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Evaluation of Factors Influencing Ramp Metering Compliance Using Controller Event–Based Data

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Abstract

Ramp metering enhances traffic mobility and safety by optimizing the flow of vehicles onto freeways. A complete realization of ramp metering benefits on freeway networks partially depends on the drivers' compliance with the ramp meter signals. Noncompliance could lead to excessive volumes entering the mainline freeway, increasing congestion, delays, and merging location safety risks. Understanding the factors influencing compliance can help design ramp metering locations and develop metering algorithms that enhance driver adherence to ensure effective operations of the ramp metering system. This study used data collected from the freeway system in Phoenix, Arizona to identify factors influencing ramp metering compliance. The measures of compliance: compliance rates and violation counts were estimated using the controller event–based (CEB) data. Linear regression models were used to examine the impacts of factors, including the number of lanes on a ramp, ramp volumes, and metering rates. A spatial transferability analysis was performed to assess the applicability of the model when used to uncover route-specific factors influencing drivers' compliance to ramp metering signals. Results revealed that mainline volume, upstream average annual daily traffic (AADT), percentage of time a ramp experienced queueing, ramp volume, ratio of ramp volume to metering rate, number of lanes, ramp length, route, peak hours, ramp speed, mainline speed, and metering rate significantly contributed to drivers' compliance with ramp metering signals. These results could be used by transportation departments to optimize the existing ramp metering strategies and plan for future deployments of ramp metering signals.

Keywords

operations, ramp metering, traffic management systems, ITS

Ramp metering is a key traffic management strategy designed to manage traffic flow and reduce delays by controlling the rate at which vehicles enter freeways (*1*–*3*). Efficient ramp metering ensures low freeway congestion levels, safe merging segments, and short ramp delays (*4*, *5*). However, the efficacy of ramp metering hinges significantly on driver compliance (*1*, *5*–*7*). Compliance occurs when vehicles pass the ramp signal during the green phase, while noncompliance occurs when vehicles pass during the red phase (*7*). As shown in Figure 1, which provides a simplified diagram of ramp metering, vehicles traveling on the ramp pass several key detection points: the queue detector, demand detector, and passage detector. For the purpose of this study, compliance and noncompliance are defined by whether a vehicle actuates the passage detector during the green or red phase, respectively. Noncompliance can result in excessive volumes entering the mainline freeway and pose safety risks as traffic fails to integrate smoothly onto freeways (*1*, *2*, *5*, *7*, *8*).

Measuring compliance is crucial for monitoring, evaluating, and improving the performance of ramp metering signals. Previous studies have faced challenges in collecting extensive data on driver behavior, often relying on short-term video data collection at specific locations (*5*, *7*). While these video-based methods are valuable for capturing snapshots of driver behaviors, they are inherently

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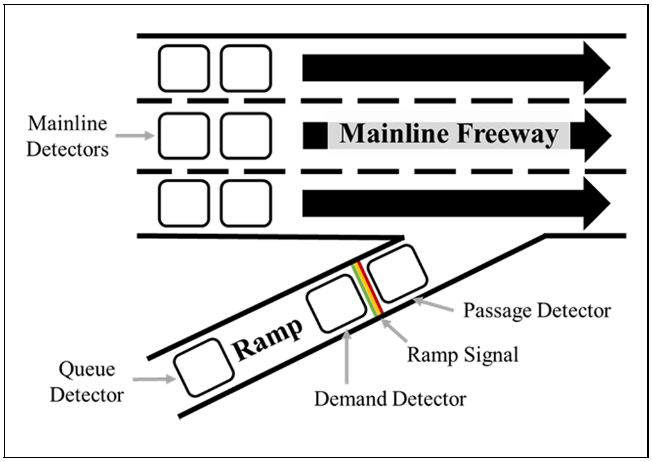

Figure 1. Simplified diagram of ramp metering detection points.

limited in scope and duration. These limitations mean that previous research only covers brief periods and is constrained to specific locations, making it difficult to generalize findings or understand long-term trends and variations. Consequently, these approaches lack long-term viability for application by departments of transportation (DOT) as they require sustained monitoring and comprehensive analysis.

The emergence of controller event–based (CEB) data offers an opportunity to evaluate ramp metering compliance over extended periods and across various ramp locations. This data-driven approach allows for a more robust and scalable analysis, enabling better-informed decisions to enhance traffic management strategies. CEB data provides a comprehensive and continuous data set, capturing detailed and nuanced information over time. Unlike traditional aggregated traffic data, which can obscure crucial details and is susceptible to noise, CEB data allows for analyzing real-time events and trends, offering a clearer picture of driver behaviors and their changes over extended periods (*9*). Recent research has demonstrated the value of CEB in various aspects of traffic operations, including predicting pedestrian volumes at intersections (*10*), queue length estimation (*11*, *12*), and volume estimation (*13*), showcasing the potential of CEB data in predicting traffic dynamics. Furthermore, CEB has been used in a multitude of driver behavior studies, such as modeling stop-and-go behavior, predicting red-light running (*14*, *15*), and dilemma zone modeling (*16*), underscoring the potential of event-based data in elucidating long-term trends.

Identifying factors contributing to compliance or noncompliance is another step toward improving ramp meter performance. Understanding these factors, particularly those related to the infrastructure, location, or geometric design, could assist agencies in three areas: 1) identifying ramps expected to have complying drivers to get the full benefits of deploying ramp metering signals; 2) designing ramps to encourage compliance, such as two-lane ramps versus one-lane ramps; and 3) considering compliance when developing ramp metering rate algorithms and strategies to ensure the full effectiveness of ramp metering systems. Prior research has reported the ramp metering compliance rate without fully understanding the factors leading to noncompliance at different locations or has viewed compliance as a secondary objective or variable in a model of freeway mobility or safety (*5*, *7*).

Few studies have evaluated ramp metering compliance in attempts to identify factors influencing it and develop strategies that could promote it. Sun et al. (*5*) implemented temporary ramp meters preceding work zones in Columbia, MO, and found significant differences in compliance based on vehicle classification, signal timing, and congestion level on the mainline freeway. Ramps with mixed passenger cars (PC) and commercial motor vehicles (CMV) showed higher compliance than those with only PCs. Sites employing two-section heads exhibited a compliance rate between 45% and 55%. The site with the highest compliance rate of 75% remains lower compared with that of permanent ramp meter locations, likely attributable to a lack of familiarity with ramp meters in the area (*5*, *7*). Notably, within sites employing three-section heads, green time significantly influenced compliance. In addition, platooning vehicles led to higher compliance than single vehicles. Piotrowicz and Robinson (*3*) corroborated these findings by reporting that noncompliance is contagious as the violations accumulate rapidly once one vehicle refuses to stop, leading to an ineffective system.

While studies such as Sun et al. (*5*) and Zhu (*7*) have examined compliance at temporary ramp meters and identified factors such as vehicle classification and platooning behavior, the literature on permanent ramp meters is limited in its methodological rigor and geographic scope. Most existing studies mention compliance as an observed outcome but do not statistically assess factors contributing to compliance. For instance, Piotrowicz and Robinson (*3*) describe the status of ramp metering in the United States as having good compliance rates in San Diego, Los Angeles, Minneapolis, and St. Paul; however, these studies do not specify statistical methodology, and the criteria for "good" compliance remain vague. Similarly, reports on general ramp meter compliance suggest that targeted enforcement and enhanced signage can improve compliance rates (*2*, *3*). However, empirical data specific to ramp meter enforcement affecting compliance are not provided. This leaves a gap, where studies such as those by Grzybowska et al. (*8*) highlight that further research on ramp meter user compliance and satisfaction is important.

Our study addresses these gaps through several key contributions, offering actionable insights for policymakers and practitioners:

- An in-depth analysis of permanent ramp meters and the various factors affecting compliance. This includes examining geometric configurations, such as dual- and single-lane ramp meters, along with different traffic characteristics, to understand their influence on compliance.
- A methodology that leverages continuous data, specifically CEB data, rather than the temporary data used in previous studies. This consistent, ongoing data source enables effective compliance monitoring and supports long-term analysis.

The investigation enhances the understanding of ramp metering strategies and offers valuable insights for transportation agencies and policymakers. Practical implications include identifying the factors that affect compliance, enabling the development of more effective ramp metering strategies, policies, and the continued examination of ramps over time.

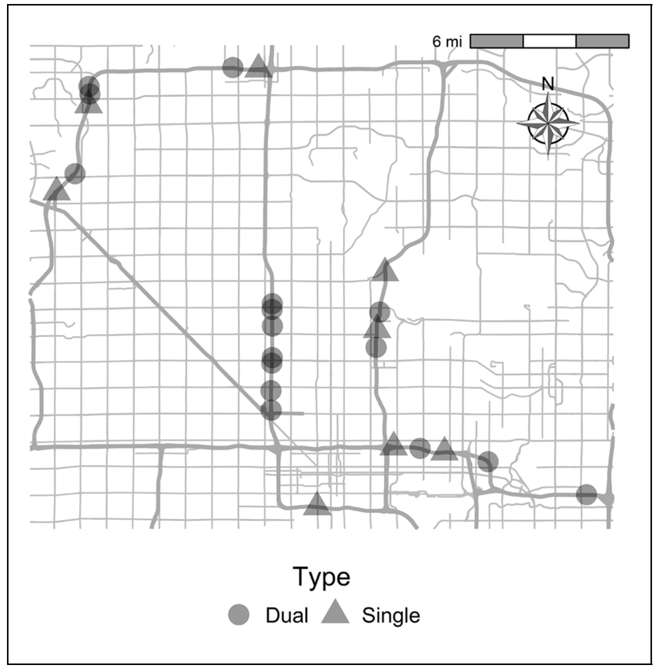

Figure 2. Map of study site locations.

Study Sites and Data

Site Characteristics

The Phoenix Metropolitan Area has a total of 263 ramp meters, with this study focusing on 24 ramp meters across various cities, including Phoenix, Peoria, and Tempe, Arizona. These cities were selected for their diverse urban landscapes and varying traffic conditions, representing a range of driver behaviors and environments. Figure 2 illustrates the locations of the 24 ramp meters used in this study, which were spread across four different routes: Interstate 17 (I-17), Loop 202 (L-202), Loop 101 (L-101), and State Route 51 (SR-51). Of these locations, 16 are dual-lane ramp meters, and eight are single-lane ramp meters, all operated using the Arizona Department of Transportation's (DOT) adaptive metering algorithm. The study was based on high-frequency CEB data collected for three months (March 1, 2023 through May 30, 2023), yielding nearly 100 million data rows across all study ramps and mainline areas before aggregation. In addition, previous studies have shown that at least two months of data is sufficient for ramp metering assessment (*17*).

Data

The analysis was based on three data sets: traffic data, geometric characteristics data, and CEB data. The traffic data—comprising ramp volumes, ramp speeds, mainline volumes, and mainline speeds—were provided by Arizona DOT. Ramp volumes were collected from the stop bar loop detectors at ramp meters in 20-s intervals. The mainline volumes and speeds were collected from freeway loop detectors during the same period and intervals. The ramp speeds were gathered using INRIX probe vehicle speed data. All speeds and volumes were aggregated into 15-min increments. This aggregation approach allowed us to address missing or anomalous data points by averaging available values within each interval, minimizing the impact of isolated gaps or sensor errors. In cases of prolonged data absence, the extensive data volume allowed us to exclude these periods without compromising the reliability of our analysis. This method aligns with previous studies (*17–19*) that have successfully used similar time interval aggregation to manage data gaps and maintain data reliability. The traffic data also include the average annual daily traffic (AADT) values that were obtained from the MS2 traffic count database system.

The geometric characteristics data included the ramp length and the number of lanes at each ramp metering signal. Ramp lengths were measured using Google Maps, with measurements taken from the stop bar to the point where the ramp diverged from the arterial road. In addition, Arizona DOT provided data on the ramp meter types corresponding to specific ramp meter IDs. The ramp types (e.g., single-lane versus dual-lane ramp meter) were also verified with Google Maps.

The CEB data were collected from the ramp meter cabinets during the study period. Once preprocessed, CEB data include information on metering rates, queueing, and violation events. CEB data stores all events made by the signal controller (e.g., signal phase changes) and the loop detectors (e.g., detector actuations), along with the timestamps of when these events occur on the ramp. Specifically, the data records signal phase changes, detailing the start and end times of green and red intervals, and loop detector actuations, capturing the exact moment a vehicle actuates a detector "on" and "off." This data are stored in the cabinet at the side of the road and delivered through MaxView, an advanced traffic management system (ATMS) to Arizona DOT. The constant recording of events at a high resolution (e.g., 0.1 sec) allows for detailed monitoring of ramp meter operations and driver compliance. This comprehensiveness of CEB data, capturing both the signal controller actions and the corresponding vehicle responses, makes it a valuable resource for assessing potential violations and understanding driver behavior.

Methodology

This section describes the methodology to evaluate factors affecting ramp metering compliance using controller event data. The methodology is divided into five steps: mapping the CEB data, estimating the compliance metrics, selecting model variables, fitting a regression model, and testing the transferability of the model on other ramp metering locations. The following sections discuss the methodology in detail.

CEB Data Mapping

The CEB data focus on specific occurrences and their exact timing, offering precise and granular details, especially for capturing asynchronous events. In contrast, time series data collects observations at regular intervals, which can miss fine details or include irrelevant data. While CEB data provide detailed insights into individual events, they often need to be mapped to time-series data to analyze patterns and trends over time, helping to understand behaviors such as ramp meter performance during specific periods.

In mapping the data set to a time series, queueing status is represented as $Q^p_{m,l}$, where Q denotes queueing, m specifies the ramp meter, l indicates the lane, and p represents the time period. This notation enables identification of whether a given ramp meter m experienced queueing in lane l during period p. Similarly, ramp metering rates are denoted as R^p_m, where R indicates the metering rate at meter m during period p; as metering rates apply uniformly across all lanes, the lane l is not specified for R.

The CEB data were retrieved from an SQL server, resulting in a set, *EBData*, comprising tuples containing an event timestamp t_e, a ramp meter ID m from the set of all ramp meters M, an event ID e_i, and an event parameter p_e. These tuples are sorted in ascending order by m and t_e. A time series was generated from the initial to the final event timestamp, with each 1-min time period p spanning the entire interval between these two timestamps, creating a set of time periods $\hat{P}$.

The events used are 1,170 and 1,171 (lane one queue sensor off and on, respectively), 1,172 and 1,173 (lane two queue sensor off and on, respectively), and 1,058 (ramp meter active rate update). For events 1,170 to 1,173, only data items with a parameter $p_e = 1$ are used, corresponding to a level one queueing as defined by Arizona DOT. This level indicates that the queue occupancy has reached a threshold of 50% or greater for the queueing sensor. For each lane l of each ramp meter m, the time periods p between ramp queue sensor "on" and "off" events are flagged as $Q^p_{m,l} = 1$. Similarly, metering rates are assigned to the corresponding period p in which they are active. If either lane was flagged as having queueing during period p, the ramp meter m was considered to be queueing during that period. While the calculated queueing during the time period can be influenced by the placement of the queue detector and the established occupancy threshold values, these factors are generally consistent across similar set-ups. Thus, the methodology employed in this study, along with the use of a queueing variable, is beneficial for evaluating the factors affecting compliance. The event-based data time series mapping algorithm is detailed as pseudocode below in Table 1.

Compliance Metrics Estimation

This study uses the violation counts and compliance rate to comprehensively evaluate the factors affecting compliance. Violation counts offer insight into the magnitude or frequency of noncompliance events and benefit agencies by providing an understanding of compliance patterns. The violation count, VC^p, represents the number of vehicles noncompliant with the ramp meter during a 15-min period p. This count was obtained from the CEB data, with each violation recorded under a specific violation event ID (1205); the total number of events was then aggregated for each 15-min period. Noncompliance is defined as a vehicle passing over the loop detector while the signal is red, triggering the controller to record the violation event ID.

The compliance rate is a commonly used metric used to assess a ramp's effectiveness in metering traffic and to measure the severity of noncompliance relative to ramp volume. The compliance rate is denoted as CR^p, and calculated as the ratio of compliant vehicles to the total ramp volume:

Table 1. Pseudocode to Map Event-Based Data to a Time Series

Event-Based Data Time Series Mapping Algorithm
Input: Event-based data *EBData*, zeroed queueing binary time series $Q^{p}_{m,l}$, empty ramp metering time series R^{p}_{m}, and set of time periods $\hat{P}$.
Output: Time series of binary indicating queueing ($Q^{p}_{m,l}$) and metering rates (R^{p}_{m}).
for each $\{t_e, m, e_i, p_e\} \in EBData$ **do**
  if $e_i = 1170$ **and** $p_e = 1$ **do** // lane one queue sensor off
    $t_{off} = t_e$
    $t_{on} = last(t_e, 1171)$ // last lane one queue on timestamp
    for $p \in \hat{P}$ **do**
      if $p \geqslant t_{on}$ **and** $p < t_{off}$ **do** // if period p between queue on and off events
        $Q^{p}_{m,1} = 1$ // set lane one as queueing
    end for
  if $e_i = 1172$ **and** $p_e = 1$ **do** // lane two queue sensor off
    $t_{off} = t_e$
    $t_{on} = last(t_e, 1173)$ // last lane two queue on timestamp
    for $p \in \hat{P}$ **do**
      if $p \geqslant t_{on}$ **and** $p < t_{off}$ **do** // if period p between queue on and off events
        $Q^{p}_{m,2} = 1$ // set lane two as queueing
    end for
  if $e_i = 1058$ **do**
    $t_{update} = t_e$
    $t_{initial} = last(t_e, 1058)$ // last metering rate update timestamp
    $rate = p_e^{t_{initial}}$ // last metering rate set is active rate up through t_e
    for $p \in \hat{P}$ **do**
      if $p \geqslant t_{initial}$ **and** $p < t_{update}$ **do** // if period p between rate update events
        $R^{p}_{m} = rate$ //set rate to that active during period p
    end for
end for
return $\left\{Q^{p}_{m,l}, R^{p}_{m}\right\}$

$$CR^p = \frac{CV^p}{VR^p} \tag{1}$$

where

- CR^p is the compliance rate at time period p,
- CV^p is the number of compliant vehicles during time period p, and
- VR^p is the total ramp volume (vehicles entering the freeway) during time period p.

Model Variables Selection

The variables considered in the analysis included the time of day, ramp meter type, ramp volume, ramp metering rate, the ratio of volume to metering rate, henceforth referred to as rate capacity ratio, and the percent of the time a ramp experienced queueing, henceforth referred to as percent queueing because of their intricate relationship with compliance metrics. The ramp meter type had two categories based on the ramp metering locations included in the study. The 24 ramps chosen exhibited a broad range of lengths from 265 ft to 2000 ft, as illustrated in Figure 3*a*. Single-lane ramps typically have longer lengths than dual-lane ramps, reflecting both the need to accommodate all traffic entering with only one lane and the limited space in dense urban environments. Single-lane ramps tend to have their stop bar and meter positioned closer to the mainline, as they do not require additional space for merging. This positioning can also contribute to their overall length. Notably, this study's site selection demonstrates diversity across ramp lengths, with several dual-lane ramps surpassing the lengths of single-lane counterparts.

Figure 3*b* shows the AADT of the ramps, ranging from 5,433 vehicles per day (vpd) to 17,082 vpd. Both the ramp length and ramp AADT are important factors in capacity and congestion management and may play a role in influencing drivers' compliance.

The ramp metering volume was not altered and was applied as was collected from the loop detectors. The metering rate was determined by Arizona DOT's adaptive metering algorithm for effective traffic management, and exploring these relationships offers insights into the dynamics of ramp metering systems. The rate capacity ratio was a variable derived from the collected data, included in the analysis for analyzing spatial patterns, as it indicates which locations have volumes at or exceeding the ramp metering rate set by Arizona DOT. While volume and metering rate individually provide useful information about a selected ramp, taking the ratio of ramp volumes to the metering rate offers a holistic view of the

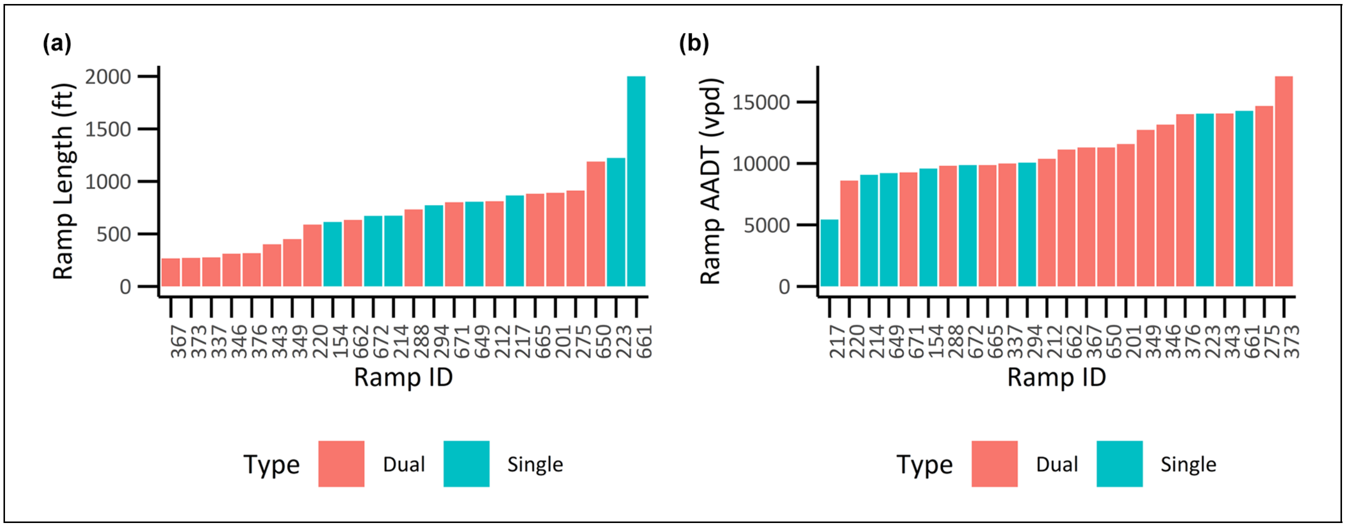

Figure 3. Ramp characteristics by type: (*a*) ramp length; and (*b*) ramp average annual daily traffic (AADT).

relationship between these two variables. The rate capacity ratio, R_{cr}^t, was computed using:

$$R_{cr}^t = \frac{V_r^t}{R^t} \tag{2}$$

where

- R_{cr}^t represents the rate capacity ratio,
- V_r^t denotes the ramp volume, and
- R^t indicates the metering rate all in each time t.

Percent queueing is the percentage of time within each 15-min period where queueing occurred. The peak hours were from 6:00 a.m. to 9:00 a.m. and from 3:00 p.m. to 6:00 p.m. based on information provided by Arizona DOT, with all other hours being considered off-peak.

A general understanding of driver behavior led to the recognition that factors such as speed and the time of day are likely correlated with compliance. Employing a correlation threshold of 0.75, highly correlated variables were identified and removed from the modeling process. Figure 4 presents the correlation matrix for the following variables: mainline volume, upstream AADT, ramp volume rate capacity ratio, ramp meter type, ramp length, route, peak hours, ramp speed, mainline speed, metering rate, and percent queueing.

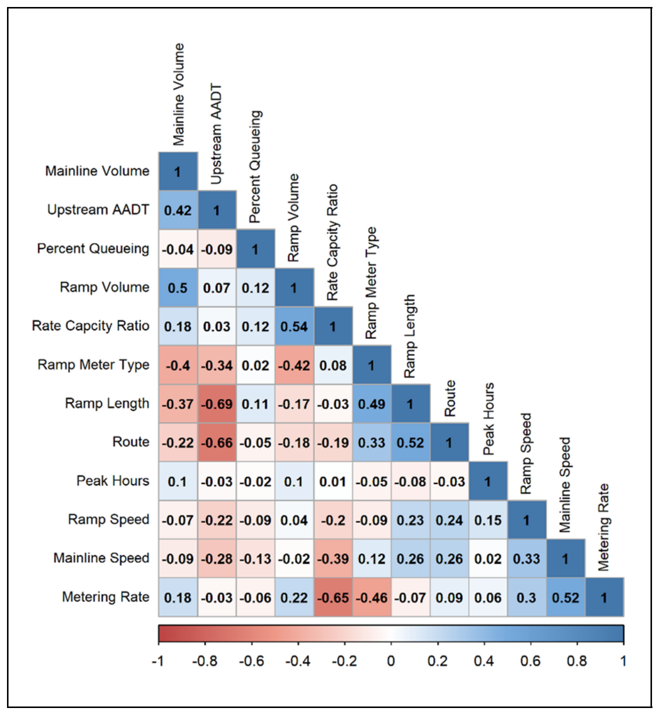

Figure 4. Correlation matrix of the variables included in modeling.
Note: AADT = average annual daily traffic.

Regression Analysis

Ordinary least squares (OLS) regression was employed to evaluate factors affecting ramp meter compliance after removing highly correlated variables. The OLS regression model was applied in two phases: first, on a network-wide scale to capture spatial effects among various routes and gain insights into system-wide dynamics; second, the model was applied without route-specific variables for a transferability analysis. OLS regression was used because it aids in assessing how variables can estimate instances of noncompliance and quantitatively determines statistically significant factors affecting compliance metrics. To refine the model, backward elimination was employed to include all available variables in the OLS regression and iteratively remove the statistically insignificant ones.

Backward elimination allowed for discerning the most effective variables, with lower p-values indicating superior statistical significance. All analyses were performed using R Statistical Software (R Core Team 2022).

The OLS regression is fundamental in statistical analysis because of its simplicity and interpretability when modeling the relationship between variables. The general form of an OLS model is:

$$y_i = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \varepsilon_i \tag{3}$$

where

- y_i is the dependent variable at the i -th observation,
- β_0 is the intercept, and
- β_j are the coefficients of the independent variables.

The term x_{ij} represents the values of the j -th independent variable for the i -th observation. The error term ε_i accounts for deviation of the observed values from the predicted values, assuming it is normally distributed with a mean of zero and constant variance. In this model β_0 represents the expected value of y_i when all x_{ij} are zero, and β_j quantifies the change in y_i associated with a one-unit change in x_{ij}, holding other variables constant.

The coefficients β_0 and β_j are estimated using the OLS method, which minimizes the sum of squared errors (SSE):

$$SSE = \sum_{j=1}^{m} \left(y_i - \beta_0 - \sum_{j=1}^{n} \beta_j x_{ij} \right)^2 \tag{4}$$

The OLS estimates β_0 and β_j are those that minimize the SSE, providing the best linear unbiased estimates of the model parameters (*20*).

Transferability Analysis

A model spatial transferability test was conducted to further validate the developed linear regression models. Figure 5 below displays a map showing the route selected for testing in red and the ramp meters used for training the model in blue. This analysis involved redeveloping the linear regression model excluding any route-specific characteristics to assess the feasibility of a simplified model for estimating compliance levels of a ramp. The objective was to determine if the developed model will be predictive in a localized context without the inclusion of specific route variables on new data by the redeveloped model. By applying the simplified model to SR-51, we evaluated its performance and practicality, thereby providing insights into the generalizability and potential implementation of the model for future ramp construction planning. Linear regression was selected for the transferability analysis because of its simplicity and interpretability, aligning with our focus on identifying factors that affect compliance. Similar studies, such as Apronti et al. (*21*), have also applied linear regression to bounded count data with success, particularly when the data distribution minimizes the risk of extrapolation beyond bounds. In our case, the distribution of ramp meter data (where violation counts are greater than zero and compliance rates are between 0 and 1) helped mitigate such risks, supporting the model's applicability.

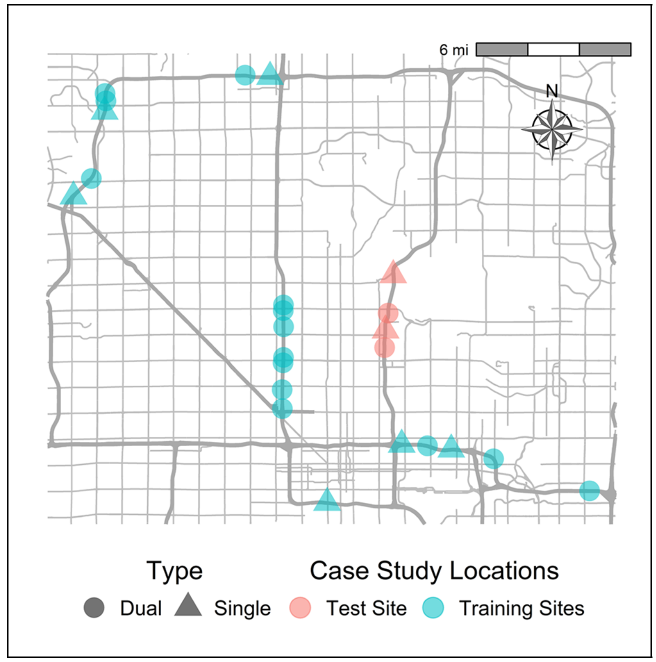

Figure 5. Map of testing and training sites.

Results and Discussion

Exploratory Data Analysis

Understanding the interplay between ramp meter compliance metrics—compliance rate and violation count—and factors such as metering rate, is crucial for effective modeling and estimation of these metrics. An exploratory data analysis (EDA) was conducted to determine possible patterns and relationships between various factors and ramp metering compliance metrics. Note that the violation counts were initially collected for the entire ramp. However, to make a fair comparison between dual-lane and single-lane ramps, the average violation count per lane was calculated by dividing the total violations at dual-lane ramps by two.

Figure 6*a* depicts the relationship between the count of violations per lane in a 15-min bin and the corresponding ramp volumes. For single-lane ramps, no discernible pattern between violations and ramp volumes is observed, indicating that the number of violations does

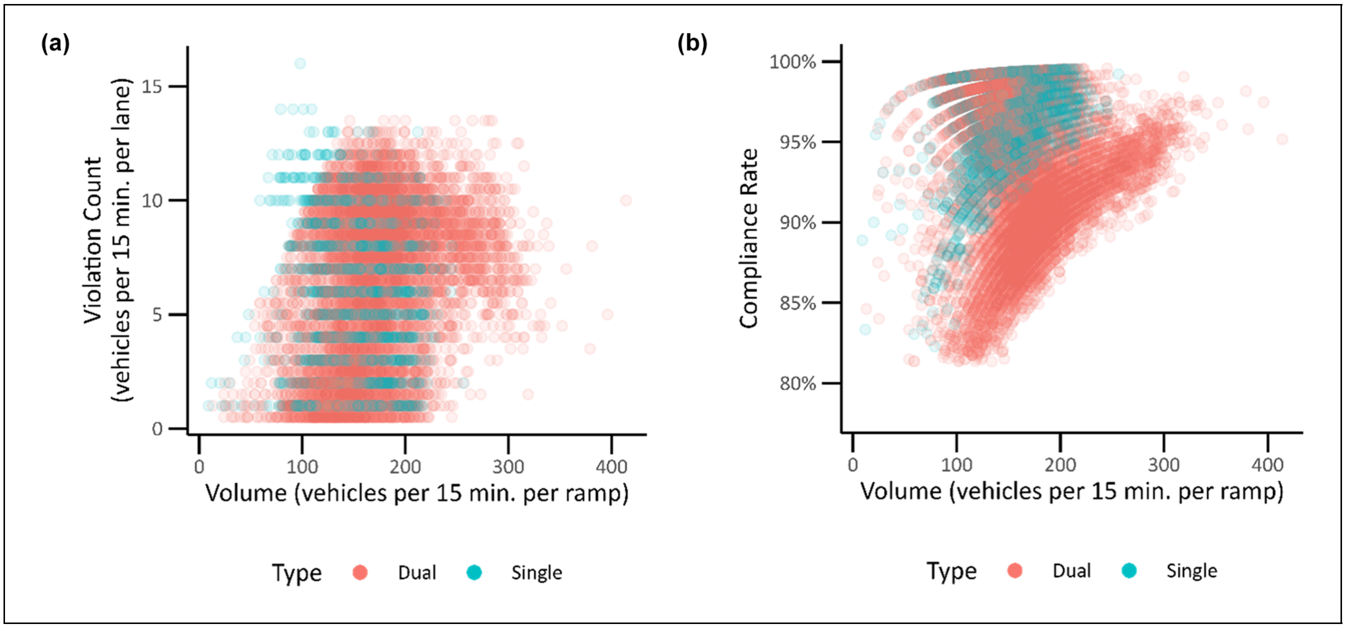

Figure 6. Relationship between compliance metrics and ramp volumes: (*a*) violation count versus ramp volume; and (*b*) compliance rate versus ramp volume.

not consistently increase or decrease with traffic volume. In contrast, dual-lane ramps exhibit a slightly linear relationship, where the number of violations tends to increase as ramp volumes rise. This suggests that higher volumes on dual-lane ramps may lead to more violations.

Figure 6*b* demonstrates the relationship between the overall compliance rate and ramp volumes. Since the compliance rate is measured across the entire ramp rather than per lane, it provides a holistic view of ramp compliance relative to traffic volume. The data shows that there are instances of high compliance rates at lower ramp volumes, aligning partially with the trends observed in violation counts. However, notably, most instances of noncompliance occur at lower volumes, which is evident as compliance rates rarely drop below 90%, and when they do, it tends to happen at lower volumes. This inverse relationship indicates that as ramp volumes decrease, noncompliance tends to increase.

In addition to the volume considerations, the analysis explored the complex relationship between compliance metrics and metering rate. Figure 7 reveals that both compliance metrics exhibit a quadratic relationship with metering rates for single-lane and dual-lane ramps. The quadratic fit was selected for subsequent analysis because of its higher R^2 value (0.21), compared with the linear ($R^2 = 0.02$) and square root ($R^2 = 0.01$) fits. Although the R^2 is modest, it still demonstrates that a quadratic fit explains substantially more variance than other relationships that were tested. Figure 7*a* shows that single-lane ramps have a high point of noncompliance at a metering rate of around 200 vehicles per 15 min. Dual-lane ramps exhibit a similar pattern, with noncompliance peaking at around the same metering rate. This quadratic relationship suggests that as metering rates approach 200 vehicles per 15 min, the number of violations increases as the square of the change in metering rate. Figure 7*b* illustrates the relationship between compliance rate and metering rate. Compliance rates are like violation counts but offer a more balanced view as they incorporate volume in their calculations. Both single-lane and dual-lane ramps show a high point of noncompliance at a metering rate of around 200 vehicles per 15 min, reflecting the inverse relationship between compliance rates and violation counts. Overall, Figure 7 demonstrates that the metering rate plays a crucial role in influencing compliance, and single-lane ramps are generally better performing than dual-lane ramps in maintaining higher compliance rates and lower violation counts.

An independent variable that provides a broader perspective is the concept of rate capacity ratios, calculated as the ratio of ramp volume to metering rates. The data are fitted with a square root function to illustrate the overall trend of noncompliance instances. The square root function was chosen because it effectively captures the relationship between noncompliance and rate capacity ratio increases, particularly in a visual context. This approach helps to understand the mathematical nature of the relationship between the rate capacity ratio and noncompliance, which is valuable for guiding future modeling efforts in this study. Figure 8*a* and *b*

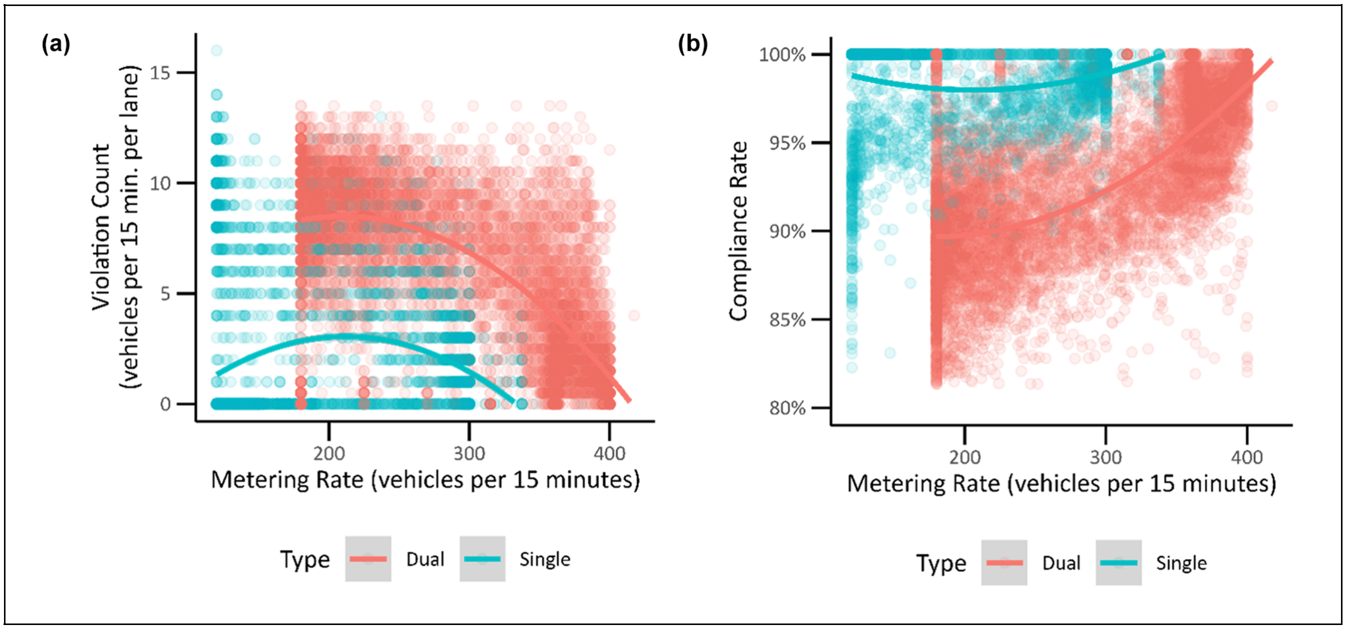

Figure 7. Relationship between compliance metrics and metering rate: (*a*) violation count versus metering rate; and (*b*) compliance rate versus metering rate.

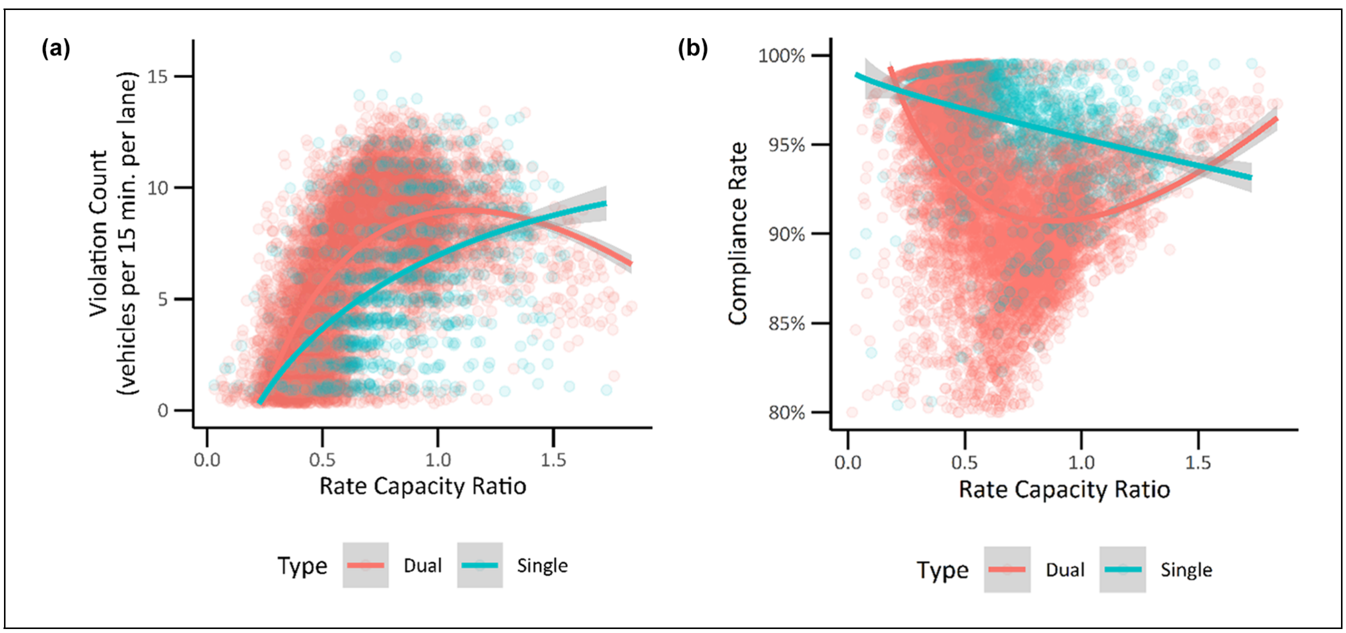

Figure 8. Relationship between compliance metrics and rate capacity: (*a*) violation count versus rate capacity; and (*b*) compliance rate versus rate capacity.

demonstrate that the peak number of noncompliant vehicles occurs when the rate capacity ratio is between 0.85 to 0.9, indicating ramp volumes are approximately 85% to 90% of the metering rate's specified volume. Across all compliance metrics, the rate capacity ratio reinforces previous findings on metering rate, highlighting that dual-lane ramp meters tend to exhibit higher noncompliance rates.

Figure 9*a* and *b*, display boxplots to examine the compliance metrics across the four routes within the study network and the effect of ramp meter type. Figure 9*a* reports no instances for single-lane ramps on L-202,

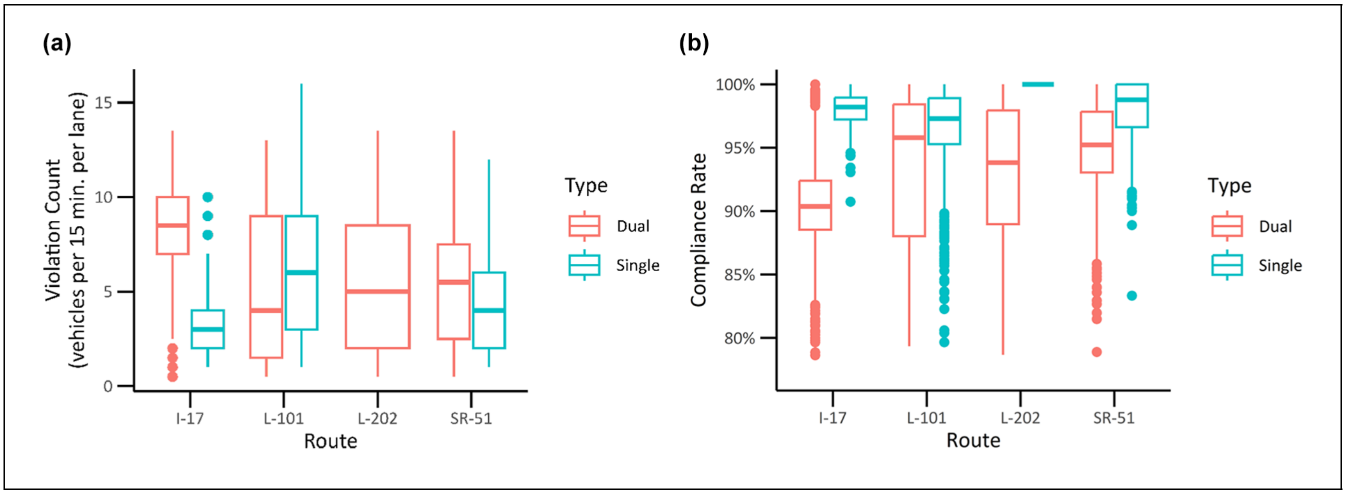

Figure 9. Relationship between compliance metrics and route: (*a*) violation count versus route; and (*b*) compliance rate versus route.

while Figure 9*b* does because there were no detector-reported instances of noncompliance on L-202. Conversely, the compliance rate is based on volume and compliant vehicles, resulting in a display of 100%. Across all routes, dual-lane ramp meters consistently exhibited lower compliance and higher instances of violations compared with their single-lane counterparts. An exception is observed in the L-101 route. Here, the median value of violations per lane for dual-lane ramps shows few noncompliant vehicles. However, when incorporating vehicle volume into the compliance metric (as in compliance rates), dual-lane ramps on L-101 still exhibit higher noncompliance, thus aligning with the findings of other routes. Furthermore, this observation highlights the importance of using a holistic approach and incorporating multiple compliance metrics.

The previous analysis indicates that there are likely spatial implications for the compliance of ramp meters in the study freeway network. Figure 10 shows the averaged values for violation counts at each ramp meter location. There is no map to display the compliance rate because it is simply the proportion of non-violators and yields a very similar figure. Notably, L-101, previously found to display higher median levels of violation count and compliance rate than other routes, shows high levels of compliance. The location where L-101 and I-17 connect is the only location on this route where the compliance rate drops significantly. This speaks to the interaction effects between routes. Furthermore, I-17, comprised mainly of dual-lane ramp meters and located in a dense urban area, has the highest count of violations and lowest compliance rate. However, when looking at L-202, comprised of both dual-lane and single-lane ramp meters, the dual-lane locations continue to yield worse levels of compliance. This likely speaks to the effects of ramp meter type as opposed to spatial characteristics.

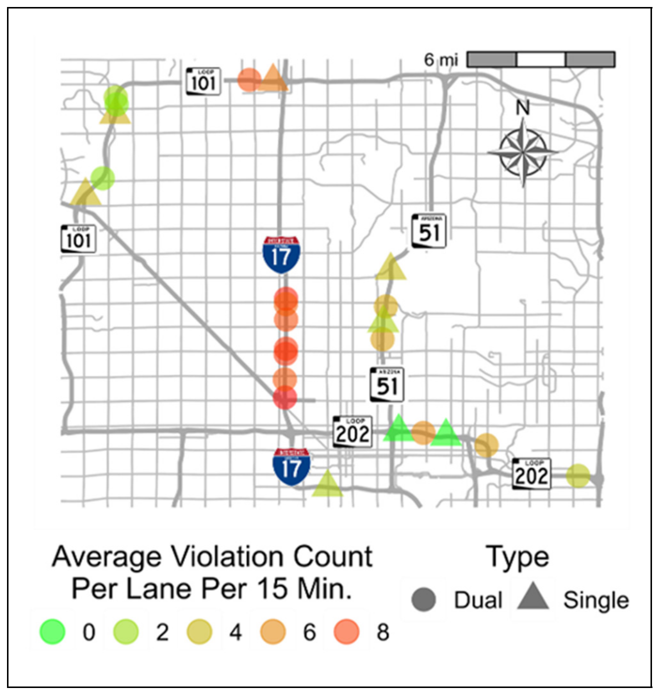

Figure 10. Map of average violation count.

Regression Analysis

The OLS were fit to evaluate factors influencing violation counts and compliance rates. The initial consideration for independent variables stemmed from insights gained during EDA, which highlighted variables such as the square root of the rate capacity ratio, volume, and metering rate as having a significant relationship with the compliance metrics. To further ensure the absence of multicollinearity, a variance inflation factor (VIF) test was conducted, and any variable exceeding a

Table 2. Model Regression Results

Variables	Violation Counts Model			Compliance Rate Model		
	Estimate	Std Error	P-Value	Estimate	Std Error	P-Value
Intercept (α)	0.906 ***	4.42e-2	<2e-16	0.905 ***	2.28e-3	<2e-16
L-101 (β_1) [Base = L-202]	0.687 ***	1.51e-2	<2e-16	-2.49e-2 ***	7.40e-4	<2e-16
SR-51 (β_2) [Base = L-202]	0.193 ***	1.65e-2	<2e-16	N/A		
I-17 (β_3) [Base = L-202]	0.183 ***	1.96e-2	<2e-16	-1.18e-2 ***	9.82e-4	<2e-16
Dual-Lane (γ_1) [Base = Single-Lane]	0.702 ***	1.57e-2	<2e-16	-5.99e-2 ***	7.89e-4	<2e-16
V_r^t (δ_0)	3.20e-3 ***	1.32e-4	<2e-16	-1.48e-4 ***	6.76e-6	<2e-16
$Volume_{ML}$ (δ_1)	3.94e-3 ***	7.57e-5	<2e-16	-1.75e-4 ***	3.94e-6	<2e-16
$Speed_{ML}$ (δ_2)	-8.01e-3 ***	4.28e-4	<2e-16	4.90e-4 ***	2.27e-5	<2e-16
R^t (δ_3)	-2.73e-3 ***	8.07e-5	<2e-16	1.99e-4 ***	4.16e-6	<2e-16
RampLength (δ_4)	-8.72e-4 ***	2.69e-5	<2e-16	3.61e-5 ***	1.31e-6	<2e-16
UpstreamAADT (δ_5)	-1.29e-5 ***	7.35e-7	<2e-16	8.92e-7 ***	3.59e-8	<2e-16
Peak (δ_6)	0.185 ***	1.57e-2	<2e-16	-7.48e-3 ***	8.16e-4	<2e-16
Q_m^p (δ_7)	0.298 *	1.23e-1	0.015	-3.68e-2 ***	6.49e-3	<2e-16

Note: AADT = average annual daily traffic; Significance level codes: "***" 0.001 "**" 0.01 "*" 0.05.

VIF threshold of 10 was removed, following common practices in the literature (*22*, *23*). Only one variable, the rate capacity ratio, exceeded this threshold and was therefore excluded from the models. When modeling the violation count, the target variable ranged from 0 violations to 16 violations in a 15-min interval per lane. Since it is impossible for there to be a negative number of noncompliant drivers, we performed a log transformation on the violation count to ensure no negative predictions. The violation count model as displayed by Equation 5 yielded an adjusted R^2 value of 0.6757, indicating that the model can explain 67.57% of the variance in the data set, after adjusting for the number of predictors.

$$V_c^t = \alpha + \beta Route + \gamma Type + \delta_0 V_r^t + \delta_1 MLVolume + \delta_2 MLSpeed + \delta_3 R^t + \delta_4 RampLength + \delta_5 UpstreamAADT + \delta_6 Peak + \delta_7 Q_m^p \tag{5}$$

The compliance rate was modeled using the same method incorporating backward elimination, and the resultant adjusted R^2 value is 0.6394. The statistically significant variables are shown in Equation 6:

$$C_r^t = \alpha + \beta Route + \gamma Type + \delta_0 V_r^t + \delta_1 MLVolume + \delta_2 MLSpeed + \delta_3 R^t + \delta_4 RampLength + \delta_5 UpstreamAADT + \delta_6 Peak + \delta_7 Q_m^p \tag{6}$$

Dummy variables were introduced to model the categorical variables of route and type. Of the four routes, L-202 was selected as the baseline route. Between the two ramp meter types, single-lane ramps were the selected baseline value. With regard to the time of day that was considered, only the hours when ramp metering occurred were included in the model from 6:00 a.m. to 10:00 p.m. It is worth noting that certain variables, such as the dummy variables for route (e.g., β_1, β_2, β_3), have multiple permutations corresponding to different levels of the category, which become one-hot encoded. For instance, $\beta * Route$ represents each level of $\beta_x * Specific\ Route\ Name$, as shown in Table 2.

Table 2 presents the regression outputs for both the violation count model and the compliance rate model, summarizing their statistical significance. The backward elimination process ensured that only variables significant at the 5% level were included in the models, although some variables were significant at higher levels. Instances marked "N/A" indicate that a variable was significant in one model but not the other. The intercept (α) of both models provides a value of compliance given all other variables being equal to zero. It indicates that the base level of compliance corresponds to a compliance rate of 90.5% or around 1 violation per lane in a 15-min bin.

The ramp meter type variable (γ) indicates that, compared with single-lane ramps, dual-lane ramp meters decrease the compliance rate by around 6%, which corresponds to an increase of approximately 0.7 drivers per 15-min per lane. This could have major implications for agencies considering constructing ramp metering signals at single-lane or dual-lane ramp meters, encouraging agencies to consider how compliance may affect the effectiveness of the ramp metering signals based on the type constructed.

The previously discussed variables were one-hot encoded variables and are directly related to the compliance metrics, while the following variables discussed are numeric and require the estimate to be multiplied by the variable itself. For instance, a ramp volume of 500 vehicles per 15-min per lane will increase the number of violations by around 1.6 (estimate from the count model times the ramp volume: 0.00320×500).

The ramp volumes per lane and the mainline freeway volumes both had positive estimates for the violation count and negative estimates for the compliance rate model, indicating that higher volumes on the ramp and the mainline freeway both result in a proportionally increasing number of violations. This is confirmed by the negative estimates for the compliance rate model that highlight how higher volumes result in a lower compliance rate. This is reasonable because higher volumes may suggest the presence of more impatient drivers deliberately running the red light (*2*, *24*, *25*). Additionally, previous research has shown that violations can be infectious, with one leading to many, particularly in high-volume traffic (*3*). A probable explanation for this would be impatient drivers, who are frustrated by waiting in a queue for an extended period, while lower volumes might result in a lower proportion of compliant vehicles, possibly as a result of a reduced sense of accountability or a diminished perception of social observation from other drivers.

The mainline speed was a factor significantly affecting compliance. The results from both models indicate that higher speeds on the mainline freeway were associated with higher compliance rate and a lower number of violations. A possible explanation for this would be that higher speeds on the mainline freeway are correlated with less congestion on the freeway resulting in a higher metering rate set by the Arizona DOT adaptive metering algorithm. If the rate is higher, drivers may be more willing to abide by the meter as the wait time is not as high. While mainline speeds were statistically significant, ramp speeds were removed because of insignificance in predicting compliance, as determined by a p-value above the 5% threshold in our backward elimination process. Practically, this suggests that speed management on ramps may not effectively address noncompliance issues, potentially guiding practitioners to prioritize other variables such as ramp length or metering rate.

The metering rate demonstrates a positive correlation with compliance rate and a negative correlation with violation count. For example, a metering rate of 400 vehicles per 15 min results in approximately 8% ($0.000199 \times 400 = 0.08 \approx 8\%$) increased compliance, or around one additional violation ($0.00273 \times 400 = 1.01 \approx 1$). Ramp length and upstream AADT also show positive estimates for both models. One possible explanation to explain why longer ramps are associated with greater compliance is that longer ramps allow more time for drivers to notice and respond to meters. Prior research has emphasized the importance of sight distance and visibility in reducing red-light running, a principle that likely applies to ramp meters as well (*26*, *27*). With regard to AADT, higher AADT may indicate the presence of platooning. Previous studies have shown that small platoons can increase compliance, provided that the leading vehicle comes to a stop (*5*).

The peak hour variable indicated an increase in the number of violations, and a decrease in compliance rate. This is an intuitive result as higher volumes and greater driver impatience is expected during peak hours. Percent queueing was significant in predicting both violation counts and compliance rate. This too is an expected result as queueing at ramp meters is also likely related to impatient driving behavior, such as running red lights.

The route variable (β) plays a significant role in evaluating ramp meter compliance. Using L-202 as the reference variable, the results of the violation count model highlight positive estimates, implying that all other routes have various site-specific characteristics (e.g., demographics, road conditions, geometric characteristics) that increase the number of violations. Specifically, L-101 shows a substantial increase in violations of about 0.7 per lane, while SR-51 and I-17 show a smaller increase of approximately 0.19. Notably, violation count and compliance rate are inverse metrics: an increase in violations typically corresponds to a decrease in compliance. However, SR-51 was found to be insignificant in the compliance rate model, meaning that while the absolute number of violations on SR-51 may be higher, its compliance rate—when accounting for volume—is not significantly different from that of L-202. This distinction highlights that violation count measures magnitude, whereas compliance rate provides a volume-adjusted perspective on driver behavior at ramp meters.

With the regression analysis results providing insights into the influence of key variables on ramp meter compliance, several practical implications emerge for transportation practitioners and policymakers. For instance, dual-lane meters, which are often favored for their queue management capabilities and vehicle throughput, show a tendency to reduce compliance rates. This trade-off between operational benefits and compliance levels is critical when planning new ramp installations. Additionally, the observed link between increased ramp length and reduced violations suggests that design optimizations, such as ramp length adjustments, may be more effective than ramp speed management in enhancing compliance. These findings offer agencies actionable guidance, helping to prioritize interventions that balance operational demands with compliance and safety outcomes.

Spatial Transferability

From the EDA and the regression analysis, it is evident that the violation count model is most likely to yield the highest accuracy in predicting compliance. Furthermore, the compliance rate can be derived from the violation count. This is crucial since the violation count is the only compliance metric that can be directly derived from the loop detectors and ramp controllers. Further, the regression analysis demonstrated that the violation count model explained a higher proportion of variance compared with the compliance rate model, as indicated by a higher R^2 value.

To validate our findings, we retrained the model, excluding the route variable from the independent variables. This approach aims to study the transferability of our results within Arizona and assess whether the factors affecting ramp meter compliance identified in this study can be effectively applied in future research on real-time prediction. This would enhance the support provided to transportation departments beyond the contributions of this study. The altered model equation is shown below in Equation 7:

$$V_c^t = \alpha + \gamma Type + \delta_0 V_r^t + \delta_1 MLVolume + \delta_2 MLSpeed + \delta_3 R^t + \delta_4 RampLength + \delta_5 UpstreamAADT + \delta_6 Peak + \delta_7 Q_m^p \tag{7}$$

Notably, in removing the route variable, all other selected variables were statistically significant to the 5% level. To evaluate the model, fivefold cross-validation was used, the training-validation data set was divided into five equal parts. This training-validation data set was comprised of ramp meter data from I-17, L-202, and L-101, excluding SR-51 to test for spatial transferability and generalizability. For each fold, the model was trained on four of the parts and validated on the remaining part. The data splits were randomly sampled and not based on any timestamp-specific or route-specific characteristics. This process was repeated five times, each time with a different fold as the validation set. The average R^2 value from cross-validation was 0.6595, suggesting that even without the route variable, the model could effectively interpret a significant portion of the variance.

The model was then retrained on all the available training data. As mentioned, this training data comprised all ramp meter data excluding SR-51. When this simplified model was applied to the unseen SR-51 corridor, the model performed well in predicting the number of violations in a 15-min period per lane (V_c^t), although it struggled when the number of violations increased to a high number, as indicated by the dispersion observed in the Figure 11 true versus predicted plot. The relatively high R^2 value in the transferability analysis indicates the model is fairly generalizable, holding promise for predicting violations at ramp meters across different locations. Furthermore, it suggests potential for practical application in predicting violations at ramp meters even before deployment. However, future improvements are needed to achieve the level of predictive accuracy required for optimal use by agencies.

Conclusions

Ramp meters are designed to manage traffic flow and reduce delays by controlling the rate at which vehicles enter highways. Many transportation agencies now need support in evaluating ramp meter compliance, as noncompliance can undermine the benefits of ramp metering and increase safety risks and environmental impacts. Agencies face limitations in collecting extensive driver behavior data to analyze compliance. This has led to studies focusing on few ramp metering locations, shorter study periods, and analysis on the compliance rates without a comprehensive look at what influences driver compliance to the ramp metering signals.

The objective of this study was to analyze and determine factors that may lead to noncompliance of network-wide permanent ramp meters. This study involved four corridors and 24 ramp meters across the Phoenix Metropolitan Area. Two months of controller event–based data and traffic data were collected for the

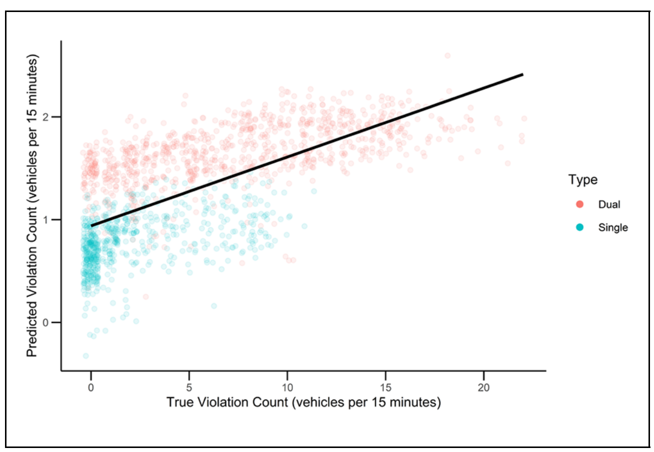

Figure 11. Actual versus predicted values of the violation count model.

analysis and were supported with the geometric attributes data. Two compliance metrics were used to analyze various features of compliance: violation count and compliance rate. The methodology involved mapping the controller event–based data and linking it to the traffic volume data, before the statistical and spatial transferability analyses.

An EDA revealed many possible patterns in the relationship between ramp length, volume, metering rate, and so forth, and the compliance metrics. With a better understanding of the factors that influence noncompliance, modeling was conducted. Results revealed that higher volumes and lower metering rates are often correlated with higher noncompliance. With regard to the rate capacity ratio, although it may intuitively seem that most cases of noncompliance would occur when the rate capacity ratio is greatly exceeded, most violations occurred around 0.9. Furthermore, the results underscore the complexity and variability of ramp meter compliance across different ramp types and routes. The positive estimate for dual-lane ramps suggests a notable increase in violation counts. This finding offers transportation agencies an important perspective: while dual-lane ramps are highly effective for managing queue lengths, they may also be associated with increased noncompliance, which could influence the overall benefits of ramp metering. Another interesting finding is the insignificance of ramp speed on noncompliance, suggesting that ramp speed management may not significantly enhance compliance. However, future research could explore the impact of sight distance on compliance, given that longer ramps are associated with better compliance.

Analyzing compliance metrics across routes reveals the benefits of employing a secondary metric for evaluation. While compliance rates offer a balanced perspective, using violation counts provides insight into the magnitude of noncompliance. Regression analysis showed that variables in the violation count model generally had opposite signs compared with those in the compliance rate model, except for SR-51, highlighting significant levels of noncompliance on this particular route. The findings from the transferability analysis demonstrated that the simplified violation count model has significant potential, despite room for improvement. Training on three routes and predicting violations on an unseen route (SR-51) proved effective, suggesting the model's generalizability and utility in traffic management. This case study reinforces the model's potential to predict ramp meter violations across various corridors effectively.

While this study focuses on ramp meters in the Phoenix Metropolitan Area, which encompasses various cities and offers a wide range of urban conditions and driver behaviors, the findings may not fully generalize to other states with different traffic cultures and regulations. In addition, this analysis did not account for factors such as signal timing adjustments, the formation of multiple-vehicle platoons, varying vehicle-release methods, or enforcement measures that could influence compliance. However, areas with similar ramp metering configurations and traffic characteristics can apply these findings to assess and improve compliance. Furthermore, the results from this study can provide agencies with methods to analyze their existing ramp meters and make informed, actionable decisions with regard to where and when to implement ramp metering. Future research could focus on: a) developing predictive models to forecast noncompliance at ramp meters; b) evaluating seasonal or weather-related variations in compliance; c) examining the impact of different vehicle-release methods and enforcement policies on compliance rates; and d) assessing how noncompliance may affect the safety and efficiency benefits typically associated with ramp meters. These areas could support agencies in refining metering strategies to enhance traffic flow and safety under diverse conditions.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: A. Cottam, H. Haule, and Y.-J. Wu; data collection: G. Geffen and A. Cottam; analysis and interpretation of results: G. Geffen and A. Cottam. Author; draft manuscript preparation: G. Geffen and Y.-J. Wu. All authors reviewed the results and approved the final version of the manuscript.

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