\mathrm{f(x)} = \left(1 + \exp(-x)\right)^{-1} \tag{6}$$

- The hyperbolic tangent function

$$\mathrm{f(x)} = \left(\exp(x) - \exp(-x)\right)/\left(\exp(x) + \exp(-x)\right) \tag{7}$$

In this study, a total of 9 (=3^2) different combinations of the most widely used activation functions in the MLP network were considered as alternatives of hidden activation and output activation for selecting the learning structure, which consist of 1) the identity function, 2) the sigmoid function and 3) the hyperbolic tangent function as seen in Equations (5), (6), and (7). Hidden activation represents the activation function working for the hidden layer, while output activation indicates the activation function intended for the output layer.

6.3.2.2 Training Algorithms

One of the challenging problems when employing the neural networks is training the network because an ANN adjusts its structure during the learning process (Chen and Yao 2008). The connection weights are unknown parameters that can be estimated by a training algorithm (Vijayalakshmi and Sugumar 2016).

The Back Propagation (BP) algorithm is a traditionally well-known method for training an MLP feedforward neural networks (Lahmiri 2011; Mohammadi and Zangeneh 2016). The BP algorithm is formed in a supervised learning and produces a response based on random weights. Through an iterative process by changing weights, the error rate between the network output and actual (target) values decreases. This computational procedure starts from the output neuron and continues backwards (Mohammadi and Zangeneh 2016; Vijayalakshmi and Sugumar 2016).

The weights in the standard BP network are adjusted through the gradient descent algorithm. The gradient descent algorithm is a first-order algorithm that attempts to move incrementally to lower points in search space successively in order to reach a minimum (Bissacot et al. 2016; Mohammadi and Zangeneh 2016). This method updates the weights and biases in the negative gradient direction (Dao and Vemuri 2002; Lahmiri 2011). The new weight vector is adjusted as follows (Equation (8)):

$$\Delta \boldsymbol{w}_k = \boldsymbol{w}_{k+1} - \boldsymbol{w}_k = -\alpha \cdot \boldsymbol{g}_k \tag{8}$$

Where $\Delta \boldsymbol{w}_k$ is a vector of changes in weights, α is the learning rate determining the length of the weight update, and $\boldsymbol{g}_k$ is the current gradient of the error related to the weight vector.

The inefficiency of the gradient descent algorithm is drawn from its poor selection of the minimization direction and step sizes to reach the minimum error (Van Der Smagt 1994). In this regard, the standard BP network has a slow convergence in learning, while being often confined to the local minima (Lahmiri 2011). To overcome this hurdle, some previous studies introduced advanced BP algorithms, such as Conjugate Gradient (CG) and Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton (Bissacot et al. 2016; Dao and Vemuri 2002; Lahmiri 2011; Mohammadi and Zangeneh 2016). The both are currently widely used numerical techniques using the second-order methods, which allow networks to avoid local minima and provide much faster convergence than the standard BP algorithm (Bissacot et al. 2016; Dao and Vemuri 2002; Lahmiri 2011; Mohammadi and Zangeneh 2016). The CG algorithms provide convergence through a series of line searches based on error space. A line search is implemented along with the conjugate gradient direction to adjust the step size at each iteration that can minimize the performance function along the search line (Dao and Vemuri 2002; Lahmiri 2011).

BFGS quasi-Newton method is implemented based on Newton's method. As an alternative to the CG methods, Newton's method often converges faster than the CG methods (Dao and Vemuri 2002). The weight update used in Newton's method is shown in Equation (9).

$$\Delta \boldsymbol{w}_k = \boldsymbol{w}_{k+1} - \boldsymbol{w}_k = -\boldsymbol{H}_k^{-1} \cdot \boldsymbol{g}_k \tag{9}$$

Where $\Delta \boldsymbol{w}_k$ is a vector of changes in weights, $\boldsymbol{g}_k$ is the current gradient of the error related to the weight vector, and $\boldsymbol{H}_k$ is the Hessian matrix at the current values of the weights and biases, which is a square matrix of a scalar function's second-order partial derivations. If the Hessian matrix is large, it becomes complex and requires high memory, causing longer time to compute $\Delta \boldsymbol{w}_k$. However, an advanced class of Newton's methods called quasi-Newton developed by Broyden, Fletcher, Goldfarb, Shanno (BFGS) does not require intensive calculation, which is often known as the most sophisticated method for solving unconstrained problems (Alekseev et al. 2009; Dao and Vemuri 2002). As a batch update method, BFGS quasi-Newton algorithm updates the average gradient of the error space of all cases before updating the weights once at the end of each iteration. BFGS algorithm converges in fewer steps than CG methods, which is more robust than CG (Alekseev et al. 2009; Dao and Vemuri 2002).

6.3.2.3 Determining the Number of Hidden Nodes

Long training time and complex internal structure of a network depend on determining the number of hidden layers and nodes within a network structure. Especially, the number of hidden nodes plays a pivotal role in achieving the most efficient network because it directly governs the performance of model as the stability of the network is estimated by error. In general, a network having a higher number of hidden nodes might improve the model performance as it increases the number of curves in the network output function (Russell and Norvig, 2003). However, an exceeding number of hidden nodes tends to deepen the local minima problem by causing overfitting or too few would result in the ineffectiveness of the network model (Sun 2012; Xu and Chen 2008).

To overcome the difficulty, there have been a number of studies to develop methods to select the optimal number of hidden nodes to use in a network model, due to a lack of standard procedure for creating the most effective and efficient network. Some methods adapting the constructive approach start with an undersized number of hidden nodes and add nodes to them. The other methods through pruning approach start with oversized network and then prunes the less significant nodes while weighting to find the smallest size of the network. Fletcher et al. (1998) developed a method of determining the optimal number of hidden nodes in a traditional three-layered network. Their proposed method is conducted based on an iterative process, by increasing the number of hidden nodes upon a statistical analysis of errors. They pointed out that inaccurate fit to the target function is caused by too few nodes while an exceeding number of hidden nodes learn a large amount of the training data and are thus incapable of generalizing to other data. The authors concluded that the optimal number of hidden nodes should be selected based on the minimum number of hidden nodes that lead to the minimum error in a network. Subramanian et al. (2004) initialized the number of hidden nodes using

Kolmogorov's Theorem. This theorem guides that a sufficient number of hidden nodes comes from twice the number of input nodes plus one ($N_h = 2N_i + 1$), which is referred as an ideal baseline to decide the number of hidden nodes and thus to be tailored to a specific use of networks (Resop 2006). Ke and Liu (2008) proposed a formula by testing 40 cases: $N_h = \left(N_i + \sqrt{N_p}\right)/L$ where N_i is the number of input nodes, N_p is the number of input sample, and L is the number of hidden layer. Trenn (2008) found the necessary number of hidden nodes using two hidden layers, which are formulated by $N_{h1} = (N_i + N_o - 1)/2$ for the first hidden layer and $N_{h2} = (N_i - N_o + 1)/2$ for the second hidden layer, where N_i is the number of inputs, and N_o is the number of outputs. Sheela and Deepa (2013) reviewed various methods to select the optimal number of hidden nodes in ANN for the past twenty years. Through the simulation results, the authors underlined that the minimum error among network models that include each different number of hidden nodes is the key for determining the best number of hidden nodes, rather than relying only on the formula.

Even though many researchers have been implemented various methods for selecting the number of hidden nodes, these still cannot guarantee of selecting the number of hidden nodes (Sheela and Deepa 2013). A key reason is that a number of variables, their types (e.g., numerical, ordinal, and categorical), and their numerous combination cases depending on a specific purpose in modeling networks significantly affect the determination of the number of hidden nodes as network variables include the number of inputs and outputs, training and test dataset sizes, network architecture, and types of activation functions (Sarle 1994; Sheela and Deepa 2013).

6.3.3 Stage III: Determining the Learning Structure

Stage III is to determine the learning structure on aspects of training algorithm, activation functions and the optimal number of hidden nodes. Throughout previous studies, the proposed learning model employed the BFGS algorithm to predict long-term traffic flow before and during construction near the CBD. Based on the selected training algorithm, activation functions and the number of hidden nodes for the proposed network learning model were then determined by evaluating the minimum error among a number of network alternatives, utilizing the automated neural network search module provided by Dell's STATISTICA software.

When developing an MLP feedforward neural network, the collected data are divided into three different data sets of training, validation, and test (Gutierrez-Osuna 2005). The training set is used in learning the model, while identifying the optimal weight with a BP algorithm to minimize the network error. The validation (i.e., cross-validation) set is a key to seeking for the optimal number of hidden nodes that holds the minimum error, while monitoring errors during the training process and determining an appropriate stopping point for the BP algorithm. On the other hand, the test set is excluded from the training process. The test set is employed only to assess the performance of a fully-trained network model, while measuring the generalization ability of the network model.

In this study, a total of 17,518 multi-contextual data were divided randomly into three sets with the following proportions: 1) training set (60% of the original dataset); 2) cross-validation set (20% of the original dataset); and 3) test set (20% of the original dataset). Figure 13 shows the network search process to determine the most suitable learning structure for the proposed learning model.

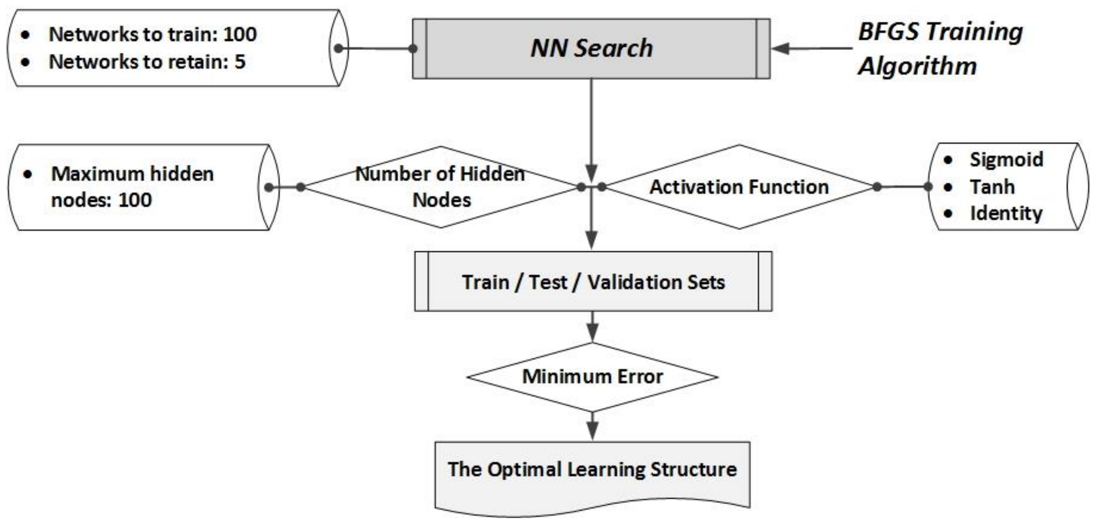


Figure 13 Network search process to determine the learning structure

The procedure of the network search started with establishing the total number of networks to train. A total of 100 networks were considered as alternatives to the learning structure. Among these alternatives, five networks were retained for the short-list. Finally, the learning structure was determined based on the minimum error, among the shortlisted networks having each different number of hidden nodes and combination of activation functions. The maximum number of hidden nodes in the hidden layer was set as 100. In other words, a trial-and-error method for determining the number of hidden nodes was applied with the increment of hidden nodes from 1 to 100 nodes in the hidden layer of 100 different network alternatives having different combinations of activation functions.

For each different network that commonly employs BFGS algorithm for training the model, the maximum number of training cycles (i.e., epochs) was set as 1,000 in a way to determine the appropriate stopping point of the training process. An epoch represents a single completion of training all the given data (NeuroDimension Inc 2010). Through the automated neural network search, the shortlisted learning structures were obtained as shown in Table 8. Each network has its name depending on the complete multilayer network architecture, including the number of inputs, hidden nodes, and outputs. For example, the network named by 26-54-2 refers to an MLP feedforward network with 26 inputs, 54 nodes in the hidden layer, and 2 outputs.

Table 8 Shortlisted Network Learning Structures

Network Name	Training Error	Test Error	Validation Error	Algorithm / Epochs	Hidden Activation	Output Activation
26-75-2	106302.2	130078.8	139280.7	BFGS 780	Sigmoid	Identity
26-49-2	106597.4	139161.5	145476.6	BFGS 419	Sigmoid	Sigmoid
26-54-2	108947.1	123371.7	**131927.9**	BFGS 781	Sigmoid	Identity
26-30-2	112767.6	121639.8	134690.1	BFGS 867	Sigmoid	Identity
26-62-2	119128.3	135426.6	146063.0	BFGS 509	Tanh	Tanh

The network named by 26-54-2 was selected as the final learning structure, by looking at the error in the validation set. As stated previously, validation set plays a significant role in determining the number of the hidden nodes. As shown in Table 9, the 26-54-2 holds the minimum error in the validation set comparing with the other shortlisted networks. In addition, the sigmoid function for the hidden layer and the identity function for the output layer appear through this learning structure, by completing the training process with 781 epochs under BFGS algorithm. Figure 14 illustrates the determined structure of the proposed multi-contextual learning model.

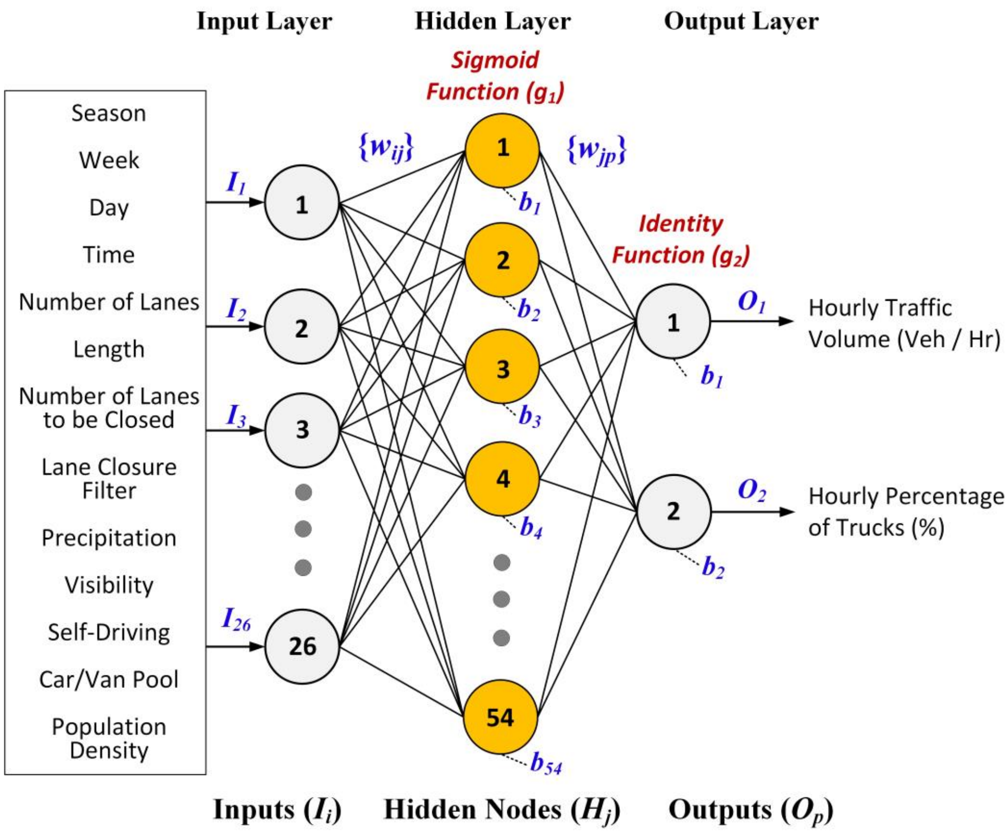


Figure 14 The proposed multi-contextual learning model structure

In a nutshell, critical components for developing the learning model were determined through the automated neural network search, leading to 54 nodes in the hidden layer and the sigmoid function for the hidden layer and the identity function for the output layer as activation functions. Through the network search, the network learning structure was confirmed on aspects of its activation functions and the number of hidden nodes. The mathematical form of the proposed learning model is shown in Equation (10).

$$O_p = \sum g_2 \left(\sum_j \left(w_{jp} \cdot \; g_1 \big(\sum_i \big(w_{ij} \; \cdot \; I_i \big) + \; b_j \big) \right) + \; b_p \right) \tag{10}$$

Where O_p is the value of p^{th} output node (p=1, 2) for the predicted long-term traffic flow and the percentage of trucks within a specific long-term traffic flow, I_i is the value of i^{th} input node (i=1, 2, 3, …, 26) within the multi-contextual frames including highway facility functional information, weather conditions, and socio-demographic characteristics, w_{ij} is the weight of a link connecting the i^{th} node in the input layer and the j^{th} node in the hidden layer, w_{jp} is the weight of a link connecting the j^{th} node (j=1, 2, 3, …, 54) in the hidden layer and the p^{th} node in the output layer, and b_j and b_p are the network biases in the hidden layer and the output layer, respectively. g_1 is the hidden activation defined by the sigmoid function as seen in Equation (11), while g_2 is the output activation defined by the identity function as shown in Equation (12):

$$g_1\,(x) = \;(1 + \exp(-x))^{-1} \tag{11}$$

$$g_2\,(x) = \; x \tag{12}$$

6.3.4 Stage IV: Developing the Multi-Contextual Learning Model

In Stage IV, the confirmed 26-54-2 network with the sigmoid function and the identity function was re-trained in order to achieve more accurate and reliable learning model. Without re-training the confirmed learning structure, it would be difficult to achieve more accurate and reliable learning model because 60% of training set, 20% of validation set, and 20% of test set for training the model are generated by the random samples within the total dataset.

To address this issue, this research phase was conducted through the same procedure with the learning structure search, by holding the number of hidden nodes and two activation functions (i.e., sigmoid and identity functions). To improve the accuracy and reliability of the model that is dependent on the randomly selected three different datasets (i.e., training, validation, test sets), a total of five different 26-54-2 networks were retained for the short-list by training 100 different 26-54-2 networks completed by each different epoch that shows the convergence velocity. For each network, the maximum number of epochs was set as 1,000.

Table 9 shows the results of the shortlisted learning model. In addition to looking at the validation error, it is noteworthy that the minimum value of test error served as the key for determining the final model because the test set aims to assess the performance of a fully-trained network model as well as measure the generalization ability of the network model. As the final model for predicting long-term traffic flow before and during construction, the model 26-54-2 with BFGS 646 was selected based on its test and validation errors.

Table 9 Shortlist for the Proposed Learning Model

Training Algorithm / Epochs	Training Error	Test Error	Validation Error
BFGS 679	120809.1	145585.5	157060.3
BFGS 646	115530.5	**126502.4**	**137907.1**
BFGS 400	134271.3	145370.0	158250.4
BFGS 635	110737.6	130180.9	139050.3
BFGS 792	109440.4	131382.7	141144.8

The BFGS 646 indicates the BFGS algorithm followed by 646 epochs, which means that this network model was found at the 646th cycle. Figure 15 shows the training and testing error rates during 646 epochs.

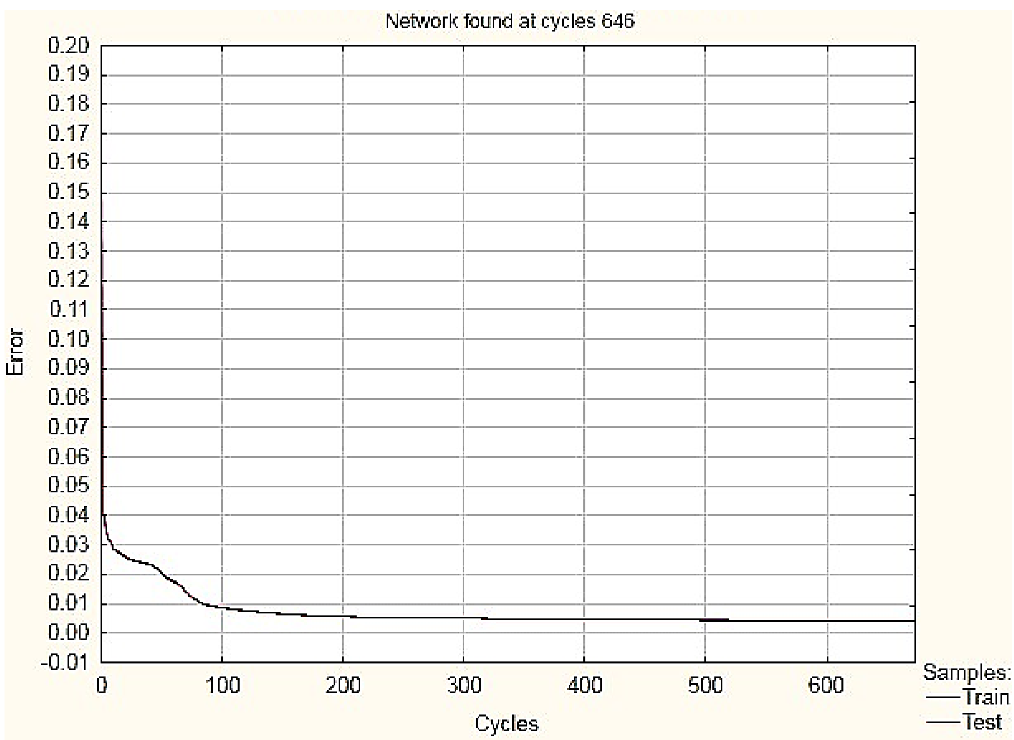


Figure 15 Error rates of training and test sets

6.3.5 Stage V: Evaluating the Learning Performance

Stage V aims to validate the robustness of the improved learning model, by comparing the prediction values with the actual historical traffic data. Figure 16 and Figure 17 present the results of comparisons between prediction and actual values of 24-hr traffic flow and the truck percentage at the weekly scale, respectively.

As shown in Figure 16 and Figure 17, there was no significant difference between prediction and actual values a specific time during weekdays and weekends. However, the comparison during holidays caused a difference between two values because a small number of sample size during holidays of the year resulted in limited learning ability through the proposed model.

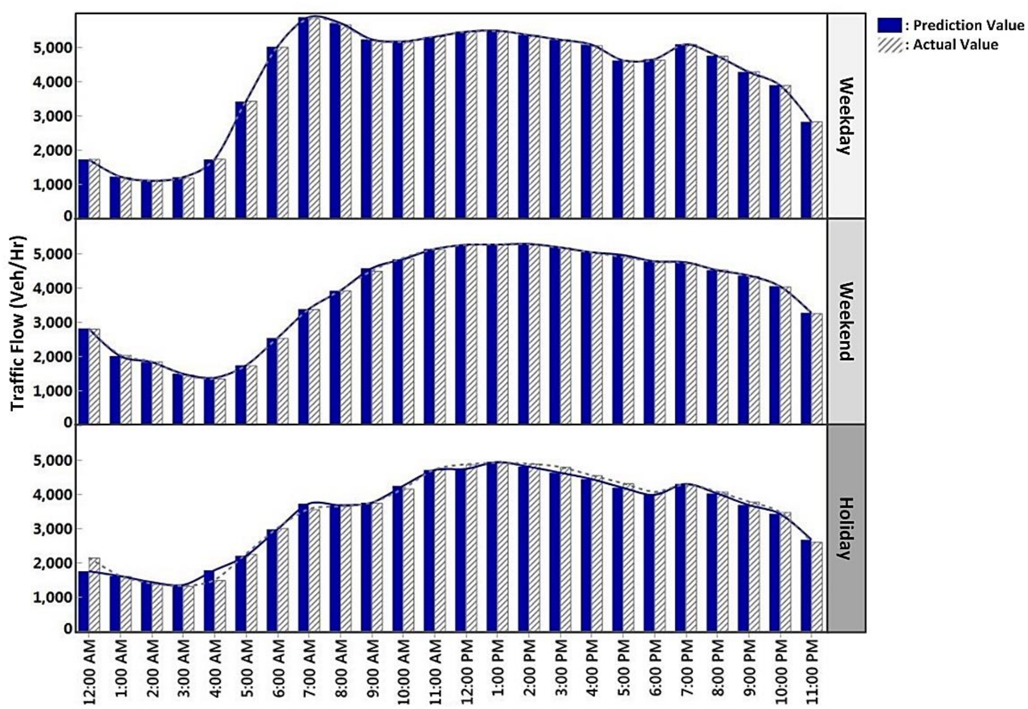


Figure 16 Comparison of prediction and actual values: traffic flow at the weekly temporal scale

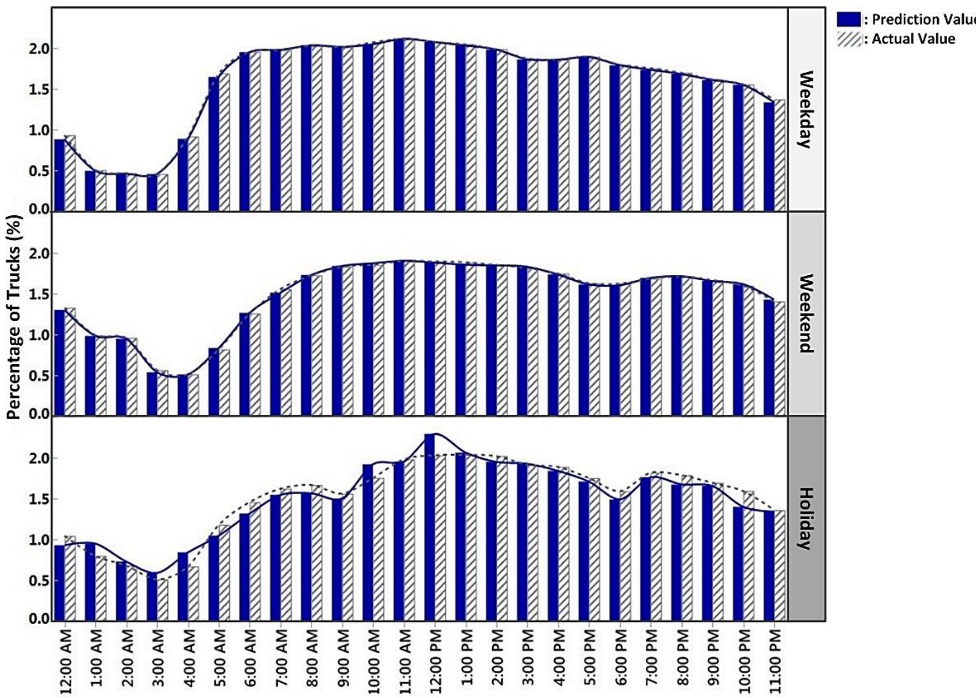
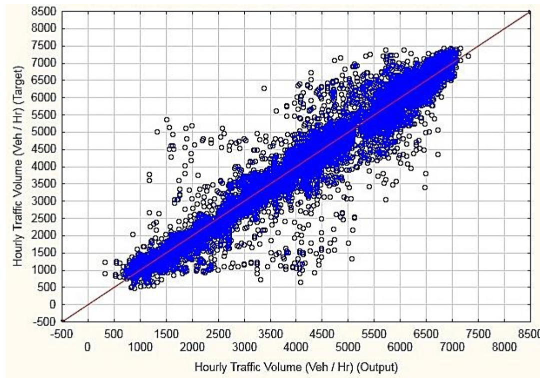


Figure 17 Comparison of prediction and actual values: truck percentage at the weekly temporal scale

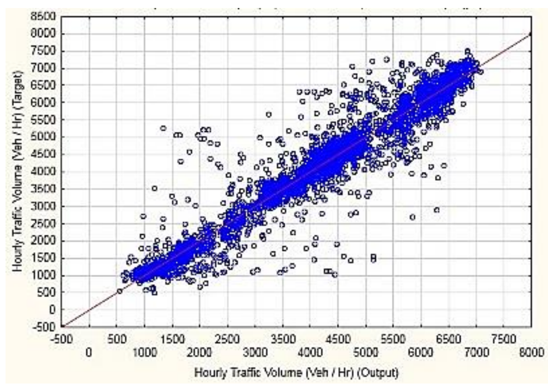
To scientifically measure the learning performance, the learning outcomes including the long-term traffic flow and the percentage of trucks were measured by correlation coefficients between prediction values (i.e., outputs) and actual values (i.e., targets) associated with the training, validation, and test datasets, separately. The correlation coefficient (*r*) quantifies the strength of relation (i.e., the goodness of fit) between actual and prediction values, ranging from -1 to 1. Figure 18 shows the goodness of fit with the high correlation coefficients between actual and prediction values of hourly traffic flow. The results of the correlation coefficients ranging from 0.954650 to 0.962356 confirmed that there exist significant relationships between actual and prediction values along with three different datasets.

Training Set



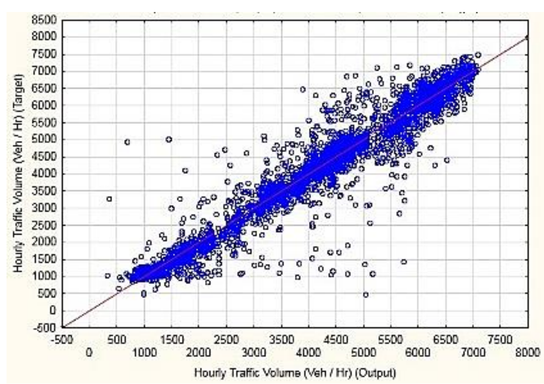
r=0.962356

Cross-Validation Set



r=0.954650

Test Set



r=0.960077

Figure 18 Validating the learning performance: actual versus predicted traffic flow rates

Figure 19 shows the goodness of fit with the high correlation coefficients between actual and prediction values of the percentage of trucks within the corresponding traffic flow. The results of the correlation coefficients ranging from

0.905169 to 0.945625 confirmed that there exist significant relationships between actual and prediction values along with three different datasets.

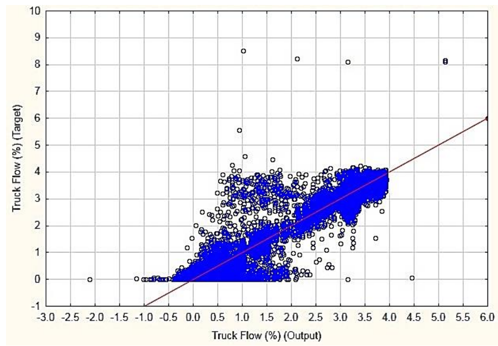
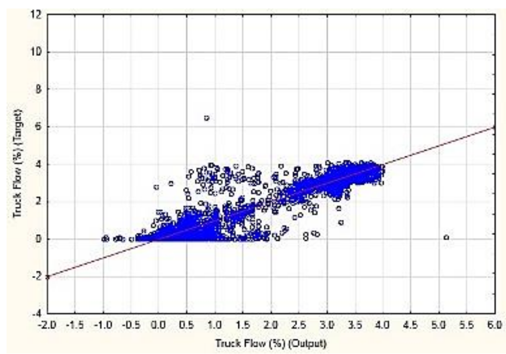
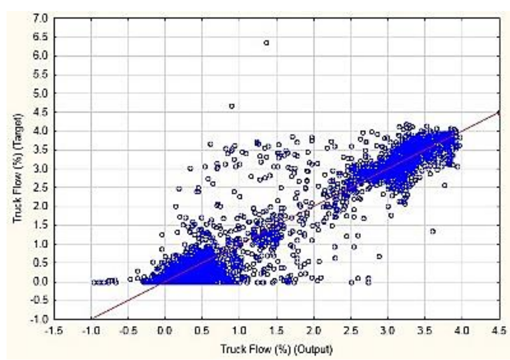
Training Set		*r*=0.942599
Cross-Validation Set		*r*=0.905169
Test Set		*r*=0.945625

Figure 19 Validating the learning performance: actual versus predicted truck percentages

The adequacy of the proposed multi-contextual learning model was also validated by examining scatter plots of the standard residuals versus the predicted values: 1) hourly traffic flow rates as shown in Figure 20; and 2) truck percentages in the corresponding traffic flows as seen in Figure 21. Looking at the scatter plots serves a pivotal role in detecting heteroscedasticity issue that can produce biased results by overestimating the goodness of fit. The scatter plots confirmed that the residuals are randomly spread out without any systematic patterns, which suggest that there is no significant evidence of heteroscedasticity in the proposed learning model.

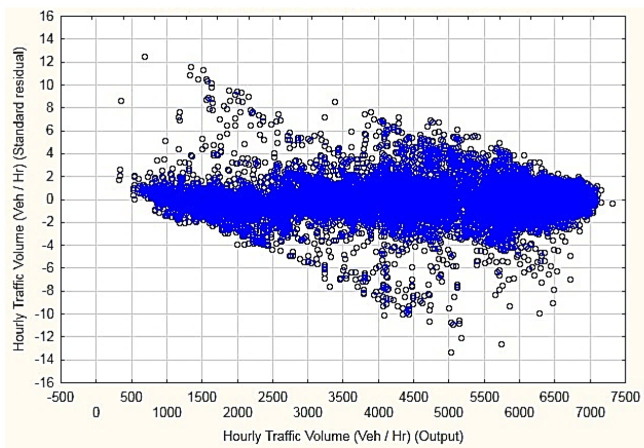


Figure 20 Scatter plot of standard residuals: predicted traffic flow rates

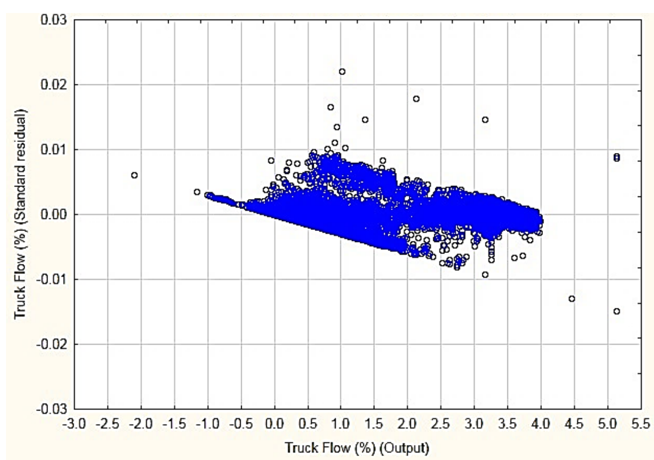


Figure 21 Scatter plot of standard residuals: predicted truck percentages

6.4 Illustrative Examples: Learning Outcomes Versus Multi-Contextual Frames

The objective of this research phase is to investigate the effect of multi-contextual frames on the predicted traffic flow for work zones, through illustrative examples. In order to take comparable results, the following conditions of highway work zones were commonly applied to all the multi-contextual frames through the proposed learning model:

- Number of lanes: 3;
- Number of lanes to be closed: 1;
- 12 feet of lane width, having shoulders; and
- Work zone length: 1 centerline-mile.

Based on these common work zone conditions, the potential traffic flow and the percentage of trucks within the corresponding traffic flow were illustrated by looking at the effect of each context frame, including temporal, weather, and socio-demographic frames.

6.4.1 Temporal Context Frame

The temporal frame includes a season of the year and day of the week contexts. To avoid biased comparisons of the temporal effect, weather and socio-demographic contexts were fixed by holding the average value of each multi-contextual variable as follows:

- Precipitation: 0.028 inches;
- Visibility: 8.996 miles;

- Self-driving: 41.854%;
- Car/vanpooling: 8.245%; and
- Population density: 1,454 ppl/sqmi.

6.4.1.1 Seasonal Context

Figure 22 shows the seasonal context learning pattern of three-lane highway traffic flow and truck percentage under single lane closure.

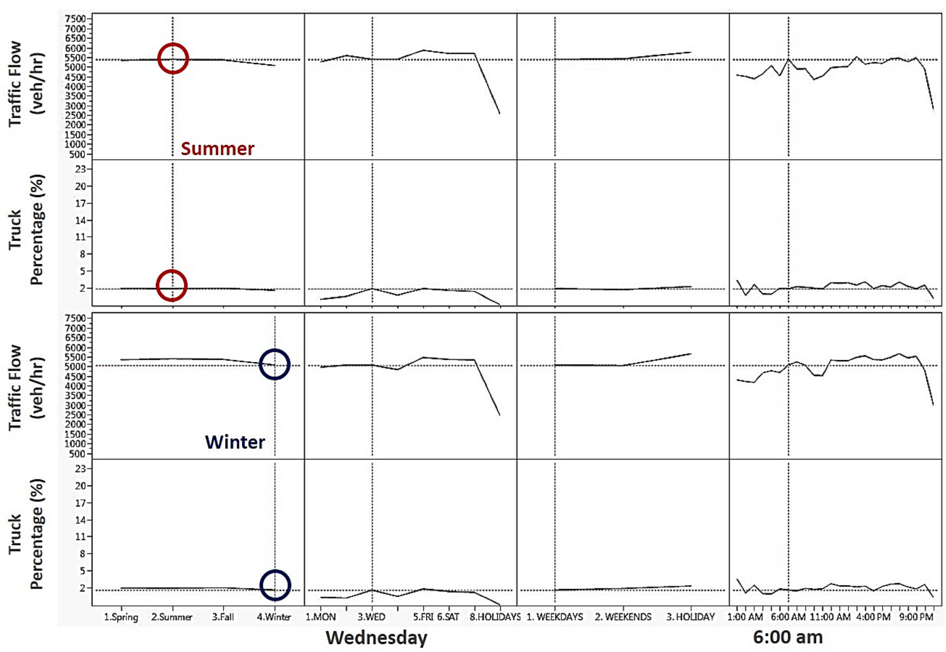


Figure 22 Illustrative examples of the seasonal context

As shown in Figure 22, there are no significant difference among spring, summer, and fall seasons, whereas the winter season is significantly different from the other seasons. As an illustrative example, the effect of seasonal context frame was explored by comparing summer with winter seasons, based on the fixed condition of 6 am on Wednesdays. As shown in Table 10, the results revealed that the both prediction values were differentiated by the seasonal context, which means that there would be a higher potential to have heavier traffic during summer compared to the winter season.

Table 10 Learning Outcomes Under the Seasonal Context

Prediction Value	Summer (June-August)	Winter (December-February)
Traffic Flow (veh/hr)	5,398.50	5,071.38
Truck Percentage (%)	1.87	1.55

6.4.1.2 Daily Context

Figure 23 indicates the learning pattern for capturing the effect of a certain day of the week under single lane closure.

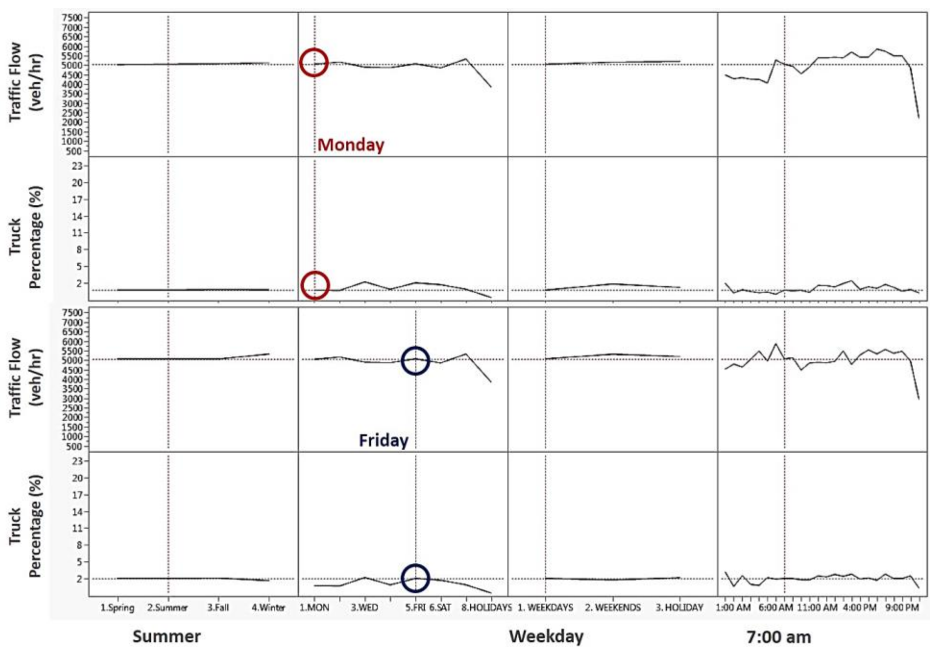


Figure 23 Illustrative examples of the daily context

As an illustrative example to capture the effect of daily context frame, traffic flow and the corresponding truck percentage on Mondays and Fridays were achieved through the multi-contextual learning model. As shown in Figure 23 and Table 11, the learning pattern compared the prediction values on Monday with those on Friday 7 am during the summer season. The results indicate that the morning traffic flow on Friday was slightly higher than Monday's traffic flow under single lane closure, while the percentage of trucks within the corresponding traffic flow (i.e., traffic flow rate at 7 am) on Friday was still much higher than those on Monday.

Table 11 Learning Outcomes Under the Daily Context

Prediction Value	**Monday**	**Friday**
Traffic Flow (veh/hr)	5,047.58	5,069.44
Truck Percentage (%)	0.75	2.02

6.4.2 Weather Context Frame

To take comparable results under the weather context frame, temporal and socio-demographic contextual frames were fixed with the following characteristics:

- Season: Summer;
- Day of the week: Friday;
- Time of the day: 6 am;
- Self-driving: 41.854%;
- Car/vanpooling: 8.245%; and
- Population density: 14545 ppl/sqmi.

Under these common fixed conditions, the weather effect was drawn as the combination of precipitation and visibility contexts. These two different contextual variables are interdependent in general. For example, on rainy days, it would be difficult for road users to look further. As illustrative examples as shown in Figure 24, among various combinational cases of weather contextual variables, the learning outcomes were focused on the comparison between the following two different weather conditions:

- Case I: Precipitation is 0 inch, and visibility is 10 miles; and
- Case II: Precipitation is 2 inches, and visibility is 6 miles.

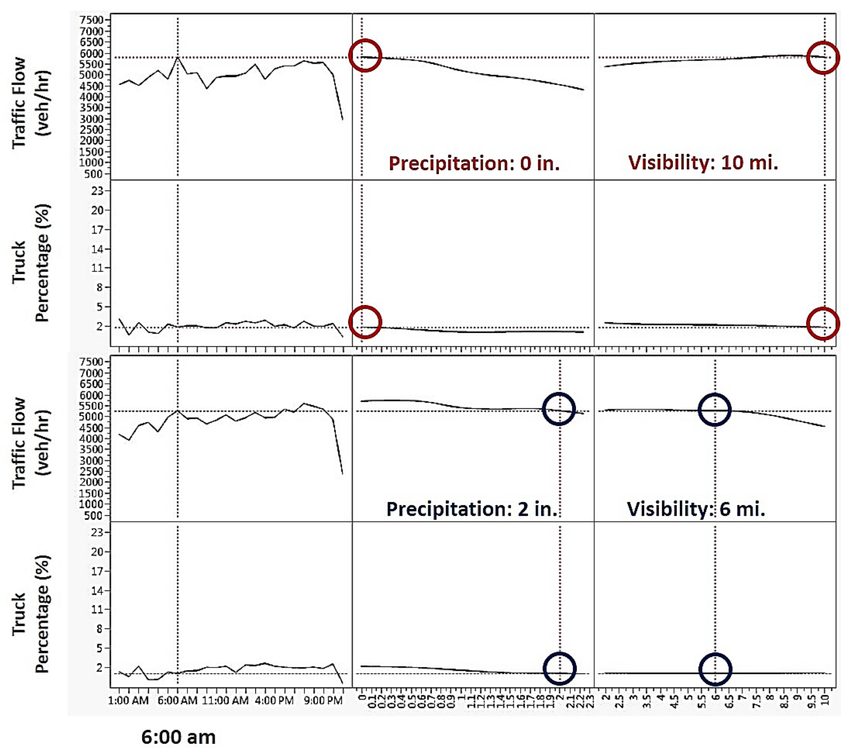


Figure 24 Illustrative examples of the weather context

As seen in Table 12, weather conditions on the aspect of precipitation and visibility significantly affected the traffic variations under single lane closure. In other words, the bad weather condition (Case II) caused a reduction in traffic flow and the corresponding truck percentage, compared to Case I.

Table 12 Learning Outcomes Under the Weather Context

Prediction Value	Case I	Case II
Traffic Flow (veh/hr)	5,805.90	5,261.14
Truck Percentage (%)	1.79	1.04

6.4.3 Socio-Demographic Context Frame

The following common fixed conditions under temporal and weather context frames were applied to the multi-contextual learning model to investigate the prediction values along with the socio-demographic contextual frame:

- Season: Summer;
- Day of the week: Friday;
- Time of the day: 6 am;
- Precipitation: 0.028 inches; and
- Visibility: 8.996 miles.

6.4.3.1 Commute Mode Context

To investigate the difference of traffic flow and the truck percentage under the commute mode context, 14,545 of population density was commonly used in the multi-contextual learning model. The commute mode context included two different variables that serve as major commute modes on highways, such as self-driving and car/vanpooling. The multi-contextual learning model compared the corresponding prediction results through three different combinations of commute modes as follows:

- Case I (Baseline): 40% of self-driving and 8% of car/vanpooling;
- Case II: 45% of self-driving and 8% of car/vanpooling; and
- Case III: 40% of self-driving and 10% of car/vanpooling.

Figure 25 shows the learning patterns for the commute modes during construction, which represent that there is slightly positive relation between the commute modes and the prediction variables.

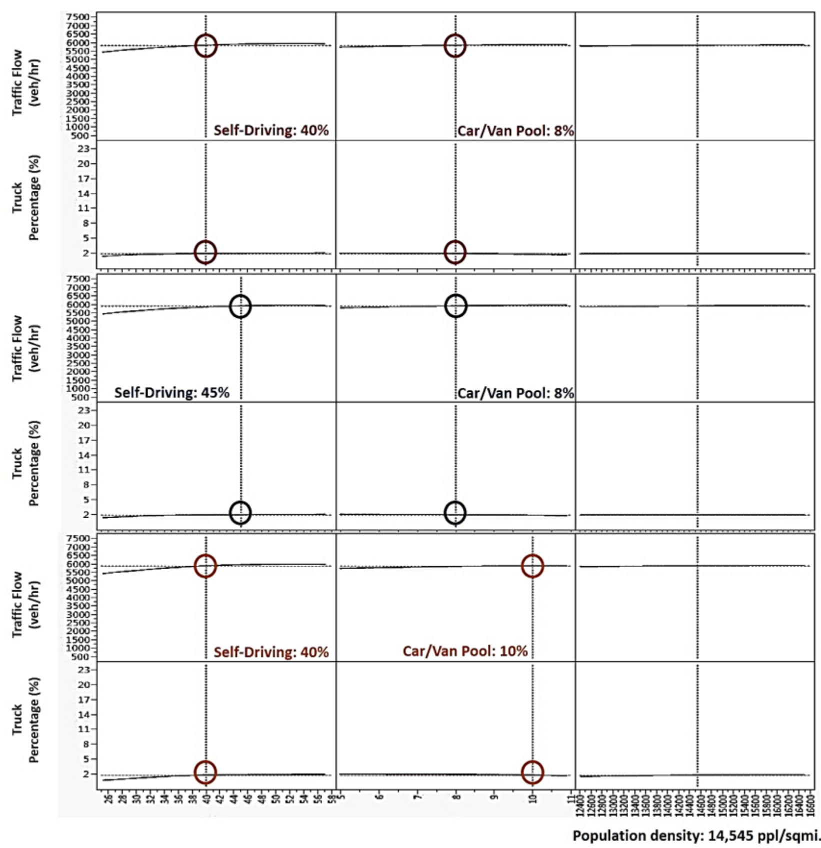


Figure 25 Illustrative examples of the commute mode context

As seen in Table 13, the learning outcomes of three different cases revealed that increasing percentage of self-driving or car/vanpooling led to heavier traffic flow. However, the percentage of trucks within the corresponding traffic flow overall was not significantly affected by the commute mode. It is noteworthy that the commute modes used in the learning model are focused on the passenger car, rather than trucks.

Table 13 Learning Outcomes Under the Commute Mode Context

Prediction Value	**Case I**	**Case II**	**Case III**
Traffic Flow (veh/hr)	5,836.72	5,896.03	5,871.21
Truck Percentage (%)	1.87	1.90	1.71

6.4.3.2 Population Density Context

As noted earlier, population density used in this study represents Census track areas in the CBD adjacent to the traffic analysis zone. To lead comparable results if there would be changes in the population density, the other commute mode context variables were drawn as the following fixed condition, using the corresponding average values:

- Self-driving: 41.854%; and
- Car/vanpooling: 8.245%.

As illustrative examples, three different population density characteristics were compared with each other, such as 13,500, 14,500, and 15,500 ppl/sqmi. Figure 26 illustrates the learning pattern for the population density context, by holding the other socio-demographic contextual variables. As depicted in Figure 26 and Table 14, the learning outcomes of three different cases revealed that increasing population density resulted in slightly heavier traffic flow under single lane closure. However, the percentage of trucks within the corresponding traffic flow was not significantly affected by the population density. It is considered that truck flow tends to be drawn as pass-through traffic. In other words, increasing population density would affect traffic congestion due to passenger cars, rather than trucks.

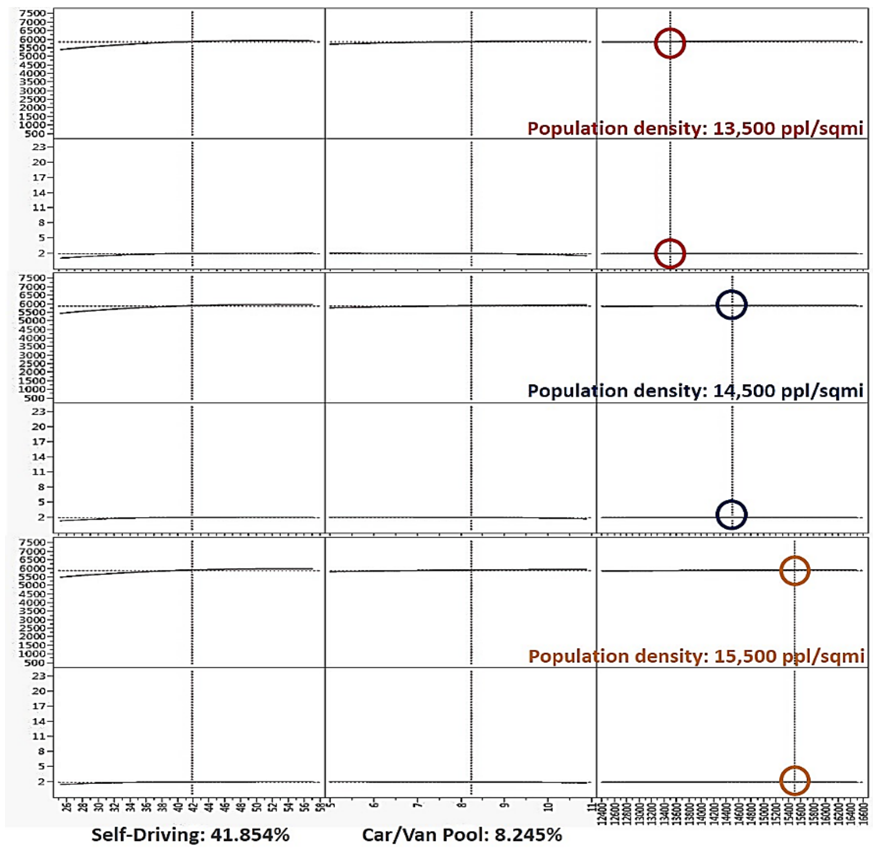


Figure 26 Illustrative examples of the population density context

Table 14 Learning Outcomes Under the Population Density Context

Prediction Value	**Population Density (ppl/sqmi)**		
	13,500	**14,500**	**15,500**
Traffic Flow (veh/hr)	5,848.81	5,868.25	5,880.62
Truck Percentage (%)	1.86	1.88	1.88

6.5 What-If Traffic Flow Rates and Truck Percentages Before/During Construction

The potential long-term traffic flows before and during construction were achieved through the proposed learning model, starting with the lane closure filter that specifically aims to classify the traffic flow before and during construction. In order to take comparable results, 1 centerline-mile work zones for a four-lane highway in a single direction toward the CBD were undertaken for the what-if lane closure schemes. Three different lane closure schemes and highway facility functional information are illustrated in Figure 27.

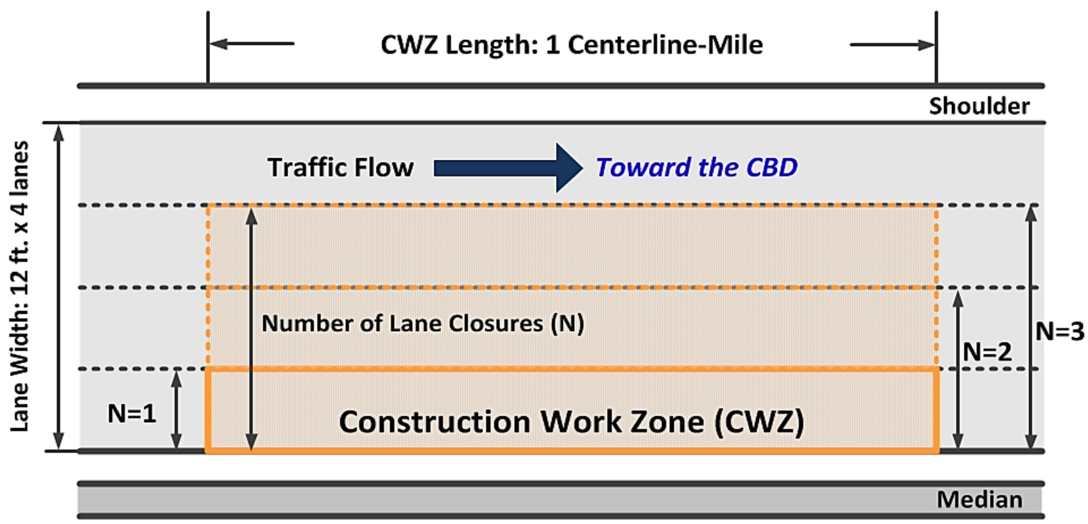


Figure 27 Highway facility information for what-if lane closure schemes

In addition, the average values of multi-contextual variables in the weather and socio-demographic context frames were considered as common fixed conditions, as shown in Table 15.

Table 15 Multi-Contextual Dataset: Common Fixed Conditions and What-If Conditions

Context	Variable	Common Fixed Conditions	What-If Conditions
Temporal	Season	Spring (March-May)	-
	Week	-	24/7
	Day	-	
	Time	-	
Highway	Number of lanes	4	-
	Lane width	12 feet	-
	Shoulder	Yes	-
	Work zone length	1 centerline-mile	-
	Number of lanes to be closed (N)	-	N=[0, 1, 2, 3]
	Lane closure filter	-	Yes/No
Weather	Precipitation	0.028 inches	-
	Visibility	8.996 miles	-
Socio-Demographic	Population density	14,545 ppl/sqmi.	-
	Self-driving	41.854%	-
	Car/vanpooling	8.245%	-

The results of what-if long-term traffic flows were classified into two prediction values: 1) 24/7 traffic flow rate before and during construction, and 2) the corresponding truck percentage. The prediction values were achieved simultaneously from the multi-contextual learning model along with the number of lane closures at the daily temporal scale. Figure 28 and Figure 29 show the potential 24/7 traffic flow and truck percentages before and during construction, respectively.

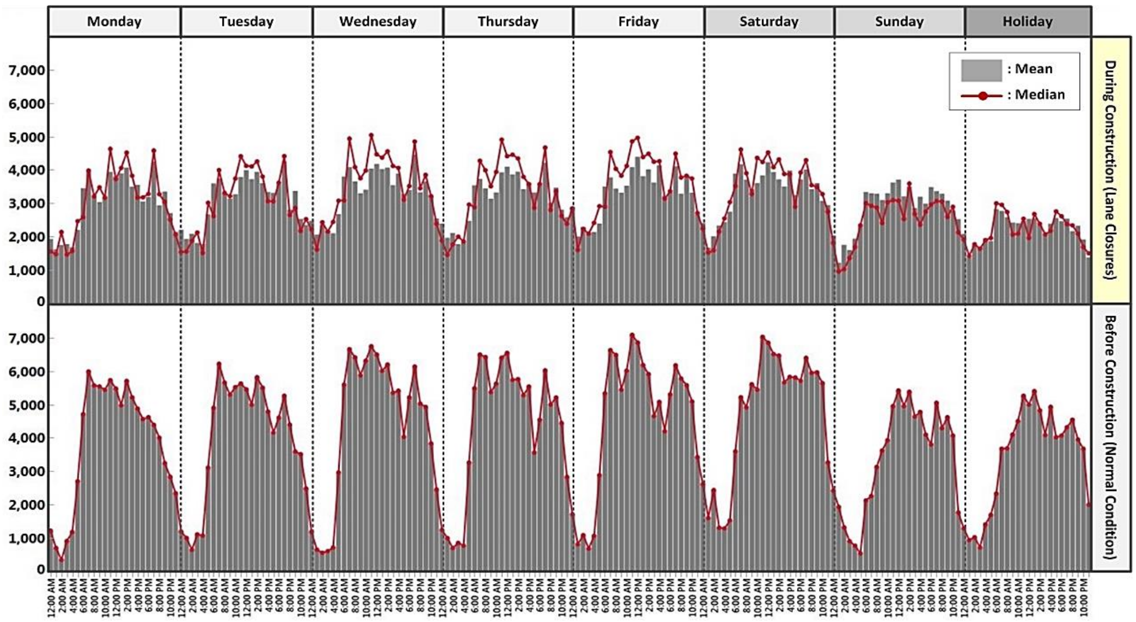


Figure 28 24/7 traffic flow rates before and during lane closure

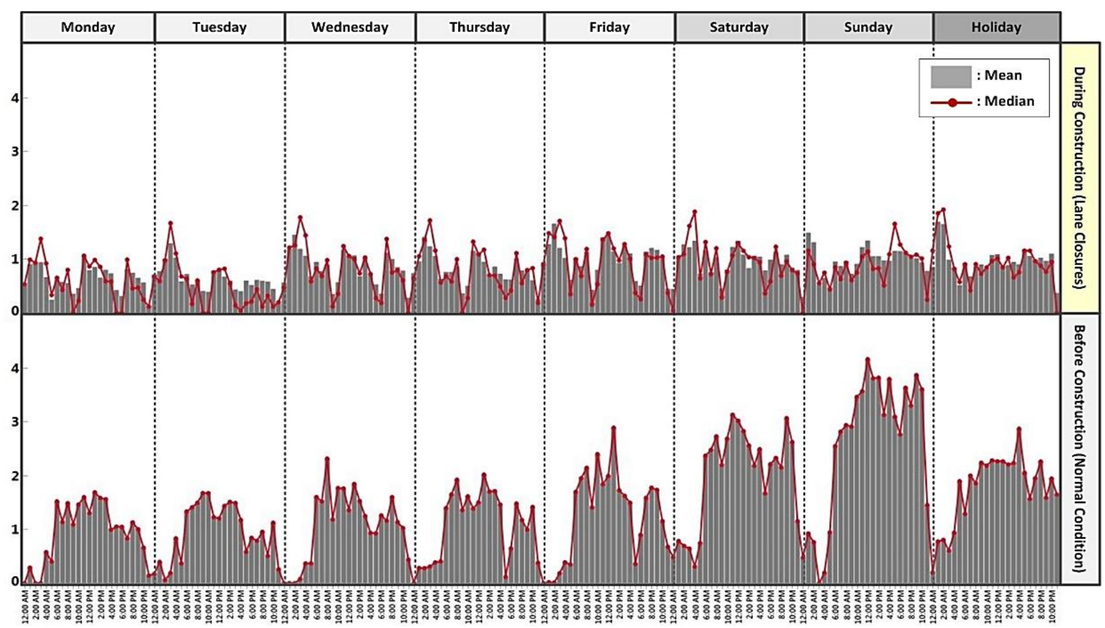


Figure 29 Percentages of trucks within the corresponding traffic flow before and during lane closure

6.6 Summary of Phase II

This research phase attempted to develop the multi-contextual learning model to predict benchmarking long-term traffic flow before and during lane closure simultaneously, by employing the multi-contextual characteristics. The validation study showed that the proposed multi-contextual FNN yields an accurate prediction rate of long-term traffic impact of CWZs, which proves that the framework is repeatable and verifiable to other traffic regions. Table 16 shows a summary of the five-stage process of developing and validating the proposed learning model via MLP FNN.

Table 16 A Summary of the Developing Process of the Proposed Multi-Contextual Learning Model

Stage	Objective	Outcomes
Stage I: Architecture	Establish an MLP feedforward neural network for the proposed multi-contextual learning model	▪ Three layered feedforward network ▪ The number of input nodes (26) and output nodes (2)
Stage II: Critical Components	Identify critical components affecting MLP neural networks	▪ Alternatives of activation functions ▪ Training algorithms ▪ The number of hidden nodes
Stage III: Learning Structure	Determine the most appropriate activation functions and the number of hidden nodes	▪ BFGS quasi-Newton method for training the network ▪ Sigmoid function for the hidden layer ▪ Identity function for the output layer ▪ 54 hidden nodes
Stage IV: Multi-Contextual Learning Model	Achieve more accurate and reliable the learning model based on the confirmed 26-54-2 network's learning structure	▪ Network 26-54-2 using the BFGS training algorithm followed by 646 epochs
Stage V: Validation	Assess the learning performance of the proposed model	▪ Significant relationships between actual and prediction values along with train, test, and validation sets, through the correlation coefficients

7. PHASE III: MODELING WORK ZONE TRAVEL TIME DELAY IMPACT

When this study was initially undertaken, gaps in existing body of knowledge were identified and underlined on the aspect of the potential long-term traffic flow that can be incorporated into work zone delay analysis. In addition, it was noted that accurate and reliable information about expected travel time is fundamental for the traveling public to make better-informed decisions about their trips and to find the optimal alternate routes, thereby improving the safety potentially and mobility directly during construction. However, it is still challenging to predict reliable and realistic traffic flow for incorporation into modeling work zone delay prediction.

The objective of this research phase is to model the impact of nighttime construction in heavily trafficked urbanized downtown areas, on the aspect of travel time delay trend under what-if lane closure schemes. In pursuit of the objective of this research phase, the predicted traffic flow and truck percentages obtained from the proposed multi-contextual learning model were incorporated into the proposed curve fitting models that reinvent the Bureau of Public Roads (BPR) function in order to address the nighttime construction work zone delay impact.

7.1 The BPR Function for Travel Time Estimation

The BPR function is one of the most widely used volume-delay functions (VDFs, also known as link-congestion functions) that specify the impact of highway capacity on travel times or travel speeds (Mtoi and Moses 2014). The standard BPR curve was originated by the freeway speed-flow curves in the 1965 HCM, which is developed by the BPR (now the FHWA) (Moses et al. 2013; Mtoi and Moses 2014). The BPR function has been widely used in traffic demand modeling as it requires a small number of data input parameters having the simple mathematical form. The BPR function is dependent on the volume to capacity ratio, as shown in Equation (13).

$$t = t_0 \cdot \left[1 + \alpha \cdot \left(\frac{V}{C}\right)^{\beta}\right] \tag{13}$$

Where

t: travel time on a particular link;

t_0: free flow travel time on the link;

V: traffic flow rate;

C: capacity; and

α, β: parameters.

The coefficient of the BPR function α is often set at 0.15 and β is often set at 4 (Moses et al. 2013; Zheng et al. 2014). As seen in Equation (14), free flow travel time (t_0) of the traffic over a segment of the potential work zone length (l) at the free flow speed (v_0) is:

$$t_0 = l/v_0 \tag{14}$$

This link-congestion function is robust to formulate the relationship between traffic flow and travel time, thereby estimating the travel time on a particular link. However, the BPR function cannot reveal the travel time variability during construction accurately, due to a lack of the capability to estimate the difference between recurrent congestion under normal traffic conditions and traffic congestion caused by the presence of a CWZ. In addition, the existing form of BPR function cannot effectively and efficiently represent benchmarking travel time delays under what-if nighttime construction alternatives, due to a lack of lane closure parameters in the formulation. Furthermore, the existing form of BPR function cannot generalize the potential work zone travel time delay as it is dependent on a particular length of roadway segment, which means that the current form is very project-specific.

Therefore, in this study, the standard BPR function is transformed into the proposed curve fitting models that specifically aim to graphically and mathematically achieve the travel time delay trend under prevailing traffic conditions as well as under what-if lane closure schemes for nighttime construction in heavily trafficked urbanized downtown areas, which can be generalized.

7.2 What-If Lane Closure Schemes

A number of what-if lane closure schemes for nighttime construction of four-lane directional highways were established to model the travel time delay trends, as depicted in Figure 30.

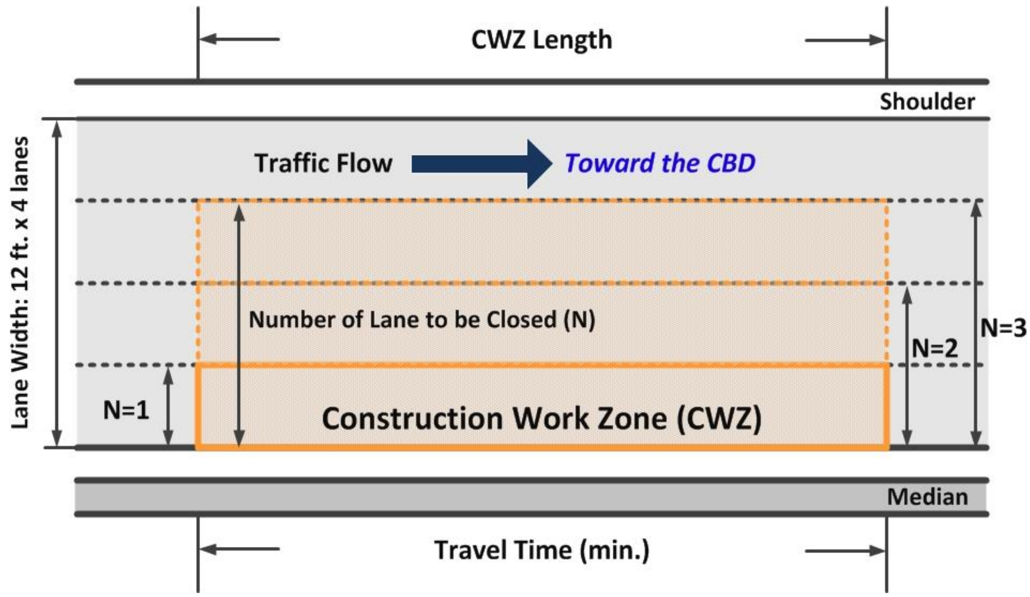


Figure 30 What-if lane closure schemes for quantifying the nighttime work zone delay impact

For the nighttime construction, the construction time period ranging from 9:00 pm-6:00 am during weekdays (including the 8:00 pm-11:59 pm nighttime on Sundays) was employed. What-if lane closure schemes represent the number of lanes to be closed (*N*) ranging from 1 to 3 out of 4 lanes, while the recurrent congestion without any work zone (*N*=0) serves as the baseline to compare the work zone impact. The following highway facility information was considered as common fixed conditions: 1) width of the lane is 12.0 feet; and 2) none of the inner shoulder.

7.3 Stage I: Stereotypical Traffic Volume-Adjusted Capacity Ratios

The highway capacity is defined as the maximum traffic service flow during a given time period under normal highway traffic conditions, which can be selected from the HCM (Choi et al. 2013; Transportation Research Board 2010). Free flow capacity (i.e., basic capacity) is usually assumed that under prevailing traffic conditions capacity ranges from 2,200 to 2,300 passenger car per hour per lane (pcphpl), while capacity during construction ranges from 1,200 to 1,600 pcphpl for lane drop only (Choi et al. 2013; Transportation Research Board 2010). The basic capacity under these two different traffic conditions varies due to a number of factors affecting the capacity (Transportation Research Board 2010):

- Project location;
- Percentage of heavy vehicles (H): H = 100 / [100 + P(PCE−1)], where P = percentage of trucks, and PCE = passenger car equivalent factor (i.e., passenger car / heavy vehicle);
- Width of lanes (W): W=1.00 if width is 12.0 feet, W=0.95 if width is 11.0 feet, and W=0.90 if width is 0.90;
- Shoulder and lateral clearance (S): S=1.00 if both shoulders are available, S=0.95 if one shoulder is available, and S= 0.90 if there are no shoulders available; and
- Number of lanes opened to traffic (N').

Especially, in terms of the PCE, it is widely assumed that a truck equals to 1.5 passenger cars, while setting 2.5 for rolling type or 4.5 for mountainous type of the project terrain (Choi et al. 2013). By taking into account the aforementioned factors, the basic capacity can be adjusted through Equation (15):

$$Adjusted\ Capacity = Basic\ Capacity\ \times H\ \times W\ \times S\ \times\ N' \tag{15}$$

Based on Equation (15), adjusted capacity before and during construction for incorporation into the BPR function was achieved as seen in Equations (16) and (17). Under normal traffic conditions 2,300 pcphpl and 1,600 pcphpl during construction for multi-lane directional highways were applied, along with the common fixed conditions: PCE = 1.5; W=1; and S=0.95.

$$C_n^* = 2{,}300 \times \frac{100}{[100+P^* \cdot (1.5-1)]} \times 1 \times 0.95 \times 4 \tag{16}$$

$$C_w^* = 1{,}600 \times \frac{100}{[100+P^* \cdot (1.5-1)]} \times 1 \times 0.95 \times N' \tag{17}$$

Where

C_n^*: Adjusted capacity before lane closure (veh/hr);

C_w^*: Adjusted capacity during lane closure (veh/hr);

P^*: Predicted truck percentages obtained from the proposed multi-contextual learning model; and

N': Number of lanes to be opened ($N' = 1 - N$, ranging from 1 to 3).

To capture the potential traffic demand reduction using the ratio of traffic flow rate to adjusted capacity before or during construction (V/C ratio), the adjusted capacities obtained from Equations (16) and (17) were integrated with the predicted long-term traffic flow rates achieved through the proposed multi-contextual learning model. As the result, the potential traffic volumes and adjusted capacities under prevailing traffic conditions and under what-if lane closure schemes for the nighttime construction were illustrated as shown in Figure 31.

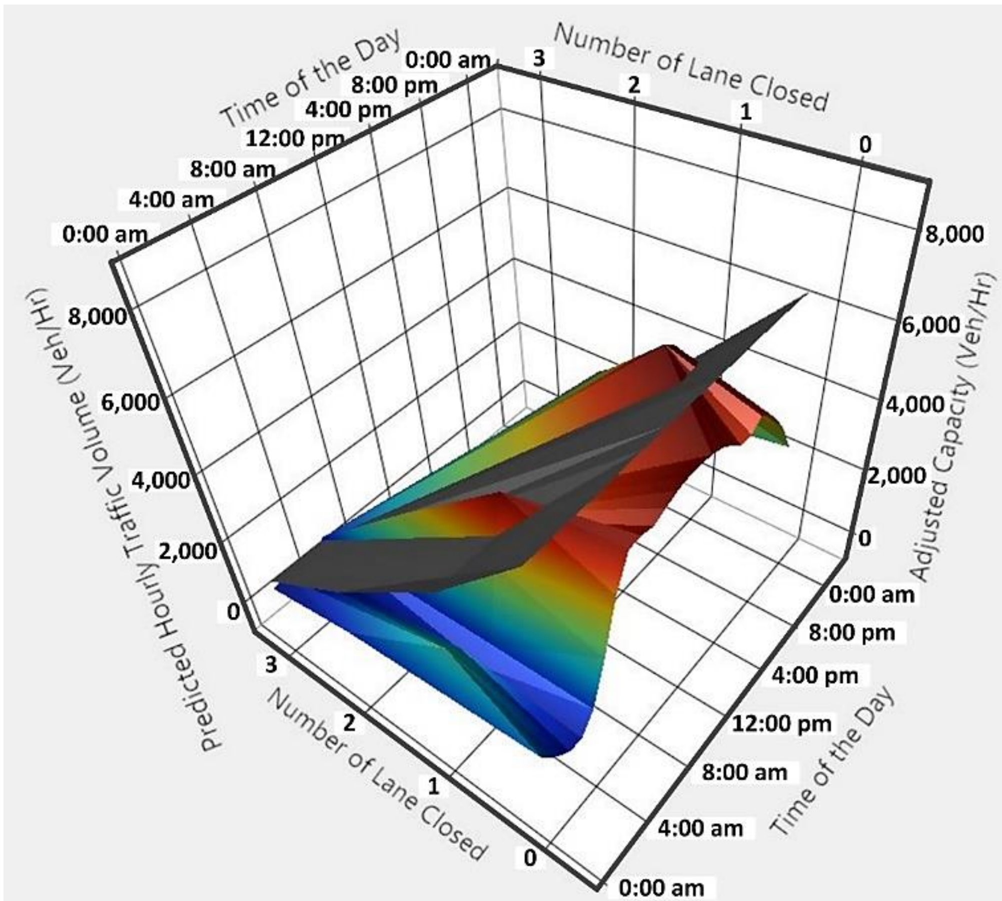


Figure 31 Predicted traffic volume and capacity pattern before and during nighttime construction

Figure 31 and Figure 32 specifically illustrate changes in traffic volume and the corresponding capacity on an hourly basis for the period of the nighttime construction, while capturing the impact of lane closures.

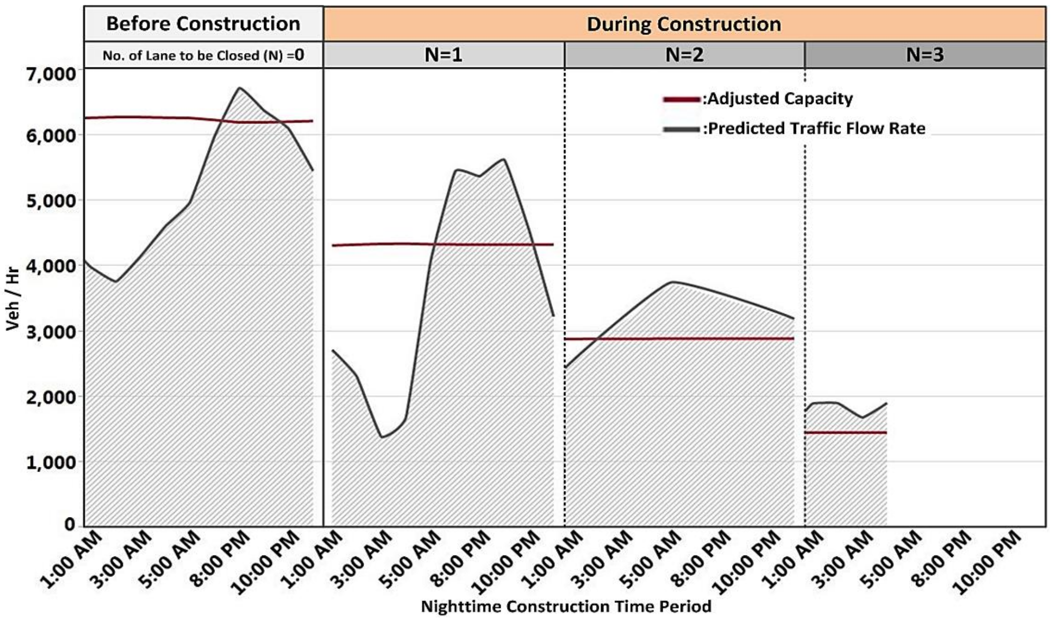


Figure 32 Comparisons of predicted traffic flow rates and the corresponding capacities before and during nighttime construction

The changes in traffic volume and capacity represent that as the number of lanes closed to traffic increases the both potential traffic flow rates and the corresponding capacities are reduced, reflecting the traffic demand reduction due to lane closures. In other words, under prevailing traffic conditions (*N*=0) traffic flow rates are under the adjusted capacity before construction, whereas during lane closure (*N*=1, 2, and 3) traffic flow rates exceed the adjusted capacity during construction.

Based on the results of traffic flow rates versus adjusted capacity (see Figure 31 and Figure 32), Figure 33 shows the results of predicted traffic volume-capacity (V/C) ratios before ($\frac{V_n^*}{C_n^*}$) and during ($\frac{V_w^*}{C_w^*}$) lane closure for the time period of nighttime construction at daily scales (9:00 pm to 6:00 am during weekdays and 8:00 pm to 11:59 pm on Sundays). To illustrate heavily trafficked and frequent traffic conditions before and during lane closure, the maximum V/C ratios and 50% of the predictions are highlighted in Figure 33.

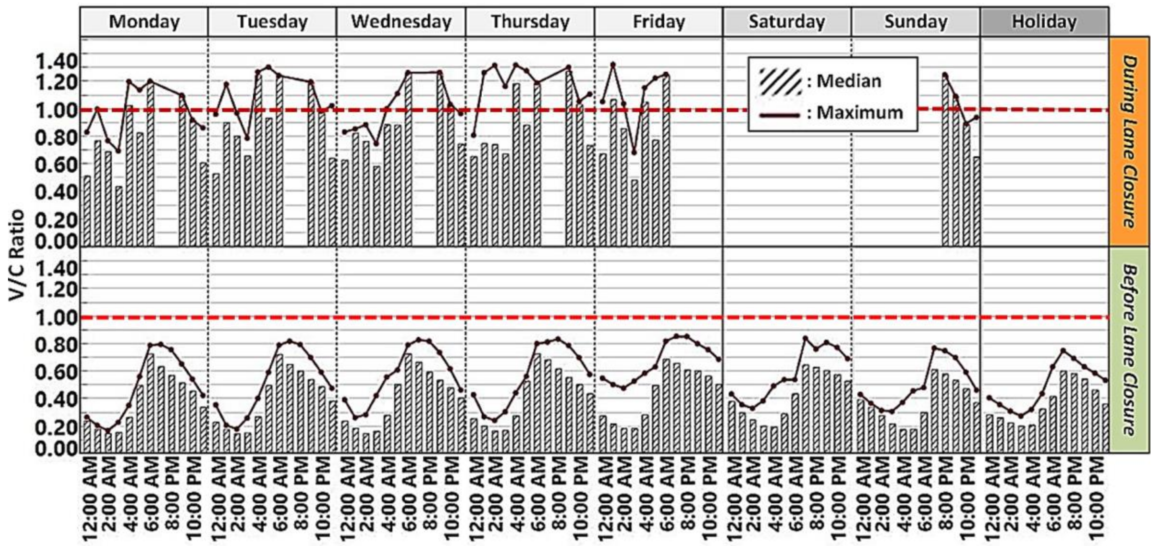


Figure 33 Estimated V/C ratios before and during nighttime construction

7.4 Stage II: Nighttime Travel Time Delays Before and During Construction

This research phase focuses on modeling the nighttime construction work zone delay impact by achieving the generalized travel time delay trend under what-if lane closure schemes for nighttime construction in heavily trafficked downtown areas having the CBDs. As stated previously (Section 7.1), there remains questionable about the effectiveness and efficiency of the existing VDF, especially the BPR function. In this research stage, the standard BPR function is transformed into the proposed curve-fitting models that specifically aim to graphically and mathematically achieve the travel time delay trend under prevailing traffic conditions as well as under what-if lane closure schemes for nighttime construction in heavily trafficked urbanized downtown areas.

When addressing the nonlinearity of parameters, curve-fitting is efficient and effective to achieve the most appropriate equation through various forms, such as exponential, power, logarithmic, trigonometric, and polynomial forms (McDonald 2009). Curve-fitting might or might not utilize (curvi)linear or nonlinear regression. Any kind of regression models is the study of the relationship between single or several predictors and the responses, which means that a regression model does not rely only on curve fitting. The term of curve-fitting in a regression model is used to denote whether the training data set is matched or failed to generalize for new data points. In the other case, if curve-fitting is not used in a regression model it specifically aims to estimate the forecasting formula that fits very well with the data trend line, not examining the statistical relationship between independent and dependent variables.

In this regard, this research phase is centered on creating new equations by transforming the BPR function into the proposed curve-fitting models that can address the potential travel time delay trend under normal traffic conditions as well as arbitrary lane closure scenarios for nighttime construction work zones on multilane urban highways near the CBD, by utilizing the predicted values of long-term traffic flow rates and truck percentages that are achieved from the proposed multi-contextual learning model.

7.4.1 Travel Time Estimation Using the BPR Function

As the pre-process, each potential travel time before (t_n) and during (t_w) the nighttime construction was estimated by the BPR function firstly, as seen in Equations

(18) and (19). Free flow speed (v_0) data used in this study were collected from the multiple sensor readings via the Caltrans PeMS (Caltrans 2012), ranging from 63 to 64 miles per hour (mph) over the study year. In addition, the coefficients of the BPR function were set as $\alpha = 0.15$ and $\beta = 4$ (Moses et al. 2013; Zheng et al. 2014).

$$t_n = t_0 \cdot \left[1 + \alpha \cdot \left(\frac{V_n^*}{C_n^*}\right)^{\beta}\right] \tag{18}$$

$$t_w = t_0 \cdot \left[1 + \alpha \cdot \left(\frac{V_w^*}{C_w^*}\right)^{\beta}\right] \tag{19}$$

Where $t_0 = l/v_0$.

7.4.2 Curve-Fitting Models for Travel Time Delay Trends

The proposed travel time delay model specifying grouping variables of the percentile lane closure estimates separate model parameters for each level of the grouping variable. To model the generalized travel time delay trend, what-if number of lanes to be closed in count unit was converted to that in percentage unit, and travel time delay in minutes was also converted to the percentile travel time delay.

As an explanatory approach, among various curve-fitting forms such as logistic, polynomial, exponential growth, and Gaussian peak curves, the third-order polynomial (i.e., cubic) fitting was finally selected by measuring the accuracy of these alternatives of fitting forms. The following is the generalized form of the proposed curve-fitting equation (Equation (20)):

$$Travel\ Time\ Delay\ (t_d^i) =$$
$$\beta_0 + \beta_1 \cdot (V/C\ \ Ratio) + \beta_2 \cdot (V/C\ \ Ratio)^2 + \beta_3 \cdot (V/C\ \ Ratio)^3 \qquad (20)$$

Where

i: the percentage of the number of lanes (*N*) to be closed to the traffic during nighttime construction, specifically from 9:00 pm to 6:00 am on weekdays and 8:00 pm to 11:59 pm on Sundays:

- If $N = 0$, $t_d^i = \frac{(t_n - t_0)}{t_0} \times 100$ (%);
- If $0 < N < 4$, $t_d^i = \frac{(t_w - t_n)}{t_n} \times 100$ (%); and

$V/C\ \ Ratio$: the ratio of traffic flow rate to adjusted capacity before or during construction through the predicted outcomes from the multi-contextual learning model.

By using the Equation (20), the proposed curve-fitting was classified into four different groups to address the distinct trend in travel time delay under normal traffic flow conditions including recurrent traffic congestion (number of lanes to be closed (N)=0%) and what-if lane closure schemes with N=25%, N= 50%, and N=75%. Table 17 shows a summary of results of fit curves to these groups.

Table 17 Results of Fit Curves to Lane Closure Groups

Group by Number of Lanes to be Closed (N)	**Parameter**	**Estimate**	**Std. Error**	**R^2**
N=0: Normal traffic condition including reccurrent traffic congestion	Intercept	-0.487	0.003	0.99
	Slope	5.733	0.024	
	Quadratic	-21.149	0.052	
	Cubic	30.453	0.033	
N=25%	Intercept	-4.790	0.103	
	Slope	27.976	0.403	
	Quadratic	-57.195	0.499	
	Cubic	49.047	0.196	
N=50%	Intercept	-5.375	0.130	
	Slope	30.160	0.514	
	Quadratic	-59.961	0.644	
	Cubic	50.170	0.256	
N=75%	Intercept	-4.338	0.056	
	Slope	26.389	0.231	
	Quadratic	-55.444	0.298	
	Cubic	48.441	0.121	

As seen in Table 17, an R-squared value of 0.99 indicates a highly accurate fit between the estimated percentile travel time delay through the BPR function and the predicted percentile travel time delay through the proposed curve-fitting. The following four different third-order polynomial fitting equations for predicting the unique trend in travel time delay under what-if nighttime lane closure schemes were finally generated, and each of trends is illustrated in Figure 34.

$$t_d^0 = -0.487 + 5.733 \cdot (V/C\ \ Ratio) - 21.149 \cdot (V/C\ \ Ratio)^2 + 30.453 \cdot (V/C\ \ Ratio)^3 \tag{21}$$

$$t_d^{25} = -4.79 + 27.976 \cdot (V/C\ \ Ratio) - 57.195 \cdot (V/C\ \ Ratio)^2 + 49.047 \cdot (V/C\ \ Ratio)^3 \tag{22}$$

$$t_d^{50} = -5.375 + 30.160 \cdot (V/C\ \ Ratio) - 59.961 \cdot (V/C\ \ Ratio)^2 + 50.170 \cdot (V/C\ \ Ratio)^3 \tag{23}$$

$$t_d^{75} = -4.338 + 26.389 \cdot (V/C\ \ Ratio) - 55.444 \cdot (V/C\ \ Ratio)^2 + 48.441 \cdot (V/C\ \ Ratio)^3 \tag{24}$$

Where

t_d^0 : Predicted travel time delay in percentile under normal traffic conditions;

t_d^{25}: Predicted travel time delay in percentile under 25% lane closure conditions;

t_d^{50}: Predicted travel time delay in percentile under 50% lane closure conditions;

and

t_d^{75}: Predicted travel time delay in percentile under 75% lane closure conditions.

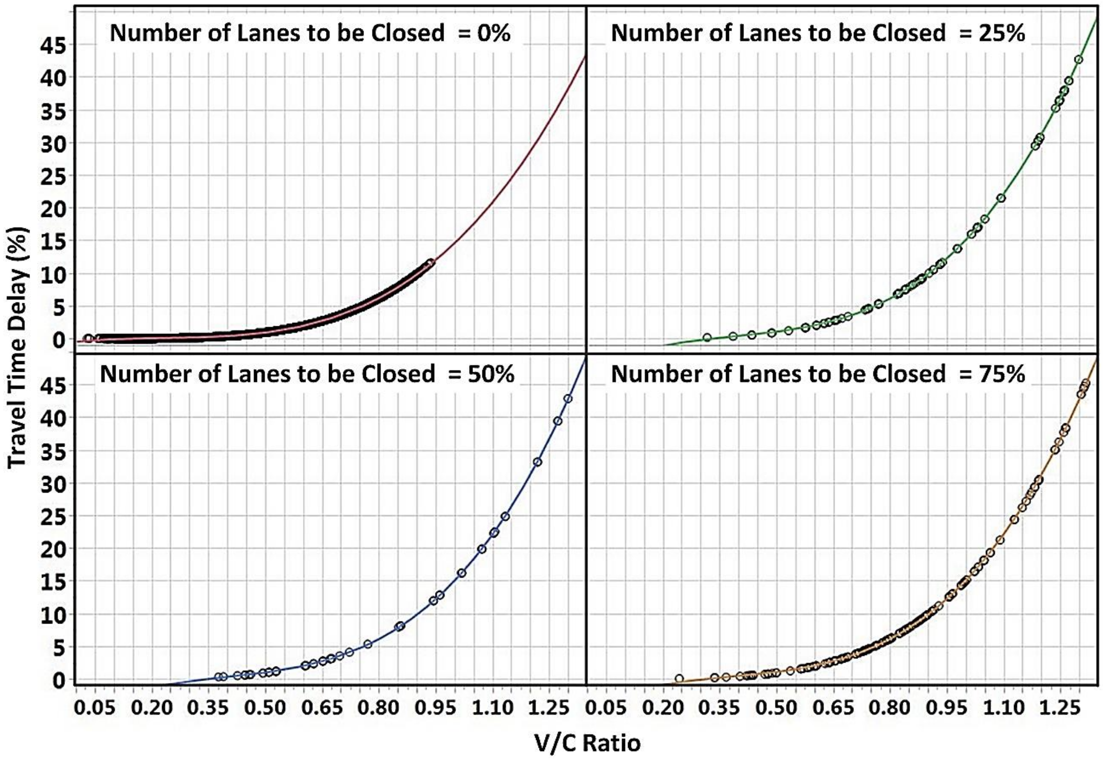


Figure 34 Third-order polynomial curve-fitting models for predicting the nighttime construction work zone travel time delay impact

7.4.3 Practicality of the Models: Quantification of Travel Time Delay Impact

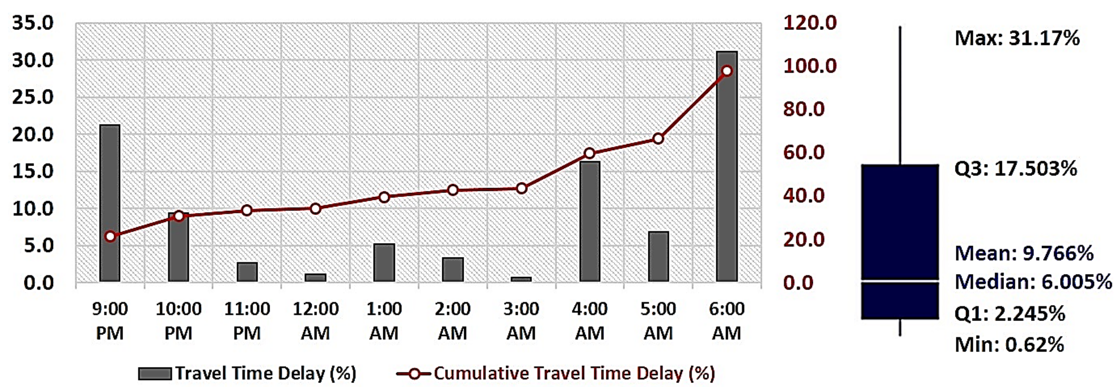
The practicality of the proposed approach to predict the nighttime work zone travel time delay was demonstrated through the following hypothetical example. It was assumed that the multilane highway construction work would occur at night between 9:00 pm on Sunday and 6:00 am on Monday adjacent to a downtown area having the CBD where AADT volumes are over 250,000, while proving dynamic lane configuration during a certain construction time period. As seen in Table 18, a combination of 25%, 50%, and 75% of lane closure configurations was assumed to represent dynamic lane configurations. In addition, median values of estimated V/C ratios at a particular time on a certain day of the week were applied for demonstrating the practicability of the proposed curve-fitting models. Table 18 summarizes what-if nighttime construction conditions and predicted percentile travel time delay at a certain time under the corresponding lane closure scheme.

Table 18 A Hypothetical Example: Predicted Nighttime Work Zone Trave Time Delays

Day of the Week	**Time of the Day**	**Number of Lanes to be Closed (%)**	**Predicted V/C ratio***	**Curve-Fitting Equation**	**Predicted Travel Time Delay (%)****
Sunday	9:00 pm	25	1.09	Equation (22)	21.26
	10:00 pm	25	0.889	Equation (22)	9.34
	11:00 pm	50	0.648	Equation (23)	2.64
Monday	0:00 am	50	0.51	Equation (23)	1.06
	1:00 am	75	0.767	Equation (24)	5.14
	2:00 am	75	0.686	Equation (24)	3.31
	3:00 am	75	0.432	Equation (24)	0.62
	4:00 am	50	1.02	Equation (23)	16.25
	5:00 am	25	0.824	Equation (22)	6.87
	6:00 am	25	1.2	Equation (22)	31.37

*: Median values of predicted V/C ratios (obtained from Figure 30)
**: Predicted values obtained from the corresponding curve-fitting equations

Figure 35 illustrates the results of the hypothetical example, in line with the predicted work zone travel time delays seen in Table 18. A histogram shows the predicted percentile travel time delay at a certain time during construction, while a line graph displays the cumulative percentile travel time delay (97.7%) during the overall construction time period. In addition, a box plot presents the statistical distribution of the predicted travel time delay. As depicted in Figure 35, the maximum travel time delay would occur at 6:00 am on Monday by having 31.17% additional travel time due to 25% of lane closure for the nighttime construction, compared to the travel time under normal traffic conditions. On the other hand, despite 75% of lane closure, only 0.62% additional travel time delay would occur at 3:00 am on Monday, due to the minimum V/C ratio during the construction time period. As shown in the box plot, this nighttime construction under dynamic lane configuration would cause the traveling public to take the average 9.766% additional travel time due to the planned nighttime construction.



(a) Predicted percentile travel time delays (b) Box plot

Figure 35 Nighttime work zone delay impact prediction

7.5 Stage III: Model Verification and Validation

When creating a quantitative and predictive model, model verification and validation processes are essential for quantified confidence in the model's accuracy and reliability (Carson 2002; Choi et al. 2016; Thacker et al. 2004). Both verification and validation processes provide scientifically proven evidence of the model's accuracy or reliability for a specific intended use, not all possible scenarios (Thacker et al. 2004).

Verification aims to determine whether an established model can accurately represent the results obtained from its benchmark model. On the other hand, validation is attempted to evaluate whether an established model can accurately incorporate experimental or real-world situations, by comparing the end results obtained from the established model with those collected from the real-world situations (Carson 2002; Thacker et al. 2004).

To this end, this research phase aims to scientifically verify and validate the proposed curve-fitting models by measuring forecasting accuracy, as shown in Figure 36. Model verification was performed by comparing the curve-fitting models with the benchmarked BPR function. The robustness of the curve-fitting models was validated through actual-to-predicted comparison study with three different real-world projects that are completed at different spatiotemporal scales.

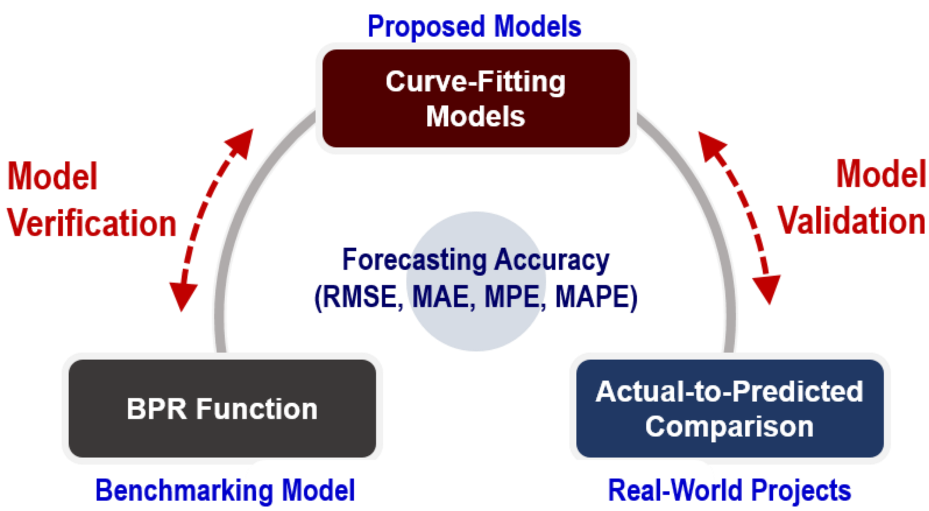


Figure 36 Model verification and validation

7.5.1 Measuring Forecast Accuracy

The robustness of the proposed curve-fitting models to predict the potential travel time delay was verified and validated by measuring forecast accuracy through the most widely used four different methods: the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Mean Percentage Error (MPE), and the Mean Absolute Percentage Error (MAPE).

In general, a certain forecast error (e_i) is the difference between the certain actual value (y_i) and the corresponding predicted value ($\hat{y}_i$) in the same data set ($e_i = y_i - \hat{y}_i \ where\ i = 1 \dots n;\ and\ n\ is\ number\ of\ predictions$) (Hyndman 2014). Since the actual and predicted values are on the same scale, these errors are on the same scale, so-called scale-dependent errors. The most commonly used scale-dependent accuracy measures include the RMSE based on the squared errors and the MAE based on the absolute errors (Hyndman 2014; Woschnagg and Cipan 2004). The RMSE represents a quadratic scoring rule to measure the average magnitude of the errors. As shown in Equation (25), the errors are squared first and then averaged over the sample. The square root of the average error is finally calculated. When utilizing the RMSE, its sensitivity to outliers is often issued because the errors are squared before they are averaged (Chai and Draxler 2014). In other words, the RMSE is useful for certain cases when large errors are particularly undesirable because the RMSE gives a higher weight to larger errors (Saigal and Mehrotra 2012).

$$RMSE = \sqrt{mean\ (e_i^2)} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{25}$$

Alternatively, the MAE is a linear scoring rule, which means that all the errors are weighted equally so less sensitive to large deviations, compared to the RMSE (Woschnagg and Cipan 2004). The MAE is the average over the absolute values of errors, as seen in Equation (26).

$$MAE = mean\ (|e_i|) = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{26}$$

As scale-independent measures, a relative measure of accuracy is also widely used based on percentage errors (PEs), such as the MPE and MAPE (Choi et al. 2016; Hyndman 2014; Makridakis et al. 2008). The MPE considers the direction of errors by measuring positive or negative values in order to specify the tendency of overfitting or underfitting, whereas the MAPE focuses on measuring the magnitude of errors incurred by the prediction (Makridakis et al. 2008). Measuring the MPE and the MAPE starts with calculating the PE, the percentile difference between the actual and predicted values, as seen in Equation (27).

$$PE_i = (y_i - \hat{y}_i)/y_i \times 100\ (\%) \tag{27}$$

To measure the MPE, all of the percentage errors are averaged over the sample, as shown in Equation (28).

$$MPE = \frac{1}{n}\sum_{i=1}^{n} PE_i \tag{28}$$

In terms of the MAPE, all of the absolute percentage errors are averaged, as seen in Equation (29).

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} |PE_i| \tag{29}$$

In general, the forecast accuracy based on the MAPE can be assessed by the following interpretation ranges that are suggested by Lewis (1982) (Choi et al. 2016; Ofori et al. 2012):

- Less than 10%: Highly accurate forecasting;
- 10-20%: Good forecasting;
- 21-50%: Reasonable forecasting; and
- 51% or more: Inaccurate forecasting.

As a way to interpret the results, the lower value of errors, the more accurate prediction. For model verification, y_i represents the i^{th} estimated percentile travel time delay obtained from the BPR function that includes the predicted traffic flow and truck percentages through the multi-contextual learning model, while $\hat{y}_i$ indicates the i^{th} predicted percentile travel time delay achieved from the proposed curve-fitting formulations (i.e., trend lines). In addition, for model validation, y_i represents the i^{th} actual travel time index that includes the predicted traffic flow and truck percentages achieved from the PeMS database, while $\hat{y}_i$ indicates the i^{th} predicted travel time index achieved from the proposed curve-fitting formulations (i.e., trend lines).

7.5.2 Model Verification: Curve-Fitting Models Versus BPR Function

At the onset of this study, the primary goal of Stage II in Phase III was to create a quantitative and predictive model that can effectively and efficiently represent benchmarking travel time delays under what-if nighttime construction alternatives and be independent on a particular length of roadway segment, which enable the proposed model to overcome drawbacks in the existing BPR function, but having the equivalent effect with the BPR function. To scientifically verify the accuracy of the proposed curve-fitting models, the predicted travel time delays achieved from the proposed models were compared to the estimated travel time results obtained from the benchmarked BPR function, by measuring forecast accuracy through RMSE, MAE, MPE, and MAPE.

Table 19 summarizes the results of the forecast accuracy measures according to the RMSE, MAE, MPE, and MAPE. Specifically, scale-dependent errors (RMSE and MAE) indicates acceptable values (RMSE=0.028 and MAE=0.003), from the perspectives of rules of quadratic and linear scoring. The MAPE was within the limits of reasonable forecasting (MAPE=33.3%), while the positive 25.7% of the MPE would be reasonable.

Table 19 Accuracy of Models: Curve-Fitting Versus BPR Function

Scale-Dependent Errors		**Scale-Independent Errors (%)**	
RMSE	MAE	MPE	MAPE
0.028	0.003	25.7	33.3

7.5.3 Model Validation: Actual-to-Predicted Comparison

The practicality of the proposed models was demonstrated and validated through "actual-to-predicted" comparison study with three real-world highway construction projects across the State of California. As depicted in Figure 37, three different nighttime construction projects adjacent to Downtown Sacramento, Downtown San Diego, and Downtown Oakland were completed at different spatiotemporal scales, compared to the baseline zone in this study, Downtown LA.

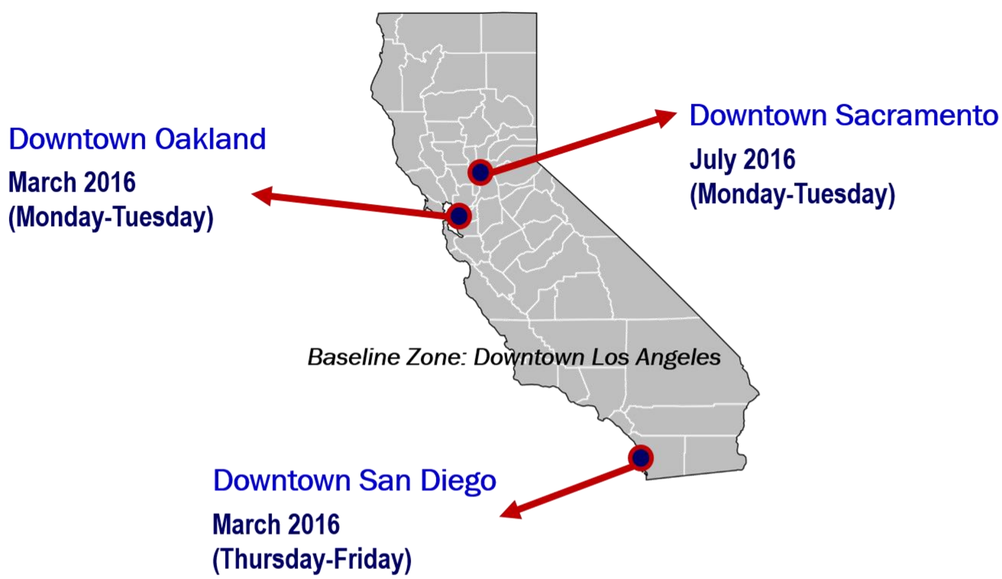
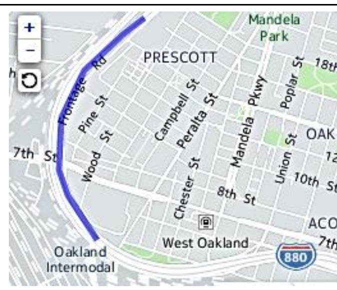


Figure 37 Real-world nighttme construction projects at different spatiotemporal scales

In detail, Table 20 summarizes project locations, specific lane closure IDs, and project durations at timely and daily scales, which were extracted from the PeMS database.

Table 20 A Summary of Nighttime Construction Projects in Large Urban Cores

Downtown Location	Construction Zone	Closure ID	Highway	Project Duration
Sacramento, CA		C5VB	I-5N	07/25/2016 - 07/26/2016 (Monday - Tuesday) 9:00 pm - 6:00 am
San Diego, CA		P5BA	I-5N	03/31/2016 - 04/01/2016 (Thursday - Friday) 11:00 pm - 5:00 am
Oakland, CA		C880GA	I-880N	03/23/2016 - 03/24/2016 (Monday - Tuesday) 10:00 pm - 5:00am

For each of these case studies, median values of estimated V/C ratios at a particular time on a certain day were applied to demonstrate the practicability of the proposed curve-fitting models. As the results, the potential percentile travel time delays during the corresponding lane closure were quantified. Subsequently, in order to directly compare with actual travel time parameter provided by PeMS (i.e., travel time index (TTI)), the predicted travel time delays were transformed into a form of the TTI. TTI is defined as the ratio of the average travel time to the free-flow travel time in a certain area, and PeMS computes the TTI by applying 60 mph of the free-flow speed (The PeMS Forum 2009).

Table 21 Case Study: Travel Time Delay during Nighttime Construction in Large Urban Cores

Construction Zone	**Time of the Day**	**No. of Lanes Closed (%)**	**Predicted V/C Ratio***	**Curve-Fitting Equation**	**Predicted Travel Time Delay (%)**	**Predicted Travel Time Index**	**Actual Travel Time Index**
Downtown Sacramento, CA I-5N	9:00 pm	75	1.09	Equation (24)	21.29	1.213	0.9
	10:00 pm	75	0.915		10.50	1.110	1.2
	11:00 pm	75	0.606		2.07	1.021	0.9
	0:00 am	75	0.529		1.28	1.013	0.9
	1:00 am	75	0.899		9.77	1.100	0.9
	2:00 am	75	0.799		6.06	1.061	0.9
	3:00 am	75	0.655		2.77	1.030	0.9
	4:00 am	75	1.25		36.63	1.376	0.9
	5:00 am	75	0.933		11.36	1.114	0.9
	6:00 am	75	1.24		35.49	1.355	1.1
Downtown San Diego, CA I-5N	11:00 pm	25	0.734	Equation (22)	4.33	1.043	0.9
	0:00 am	25	0.672		3.07	1.037	0.9
	1:00 am	25	1.06		19.02	1.190	0.9
	2:00 am	25	0.856		8.01	1.080	0.9
	3:00 am	25	0.479		0.88	1.000	0.9
	4:00 am	25	1.05		18.31	1.183	0.9
	5:00 am	25	0.771		5.26	1.053	0.9
Downtown Oakland, CA I-880N	10:00 pm	25	0.915	Equation (22)	10.50	1.110	1
	11:00 pm	25	0.606		2.07	1.021	1
	0:00 am	25	0.529		1.26	1.013	0.9
	1:00 am	25	0.899		9.77	1.100	0.9
	2:00 am	25	0.799		6.07	1.061	0.9
	3:00 am	25	0.655		2.78	1.030	0.9
	4:00 am	25	1.25		36.61	1.370	0.9
	5:00 am	25	0.933		11.36	1.114	0.9

*: Median values of predicted V/C ratios (obtained from Figure 30)

As the validation results shown in Table 3, RMSE and MAE values range from 0.184 to 0.245, which indicate accurate measures. The negative values of MPEs ranging from -20.41 to -21.90% represent the overfitting, which means that the sensored TTI for the three different downtown areas are within the pessimistic results of predicted TTI. Meanwhile, the MAPEs ranging from 20.41 to 22.27% revealed that the proposed models are acceptable for predicting travel time delays caused by nighttime construction in heavily trafficked downtown areas. In a nutshell, the validation study results conveyed a conclusion that the proposed methodology would be repeatable to a downtown area at a disparate location because the observed volumes of traffic for Downtown LA are representative by providing pessimistic prediction results of potential travel time delay at CWZs in large urban cores.

Table 22 Accuracy Validation of Models: Errors of Travel Time Index

Case Study Region	RMSE	MAE	MPE (%)	MAPE (%)
Downtown Sacramento, CA	0.235	0.207	-20.77	22.27
Downtown San Diego, CA	0.196	0.184	-20.41	20.41
Downtown Oakland, CA	0.245	0.190	-21.90	21.90

7.6 Summary of Phase III

This research phase aimed to model the impact of nighttime construction in heavily trafficked urbanized downtown areas, on the aspect of travel time delay under what-if lane closure schemes. As the most widely used VDF, the BPR function that specifies the impact of highway capacity on travel times or travel speeds has been widely used in traffic demand modeling as it requires a small number of data input parameters having the simple mathematical form. However, it was found that the existing form of the BPR function cannot address the travel time variability during construction accurately. The BPR function does not have the capability to estimate the difference between recurrent congestion and non-recurrent congestion at CWZs, due to a lack of lane closure parameters in the formulation. In addition, the existing form of BPR function cannot be generalized as it is dependent on a particular length of roadway segment, which is very project-specific.

This research phase were conducted through a three-stage process:

1. As the pre-process, the adjusted capacities of highway facilities before and during construction were computed, which incorporates the predicted truck percentages obtained from the proposed multi-contextual learning model as one of capacity adjustment factors. By integrating the predicted traffic flow rates achieved from the proposed multi-contextual learning model with the predicted adjusted capacities, the V/C ratios at the hourly temporal scale before and during construction were then obtained.
2. Using the predicted stereotypical V/C ratios, the standard BPR function was transformed into the proposed four different third-order polynomial curve-fitting models that specifically aim to graphically and mathematically achieve the percentile travel time delay under prevailing traffic conditions as well as under what-if lane closure schemes for nighttime construction in heavily trafficked urbanized downtown areas. The practicality of the proposed models was then demonstrated through a hypothetical example.

3. The robustness of models was statistically verified and validated by measuring accuracy through RMSE, MAE, MPE, and MAPE. All the accuracy measures confirmed that the proposed curve-fitting models are robust to predict nighttime work zone travel time delay on critical urban highways near heavily trafficked downtown areas.

8. SUMMARY AND CONCLUSIONS

Impact assessments of highway CWZs are essential for rehabilitating and reconstructing aging highways, as mandated by a federal rule. This rule enforces all STAs to conduct traffic impact analyses in a viable way to improve safety and mobility during construction. For a successful TMP, impact assessments of CWZ are essential, but they are also very difficult to perform. Especially, these assessments are challenging to perform for projects located in large urban areas with relatively dense roadway networks. A key reason is that it is difficult to benchmark traffic patterns (i.e., traffic flow and/or travel time) and quantify the potential traffic impact of CWZs for planned future projects.

Although many research efforts have been made to overcome this difficulty, most existing approaches are often univariate, project-specific, and short-term, thus incapable of benchmarking the potential traffic impact of CWZs for planned future highway infrastructure improvement projects. In addition, most existing models cannot reveal the travel time variability before and during construction accurately due to a lack of the capability to estimate the difference between recurrent traffic congestion under normal traffic flow conditions and traffic flow congestion caused by the presence of a CWZ simultaneously.

To advance the existing body of knowledge about traffic flow prediction for the betterment of impact assessments of CWZs, knowledge gaps emerged from the extensive review of previous studies:

1. Many studies have endeavored to find solutions to the nonlinear complexity of traffic data and have reported that ML approaches are effective and efficient for not only analyzing large quantities of traffic data but also predicting traffic patterns and recommending courses of action. However, the literature search concludes that most previous ML studies to date were focused on predicting "short-term" traffic flow under a normal condition, and therefore, knowledge about learning the long-term impact of urban highway work zones is largely missing.
2. Despite a sizeable body of research, little scientific work has been done on holistic approaches to obtaining the most realistic and reliable traffic flow patterns. Existing approaches are inadequate with regards to predicting traffic flow within a distinct set of clusters, because they fail to incorporate the unique characteristics of the particular cluster into the prediction model. These exclusive characteristics should be construed as multiple contexts such as spatial, temporal, weather, socio-demographic, and highway facility function conditions. In this regard, there remains a significant gap in the existing knowledge regarding the most effective and accurate prediction techniques for predicting potential traffic flows before and during lane closures and how multi-contextual characteristics can be effectively incorporated into the prediction models.
3. Existing methods to perform the CWZ traffic analysis are conducted through either simple macroscopic or microscopic levels. Most of the simple macroscopic models are easy to use but complicated when it comes to determining adjustment

factors, and require a huge amount of detailed input information about roadway networks. In addition, current microscopic models cannot capture global descriptions of the traffic flow rate, density, and velocity because they use simplistic models with synthetic datasets to represent the temporal aspect of the road network, instead of using real-world traffic data.

4. It is important to identify effective and efficient validation methods to test whether traffic data obtained from multiple sensor readings can be repeatable and reproducible on a certain temporal scale; this is necessary for the projection of a particular single cluster's characteristics. Although many previous studies reported that Repeatability and Reproducibility (R&R) analyses can be used to determine the most accurate and precise measurement systems, very little is known about R&R studies for transportation applications. Especially, there is a lack of research on testing the robustness of collected data to investigate the precision of traffic sensor readings; this information is necessary for the management and validation of archived traffic data that must occur before a traffic data analysis can be conducted.

To fill these gaps, this study aimed to create a decision-support analytical framework and test if it can reliably predict the potential impact of a CWZ under arbitrary construction planning and management scenarios. This study proposed a big-data-driven decision-support model "Multi-contextual learning for the Impact of Critical

Urban highway work Zones" (MICUZ). MICUZ specifies three specific sub-objectives as follows:

1. Testing whether traffic flows extracted from archived multiple sensor readings can be repeatable and reproducible, thereby validating the robustness of the collected sensored data whether they can represent the temporal traffic flow under prevailing traffic conditions and lane closure within a distinct set of spatial clusters.
2. Accurately and reliably predicting long-term traffic flow under prevailing traffic conditions and lane closures, via the proposed multi-contextual learning model that employs ANN.
3. Modeling the impact of CWZ on the aspect of travel time delay trend through the proposed curve-fitting models that specifically quantify and generalize travel time delay trends for nighttime construction in large urban cores.

MICUZ specifically focused on modeling and predicting the traffic impact of CWZs on the aspect of travel time delays to assess the level of motorist's inconvenience caused by the presence of a CWZ in heavily trafficked large urban corridors. To define large urban corridors, MICUZ addresses critical highways in large urban cores, where the Annual Average Daily Traffic (AADT) volume is over 250,000. Among various urban sets of heavy AADT clusters that were examined, the City of Los Angeles (LA) in the state of California was chosen for this study because LA has been named the city with the worst traffic in the United States. Therefore, the learned knowledge through the case of LA would be applied to other critical urban highway systems with similar characteristics but where sensor data are not available.

As the traffic flow analysis zone, Interstate highways adjacent to the Central Business District (CBD), simply known as “Downtown LA,” were selected for this study. In detail, highway directions toward the CBD including I-10 East and I-110 South were served as the traffic flow analysis network. In general, the CBD is characterized by a key urban structure type and commercial land use (i.e., retail and service business). CBDs commonly appear through large cities and is home to numerous economic activities that are significantly affected by changes in the transportation system. Therefore, the selected scope of this study would be applicable for analyzing the potential traffic impact in other large urban cores.

A total of 17,518 traffic sensor readings on Interstate highways (I-10 East and I-110 South) adjacent to the CBD were extracted from the PeMS database. Hourly traffic volumes that include the percentage of trucks within the corresponding traffic flow are collected during the whole year in 2014 (0:00 am on January 1 to 11:59 pm on December 31, 2014). In addition to traffic sensor readings, multi-contextual datasets were collected in order to improve the accuracy of prediction of the proposed network learning model, including highway facility functional information, weather conditions, and socio-demographic characteristics. Highway facility functional variables were collected from the PeMS to capture the impact of the existing highway capacity condition on the traffic flow variation under normal condition as well as the potential traffic flow during lane closures. The weather conditions including the historical datasets of daily precipitation and visibility in 2014 were collected from the QCLCD database provided by NOAA. As socio-demographic characteristics, Population density in the Census areas adjacent to the traffic flow analysis zone was collected from Census Tracts of California. In addition, percentages of main commute modes on the highways, such as self-driving and car/vanpooling, were collected from the LA Department of City Planning.

The following are a summary of modeling process followed by the proposed MICUZ framework and the results of each modeling phase:

1. Phase I attempted to test whether multiple traffic sensor readings for traffic flow would be applicable to spatiotemporally similar characteristics of roadway networks. Multiple sensor readings within a spatiotemporally distinct set of clusters, such as highway traffic flow variations adjacent to a CBD at a specific time on a particular day, would result in biased results when predicting the potential traffic flow under similar conditions. To tackle this issue, MICUZ adopted Wheeler's HG method to determine the repeatability and reproducibility of temporally classified traffic flow measurements before construction (Stage I) and those of nighttime work zone traffic flow (Stage II) on an hourly temporal scale. The results confirmed that both Stage I and II analyses were scientifically validated by meeting with the R&R criteria and the class classification monitors developed by Wheeler. It was found that traffic flow measurements during lane closures were relatively simpler and periodical within the urbanized downtown area, and could then be translated into work zone characteristics. In general, work

zones are relatively small areas, and certain restrictions are often applied to work zone traffic such as no lane changing, lowered speed limits, highway patrol-enforced traffic control, and so on. In this regard, it was concluded that work zone traffic flow data from urban downtown areas is more repeatable and reproducible than data regarding normal conditions.

2. Through Phase II modeling process, the proposed multi-contextual learning model was developed and validated through the MLP FNN to predict long-term traffic flow and the corresponding truck percentages before and during construction, by employing the multi-contextual characteristics. The predicted outcomes were then incorporated into the proposed curve-fitting models specifically aiming at predicting the impact of CWZs in terms of travel time delay (Phase III). Phase II included a five-stage process as follows:

    1) An architecture of the proposed network learning model was created based on the MLP network, which is suitable for large-scale problems. As an MLP network, the proposed network was designed with three layers of neurons that are interconnected: 1) an input layer; 2) one hidden layer; and 3) an output layer. Multi-contextual variables used in the proposed network learning model consisted of a total of 26 input variables and 2 prediction target variables (outputs), which includes a total of 17,518 supervised data samples. All the multi-contextual variables (inputs) were mapped on the corresponding outputs, which represents the proposed learning model centers on the supervised learning of artificial neural networks.

2) To better determine the learning structure, critical components affecting the performance of the MLP networks were identified through previous studies on aspects of activation functions, training algorithms, and the number of hidden nodes. The learning structure for the proposed model was then determined on aspects of training algorithm, activation functions and the optimal number of hidden nodes. The performance of neural networks is significantly affected by the connection weights and activation functions. The connection weights are unknown parameters that can be estimated by a training algorithm. Throughout the literature review, the proposed learning model employed the BFGS algorithm to predict long-term traffic flow before and during construction near the CBD.
3) These critical components were determined through the automated neural network search, resulting in 54 nodes in the hidden layer and the sigmoid function for the hidden layer and the identity function for the output layer as activation functions.
4) In order to improve the accuracy and reliability of the determined learning structured model depending on the randomly selected three different datasets (i.e., training, validation, test sets), a total of five different 26-54-2 networks were retained for the short-list by training 100 different 26-54-2 networks completed by each different epoch showing the convergence velocity. As the final model, the multi-contextual learning model 26-54-2 with BFGS 646 was selected based on its test and validation errors. The BFGS 646 indicates the

BFGS algorithm followed by 646 epochs, which means that this network model was found at the 646th cycle.

5) The learning outcomes, including the long-term traffic flow and the percentage of trucks, were measured by correlation coefficients between prediction values and actual values associated with the training, validation, and test datasets, separately. The results of the correlation coefficients, which ranged from 0.954650 to 0.962356, confirmed that there exist significant relationships between actual and prediction values from the three different datasets.

3. Phase III aimed to model the impact of nighttime construction in heavily trafficked urbanized downtown areas, on the aspect of travel time delay trend under what-if lane closure schemes. As the pre-process, the adjusted capacities of highway facilities before and during construction were computed, which incorporates the predicted truck percentages obtained from the proposed multi-contextual learning model as one of capacity adjustment factors. Based on the predicted V/C ratios (Stage I), four different third-order polynomial curve-fitting models were created to directly address the potential travel time delay under prevailing traffic conditions as well as under lane closure for the nighttime construction, which reinvent the existing BPR function appropriately (Stage II). The robustness of models was statistically verified and validated by measuring accuracy through RMSE, MAE, MPE, and MAPE (Stage III).

Table 20 summarizes the results of the proposed MICUZ modeling framework.

Table 23 A Summary of Results: The Proposed MICUZ Modeling Framework

Phase	**Outcomes**	**Approach**	**Stage**	**Results**
Phase I: Robustness Check	Repeatability and Reproducibility (R&R) of Collected Data	Wheeler's HG Method	Stage I: Before Lane Closure	▪ Combined R&R: 28.7% ▪ Second class monitoring classification
			Stage II: During Lane Closure	▪ Combined R&R: 2.4% ▪ First class monitoring classification
Phase II: Multi-Contextual Modeling	Predicted Long-Term Traffic Flow Rates and Truck Percentages	MLP Feedforward Neural Networks	Stage I: Architecture	▪ Three layered feedforward network ▪ Number of input nodes (26) and output nodes (2)
			Stage II: Key Components	▪ Alternatives of activation functions ▪ Training algorithms ▪ Number of hidden nodes
			Stage III: Learning Structure	▪ BFGS quasi-Newton method for training the network ▪ Sigmoid function for the hidden layer; and identity function for the output layer ▪ 54 hidden nodes
			Stage IV: Final Model	▪ Network 26-54-2 using the BFGS training algorithm followed by 646 epochs
			Stage V: Model Validation	▪ Significant relationships between actual and predicted values
Phase III: Travel Time Delay Modeling	Nighttime Work Zone Travel Time Delay Trend Models	Third-Order Polynomial Fitting	Stage I: V/C Ratios	▪ Adjusted capacities before and during construction ▪ V/C ratios incorporate the outcomes from Phase II
			Stage II: Travel Time Delay Trend	▪ Four different curve fitting models for quantifying the percentile travel time delays
			Stage III: Model Verification and Validation	▪ Robust enough with respect to CWZ travel time delay trend prediction ▪ The proposed methodology is repeatable to a downtown are at a disparate location

The following are main findings of this study through Phase I to Phase III of the MICUZ framework:

1. Phase I: The R&R analysis results confirmed that variability of sensored big data was homogeneous, which made this study possible. In general, as one of key characteristics of big data, controlling the variability of big data is essential and crucial because the inconsistency of datasets would impede the analysis process. In addition, the results convey the notable conclusion that highway traffic patterns before and during construction would be simple and periodical.
2. Phase II: Use of multi-contextual datasets led accurate impact assessments of long-term traffic flow at the construction zones, based on traffic flow rates and truck percentages.
3. Phase III: Error-prone impact assessments of additional travel time under arbitrary lane closures at the construction zones were improved, through the proposed curve-fitting models.

The proposed MICUZ framework is unique as it models the impact of CWZ operations from a quantitative perspective using high-confidence real-world multi-contextual big data. Based on the proposed multi-contextual learning model via ANN, MICUZ is able to learn and generalize from a training dataset of critical urban highway systems and apply this knowledge to other highway systems with similar characteristics but where sensor data are not available.

In detail, the proposed multi-contextual learning model is expected to represent a significant leap forward in accurately and reliably predicting the long-term traffic flow rates before and during construction, which will serve as a baseline for incorporation into CWZ impact analyses that encompass travel time delay, queue length, and road user cost. These findings will provide a solid foundation for filling the gap between highway network features and the long-term benchmarking of traffic flows sourced from real-world traffic sensor data (with large quantities and high quality, both spatially and temporally) with multi-contextual characteristics. In addition, the proposed curve-fitting models have a potential to generalize the potential impact of nighttime work zone travel time delays by overcoming the hurdles inherent in the BPR function's existing form, making them very intuitive and easy to use. Furthermore, this study is the first of its kind in that it tested the temporal and spatial periodicity present among traffic flow measurements from multiple traffic sensors through a measurement system analysis. The results and findings will allow for more efficient management of measured sensor data by assessing both repeatability and reproducibility. It is expected that the MICUZ framework enables repeating a similar approach to other real-world projects in a disparate location at a different time frame. The 'actual-to-prediction' validation study performed on three disparate longitudinal downtown locations verified the repeatability and robustness of the proposed modeling framework. It conveys the fact that the proposed model would recognize how stereotypical regional traffic patterns react to existing CWZs and lane closure tactics, and generalize its understanding of those reactions to other roadway networks where work zones are planned. In this way, CWZ mobility impact assessment in urban roadway networks would be greatly improved without the need of deploying additional sensors, both in terms of accuracy of results and in reducing the effort required to perform these types of analyses.

This study conveys a notable conclusion that travelers' inconvenience can be assessed into a set of distinct signature modeling patterns. The proposed MICUZ framework provides a rigorous theoretical basis for comparatively analyzing what-if construction scenarios, enabling engineers and planners to choose the most efficient transportation management plans much quickly and accurately. This study will assist STAs and the general traveling public in understanding potential traffic flow issues attributable to construction in heavily trafficked large urban cores (i.e., downtown areas with CBDs), while improving mobility in and between CWZs and positively affecting regional development. Moreover, the proposed multi-contextual models will also help state transportation agencies quantify the reasonable rate of traffic demand reduction under various alternative lane closure scenarios in advance, while providing the traveling public both pre-trip planning and en-route guidance during construction.

The current learning model in this study forms the basis for future studies seeking to create novel computerized decision-support models applicable to any given CWZs by accurately predicting potential impacts from potential 24/7 traffic patterns, queue delays (time and queue length), and road user delay costs. The following areas should be explored in the future to fine tune the proposed model's capabilities:

- Expansion of the scope of the MICUZ framework to cover other types of traffic analysis zones, such as residential, commercial, attraction, and remote areas, in order to discover stereotypical traffic patterns and characterize them according to a set of signature traffic pattern clusters built for different levels of traffic volume;

- Expansion of the scope of the multi-contextual datasets that can represent the characteristics of the corresponding traffic analysis zone in several spatial regions;
- Incorporation of numerous what-if construction alternatives (e.g., weekday, weekend, 24/7) into the MICUZ framework in order to assess the impact of numerous alternative construction plans; and
- Development of an improved learning model that can more accurately predict potential traffic patterns and automatically predict road user costs and queue delays.

REFERENCES

Abdel-Rahim, A., Cooley, H., Gould, S., and Khanal, M. (2010). "Synthesis of Research on Work Zone Delays and Simplified Application of QuickZone Analysis Tool." <http://idahodocs.cdmhost.com/cdm/ref/collection/p16293coll3/id/241107>. (06/20, 2016).

Abdelmohsen, A. Z., and El-Rayes, K. (2016). "Optimal trade-offs between construction cost and traffic delay for highway work zones." *Journal of Construction Engineering and Management*, 142(7), 05016004.

Abdi, J., and Moshiri, B. (2015). "Application of temporal difference learning rules in short-term traffic flow prediction." *Expert Systems*, 32(1), 49-64.

Abdi, J., Moshiri, B., Abdulhai, B., and Sedigh, A. K. (2012). "Forecasting of short-term traffic-flow based on improved neurofuzzy models via emotional temporal difference learning algorithm." *Engineering Applications of Artificial Intelligence*, 25(5), 1022-1042.

Abdi, J., Moshiri, B., Abdulhai, B., and Sedigh, A. K. (2013). "Short-term traffic flow forecasting: Parametric and nonparametric approaches via emotional temporal difference learning." *Neural Computing and Applications*, 23(1), 141-159.

Abouaissa, H., Fliess, M., and Join, C. (2016). "On short-term traffic flow forecasting and its reliability." *The 8th IFAC Conference on Manufacturing Modelling, Management and Control (MIM 2016)*, Elsevier, Troyes, France, June 28-30, 111-116.

Adeli, H., and Ghosh-Dastidar, S. (2004). "Mesoscopic-wavelet freeway work zone flow and congestion feature extraction model." *Journal of Transportation Engineering*, 130(1), 94-103.

Ahmed, M. S., and Cook, A. R. (1979). "Analysis of freeway traffic time-series data by using Box-Jenkins techniques." *Transportation Research Board, 722*, 1-9.

AIAG (2002). *Measurement systems analysis (MSA)*, The Automotive Industries Action Group, Southfield, MI.

AIAG (2010). *Measurement systems analysis (MSA)*, The Automotive Industries Action Group, Southfield, MI.

Al-Kaisy, A., and Hall, F. (2003). "Guidelines for estimating capacity at freeway reconstruction zones." *Journal of Transportation Engineering*, 129(5), 572-577.

Alekseev, A., Navon, I., and Steward, J. (2009). "Comparison of advanced large-scale minimization algorithms for the solution of inverse ill-posed problems." *Optimization Methods & Software*, 24(1), 63-87.

Antony, J., Knowles, G., and Roberts, P. (1999). "Gauge capability analysis: Classical versus ANOVA." *Quality Assurance: Good Practice, Regulation, and Law*, 6(3), 173-181.

Arciszewski, T., Bloedorn, E., Michalski, R. S., Mustafa, M., and Wnek, J. (1994). "Machine learning of design rules: Methodology and case study." *Journal of Computing in Civil Engineering*, 8(3), 286-308.

Awad, M., Erdmann, T. P., Shanshal, Y., and Barth, B. (2009). "A measurement system analysis approach for hard-to-repeat events." *Quality Engineering*, 21(3), 300-305.

Bando, M., Hasebe, K., Nakayama, A., Shibata, A., and Sugiyama, Y. (1995). "Dynamical model of traffic congestion and numerical simulation." *Physical Review E*, 51(2), 1035.

Barros, J., Araujo, M., and Rossetti, R. J. (2015). "Short-term real-time traffic prediction methods: A survey." *International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS 2015)*, IEEE, Budapest, Hungary, June 3-5, 132-139.

Bayraktar, M. E., and Hastak, M. (2009). "A decision support system for selecting the optimal contracting strategy in highway work zone projects." *Automation in Construction*, 18(6), 834-843.

Ben-Akiva, M., Bierlaire, M., Koutsopoulos, H., and Mishalani, R. (1998). "DynaMIT: A simulation-based system for traffic prediction." *DACCORS Short Term Forecasting Workshop*, Citeseer, Delft University of Technology, Delft, Netherland, February 13.

Bhat, C. R., Guo, J. Y., Srinivasan, S., and Sivakumar, A. (2004). "Comprehensive econometric microsimulator for daily activity-travel patterns." *Transportation Research Record: Journal of the Transportation Research Board*, 1894(1), 57-66.

Bing, Q., Gong, B., Yang, Z., Shang, Q., and Zhou, X. (2015). "Short-term traffic flow local prediction based on combined kernel function relevance vector machine model." *Mathematical Problems in Engineering*, 2015, 1-9.

Bissacot, A., Salgado, S., Balestrassi, P., Paiva, A., Zambroni Souza, A., and Wazen, R. (2016). "Comparison of neural networks and logistic regression in assessing the occurrence of failures in steel structures of transmission lines." *The Open Electrical & Electronic Engineering Journal*, 10(1), 11-26.

Burdick, R. K., Borror, C. M., and Montgomery, D. C. (2003). "A review of methods for measurement systems capability analysis." *Journal of Quality Technology*, 35(4), 342-354.

Cai, P., Wang, Y., Lu, G., Chen, P., Ding, C., and Sun, J. (2016). "A spatiotemporal correlative k-nearest neighbor model for short-term traffic multistep forecasting." *Transportation Research Part C: Emerging Technologies*, 62, 21-34.

Caltrans (2012). "The Caltrans Performance Measurement System (PeMS)." <http://pems.dot.ca.gov/>. (09/15, 2013).

Cao, H., and Han, F. (2014). "The urban arterial traffic flow forecasting based on BP neural network." *The 4th International Conference on Instrumentation and Measurement, Computer, Communication and Control (IMCCC 2014)*, IEEE, Harbin, China, September 18-20, 393-397.

Carson, J. S. (2002). "Model verification and validation." *2002 Winter Simulation Conference*, IEEE, San Diego, CA, December 8-11, 52-58.

CBS Los Angeles (2016). "Study: L.A. Has Worst Traffic In America." <http://losangeles.cbslocal.com/2016/03/15/study-l-a-has-worst-traffic-in-america/>. (08/20, 2016).

Çetiner, B. G., Sari, M., and Borat, O. (2010). "A neural network based traffic-flow prediction model." *Mathematical and Computational Applications*, 15(2), 269-278.

Chai, T., and Draxler, R. R. (2014). "Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature." *Geoscientific Model Development*, 7(3), 1247-1250.

Chandler, R. E., Herman, R., and Montroll, E. W. (1958). "Traffic dynamics: Studies in car following." *Operations Research*, 6(2), 165-184.

Chang, G., Zhang, Y., Yao, D., and Yue, Y. (2011). "A summary of short term traffic flow forecasting methods." *The 11th International Conference of Chinese Transportation Professionals (ICCTP 2011)*, ASCE, Nanjing, China, August 14-17, 1696-1707.

Chen, C., Petty, K., Skabardonis, A., Varaiya, P., and Jia, Z. (2001). "Freeway performance measurement system: Mining loop detector data." *Transportation Research Record: Journal of the Transportation Research Board*(1748), 96-102.

Chen, L., and Chen, C. P. (2007). "Ensemble learning approach for freeway short-term traffic flow prediction." *International Conference on System of Systems Engineering (SoSE'07)*, IEEE, San Antonio, TX, April 16-18, 1-6.

Chen, M., and Yao, Z. (2008). "Classification techniques of neural networks using improved genetic algorithms." *The 2nd International Conference on Genetic and Evolutionary Computing (WGEC 2008)*, IEEE, Jingzhou, China, September 25-26, 115-119.

Chew, J. (2016). "This City Has the Worst Traffic Congestion in the U.S.", <http://fortune.com/2016/03/22/los-angeles-tomtom-traffic/>. (08/20, 2016).

Choi, K., and Bae, J. (2015). "Spatiotemporal impact assessments of highway construction: Autonomous SWAT modeling." *The 6th International Conference on Construction Engineering and Project Management (ICCEPM 2015)*, Korea Institute of Construction Engineering and Management (KICEM), Busan, South Korea, October 11-14, 294-298.

Choi, K., Kim, Y. H., Bae, J., and Lee, H. W. (2016). "Determining future maintenance costs of low-volume highway rehabilitation projects for incorporation into life-cycle cost analysis." *Journal of Computing in Civil Engineering*, 30(4), 04015055.

Choi, K., and Kwak, Y. H. (2012). "Decision support model for incentives/disincentives time–cost tradeoff." *Automation in Construction*, 21, 219-228.

Choi, K., Kwak, Y. H., and Yu, B. (2010). "Quantitative model for determining incentive/disincentive amounts through schedule simulations." *2010 Winter Simulation Conference (WSC)*, IEEE, Baltimore, MD, December 5-8, 3295-3306.

Choi, K., Lee, H. W., Bae, J., and Bilbo, D. (2016). "Time-cost performance effect of change orders from accelerated contract provisions." *Journal of Construction Engineering and Management*, 142(3), 04015085.

Choi, K., Park, E. S., and Bae, J. (2013). "Decision-support Framework for quantifying the most economical incentive/disincentive dollar amounts for critical highway pavement rehabilitation projects." Southwest Region University Transportation Center, Texas A&M Transportation Institute, College Station, TX.

Chung, Y. (2011). "Assessment of non-recurrent traffic congestion caused by freeway work zones and its statistical analysis with unobserved heterogeneity." *Transport Policy*, 18(4), 587-594.

City of Los Angeles (2016). "Home-to-Work Commute Modes." <http://planning.lacity.org/DRU/C2K/C2KFrame.cfm?geo=cd&loc=009&sgo=ct&rpt=H2W&yrx=dummy>. (03/15, 2015).

Cong, Y., Wang, J., and Li, X. (2016). "Traffic flow forecasting by a least squares support vector machine with a fruit fly optimization algorithm." *Procedia Engineering*, 137, 59-68.

Conley, T., and Dupor, B. (2011). "The American Recovery and Reinvestment Act: Public sector jobs saved, private sector jobs forestalled." <http://www.gop.gov/resources/library/documents/jobs/ohio-failed-stimulus.pdf>. (03/15, 2015).

Copeland, L. (1998). *User's Manual for QUEWZ-98*, Texas A&M Transportation Institute, College Station, TX.

Cottrell, W. D. (2001). "Empirical freeway queuing duration model." *Journal of Transportation Engineering*, 127(1), 13-20.

Dai, H., Liu, Q., Wang, F., and Gong, C. (2015). "Investigation and prediction of traffic flow in holidays in Zhejiang section of Shenhai freeway." *International Conference on Transportation Information and Safety (ICTIS 2015)*, IEEE, Wuhan, China, June 25-28, 195-201.

Dao, V. N., and Vemuri, V. (2002). "A performance comparison of different back propagation neural networks methods in computer network intrusion detection." *Differential Equations and Dynamical Systems*, 10(1&2), 201-214.

Datla, S., Sahu, P., Roh, H.-J., and Sharma, S. (2013). "A comprehensive analysis of the association of highway traffic with winter weather conditions." *Procedia-Social and Behavioral Sciences*, 104, 497-506.

Davis, G. A., Nihan, N. L., Hamed, M. M., and Jacobson, L. N. (1990). "Adaptive forecasting of freeway traffic congestion." *Transportation Research Record: Journal of the Transportation Research Board*(1287), 29-33.

Dell'Acqua, P., Bellotti, F., Berta, R., and De Gloria, A. (2015). "Time-aware multivariate nearest neighbor regression methods for traffic flow prediction." *IEEE Transactions on Intelligent Transportation Systems*, 16(6), 3393-3402.

Demiryurek, U., Banaei-Kashani, F., and Shahabi, C. (2010). "TransDec: A spatiotemporal query processing framework for transportation systems." *The 26th International Conference on Data Engineering (ICDE 2010)*, IEEE, Long Beach, CA, March 1-6, 1197-1200.

Demiryurek, U., Pan, B., Banaei-Kashani, F., and Shahabi, C. (2009). "Temporal Modeling of Spatiotemporal Networks." *The 2nd International Workshop on Computational Transportation Science (IWCTS 2009)*, Association for Computing Machinery (ACM), Seattle, WA, November 3.

Dia, H. (2001). "An object-oriented neural network approach to short-term traffic forecasting." *European Journal of Operational Research*, 131(2), 253-261.

Dixon, K., Hummer, J., and Lorscheider, A. (1996). "Capacity for North Carolina freeway work zones." *Transportation Research Record: Journal of the Transportation Research Board*(1529), 27-34.

Dixon, K. K., and Hummer, J. E. (1996). "Capacity and delay in major freeway construction zones." Center for Transportation Engineering Studies, Dept. of Civil Engineering, North Carolina State University, Raleigh, NC.

Dougherty, M. S., and Cobbett, M. R. (1997). "Short-term inter-urban traffic forecasts using neural networks." *International Journal of Forecasting*, 13(1), 21-31.

Dudek, C. L., and Richards, S. H. (1981). "Traffic capacity through work zones on urban freeways." Texas Department of Transportation, Austin, TX.

Effati, M., Thill, J.-C., and Shabani, S. (2015). "Geospatial and machine learning techniques for wicked social science problems: Analysis of crash severity on a regional highway corridor." *Journal of Geographical Systems*, 17(2), 107-135.

Ekedebe, N., Yu, W., Lu, C., and Moulema, P. (2015). "An evaluation into the efficiency and effectiveness of machine learning algorithms in realistic traffic pattern prediction using field data." *SPIE: Independent Component Analyses,* *Compressive Sampling, Large Data Analyses (LDA), Neural Networks, Biosystems, and Nanoengineering XIII*, International Society for Optics and Photonics, September 30, 94960B.

Erdmann, T. P., Does, R. J., and Bisgaard, S. (2009). "Quality quandaries*: A gage R&R study in a hospital." *Quality Engineering*, 22(1), 46-53.

Ermer, D. S. (2006). "Appraiser variation in gage R&R measurement." *Quality Progress*, 39, 75-78.

Fausett, L. (1994). *Fundamentals of neural networks: architectures, algorithms, and applications*, Prentice-Hall, Inc., Upper Saddle River, NJ.

Federal Highway Administration (2002). "Life-Cycle Cost Analysis Primer." Federal Highway Administration, Office of Asset Management, Washington, D.C.

Federal Highway Administration (2006). "Work Zone Impacts Assessment – An Approach to Assess and Manage Work Zone Safety and Mobility Impacts of Road Projects." <http://www.ops.fhwa.dot.gov/Wz/resources/final_rule/wzi_guide/index.htm>. (01/30, 2016).

Federal Highway Administration (2007). "Rule on Work Zone Safety and Mobility 23 CFR 630 Subpart J." Federal Highway Administration, Washington, D.C.

Federal Highway Administration (2011). "Guide on the Consistent Application of Traffic Analysis Tools and Methods." Federal Highway Administration, Washington, D.C.

Federal Highway Administration (2014). "6.0 Comparison of Highway Capacity Manual (HCM) and Simulation." <http://ops.fhwa.dot.gov/trafficanalysistools/tat_vol1/sect6.htm>. (6/30, 2014).

Federal Highway Administration (2014). "Facts and Statistics – Work Zone Mobility." <http://www.ops.fhwa.dot.gov/wz/resources/facts_stats/mobility.htm>. (05/30, 2016).

Federal Highway Administration (2014). "MAP-21: Moving Ahead for Progress in the 21st Century." <https://www.fhwa.dot.gov/map21>. (07/05, 2014).

Federal Highway Administration (2015). "Travel Monitoring." <http://www.fhwa.dot.gov/policyinformation/tables/02.cfm>. (10/30, 2015).

Federal Highway Administration (2015). "Work Zone and Traffic Analysis Tools." <http://www.ops.fhwa.dot.gov/wz/traffic_analysis/tools.htm>. (11/15, 2015).

Federal Highway Administration (2015). "Work Zone Impacts Assessment." <http://ops.fhwa.dot.gov/wz/resources/impact_factsheet.htm>. (1/30, 2016).

Federal Highway Administration (2016). "Fixing America's Surface Transportation Act or "FAST Act"." <http://www.fhwa.dot.gov/fastact/>. (05/31, 2016).

Fletcher, L., Katkovnik, V., Steffens, F., and Engelbrecht, A. (1998). "Optimizing the number of hidden nodes of a feedforward artificial neural network." *International Joint Conference on Neural Networks Proceedings and World Congress on Computational Intelligence 1998*, IEEE, Cambridge, MA, May 4-9, 1608-1612.

Gevrey, M., Dimopoulos, I., and Lek, S. (2003). "Review and comparison of methods to study the contribution of variables in artificial neural network models." *Ecological Modelling*, 160(3), 249-264.

Ghosh-Dastidar, S., and Adeli, H. (2006). "Neural network-wavelet microsimulation model for delay and queue length estimation at freeway work zones." *Journal of Transportation Engineering*, 132(4), 331-341.

Grant, J. L. (2014). "Short-term peak demand forecasting using an artificial neural network with controlled peak demand through intelligent electrical loading." Dissertation, University of Miami, Coral Gables, FL.

Gu, H., Lu, J., and Liu, Q. (2015). "Traffic volume prediction based on cost factor optimization of support vector machine regression." *The 15th COTA International Conference of Transportation Professionals (CICTP 2015)*, ASCE, Beijing, China, July 25-27, 621-629.

Gutierrez-Osuna, R. (2005). "Introduction to pattern analysis." *Lecture Notes*, Department of Computer Science and Engineering , Texas A&M University, College Station, TX.

Habtemichael, F. G., and Cetin, M. (2016). "Short-term traffic flow rate forecasting based on identifying similar traffic patterns." *Transportation Research Part C: Emerging Technologies*, 66, 61-78.

Hamed, M. M., Al-Masaeid, H. R., and Said, Z. M. B. (1995). "Short-term prediction of traffic volume in urban arterials." *Journal of Transportation Engineering*, 121(3), 249-254.

Hasley, A. (2013). "Washington rated the worst for traffic congestion." <http://www.washingtonpost.com/local/trafficandcommuting/washington-rated-the-worst-for-traffic-congestion--again/2013/02/04/125be724-6ee3-11e2-8b8d-e0b59a1b8e2a_story.html>. (12/02, 2013).

Hoffa, D. W., and Laux, C. M. (2007). "Gauge R&R: An effective methodology for determining the adequacy of a new measurement system for micron-level metrology." *NAIT 2007 Conference*, Association of Technology, Management, and Applied Engineering (ATMAE), Panama City Beach, FL, November 25, 139-145.

Hong, H., Huang, W., Xing, X., Zhou, X., Lu, H., Bian, K., and Xie, K. (2015). "Hybrid multi-metric k-nearest neighbor regression for traffic flow prediction." *The 18th International Conference on Intelligent Transportation Systems (ITSC 2015)*, IEEE, Las Palmas de Gran Canaria, Spain, September 15-18, 2262-2267.

Hong, H., Huang, W., Zhou, X., Du, S., Bian, K., and Xie, K. (2015). "Short-term traffic flow forecasting: Multi-metric KNN with related station discovery." *The 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2015)*, IEEE, Zhangjiajie, China, August 15-17, 1670-1675.

Hou, Y., Edara, P., and Sun, C. (2015). "Traffic flow forecasting for urban work zones." *IEEE Transactions on Intelligent Transportation Systems*, 16(4), 1761-1770.

Hourdakis, J., Michalopoulos, P. G., and Kottommannil, J. (2003). "Practical procedure for calibrating microscopic traffic simulation models." *Transportation Research Record: Journal of the Transportation Research Board*, 1852(1), 130-139.

Hu, W., Yan, L., Liu, K., and Wang, H. (2016). "A short-term traffic flow forecasting method based on the hybrid PSO-SVR." *Neural Processing Letters*, 43(1), 155-172.

Hyndman, R. J. (2014). "Measuring forecast accuracy." *Forecasting: principles and practice*, OTexts, Melbourne, Australia.

Ilonen, J., Kamarainen, J.-K., and Lampinen, J. (2003). "Differential evolution training algorithm for feed-forward neural networks." *Neural Processing Letters*, 17(1), 93-105.

Ingraham, C. (2015). "Where America's worst roads are — and how much they're costing us." <https://www.washingtonpost.com/news/wonk/wp/2015/06/25/why-driving-on-americas-roads-can-be-more-expensive-than-you-think/>. (11/01, 2015).

Innamaa, S. (2000). "Short-term prediction of traffic situation using MLP-neural networks." *The 7th World Congress on Intelligent Transport Systems*, ITS World Congress, Turin, Italy, November 6-9, 6-9.

Jain, A. K., Mao, J., and Mohiuddin, K. (1996). "Artificial neural networks: A tutorial." *Computer*(3), 31-44.

Jeffery, D., Russam, K., and Robertson, D. (1987). "Electronic route guidance by AUTOGUIDE: The research background." *Traffic Engineering & Control*, 28(10), 525-529.

Jiang, H., Zou, Y., Zhang, S., Tang, J., and Wang, Y. (2016). "Short-term speed prediction using remote microwave sensor data: Machine learning versus statistical model." *Mathematical Problems in Engineering*, 2016, 1-13.

Jiang, X., and Adeli, H. (2004). "Object-oriented model for freeway work zone capacity and queue delay estimation." *Computer-Aided Civil and Infrastructure Engineering*, 19(2), 144-156.

Jiang, Y.-P., Guo, J.-L., and Zhao, J.-W. (2013). "Short-term traffic flow's forecasting by fusing wavelet neural network and historical trend model." *Modern Computer*, 3, 26-29.

Jin, F., and Sun, S. (2008). "Neural network multitask learning for traffic flow forecasting." *International Joint Conference on Neural Networks and World Congress on Computational Intelligence 2008*, IEEE, Wan Chai, Hong Kong, June 1-6, 1897-1901.

Joubert, J. W., and Meintjes, S. (2015). "Repeatability & reproducibility: Implications of using GPS data for freight activity chains." *Transportation Research Part B: Methodological*, 76, 81-92.

Kachroo, P., and Özbay, K. M. (2012). *Feedback control theory for dynamic traffic assignment*, Springer Science & Business Media, Berlin, Germany.

Kalman, R. E. (1960). "A new approach to linear filtering and prediction problems." *Journal of Basic Engineering*, 82(1), 35-45.

Kamarianakis, Y., and Prastacos, P. (2003). "Forecasting traffic flow conditions in an urban network: Comparison of multivariate and univariate approaches."

Transportation Research Record: Journal of the Transportation Research Board(1857), 74-84.

Kamarianakis, Y., and Prastacos, P. (2005). "Space–time modeling of traffic flow." *Computers & Geosciences*, 31(2), 119-133.

Karamizadeh, S., Abdullah, S. M., Halimi, M., Shayan, J., and Rajabi, M. J. (2014). "Advantage and drawback of support vector machine functionality." *International Conference on Computer, Communications, and Control Technology (I4CT 2014)*, IEEE, Langkawi, Malaysia, September 2-4, 63-65.

Kargah-Ostadi, N. (2014). "Comparison of machine learning techniques for developing performance prediction models." *Computing in Civil and Building Engineering (2014)*, ASCE, Orlando, FL, June 23-25, 1222-1229.

Karim, A., and Adeli, H. (2003). "CBR model for freeway work zone traffic management." *Journal of Transportation Engineering*, 129(2), 134-145.

Karim, A., and Adeli, H. (2003). "Radial basis function neural network for work zone capacity and queue estimation." *Journal of Transportation Engineering*, 129(5), 494-503.

Karlaftis, M., and Vlahogianni, E. (2011). "Statistical methods versus neural networks in transportation research: Differences, similarities and some insights." *Transportation Research Part C: Emerging Technologies*, 19(3), 387-399.

Kaysi, I., Ben-Akiva, M., and Koutsopoulos, H. (1993). "An integrated approach to vehicle routing and congestion prediction for real-time driver guidance." *Intelligent Vehicle Highway Systems*(1408), 66-74.

Kazerouni, A. M. (2009). "Design and analysis of gauge R&R studies: Making decisions based on ANOVA method." *World Academy of Science, Engineering and Technology*, 52, 31-35.

Ke, J., and Liu, X. (2008). "Empirical analysis of optimal hidden neurons in neural network modeling for stock prediction." *Pacific-Asia Workshop on Computational Intelligence and Industrial Application (PACIIA 2008)*, IEEE, Wuhan, China, December 19-20, 828-832.

Keay, K., and Simmonds, I. (2005). "The association of rainfall and other weather variables with road traffic volume in Melbourne, Australia." *Accident analysis & prevention*, 37(1), 109-124.

Kim, C., and Hobeika, A. G. (1993). "A short-term demand forecasting model from real-time traffic data." *Conference on Infrastructure Planning and Management*, ASCE, Denver, CO, June 21-23, 540-550.

Knowles, G., Antony, J., and Vickers, G. (2000). "A practical methodology for analysing and improving the measurement system." *Quality Assurance: Good Practice, Regulation, and Law*, 8(2), 59-75.

Krammes, R. A., Dudek, C. L., and Memmott, J. L. (1987). "Computer model for evaluating and scheduling freeway work-zone lane closures." *Transportation Research Record: Journal of the Transportation Research Board*(1148), 18-24.

Krammes, R. A., and Lopez, G. O. (1994). "Updated capacity values for short-term freeway work zone lane closures." *Transportation Research Record: Journal of the Transportation Research Board*(1442), 49-56.

Kumar, A. (2016). "Practical on artificial neural networks." <http://cabgrid.res.in/cabin/publication/smfa/Module%20IV/4.Practical%20on%20Artificial%20Neural%20Networks%20%20_Amrender%20Kumar.pdf>. (02/01, 2016).

Kumar, K., Parida, M., and Katiyar, V. K. (2015). "Short term traffic flow prediction in heterogeneous condition using artificial neural network." *Transport*, 30(4), 397-405.

Lahmiri, S. (2011). "A comparative study of backpropagation algorithms in financial prediction." *International Journal of Computer Science, Engineering and Applications (IJCSEA)*, 1(4), 15-21.

Larsen, G. A. (2003). "Measurement system analysis in a production environment with multiple test parameters." *Quality Engineering*, 16(2), 297-306.

Ledoux, C. (1997). "An urban traffic flow model integrating neural networks." *Transportation Research Part C: Emerging Technologies*, 5(5), 287-300.

Lee, E. B., and Choi, K. (2006). "Part 1: Pavement rehabilitation: Fast-track construction for concrete pavement rehabilitation: California urban highway network." *Transportation Research Record: Journal of the Transportation Research Board*, 1949(1), 3-10.

Lee, E. B., Choi, K., and Lim, S. (2008). "Streamlined strategies for faster, less traffic-disruptive highway rehabilitation in urban networks." *Transportation Research Record: Journal of the Transportation Research Board*, 2081(1), 38-45.

Lee, E. B., and Ibbs, C. (2005). "Computer simulation model: Construction analysis for pavement rehabilitation strategies." *Journal of Construction Engineering and Management*, 131(4), 449-458.

Lee, S., and Fambro, D. (1999). "Application of subset autoregressive integrated moving average model for short-term freeway traffic volume forecasting." *Transportation Research Record: Journal of the Transportation Research Board*(1678), 179-188.

Legal Information Institute (2004). "23 CFR 630.1004-Definitions and Explanation of Terms." <https://www.law.cornell.edu/cfr/text/23/630.1004>. (04/07, 2016).

Levin, M., and Tsao, Y.-D. (1980). "On forecasting freeway occupancies and volumes (abridgment)." *Transportation Research Record*(773), 47-49.

Lewis, C. D. (1982). *Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting*, Butterworth Scientific London, UK.

Li, D.-M., and Liu, B. (2014). "Modeling and prediction of highway traffic flow based on wavelet neural network." *2014 International Conference on Machine Learning and Cybernetics (ICMLC)*, IEEE, Lanzhou, China, July 13-16, 675-679.

Lighthill, M. J., and Whitham, G. B. (1955). "On kinematic waves. II. A theory of traffic flow on long crowded roads." *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 229(1178), 317-345.

Lin, L., Wang, Q., and Sadek, A. (2013). "Short-term forecasting of traffic volume: evaluating models based on multiple data sets and data diagnosis measures."

Transportation Research Record: Journal of the Transportation Research Board(2392), 40-47.

Lingras, P., and Mountford, P. (2001). "Time delay neural networks designed using genetic algorithms for short term inter-city traffic forecasting." *Engineering of Intelligent Systems*, Springer, Berlin, Germany, 290-299.

Liu, Z., Guo, J., and Huang, W. (2016). "Artificial neural networks for short term traffic flow forecasting: Effects of training algorithms." *Transportation Research Board 95th Annual Meeting*, Transportation Research Board, Washington, D.C., January 10-14, 1-17.

Lv, Y., Duan, Y., Kang, W., Li, Z., and Wang, F.-Y. (2015). "Traffic flow prediction with big data: A deep learning approach." *Intelligent Transportation Systems, IEEE Transactions on*, 16(2), 865-873.

Ma, X., Tao, Z., Wang, Y., Yu, H., and Wang, Y. (2015). "Long short-term memory neural network for traffic speed prediction using remote microwave sensor data." *Transportation Research Part C: Emerging Technologies*, 54, 187-197.

Makridakis, S., Wheelwright, S. C., and Hyndman, R. J. (2008). *Forecasting methods and applications*, John Wiley & Sons, Hoboken, NJ.

May, A. (1990). *Traffic flow fundamentals*, Prentice Hall Inc., Upper Saddle River, NJ.

Mazaré, P.-E., Dehwah, A. H., Claudel, C. G., and Bayen, A. M. (2011). "Analytical and grid-free solutions to the Lighthill–Whitham–Richards traffic flow model." *Transportation Research Part B: Methodological*, 45(10), 1727-1748.

Maze, T., Agarwai, M., and Burchett, G. (2006). "Whether weather matters to traffic demand, traffic safety, and traffic operations and flow." *Transportation Research Record: Journal of the Transportation Research Board*(1948), 170-176.

McCulloch, W. S., and Pitts, W. (1943). "A logical calculus of the ideas immanent in nervous activity." *The Bulletin of Mathematical Biophysics*, 5(4), 115-133.

McDonald, J. H. (2009). *Handbook of biological statistics*, Sparky House Publishing, Baltimore, MD.

Memmott, J. L., and Dudek, C. L. (1984). "Queue and user cost evaluation of work zones (QUEWZ)." *The 63rd Annual Meeting of the Transportation Research Board (TRB)*(979), 12-19.

Mohammadi, N., and Zangeneh, M. (2016). "Customer credit risk assessment using artificial neural networks." *International Journal of Information Technology and Computer Science (IJITCS)*, 8(3), 58-66.

MoreSteam (2015). "Measuremt System Analysis (MSA)." <https://www.moresteam.com/toolbox/measurement-system-analysis.cfm>. (04/27, 2015).

Moses, R., Mtoi, E., McBean, H., and Ruegg, S. (2013). "Development of speed models for improving travel forecasting and highway performance evaluation." Florida State University, Florida Department of Transportation, Tallahassee, FL

Mtoi, E. T., and Moses, R. (2014). "Calibration and evaluation of link congestion functions: Applying intrinsic sensitivity of link speed as a practical consideration to heterogeneous facility types within urban network." *Journal of Transportation Technologies*, 4(2), 141-149.

Nam, D. H., and Drew, D. R. (1998). "Analyzing freeway traffic under congestion: Traffic dynamics approach." *Journal of Transportation Engineering*, 124(3), 208-212.

Napolitan, F., and Zegras, P. C. (2008). "Shifting urban priorities?: Removal of inner city freeways in the United States." *Transportation Research Record: Journal of the Transportation Research Board*, 2046(1), 68-75.

NeuroDimension Inc (2010). "NeuroSolution Help." <http://www.neurosolutions.com/documentation/NeuroSolutions.pdf>. (03/23, 2016).

Nilsson, I. M., and Smirnov, O. A. (2016). "Measuring the effect of transportation infrastructure on retail firm co-location patterns." *Journal of Transport Geography*, 51, 110-118.

Ofori, T., Ackah, B., and Ephraim, L. (2012). "Statistical models for forecasting road accident injuries in Ghana." *International Journal of Research in Environmental Science and Technology*, 2(4), 143-149.

Oh, S., Byon, Y.-J., Jang, K., and Yeo, H. (2015). "Short-term travel-time prediction on highway: A review of the data-driven approach." *Transport Reviews*, 35(1), 4-32.

Okutani, I., and Stephanedes, Y. J. (1984). "Dynamic prediction of traffic volume through Kalman filtering theory." *Transportation Research Part B: Methodological*, 18(1), 1-11.

Orndoff, C., and Papkov, G. (2011). "Effect of the 2009 American recovery and reinvestment act (ARRA) on civil engineering." *Journal of Professional Issues in Engineering Education & Practice*, 138(1), 2-9.

Osma, A. (2011). "An assessment of the robustness of gauge repeatability and reproducibility analysis in automotive components." *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 0954407011401504.

Pamuła, T. (2011). "Road traffic parameters prediction in urban traffic management systems using neural networks." *Transport Problems*, 6(3), 123-128.

Pan, B., Demiryurek, U., and Shahabi, C. (2012). "Utilizing real-world transportation data for accurate traffic prediction." *The 12th International Conference on Data Mining 2012*, IEEE, Brussels, Belgium, December 10, 595-604.

Pan, T., Sumalee, A., Zhong, R.-X., and Indra-Payoong, N. (2013). "Short-term traffic state prediction based on temporal–spatial correlation." *IEEE Transactions on Intelligent Transportation Systems*, 14(3), 1242-1254.

Pan, Y., Wang, D., Li, X., and Xiao, Z. (2015). "Error correction and wavelet neural network based short-term traffic flow prediction." *International Conference on Computer Science and Intelligent Communication (CSIC 2015)*, Atlantis Press, Zhengzhou, China, July 18-19, 83-86.

Passow, B. N., Elizondo, D., Chiclana, F., Witheridge, S., and Goodyer, E. (2013). "Adapting traffic simulation for traffic management: A neural network approach." *The 16th International Conference on Intelligent Transportation Systems (ITSC 2013)*, IEEE, The Hague, Netherlands, October 6-9, 1402-1407.

Portugal, I., Alencar, P., and Cowan, D. (2016). "A survey on domain-specific languages for machine learning in big data." *arXiv preprint arXiv:1602.07637*.

Resop, J. P. (2006). "A comparison of artificial neural networks and statistical regression with biological resources applications." MS Thesis, University of Maryland, College Park, MD.

Richards, P. I. (1956). "Shock waves on the highway." *Operations Research*, 4(1), 42-51.

Rizwan, J. M., Krishnan, P. N., Karthikeyan, R., and Kumar, S. R. (2016). "Multi layer perception type artificial neural network based traffic control." *Indian Journal of Science and Technology*, 9(5), 1-3.

Roh, H.-J., Sharma, S., and Sahu, P. K. (2015). "Modeling snow and cold effects for classified highway traffic volumes." *KSCE Journal of Civil Engineering*, 1-12.

Sadegh, A., Radwan, A. E., and Rouphail, N. M. (1988). "ARTWORK: A simulation model of urban arterial work zones." *Transportation Research Record*(1163), 1-3.

Saigal, S., and Mehrotra, D. (2012). "Performance comparison of time series data using predictive data mining techniques." *Advances in Information Mining*, 4(1), 57-66.

Santos, R., Ruppb, M., Bonzi, S., and Filetia, A. (2013). "Comparison between multilayer feedforward neural networks and a radial basis function network to detect and locate leaks in pipelines transporting gas." *Chem. Eng. Trans*, 32(1375), e1380.

Sarle, W. S. (1994). "Neural networks and statistical models." *The 19th Annual SAS Users Group International Conference (SUGI 19)*, SAS Institute Inc., Dallas, TX, April 10-13, 1-13.

SAS Institute (2007). "JMP User Guide, Release 7." SAS Institute, Cary, NC.

Scriba, T., and Seplow, Jennifer (2006). "Rule on Work Zone Safety and Mobility." *Public Roads*, 69(4).

Shahsavari, B., and Abbeel, P. (2015). "Short-term traffic forecasting: Modeling and learning spatio-temporal relations in transportation networks using graph neural networks." Department of Electrical Engineering and Computer Sciences, University of California at Berkeley, Berkeley, CA.

Shane, J. S., Kandil, A. A., and Schexnayder, C. J. (2012). *A guidebook for nighttime construction: Impacts on safety, quality, and productivity*, Transportation Research Board, Washington, D.C.

Sheela, K. G., and Deepa, S. (2013). "Review on methods to fix number of hidden neurons in neural networks." *Mathematical Problems in Engineering*, 2013.

Simovici, D. (2015). "Intelligent data analysis techniques—machine learning and data mining." *Artificial Intelligent Approaches in Petroleum Geosciences*, Springer, Berlin, Germany, 1-51.

Smith, B. L., and Demetsky, M. J. (1994). "Short-term traffic flow prediction: neural network approach." *Transportation Research Record*(1453), 98-104.

Smith, B. L., and Demetsky, M. J. (1997). "Traffic flow forecasting: Comparison of modeling approaches." *Journal of Transportation Engineering*, 123(4), 261-266.

Smith, R., McCrary, S. W., and Callahan, R. N. (2007). "Gauge repeatability and reproducibility studies and measurement system analysis: A multimethod exploration of the state of practice." *Journal of Industrial Technology*, 23(1), 2-12.

Sommer, M., Tomforde, S., and Haehner, J. (2015). "A Systematic study on forecasting of traffic flows with artificial neural networks." *The 28th International Conference on Architecture of Computing Systems (ARCS 2015)*, VDE, Porto, Portugal, March 24-27, 1-8.

Stamm, S. (2013). "A comparison of gauge repeatability and reproducibilty methods " Dissertation, Indiana State University, Terre Haute, IN.

State of California (2016). "Census Tracts of California." <http://gis.oshpd.ca.gov/atlas/places/tract>. (01/04, 2016).

Statthopoulos, A., and Karlaftis, M. (2003). "A multivariate state space approach for urban traffic flow modeling and predicting." *Transportation Research Part C*, 11, 121-135.

Stephanedes, Y. J., Michalopoulos, P. G., and Plum, R. A. (1981). "Improved estimation of traffic flow for real-time control (discussion and closure)." *The 60th Annual Meeting of the Transportation Research Board (TRB)*(795), 28-39.

Stewart, O. T., Carlos, H. A., Lee, C., Berke, E. M., Hurvitz, P. M., Li, L., Moudon, A. V., and Doescher, M. P. (2016). "Secondary GIS built environment data for health research: Guidance for data development." *Journal of Transport & Health*, 3(4), 529-539.

Su, H., Zhang, L., and Yu, S. (2007). "Short-term traffic flow prediction based on incremental support vector regression." *The 3rd International Conference on Natural Computation (ICNC 2007)*, IEEE, Haikou, China, August 24-27, 640-645.

Subramanian, N., Yajnik, A., and Murthy, R. S. R. (2004). "Artificial neural network as an alternative to multiple regression analysis in optimizing formulation parmaeters of cytarabine liposomes." *AAPS PharmSciTech*, 5(1), 11-19.

Sun, J. (2012). "Learning algorithm and hidden node selection scheme for local coupled feedforward neural network classifier." *Neurocomputing*, 79, 158-163.

Tan, H., Wu, Y., Shen, B., Jin, P. J., and Ran, B. (2016). "Short-term traffic prediction based on dynamic tensor completion." *IEEE Transactions on Intelligent Transportation Systems*, 1-11.

Tang, J., Xu, G., Wang, Y., Wang, H., Zhang, S., and Liu, F. (2013). "Traffic flow prediction based on hybrid model using double exponential smoothing and support vector machine." *The 16th International Conference on Intelligent Transportation Systems (ITSC 2013)*, IEEE, The Hague, Netherlands, October 6-9, 130-135.

Taubenböck, H., Klotz, M., Wurm, M., Schmieder, J., Wagner, B., Wooster, M., Esch, T., and Dech, S. (2013). "Delineation of central business districts in mega city regions using remotely sensed data." *Remote Sensing of Environment*, 136, 386-401.

Texas A&M Transportation Institute (2012). "2012 Urban Mobility Report." *TTI's Annual Urban Mobility Report*, Texas A&M Transportation Institute, College Station, TX.

Thacker, B. H., Doebling, S. W., Hemez, F. M., Anderson, M. C., Pepin, J. E., and Rodriguez, E. A. (2004). "Concepts of model verification and validation." Los Alamos National Lab., Los Alamos, NM.

The PeMS Forum (2009). "The PeMS Glossary." <http://pemsforum.dot.ca.gov/?page_id=79>. (10/20, 2016).

Tiefeng, W. (2010). "Study of improved BP neural network on forecasting city traffic flow." *Transportation Science & Technology*, 242(5), 92-94.

Transportation Research Board (2010). *Highway Capacity Manual*, National Research Council, Washington, D.C.

Trenn, S. (2008). "Multilayer perceptrons: Approximation order and necessary number of hidden units." *IEEE Transactions on Neural Networks*, 19(5), 836-844.

TRIP (2014). "California Transportation by the Numbers: Meeting the State's Need for Safe and Efficient Mobility." <http://www.tripnet.org/docs/CA_Transportation_by_the_Numbers_TRIP_Report_Sep_2014.pdf>. (05/25, 2016).

Ullman, G. (1996). "Queuing and natural diversion at short-term freeway work zone lane closures." *Transportation Research Record 1529, Transportation Research Board, Washington, D.C.*, 19-26.

Vadakpat, G., Stoffels, S., and Dixon, K. (2000). "Road user cost models for network-level pavement management." *Transportation Research Record: Journal of the Transportation Research Board*, 1699(1), 49-57.

Van Der Smagt, P. P. (1994). "Minimisation methods for training feedforward neural networks." *Neural Networks*, 7(1), 1-11.

Van Lint, J., Hoogendoorn, S., and Van Zuylen, H. (2002). "Freeway travel time prediction with state-space neural networks: Modeling state-space dynamics with recurrent neural networks." *Transportation Research Record: Journal of the Transportation Research Board*, 1811(1), 30-39.

Vijayalakshmi, B., and Sugumar, R. (2016). "Design of a predictive model for congenital heart disease using neural networks." *Middle-East Journal of Scientific Research*, 24(1), 120-127.

Vlahogianni, E. I., Karlaftis, M. G., and Golias, J. C. (2005). "Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach." *Transportation Research Part C: Emerging Technologies*, 13(3), 211-234.

Vovsha, P., and Bradley, M. (2006). "Advanced activity-based models in context of planning decisions." *Transportation Research Record: Journal of the Transportation Research Board*, 1981(1), 34-41.

Wei, D., and Liu, H. (2013). "An adaptive-margin support vector regression for short-term traffic flow forecast." *Journal of Intelligent Transportation Systems*, 17(4), 317-327.

Weingroff, R. F. (1996). "Creating the Interstate System." *Public Roads*, 60(1), 10-17.

Wheeler, D. (2006). *EMP (evaluating the measurement process) III: Using imperfect data*, Statistical Process Control (SPC) Process, Knoxville, TN.

Wheeler, D. J. (2006). "An honest gauge R&R study." *2006 ASQ/ASA Fall Technical Conference*, Statistical Process Control (SPC) Process, Columbus, OH, October 12, 1-19.

Whittaker, J., Garside, S., and Lindveld, K. (1997). "Tracking and predicting a network traffic process." *International Journal of Forecasting*, 13(1), 51-61.

Williams, B. M., Durvasula, P. K., and Brown, D. E. (1998). "Urban freeway traffic flow prediction: Application of seasonal autoregressive integrated moving average and exponential smoothing models." *Transportation Research Record: Journal of the Transportation Research Board*, 1644(1), 132-141.

Woschnagg, E., and Cipan, J. (2004). "Evaluating forecast accuracy." <http://homepage.univie.ac.at/robert.kunst/procip.pdf>. (08/13, 2016).

Xu, S., and Chen, L. (2008). "A novel approach for determining the optimal number of hidden layer neurons for FNN's and its application in data mining." *The 5th International Conference on Information Technology and Applications (ICITA 2008)*, IEEE, Cairns, Queensland, Australia, June 23-26, 23-26.

Xu, Y., Kong, Q.-J., and Liu, Y. (2013). "Short-term traffic volume prediction using classification and regression trees." *2013 Intelligent Vehicles Symposium (IV)* IEEE, Gold Coast City, Australia, June 23-26, 493-498.

Yao, Y.-f., and Cao, F. (2006). "Short-time traffic flow prediction based on ARIMA." *Technology & Economy in Areas of Communications*, 35(3), 105-107.

Yu, C., and Lam, K. C. (2014). "Applying multiple kernel learning and support vector machine for solving the multicriteria and nonlinearity problems of traffic flow prediction." *Journal of Advanced Transportation*, 48(3), 250-271.

Yu, H., Xie, T., Paszczynski, S., and Wilamowski, B. M. (2011). "Advantages of radial basis function networks for dynamic system design." *IEEE Transactions on Industrial Electronics*, 58(12), 5438-5450.

Yu, Z., Sun, T., Sun, H., and Yang, F. (2015). "Research on combinational forecast models for the traffic flow." *Mathematical Problems in Engineering*, 2015, 1-10.

Zanobini, A., Sereni, B., Catelani, M., and Ciani, L. (2016). "Repeatability and reproducibility techniques for the analysis of measurement systems." *Measurement*, 86, 125-132.

Zhang, H. (2000). "Recursive prediction of traffic conditions with neural network models." *Journal of Transportation Engineering*, 126(6), 472-481.

Zhang, Y., and Ye, Z. (2008). "Short-term traffic flow forecasting using fuzzy logic system methods." *Journal of Intelligent Transportation Systems*, 12(3), 102-112.

Zhang, Y., Zhang, Y., and Haghani, A. (2014). "A hybrid short-term traffic flow forecasting method based on spectral analysis and statistical volatility model." *Transportation Research Part C: Emerging Technologies*, 43, 65-78.

Zheng, H., Nava, E., and Chiu, Y.-C. (2014). "Measuring networkwide traffic delay in schedule optimization for work-zone planning in urban networks." *IEEE Transactions on Intelligent Transportation Systems*, 15(6), 2595-2604.

Zheng, Z., and Su, D. (2014). "Short-term traffic volume forecasting: A k-nearest neighbor approach enhanced by constrained linearly sewing principle component algorithm." *Transportation Research Part C: Emerging Technologies*, 43, 143-157.

Zhu, J. Z., Cao, J. X., and Zhu, Y. (2014). "Traffic volume forecasting based on radial basis function neural network with the consideration of traffic flows at the adjacent intersections." *Transportation Research Part C: Emerging Technologies*, 47, 139-154.

Zhu, Y., and Ahmad, I. (2008). "Developing a realistic-prototyping RUC evaluation tool for FDOT." Florida International University, Florida Department of Transportation, Miami, FL.

Zhu, Y., Ahmad, I., and Wang, L. (2009). "Estimating work zone road user cost for alternative contracting methods in highway construction projects." *Journal of Construction Engineering and Management*, 135(7), 601-608.