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A Framework for Performance-Based Traffic Operations Using Connected Vehicle Data

Md Ahsanul Islam
Civil, Construction, & Environmental Engineering
University of Alabama at Birmingham
Birmingham, AL 35294

Virginia P. Sisiopiku, PhD
Civil, Construction, & Environmental Engineering
University of Alabama at Birmingham
Birmingham, AL 35294

Ossama E. Ramadan, PhD
Civil, Construction, & Environmental Engineering
University of Alabama at Birmingham
Birmingham, AL 35294

Mohammed Hadi, PhD
Civil and Environmental Engineering
Florida International University
Miami, FL 33174

***Abstract*— Emerging vehicle technologies such as connected vehicles (CV) technologies create new opportunities for collecting new types of transportation data that can improve the accuracy of transportation system performance measurement. The main objective of this study is to develop a methodological framework to estimate system performance measurements using 100% CV data as well as to provide a validation of the proposed framework. In doing so, the microscopic simulation software VISSIM with trajectory conversion algorithm (TCA) is used to generate CV data and specifically basic safety message (BSM). Two sets of data were considered, namely the CV-generated data and field data from the National Performance Management Research Data Set (NPMRDS). A statistical comparison of the selected performance measures between the two data sets was performed using the ANOVA: Single Factor statistical F-test. The results from the statistical test showed that the calculated F values were less than the critical values of F within 5% significance level for all performance measures tested. This finding indicates that there is no significant difference between performance measures using CV-generated data and the NPMRDS data set. Hence, the proposed framework is valid, and it can be used in practical applications.**

Keywords—Connected vehicles (CV), performance measurement, methodological framework, VISSIM, Basic Safety Message (BSM).

I. INTRODUCTION

Performance measurement is an indispensable part of effective transportation systems management. It is a topic of great interest both internationally and in the US and can play a vital role in decision making at both the federal and state levels. Proper transportation measurement and management processes help to enhance transportation system planning and operations. Estimated performance measures can be used by a system operator or planner in order to support decisions associated with these processes. Such measurements can also be used to derive information for dissemination to travelers, third-party data aggregators, traveler information service providers, and other agencies. The Federal Highway Administration (FHWA) defines Transportation Performance Management (TPM) as a “strategic approach that uses system information to make investment and policy decisions to achieve national performance goals” (FHWA 2017a).

Performance measures can be either quantitative or qualitative. Examples of quantitative performance measures include volume, density, travel time, speed, queue length, and emissions. Qualitative performance measures include user satisfaction, driver compliance, and driver frustration. Performance measures are typically estimated based on data from existing technologies such as traffic surveillance involving closed-circuit television (CCTV), machine vision equipment, and sensors such as subsurface induction loop, acoustic, and radio frequency (RF).

Connected Vehicle (CV) technologies promise to allow the estimation of performance measures currently provided by other technologies, as well as measures that cannot be collected by existing sensing technologies. Examples of additional performance measures that can be estimated from data obtained through CVs include stops, acceleration and deceleration, shockwave speeds, detailed signalized intersection movement-level measures, and the potential for crashes, to name a few.

Studies confirm that a relatively low market penetration of CV is required for estimating some performance measures, while other measures require high market penetrations to produce accurate results (Khazraeian et al., 2017; Iqbal et al., 2018; Khan et al., 2017). The availability of CV data, even at small percentages, may be sufficient to support critical transportation management functions. For example, such data can be beneficial in identifying abnormalities in data detection and processing associated with existing technologies.

Hence, the recent introduction of CV technologies created new opportunities for the use of CV data for performance measurements. However, existing studies are limited in scope as they mainly focused on the generation of specific measures such as travel time, density and queue length estimation by using CV data from different sources including the Next Generation

Simulation (NGSIM) data set (Argote et al., 2012; Hao et al., 2014; Nam et al., 2017; Qiu et al., 2010) and safety pilot model deployment (SPMD) data set (Khattak et al., 2017; Liu et al., 2016; Mousa et al., 2017; Zheng et al., 2017).

Overall, the literature review confirms that there is a lot of untapped potential in using CV data for estimation of performance measures. To address some of these issues, the objective of this study is to: (a) develop a methodological framework to estimate system performance measurements using 100% CV data to support transportation operations, management, and planning, and (b) provide a proof of concept as part of framework validation where performance measurements are compared using traditional data set like National Performance Management Research Data Set (NPMRDS) and CV data.

The following paragraphs include a. the literature review that summarizes past studies related to transportation performance measurement using CV data and contribution of this study, b. discussion on the development of a methodological framework to estimate system performance measurements using CV data, and c. the proof of concept of the study to validate the proposed methodological framework is presented. The last section of this paper offers concluding remarks.

II. Literature Review

There are several studies in the literature focusing on travel time, density, traffic volume, and queue length estimation using CV data. Mousa et al. (2017) *estimated travel times* based on Basic Safety Messages (BSM) information and found that the mean absolute errors are 13- and 20-seconds for 5- and 20-minute horizons respectively. These estimates were based on eXtreme Gradient Boosting (XGB) algorithm, and the BSM data came from a SPMD conducted in Ann Arbor, Michigan. However, this study did not account for different market penetration rates, which is an important consideration.

Zou et al. (2010) estimated travel time based on Vehicle Infrastructure Integration Probe Data (VIIPD) messages according to J2735 standards and found average travel time error percentages of 27.6%, 12.5%, and 8.2% for 1%, 5%, and 10% market penetrations, respectively. These estimates were based on traffic simulations of a hypothetical network.

Izadpanah et al. (2011) conducted a study to determine travel time using vehicle trajectory data from GPS data loggers on a freeway segment. The results showed that the measured and ground truth travel time had no significant difference.

In another study, Argote et al. (2012) estimated commonly used arterial measures of effectiveness including average speed, the average delay per unit distance, average number of stops, average acceleration noise, and queue length based on CV data obtained from NGSIM data. A drawback of this study is that it uses the vehicle ID, but does not consider the change of vehicle ID during its course of travel, as specified in the J2735 standards.

Studies focusing on *density estimation* based on CV data report that high market penetration of CVs is required in order to get accurate results. A study by Khan (2015) based on simulation modeling, showed that the use of CV data as input into an advanced estimation algorithm can provide an accuracy of at least 85% for CV penetration level of 50% or more, with the estimation accuracy increasing with the increase in the market penetration. The same study reported that density estimations that used an algorithm based on point detector data resulted in an accuracy rate between 42.5% and 62.2%. An incremental benefit-cost analysis indicated that the use of CV provides a higher return on investment, compared to the use of loop detectors. However, the study did not assess the accuracy of CV data utilization for low market penetration levels.

In a later study, Khan et al. (2017) assessed the accuracy of CV data utilization for market penetrations below the 50% market penetration level and found that 20% or more CV penetration level can provide 85% accuracy. Nam et al. (2017) also conducted a study to estimate density using probe vehicle data from the NGSIM dataset and found that estimated densities reflect ground truth density and accuracy of density increases with the increase of penetration rates.

A number of studies examined the potential of using a low sample size of probe vehicles in combination with point detector data to improve density estimation accuracy. Al-Sobky et al. (2016) conducted research to determine traffic density using two smartphones inside two vehicles and an observer to obtain count data. The results showed that measured density is close to the actual density at the 5% significance level. The error of the density estimated using this method ranges from 1.3% to 15%, with an average of 8%. However, this proposed system is not applicable for a high percentage of heavy vehicles and uninterrupted flow conditions.

In another study, Qiu et al. (2010) combined detector data with probe data to estimate density and found that the relative error for the given periods can be improved from 30% based on point sensor data, and to 4% to 6% based on point sensor data plus probe vehicle data. They used two loop detectors placed 1,000 feet apart, with two probe vehicles driven five round trips along the section. Once again, this indicates the potential of using CV data in combination with point detection to estimate density at low market penetrations of CV.

Zheng et al. (2017) estimated traffic volumes and found that the Mean Absolute Percentage Error (MAPE) of traffic volumes is in the rage of 9-12%. This estimate was based on low market penetration rates ranging from 3 to 12%. In their study, they used two sources of CV data, namely the SPMD project in the city of Ann Arbor, MI, and vehicle trajectory data in China.

Queue length estimation using CV data also requires high market penetration of CVs, as reported in the literature. Li et al. (2013) combined probe trajectory and signal timing data to estimate the queue length and found that the mean absolute percentage error decreased with the increase in market penetration. This estimate was based on microscopic simulation data. In another study, Osman et al. (2016) investigated cycle-by-cycle queue length using Basic Safety Messages (BSMs) based on shockwave analysis and found estimation errors to be between 0 and 33%. However, a study conducted by Khazraeian et al. (2017) indicated that a relatively low market penetration (around 3% to 6%) for a congested freeway is sufficient for accurate and reliable estimation of the queue length. Even at 3% market penetration, the CV-based estimation of the back of queue identification is significantly more accurate than that based on detector measurements. It was also found that CV data allows for faster detection of the bottleneck and queue formation.

Recent studies indicate that *incident detection* and collision warning can also be estimated using CV data. Wolfgram et al. (2018) detected the occurrence of incidents quickly and reliably using CV data and found that the availability of CV data can reduce the detection time, from minutes to just seconds. This finding was based on empirical and simulation data. In another recent study, Tajalli et al. (2018) investigated the vehicle collision problem at a signalized intersection using CV data and technologies based on simulation data under three sets of scenarios including various volumes of vehicles, compliance rates, and CV penetration rates. Analysis of results showed that the number of vehicle-to-vehicle (V2V) conflicts decreased from 24 to 16, to 5 and vehicle-to-pedestrian (V2P) conflicts decreases from 56 to 33, to 0 for increasing market penetration rates from 0% to 50%, to 100% respectively.

Work zone safety can also benefit from CV technologies, even at a low market penetration rate. A study conducted by Genders et al. (2016) showed that market penetration rates lower than 40% increase the safety of the traffic network, meanwhile, market penetration rates over 40% decreases the safety of the network. Authors also mentioned that work zone information through CV technologies helps to modify driving behavior and decay travel time.

The review of the literature confirms that existing studies did not consider data that can be collected in accordance with the Society of Automotive Engineer (SAE) message sets and the expected availability of the data. It should be mentioned that, according to CV data standards, no permanent vehicle identifications are assigned to any vehicles. In addition, the earlier studies have not addressed new performance measurements illustrated in Fig. 1 related to national highway system performance, freight movement on the interstate, Congestion Mitigation and Air Quality (CMAQ) program – traffic congestion, and CMAQ – on-road mobile source emissions that were recently established by FHWA in the Moving Ahead for Progress in the 21st Century (MAP-21) in 2012 (FHWA 2017b) .

To bridge these gaps, this paper addresses performance-based operations by estimating real-time performance measurement using CV data. The methodological framework development is proposed first, followed by a proof of concept based using simulated CV data from a study corridor in Birmingham, Alabama, USA.

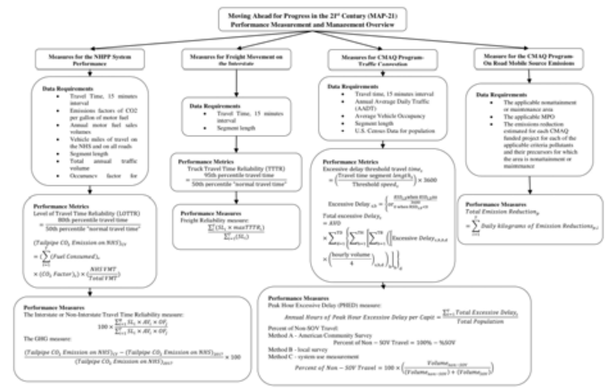

Fig. 1. MAP-21 performance measures

III. METHODOLOGY OVERVIEW

This section proposes a methodological framework to estimate the system performance measurements using 100% CV data. It involves several methods and techniques to aggregate the CV data as an input to estimate the performance measures at the traffic management center (TMC). The following section discusses in detail the proposed framework development.

A. Framework Development

A framework for transportation performance measurement system can play a vital role toward the improvement of the effectiveness and efficiency of the performance measurement analysis. Moreover, it provides a structured hierarchy of procedures and processes to guide transportation authorities, engineers, planners, and agencies in their decision making. A study by the University of Alabama at Birmingham leading to the work by (Islam, 2018) developed a novel delivery method for methodological frameworks for transportation performance measurement. Through that method, the framework is delivered as four components, namely (i) physical data flow diagram, (ii) processes and process groups hierarchical diagram, (iii) individual process designs, and (iv) logical data flow diagram.

1) Physical data flow diagram

The physical data flow diagram illustrates the physical entities of the proposed system, and the data flows between such system entities, as shown in Fig. 2. The primary challenge is to aggregate data at roadside units (RSUs), thus a new physical architecture of RSUs is also proposed in this physical data flow diagram.

2) Processes and process groups hierarchical diagram

The processes and process groups hierarchical diagram contains two sets of process groups: (a) data aggregation process groups at RSUs and (b)

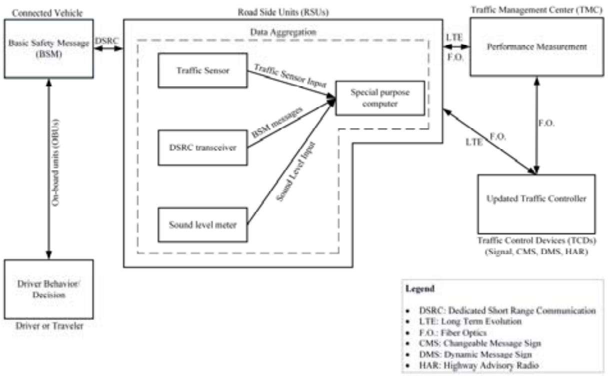

Fig. 2. Physical data flow diagram

performance measurement process groups at the turning movement counters (TMCs).

The first set (i.e., data aggregation process group) is classified into five process groups as illustrated in Fig. 3 based on the data requirements to estimate the available performance measures at TMC. They include:

- Travel Time Data Aggregation;
- Speed and Acceleration Data Aggregation;
- Volume and Headway Data Aggregation;
- Sound Level Data Aggregation; and
- Signal Group Data Aggregation.

These process groups are further grouped by relevant data aggregation at each process group.

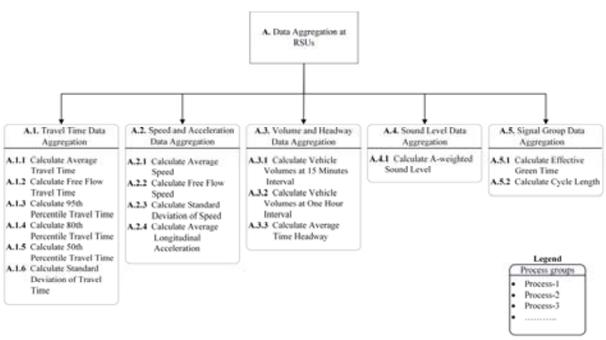

Fig. 3. Data aggregation at roadside units (RSUs)

Similarly, the second set (i.e., performance measurement process group) is classified into four process groups based on the available performance measures at TMC where each process group contains relevant performance measures as illustrated in Fig. 4. These include:

- Travel Time Reliability;
- Congestion Development Measures;
- Level of Service (LOS) Performance Measures, and
- Environmental Issues Measures.

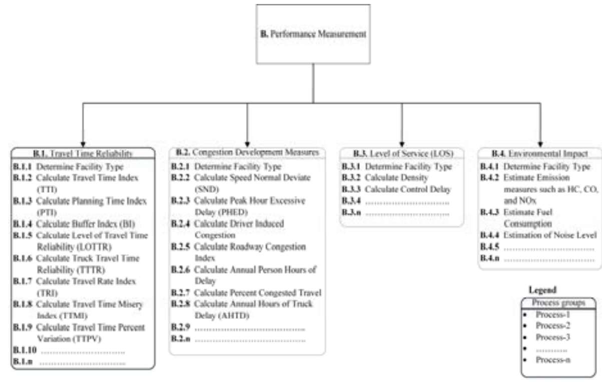

Fig. 4. Performance measurement at TMC

3) Individual process designs

As mentioned earlier, performance measurement and management are performed through sets of processes. Each individual process can be represented by its inputs, tools and techniques, and outputs. An algorithm is developed to estimate each process. For example, an algorithm to compute average travel time is illustrated in Fig. 5.

```
CV_Data = (Timestamp as time, Vehicle ID as integer, Speed as double)
CV_S15 = (15-minutes interval ID as integer, Average speed as double)
CV_TT15 = (15-minutes interval ID as integer, Average travel time as double)
Segment length, average travel time as double
RSU ID as an integer
Global Interval (i as an integer, Start time as time, End time as time)
For i = 0 to 95
    Average_Speed = Average (SELECT Speed From CV_Data
                  WHERE Global Interval (i).Start ≤ CV_Data.Timestamp ≤ Global Interval (i).End)
    CV_S15 (i) = Average_Speed
    Average_Travel Time = Segment Length/CV_S15 (i).Average_Speed
    CV_TT15 (i) = Average_Travel Time
End
Average travel time = CV_TT15.Average_Travel Time
RSU_ID = RSU ID
```

Fig. 5. Pseudocode for calculating average travel time

Details on other individual process designs, grouped by process groups as illustrated in the previous Fig. 3 and Fig. 4 are available in (Islam, 2018).

4) Logical data flow diagram

This process is the combination of processes and process groups hierarchical diagram and individual process designs. It represents the data flow diagram from the data sources to process groups and processes. It is a holistic, comprehensive data flow diagram to estimate performance measures illustrated in Fig. 6.

Fig. 6. Logical data flow diagram

IV. Results and Discussion

This section discusses in detail the proof of concept of the study to validate the proposed methodological framework.

A. *Proof of Concept Study*

In order to generate CV data for the proof of concept study, the VISSIM microsimulation platform was used to model a study corridor in Birmingham, AL. The CV data were obtained from VISSIM using the TCA tool and used to determine selected performance measures on the basis of the procedures described in the proposed methodological framework. Then performance measures obtained from CV data were compared with performance measured derived from actual field data that were available through the NPMRDS database for the study corridor. The process followed and results are discussed in detail in the following subsections.

1) Study Corridor Location

A section of I-65 in the Birmingham, AL region was chosen as the study corridor for the purpose of this study. The study corridor is almost 14.40 miles long, extending from exit 247 to exit 261A as shown in Fig. 7.

2) Development of a Simulation Model

The microscopic simulation platform VISSIM 10.00 was used to build a simulation model of the study corridor. The model was run under normal traffic conditions and produced vehicle record data that were then used as an input to generate BSMs using the TCA tool. The output data were collected from the vehicle record output, which is a .fzp file containing vehicle speed, vehicle number, link number, lane index, acceleration, simulation second, and time of the day. The model was run for one hour from 8:00 AM to 9:00 AM using traffic volumes obtained from the Alabama Department of Transportation (ALDOT). The study ran the simulation model three times and averaged the output data to calibrate and estimate the performance measures.

3) VISSIM Output Data Calibration

The VISSIM output was calibrated using field measurements available through National Performance Management Research Data Set (NPMRDS) database. The study used two statistical techniques for model calibration, namely (a) graphical techniques, and (b) ANOVA statistical single factor F-test.

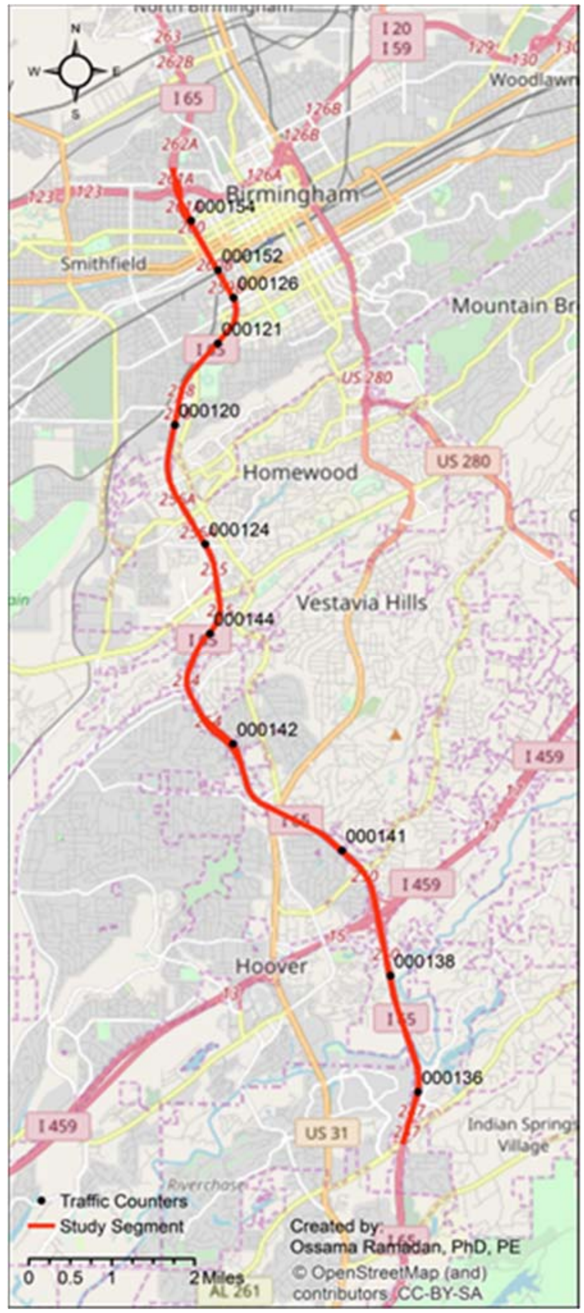

Fig. 7. Simulation test bed

The graphical techniques used in this study represent two control limits, namely the upper control limit (UCL) (which is 15% more than the field measurement value), and lower control limit (LCL) (which is less than the 15% of field measurement value). The analysis of graphical techniques results showed that VISSIM output speed data produced by the simulation model were within the upper and lower control limits of the NPMRDS data set as illustrated in Fig. 8, thus confirming the reliability of the simulation outputs.

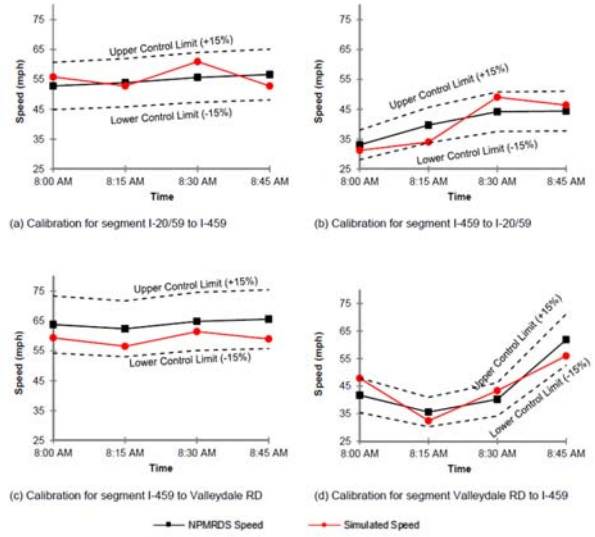

Fig. 8. VISSIM model calibration

The ANOVA statistical single factor F-test was also used to determine whether there are any statistically significant differences between the field measurement speed data and VISSIM output speed data within a 5% significance level. The F-test results showed that the calculated F value is less than the critical value of F, as shown in Table 1**Error! Reference source not found.**. Hence, there is no significant difference between VISSIM output data and filed data, which is a desirable outcome.

TABLE 1. VALIDATION OF THE SIMULATION MODEL USING ANOVA SINGLE FACTOR F-TEST

Summary

Groups	*Count*	*Sum*	*Average*	*Variance*
NPMRDS Speed	16	816.26	51.016	124.157
VISSIM Simulation Speed	16	798.91	49.931	101.769

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9.407	1	9.407	0.083	0.775	4.171
Within Groups	3388.903	30	112.963			
Total	3398.31	31				

2) TCA tool

TCA software is designed to test different strategies for producing, transmitting, and storing Connected Vehicle information (OSADP, 2015). The study used the latest version of TCA tool [Version 2.3.3] (OSADP 2015), developed by the FHWA to generate BSMs from the calibrated VISSIM output data. The study assumed a 100% market penetration rate and DSRC technology as the communication type only. A total of 14 roadside units (RSUs) were placed along the study corridor at 1-mile intervals. However, TCA software is an open source software, and the user can select market penetration rate, the communication type (DSRC or Cellular), and also specify the roadside unit location.

3) Comparison between performance measures generated using CV and NPMRDS data set

a) Hypothesis

The hypothesis of this study is that there is no significant statistical difference between a) performance measures calculated using the proposed framework and CV data considering 100% market penetration rate, and b) performance measures derived using conventional data sources such as NPMRDS.

b) Comparison

For illustration purposes, this study selected three performance measures, namely Travel Time Index (TTI), Planning Time Index (PTI), and Speed Normal Deviate (SND) to establish the proposed framework as a proof of concept. The study used the proposed algorithm to calculate average travel time, free-flow travel time, and 95th percentile travel time, average speed, and standard deviation of speed using CV BSMs. Then, these calculated values were used to estimate TTI, PTI, and SND performance measures. Moreover, TTI, PTI, and SND performance measures were also calculated by implementing the methods of (Sullivan et al., 2017) using NPMRDS data set and compared with those obtained from the CV BSMs.

An ANOVA: Single Factor statistical F-test was performed to test the abovementioned hypothesis. From the ANOVA statistical test, it was found that there was no significant difference between TTI, PTI, and SND values produced from the proposed framework using CV data and those produced from traditional data at the 5% significance level. Comparisons of the calculated F value and the critical value of F confirming these findings for TTI, PTI, and SND performance measures are available in Table 2, Table 3 and Table 4, respectively.

TABLE 2. VALIDATION OF TTI USING ANOVA SINGLE FACTOR F-TEST

Summary

Groups	*Count*	*Sum*	*Average*	*Variance*
Avg_TTI_BSMs	16	27.988	1.749	0.227
Avg_TTI_NPMRDS	16	22.952	1.434	0.257

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.793	1	0.396	1.582	0.223	3.328
Within Groups	7.266	30	0.251			
Total	8.058	31				

TABLE 3. VALIDATION OF PTI USING ANOVA SINGLE FACTOR F-TEST

Summary

Groups	*Count*	*Sum*	*Average*	*Variance*
Avg_PTI_BSMs	16	20.926	1.308	0.117
Avg_PTI_NPMRDS	16	28.168	1.761	0.722

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.639	1	1.639	3.905	0.057	4.171
Within Groups	12.591	30	0.419			
Total	14.23	31				

TABLE 4. VALIDATION OF MAX_SND USING ANOVA SINGLE FACTOR F-TEST

Summary

Groups	*Count*	*Sum*	*Average*	*Variance*
Max_SND_BSMs	16	-54.706	-3.419	47.437
Max_SND_NPMRDS	16	-3.648	-0.228	44.759

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	81.466	1	81.466	1.767	0.194	4.171
Within Groups	1382.94	30	46.098			
Total	1464.40	31				

Overall, the statistical analysis performed above confirms that there is a close agreement between the performance measures (i.e., TTI, PTI, and SND) generated from a. the proposed methodological framework using CV data generated by the VISSIM simulation platform and the TCA tool and b. actual field data obtained from the NPMRDS travel time data set. Thus, the proof of concept for the proposed framework is successful.

V. CONCLUSIONS AND RECOMMENDATIONS

Performance measurement and management are of great importance toward achieving operational effectiveness of roadways. Field or simulated data can be used to determine performance measures.

Emerging vehicle technologies, including CVs, create new opportunities for collecting new types of transportation data that can improve the accuracy of transportation system performance measurement. The proliferation of CVs is also expected to increase data quantity and quality and enable the development of new performance measures.

In light of the rapid progress in the area of CV technologies, this study developed and validated a methodological framework to estimate system performance measurements using CV data. The proposed methodological framework addressed the data aggregation issue and introduced data aggregation algorithms at RSUs to estimate performance measures.

In order to validate the proposed framework, performance measures (i.e., TTI, PTI, and SND) were calculated using traditional field data and simulated CV data for a 14-mile long freeway study segment in Birmingham, AL, and compared. The findings from the statistical comparison indicate that there is no significant difference between performance measures generated using the CV data generated through simulation and the field data recorded in the NPMRDS database. The close agreement between the findings serves as a proof of concept for the proposed framework.

It is recommended that the groundbreaking work performed in this study be followed by additional research to expand the scope of the work in the near future. At present, the study introduced twenty-four performance measures in the methodological framework. However, the framework proposed in this study can be further updated and expanded to incorporate emerging performance measures in the future. Another limitation of the study is the use of simulation data to produce CV data. Evaluation of the proposed framework using real-world CV data is also recommended. This study only considered a basic freeway section. Other facilities such as merging, diverging, and weaving sections could be considered as an extension of the current work. Moreover, consideration of different market penetration rates for CVs is also recommended to evaluate the proposed framework in future studies.

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