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Freeway and Arterial Performance Analysis with High-Resoultion Vehicle Trajectory Data

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This research investigates applying high-resolution vehicle trajectory data, derived from vehicle telematics, to facilitate freeway and arterial performance analysis in Nevada. Leveraging vehicle trajectory datasets crowdsourced through original equipment manufacturer (OEM) telematics, the research team conducted a comprehensive synthesis of common sources and types of vehicle trajectory data, identifying the uses of vehicle telemetry trajectory data to facilitate network-wide and spatially customizable representations of speed, delay, queuing, and lane-level dynamics. Key applications include regional traffic signal performance evaluation, cross-validation of freeway detector accuracy, and innovative safety analytics for school zones and vehicle passing events on two-way two-lane rural roads. To operationalize large datasets of vehicle telemetry trajectories, a software tool was developed in this research to enable agency practitioners to extract actionable insights without requiring advanced data processing expertise. This work provides a scalable framework and potential applications for state DOTs to integrate vehicle telemetry trajectory data into freeway and arterial performance evaluation practices, supporting a transition toward proactive operational and safety management and monitoring strategies and alternative approaches to data collection and analytics without sensor deployment.</td></tr>
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Freeway and Arterial Performance Analysis with High-resolution Vehicle Trajectory Data

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Executive Summary

This research investigates the emerging opportunities and practical challenges associated with using high-resolution vehicle telemetry trajectory data to support freeway and arterial performance evaluation in Nevada. Historically, transportation agencies have relied on point sensors, such as inductive loops, radar, and magnetometers, or aggregated probe-vehicle datasets to assess traffic conditions. While effective in many settings, these sources provide limited spatial coverage, inconsistent temporal resolution, and insufficient flexibility to capture detailed operational behavior across Nevada's diverse roadway network. The introduction of high-resolution vehicle telemetry trajectory data, sourced from original equipment manufacturers' telematics and embedded on-board systems, presents a new paradigm for acquiring continuous, network-wide observations of vehicle movements at multi-second granularity, enabling both microscopic and macroscopic traffic analyses with substantially greater fidelity.

This study first evaluates the characteristics, strengths, and limitations of modern trajectory data sources, including Wejo and StreetLight datasets, to inform Nevada DOT and partner agencies of the evolving data landscape. Vehicle telemetry trajectories offer broad geographic coverage, consistent resolution, and stable accuracy; however, they also impose significant challenges due to complex data structures, large storage requirements, and data delivery that demands advanced processing capabilities.

Mainly using a 15-day dataset from Wejo in 2023, along with two StreetLight sample datasets collected in 2024 and 2025, the research team conducted three major application studies: arterial traffic signal performance evaluation, freeway operational performance measurement validation, and innovative traffic safety analyses, including school zone speed evaluation and rural passing-event identification.

On arterials, stacked multi-day trajectories enable time-of-day performance measurement across 36 coordinated corridors. The proposed approach facilitates detection of signal timing issues through uniform performance evaluation standards, supporting regional corridor ranking for retiming needs.

For freeways, trajectory-based speed measurements are cross-validated with freeway detectors, revealing strong agreement at some locations and systematic mismatches at others. The study implies the possibility of applying high-resolution vehicle telemetry data to enrich and enhance freeway performance evaluation practices based on detectors.

For safety analysis, custom segmentation enables precise extraction of speeds in school zones and identification of passing events on rural highways in Nevada with lateral-offset techniques, demonstrating the potential of telemetry trajectories for large-scale traffic safety performance screening and fine-granularity traffic safety performance assessment.

To overcome the big-data processing barrier, this research developed the Systematic Trajectory Extraction Program (STEP), a practical and map interface software tool that imports raw trajectory data, applies custom segmentation, extracts performance measures, and outputs standardized measurements. STEP allows Nevada DOT staff to work directly with large telemetry trajectory datasets on local computers without requiring advanced programming expertise.

This research demonstrates that vehicle telemetry trajectory data represent a transformative resource for state DOTs. The findings provide Nevada DOT with not only a technical understanding of the data but also actionable methods, tools, and validated use cases that support data-driven freeway and arterial operational and safety analyses.

Contents

Introduction

This research explores the applications of high-resolution vehicle trajectory data in freeway and arterial performance analysis, particularly focusing on the interest of the Nevada Department of Transportation and transportation agencies in Nevada.

Vehicle trajectory data refers to the detailed spatiotemporal records of vehicle movements along a roadway. Unlike conventional traffic data sources such as loop detectors, radar, or aggregated probe data that capture information at specific points or over broad intervals of time and road segmentation, trajectory data provides a continuous record of how each vehicle moves through space and time. The richness of trajectory data enables analysis of traffic operations and safety at both microscopic and macroscopic levels with fine detail.

A trajectory typically consists of waypoints showing position and speed in vehicular movements sampled at certain resolutions, defined number of seconds per point. Trajectory datasets can be obtained from connected vehicles, third-party probe data providers, video processing, and Global Positioning System (GPS)-enabled devices.

To specify the vehicle trajectory data studied in this research, **TABLE 1** is provided below to distinguish the types of vehicle trajectory data currently used in transportation operational and safety analyses.

TABLE 1: Trajectory Data Description

Data Types	Data Description, Characteristics, and Providers	Transportation Application Examples
Trajectories Generated by Location-based Services (LBS)	Known as "probe vehicle data", generated from GPS-enabled mobile devices and applications such as smartphone, navigation apps, ride-hailing platforms, and fleet management systems. These data typically consist of timestamped latitude–longitude coordinates with significantly varying sampling rates (e.g., several seconds for navigation apps to several minutes for passive mobility apps). While the spatial and temporal resolution of these data is generally sufficient for identifying routes and estimating trip-level travel times, their accuracy can be constrained by GPS noise and inconsistent, low-resolution sampling intervals, which may limit certain transportation analysis applications. Nevertheless, these trajectory data sources typically offer extensive spatial and temporal coverage. Commercial products based	• **Travel demand analysis**: Inferring origin and destination patterns across regions. • **Corridor performance:** Estimating travel time reliability, route choice behavior, and congestion patterns. • **Multimodal transportation planning and management:** Trajectories from specific transportation modes (e.g., freight and public transit trajectories extracted from fleet management) can be used for relevant studies. • **Project evaluation**: Supporting before-and-after studies for infrastructure investments, road pricing, or major events.

	on this type of data are relatively mature, such as the Regional Integrated Transportation Information System (RITIS) platform. Data providers include INRIX, TomTom, HERE, and Streetlights from the third-party private sector. The Federal Highway Administration (FHWA) provides free access to the National Performance Management Research Data Set (NPRMDS), a national database of probe-vehicle-based speed and travel time data.	
Measured Trajectories Using Sensors	Measured trajectories are obtained through roadside or aerial sensing technologies. Common sources include fixed cameras, LiDAR, radar, and drones. These sensors track positions of all traffic, including vehicles, pedestrians, and other road users, in real time at high temporal resolutions (often 0.1–0.5 seconds). Sensor-based trajectories provide comprehensive coverage of all traffic within the sensor's field of view. However, such coverages are site-specific within the boundary of sensors' sights, resulting in limited spatial coverage. The collection of such trajectory data requires the deployment of sensors at high installation and maintenance costs. The data process is also complex, based on trajectory reconstruction and validation. Researchers for the Next Generation Simulation (NGSIM) program collected detailed vehicle trajectory data on several corridors. Data was collected through a network of synchronized digital video cameras.	• **Intersection performance analysis**: As trajectories of all intersection users can be obtained at a very detailed resolution, the data can be used to study intersection operations, safety, and multimodal transportation interactions, such as pedestrian and vehicle near misses. • **Traffic flow studies**: The data can be used to identify traffic flow characteristics along certain roadway segments, such as shockwave propagation, lane-changing behaviors, and bottleneck dynamics. • **Surrogate safety analysis**: Deriving surrogate safety indicators such as post-encroachment time and time-to-collision. • **Simulation calibration**: Providing ground-truth datasets for microsimulation and traffic flow model validation.
Connected Vehicle Trajectories	Connected vehicle data are generated from vehicles equipped with Dedicated Short-Range Communication (DSRC) or broader Vehicle-to-Everything (V2X) technology. These vehicles continuously broadcast vehicle information, such as Basic Safety Messages (BSMs) at frequencies up to 10 Hz, containing position (latitude, longitude), speed, acceleration, heading information, and basic status indicators such as brake use or turn signals all with time stamped. When sequential messages from the same vehicle are combined, they form a continuous, high-resolution trajectory suitable for traffic operational and safety analyses, offering high accuracy and temporal resolution. Trajectory data from DSRC and V2X systems are widely available through several public and	• **Real-time traffic safety and operational evaluation and management**: High-resolution (i.e., at 10 Hz) trajectories allow for examination of car-following behavior, queue dynamics, approach speeds, and responses to signal changes and identification of fine-scale acceleration, braking, and vehicle interaction patterns. These can be translated into operational performance measures and surrogate safety measures. With increasing penetration and infrastructure upgradation, connected vehicle trajectory data promises near real-time monitoring capabilities for transportation safety and operational performance. • **Emerging ITS and V2X system development**. The data provides ground truth for testing eco-driving algorithms, connected signal priority

	research deployments. Key examples include the USDOT Connected Vehicle Pilots. These sources provide direct DSRC/C-V2X message logs.	systems, cooperative adaptive cruise control (CACC), and other advanced mobility applications. Their high fidelity makes them particularly valuable for calibrating microsimulation models and validating machine learning methods.
Vehicle Telemetry Trajectories	Vehicle telemetry trajectory data is generated from embedded on-board telematics systems, OEM data streams, or fleet management platforms that transmit information to cloud servers through cellular networks. These data typically include timestamped vehicle location, speed, heading, acceleration events, and diagnostic indicators collected at intervals ranging from 1 to 5 seconds, depending on the provider and vehicle type. Telemetry-based trajectories use V2N (vehicle-to-network) communication, allowing widespread geographic coverage and capturing a substantially larger share of the vehicle population. Telemetry trajectory datasets are characterized by large spatial coverage, reflecting vehicle movements across entire regions or states, with consistent data resolution. Major providers of vehicle telemetry trajectory data include Wejo (no longer in business since 2023), StreetLight, Compass, and OEM data aggregators working with automakers. These providers consolidate data by incorporating privacy protections through hashing, ID rotation, trip segmentation, and suppression of home/work locations.	• **Regional mobility and roadway traffic operational performance evaluation**: Vehicle telemetry trajectories feature scalable coverage that makes them well suited for corridor-level and regional studies. In mobility analysis, telemetry trajectories can be used to measure travel times, delays, speeds, route choices, and congestion levels across large networks. The consistent sampling interval and broad geographic reach allow agencies to conduct before-and-after evaluations of roadway improvements, monitor peak-period bottlenecks, and assess reliability across key corridors. • **Scalable traffic safety analysis:** Vehicle telemetry events such as hard braking, rapid deceleration, and traction-control activations can serve as surrogate measures for identifying high-risk locations. These indicators may highlight areas with frequent near-miss activity, sudden speed drops, or adverse weather-related skidding, supporting network screening and systemic safety analysis. The multi-year continuity of telemetry datasets enables agencies to monitor safety performance trends and evaluate the effectiveness of countermeasures.

Because this research focuses on freeway and arterial performance measures, it requires data with broad spatial coverage, encompassing both freeways and arterials, as well as sufficient, consistent resolution to capture events that reflect operational and safety performance. For these reasons, vehicle telemetry trajectory data has been selected as the primary data source for research.

While Table 1 outlines four major types of vehicle trajectory data sources, inconsistencies in terminology across the market often lead to confusion among users. To address this issue, the following bullet points clarify key distinctions and provide standardized definitions to enhance understanding.

- **Connected Vehicles** (CV, as defined by vehicle telemetry trajectory data providers): Connected Vehicles refer to any vehicle equipped with OEM-installed telematics or embedded communication systems that transmit data to cloud servers via cellular networks. In commercial datasets, the term “connected vehicle” typically refers to cellular V2N (vehicle-to-network) data sourced from

OEM telematics, rather than DSRC or V2X roadside broadcasts. This distinction is important because the technologies based on DSRC or V2X differ significantly from cellular V2N systems. For this research, vehicle telemetry trajectories, derived from OEM telematics, are used instead of "connected vehicle trajectories" defined and called by data providers.

- **Vehicle Telematics and Mobile Telematics:** Vehicle telematics describes the on-board hardware and embedded systems that collect and transmit vehicle operating information, such as GPS position, speed, acceleration events, fuel status, and sensor activations. Telematics data is usually transmitted over cellular networks and originates from built-in systems (e.g., GM OnStar, Ford Pass, Toyota Connected Services). Mobile telematics refers to vehicle or driver data collected through smartphone applications rather than built-in vehicle systems. Mobile telematics leverage a smartphone's GPS, accelerometer, gyroscope, and communication capabilities to infer trajectory information, driving behavior, and events such as hard braking or rapid acceleration. Mobile telematics are often collected through insurance company smartphone applications, which use the phone's GPS and motion sensors to monitor driving behavior for usage-based insurance, safe-driving programs, and risk scoring. While sampling rates may be comparable to those of vehicle telematics, the accuracy of mobile telematics can vary significantly depending on device placement, app configurations, and user behavior. Today, several mobile telematics data and service providers offer traffic safety analytics solutions, with Cambridge Mobile Telematics and Michelin Intelligent Mobility being examples.

Applying Trajectory Data in Transportation Studies

Over the past 15 years, vehicle trajectory data has been increasingly utilized by state departments of transportation to analyze traffic on freeways and arterials [1]. These datasets provide detailed spatiotemporal information that enables both microscopic and macroscopic traffic studies. The fundamental components of a vehicle trajectory are summarized in **TABLE 2**.

TABLE 2: Vehicle Trajectory Data Components

Components	Format	Description
Data IDs	Alphanumeric string	Unique identifiers for trajectories and waypoints, useful for database management and programming.
Location Information	Latitude and longitude (in World Geodetic System, WGS or local coordinates)	Geospatial position of each waypoint, enabling reconstruction of vehicle movements in space.

Time Stamp	Year, month, day, hour, minute, second	Precise time of each waypoint, allowing time-series analysis of traffic flow.
Metadata	Speed, heading, vehicle details, operational events	Additional attributes such as speed, heading, vehicle type, and events (e.g., braking, acceleration) recorded at each waypoint.

Among all trajectory data components, location and time information are fundamental for traffic analysis because they enable the reconstruction of traffic flow along roads and intersections. As illustrated in **FIGURE 1**, a high-resolution trajectory plotted on a two-dimensional "time–space diagram" represents a vehicle traveling across a corridor of five intersections. The slope of the trajectory indicates instantaneous speed during movement. Consequently, stop and deceleration events can be precisely identified in both temporal and spatial dimensions, allowing detailed estimation of travel time and delay. Additional performance measures, such as surrogate safety indicators and fuel consumption, can also be derived when metadata is available.

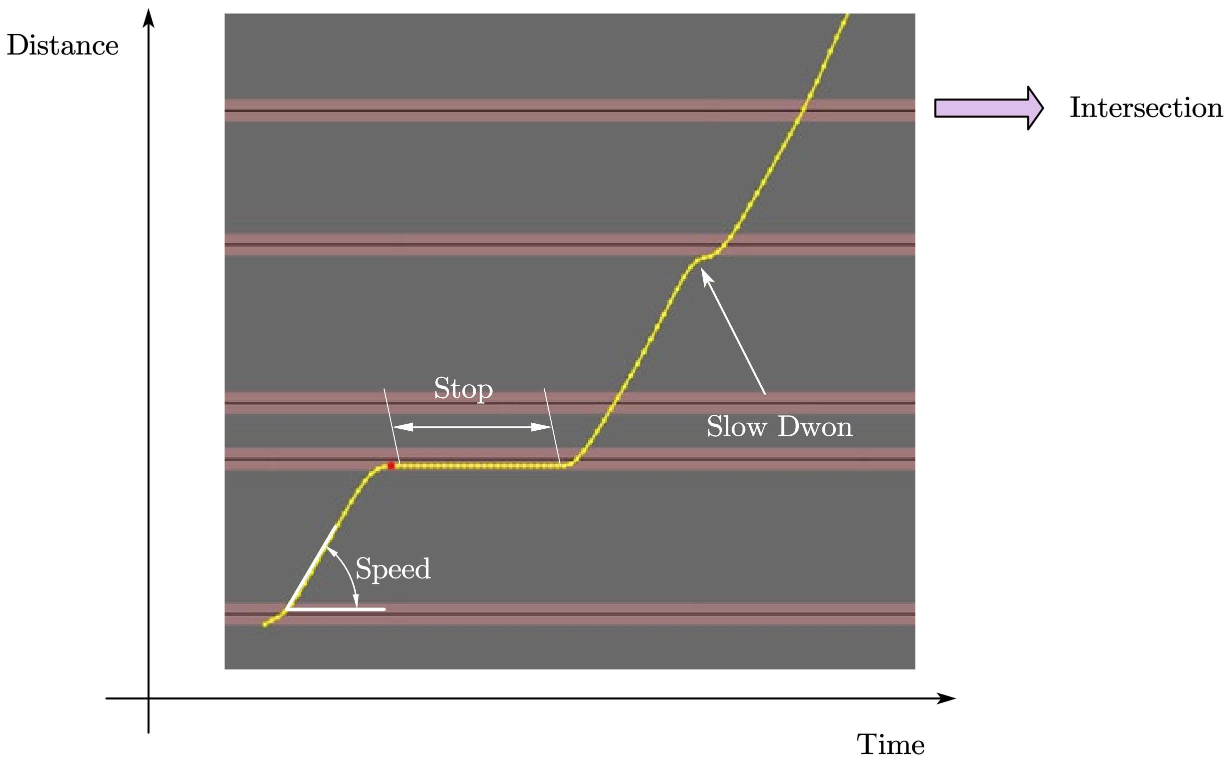


FIGURE 1: Trajectory Plotted on Time Space Diagram

Trajectory data profile directly determines the applicability and reliability of vehicle trajectory datasets in transportation studies. Key considerations include:

- **Data coverage (sample size, penetration rate, representativeness):** The spatial and temporal sampling profile influences whether trajectory-based performance measures can reasonably reflect overall traffic conditions. Higher penetration rates and consistent network-wide coverage improve the representativeness of congestion, delay, and route-choice patterns.
- **Data resolution:** The granularity of trajectory data is critical for capturing actual traffic behavior. When sampling intervals are long, for example, more than 10 seconds between consecutive waypoints, short duration stops, acceleration patterns, or queue formation may not be detectable. Higher-resolution data more accurately describe vehicle dynamics and operational conditions at intersections and along corridors.
- **Data accuracy:** Measurement errors can arise during trajectory generation. Common issues include abnormal speed values caused by GPS position jitter and missing or distorted information resulting from GPS dropouts, especially in dense urban areas or areas with poor cellular coverage. Appropriate filtering and data cleaning are necessary to ensure reliable analysis.

Overall, vehicle trajectory data enable a wide range of transportation analysis applications by providing detailed time–space information on how vehicles move through the network. These datasets support congestion and travel time monitoring, traffic signal performance evaluation, origin–destination estimation, safety screening through surrogate measures, and before-and-after assessment of roadway safety or operational improvements. When appropriately matched with roadway geometry, traffic control data, and environmental context, trajectory data offer a powerful foundation for understanding system performance, diagnosing safety and operational issues, and guiding data-driven planning and traffic management decisions.

Trajectory Data Collection and Acquisition

A notable limitation in the current trajectory data landscape is that many commercial probe vehicle data platforms and products do not offer direct access to raw point-by-point trajectory records. Instead, they commonly deliver aggregated or processed outputs, such as link travel times, speed profiles, travel demand estimates, or derived safety indicators according to pre-defined roadway segmentation.

This practice reflects privacy protection, data volume constraints, and proprietary data models but also restricts the ability of users to perform detailed and custom analyses that depend on full-resolution trajectory information. Understanding these distinctions in data access constraints is essential for selecting appropriate trajectory datasets and designing effective transportation studies.

TABLE 3 compares the applicable contexts for using aggregated trajectory measures versus raw trajectory data in transportation studies.

TABLE 3: Comparison of Transportation Studies Using Aggregated Segment-Based Data and Raw Vehicle Trajectory Data

Transportation Study Examples	Can Use Aggregated Data (Based on Pre-Defined Roadway Segmentation)	Requires Raw Trajectory Data (Point-Level Time–Location Records)
Travel Time and Congestion Monitoring	Segment-level travel times, speeds, and congestion indices are sufficient for most performance reporting.	Raw trajectory data can be required when (1) aggregated data does not align with engineering judgment and validation is necessary, or (2) detailed analysis of congestion formation and dissipation is needed across fine spatial and temporal scales.
Travel Time Reliability Analysis	Measures such as buffer index and planning time index can be computed using link- or segment-level speed data.	Raw trajectory data that reflects complete trips can be required if studies focus on point-to-point route travel times.
Mobility Performance Network Screening	Identification of recurring bottlenecks and slow-speed corridors is possible using aggregated speed/travel time surfaces.	Raw trajectory data can be required if validation is needed, particularly on rural, low-volume roadways.
Safety Performance Network Screening	Speeding events and other surrogate safety indicators are rarely captured accurately when data is aggregated by pre-defined roadway segments. For example, segment-level averages can be distorted by stops and delays at signals, which may underestimate mid-block speeding.	Raw trajectory data is required for detailed analyses of safety-related event distribution, enabling the identification of high-risk locations across large-scale network.
Origin, Route, and Destination Study	Travel demand estimation can often be generated from trip-level summaries without point-level trajectories; Basic route selection can be inferred from segment sequences. However, these data sources are typically sampled and may lack the precision needed for detailed analyses.	Raw trajectory data can be required when analyses focus on high spatial precision, such as sub-ZIP code or block-level origin–destination patterns, or when studying dynamic route-choice behavior. However, compared with aggregated measures, raw trajectories often come from a more limited and uneven sample of vehicles, sometimes concentrated within specific manufacturers or user groups, which can introduce sampling biases. In addition, for privacy protection, data providers often blur or obfuscate the precise journey start and end locations, which further constrains certain applications that rely on accurate waypoint information.
Traffic Signal Performance Evaluation	Arrival type distributions and red arrivals may be estimated using aggregated speed data. However, it is not possible to distinguish whether performance deterioration is caused by mid-block congestion or delays at signalized intersections.	Raw trajectory data are required for phase-by-phase arrivals to evaluate arterial traffic signal coordination, vehicle stopping behavior, dilemma zone analysis, and lane-based performance.

Emission Studies	Not suitable when using segment averages.	Raw trajectory data is required for capturing second-by-second speed and acceleration patterns, which enable estimation of emissions and fuel consumption.
Queue Length and Discharge Rate Estimation	Limited; segment speeds cannot reliably capture queue buildup or dissipation.	Raw trajectories are required for identifying queue onset, shockwave propagation, and discharge patterns.
Microsimulation Calibration	Not suitable as segment averages lack the necessary details.	Raw trajectories can be potentially used to calibrate car-following, lane-changing, gap acceptance, and acceleration models.
Work Zone or Incident Analysis	Segment speeds can show overall slowdowns.	Raw trajectories are required for detecting localized bottlenecks, merging behavior, and detailed driver response patterns.

Raw trajectory data has specific use cases; accessing point-by-point trajectory records may require data collection and acquisition when aggregated information cannot adequately support certain transportation analyses. Common approaches to access raw trajectory data include:

1. Deploying roadside sensors, such as cameras and LiDAR, to capture trajectories of moving traffic. Defined as “roadside sensor trajectory data”
2. Recording or crowdsourcing trajectories from GPS-enabled devices. Defined as “on-board trajectory data”

Based on these two definitions, for comparison in **TABLE 3**, raw trajectory datasets refer exclusively to on-board trajectory data, as opposed to aggregated performance measures derived from probe data. **TABLE 4** presents the differences between roadside sensor and on-board trajectory data in detail.

TABLE 4: Comparison Between Roadside sensor and On-board Trajectory Data

	Roadside Sensor Trajectory Data	On-board Trajectory Data
Spatial and Temporal Coverage	Trajectories are limited to the sensor’s detection range and are available only while the sensor is operational, typically 24/7.	Trajectories can be continuous across the roadway network as vehicles move, provided the on-board device is active during the trip.
Sample Size	Nearly all traffic (including vehicles, pedestrians, etc.) within the detection range can be captured, but no data is available outside that range.	Only vehicles equipped with on-board devices generate trajectories, typically representing a small share of total traffic.

Resolution	High resolution, typically 1–10 Hz (i.e., 1 to 0.1 seconds per point; higher Hz indicates finer resolution).	Resolution varies by device type: GPS units achieve 1–9 seconds per point; some connected vehicle applications (V2X) can enable 0.1 seconds per point; and cellphone LBS applications can be 1 second per point but also often exceed 10 seconds per point.
Accuracy	Accuracy depends on sensor measurement; errors may occur, especially for far-side waypoints. Environment can make influences.	GPS-equipped devices generally provide accurate location and time data, but inaccuracies can arise from cellphone-based trajectories.
Metadata Availability	Limited to basic measurement estimates derived through advanced computing (e.g., edge computing and AI-powered processing), such as vehicle motion characteristics.	Detailed vehicle operation status can be obtained when trajectory recordings are linked to a vehicle telemetry system.

Only few datasets of roadside sensor trajectories are currently available, in which the next-generation simulation (NGSIM) vehicle trajectory datasets have been broadly applied in research on traffic flow theory [2]. In another recent project [3], the Tennessee Department of Transportation's I-24 Mobility Technology Interstate Observation Network (MOTION) shares vehicle trajectory data extracted on a four-mile section of I-24 in the Nashville-Davidson County Metropolitan area with 294 high-definition cameras.

In general, traffic performance studies based on roadside-sensor trajectory data often suffer from limited coverage, making them suitable primarily for scientific research rather than agencies' daily performance monitoring and analysis.

On-board trajectory data is typically obtained from cellphone-based GPS or embedded GPS devices, such as automatic vehicle location (AVL) systems in transit fleets, taxi services, and commercial vehicle fleet management platforms. However, these data sources often suffer from low and inconsistent resolution, which limits their ability to capture fine-grained traffic safety and operational characteristics over custom spatial and temporal settings. Consequently, such trajectories have traditionally been applied in broader traffic planning and management efforts. And due to the nature of sampling, it is usually called "probe vehicle data" or "floating car data" in transportation studies.

Probe vehicle data has long been a critical source for travel time measurement in current practice. However, for freeway and arterial performance analysis, its limitations, such as inconsistent data resolution, can restrict the accuracy of key measurements, including traffic delays and vehicle stop occurrences [4]. A study found that probe vehicle data often exhibits highly variable sampling intervals between consecutive waypoints, ranging from as short as 1 second to as long as 10 minutes [5], which further constrains its utility for detailed operational and safety analyses. Recent applications, such as

INRIX Roadway Analytics, combine probe-vehicle trajectories with other sensor data to produce aggregated performance measures based on Traffic Message Channels (TMCs), which represent predefined roadway segments and intersection areas. While these aggregated measures are convenient, users typically lack access to raw trajectory data and cannot customize performance metrics to match specific network configurations. This lack of transparency makes it difficult to validate accuracy and limits the scope of applicable performance measures. Research has shown that such aggregated approaches could yield ineffective or misleading results [6] in certain study scenarios.

Emerging Source – Vehicle telemetry trajectory data

Vehicle telemetry data was first adopted enterprise-wide for fleet management in the early 2000s. Its use expanded significantly after 2010, and more recently, vehicle telemetry data has attracted growing interest from both the transportation industry and academia, along with several data commercialization attempts. Continuous advancements in GPS and telematics technologies are driving a paradigm shift in how public agencies collect transportation data, enabling greater efficiency in data acquisition and dissemination while reducing costs for widespread implementation [7].

There are three major strengths of vehicle telemetry trajectory data:

1. **High-resolution waypoints of complete vehicle movements**: Vehicle telemetry trajectory data is directly collected from vehicles in operation, tracking entire vehicle movements with high temporal and spatial granularities. Such high temporal and spatial granularities (e.g., less than 3 seconds per point and accurate per-street or even per-lane vehicle localization) allow for analytics regarding traffic operations. As the waypoints are continuous within a large-scale network, information, such as trip timing, trip mileage, as well as origins and destinations, can provide insights into large-scale traffic management and impact measurement. Although data providers typically protect privacy by blurring journey start and end waypoints, the remaining trajectory data still offers meaningful representation of vehicle movements across roadway networks.

2. **Detailed driving events and vehicle operation profiles**: Beyond waypoints, vehicle telemetry data includes logs of events, such as speeding, hard brakes, and other driving events, all timestamped and geo-located. These indicators are valuable for traffic safety studies. Additional metadata, such as fuel type and fuel gauge readings, can support environment-related performance evaluations. Nevertheless, please note that current data providers may not be able to release full access to such event data bundled with telemetry trajectory datasets. Nevertheless, current data providers often cannot release full access to detailed event logs bundled with telemetry trajectory datasets. While some safety performance indicators, such as high speeds and sudden speed changes, can

still be derived from trajectory data alone, their accuracy may be compromised compared to measures obtained directly from vehicle telematics.

3. **Crowd-Sourced, Infrastructure-Agnostic Data Acquisition**: Users to gain access to vehicle telemetry trajectory data does not rely on road infrastructure and sensor deployment, making it nearly ubiquitous across roadway networks. This characteristic facilitates studies in underrepresented areas and supports analyses of diverse transportation system users.

Original Equipment Manufacturer (OEM) telemetry trajectory data is gaining significant attention due to its rapidly increasing penetration across the national vehicle fleet and the inherent advantages it offers over other forms of telemetry data. Because OEM systems are embedded directly within the vehicle at the factory level, they provide consistent, high-quality trajectory information with standardized sampling logic, reliable GPS hardware, and integrated vehicle state sensors that outperform the accuracy and stability of many aftermarket or smartphone-based sources. OEM telemetry trajectory data streams often include richer vehicle context, such as braking events, stability control activation, steering inputs, or powertrain status, that cannot be captured through mobile telematics alone. In addition, OEM datasets typically achieve broader representativeness because they encompass diverse vehicle makes, models, and usage patterns, resulting in higher and more uniform penetration across geographic regions. Compared with mobile telematics, which depends on user app engagement and device placement, OEM data sources are collected passively and continuously, minimizing behavioral biases and data gaps. These advantages make OEM telemetry trajectory data one of the most reliable and scalable foundations for transportation performance analysis enhancement.

A study shows that the current penetration of telemetry trajectory data from one data provider, Wejo, in Indiana can be more than 5% of the total traffic [8]. The European initiative "eCall" mandates OEMs to integrate cellular radios into all new cars beginning in 2018 [9]. Global market estimates indicate the number of vehicles with telematics embedded will rise to 339.3 million worldwide by 2024 and that by 2030 about 95% of new vehicles sold will be equipped with vehicle telematics [10]. One currently commercialized OEM data source reports a penetration rate of approximately 3% across the U.S. Research indicates that problematic arterial operations can be identified using trajectory data with a penetration rate as low as 1% [11]. Therefore, leveraging OEM trajectory datasets alone is sufficient from a sampling perspective for transportation performance analysis.

Data in this Research

In this research, Wejo was first selected to be the primary source to acquire vehicle telemetry trajectory data. Wejo data featured a stable data resolution of 3 seconds per point and geographic precision can be

10 feet for more than 95% of the time [12]. Although several rounds of data schema and attribute updates were made by Wejo during this research and the research team's preliminary studies before 2023, the overall data resolution and geographic precision, reflected by the decimal places of waypoint latitude and longitude, as the more decimal places there are in a set of coordinates, the more precise the coordinates will be, remained consistent with the provider's claims.

FIGURE 2 exhibits an example of vehicle telemetry trajectory data provided by Wejo using the data schema in 2022 with vehicle information that was accessible. And **TABLE 5** describes the data schema in detail.


```
"dataPointId": "044862f9-88f9-4abe-bde0-dded07c567d2",
"journeyId": "02c4aee2350d42a9b8da1accfab10727f851a80b",
"capturedTimestamp": "2022-03-07T01:30:03.000-0800",
"latitude": 39.510527,
"longitude": -119.960526,
"Zipcode": "89439",
"speed": 70.86,
"heading": 262.0,
"ignitionStatus": "MID_JOURNEY",
"make": "GMC",
"model": "Sierra Limited",
"vehicleYear": "2022.0",
"bodyClass_NHTSA": "Pickup",
"fuelTypePrimary_NHTSA": "Diesel",
"fuelTypeSecondary_NHTSA": null,
"PowerTrain": "ICE",
```


FIGURE 2: Example of Vehicle Telemetry Trajectory Data Provided by Wejo (2022 Schema)

TABLE 5: Wejo's Telemetry Data Schema Description

Data Attributes	Example Value	Description
dataPointId	044862f9-88f9-4abe-bde0-dded07c567d2	Unique identifier for this individual data point. Fully anonymous to meet privacy protection requirements
journeyId	02c4aee2350d42a9b8da1accfab10727f851a80b	Identifier linking all data points belonging to the same trip. Fully anonymous to meet privacy protection requirements
capturedTimestamp	2022-03-07T01:30:03.000-0800	Timestamp (ISO format) when the waypoint record was collected
latitude	39.510527	GPS latitude of the waypoint record with decimal places of 6, implying measurements approximately 4 inches wide

longitude	-119.960526	GPS longitude of the waypoint record
zipcode	89439	Approximate postal code of the waypoint location when it was recorded
speed	70.86 mph	Instantaneous speed when the waypoint was recorded. Note that Wejo provided speed in kilometers per hour. Conversion into miles per hour was made by the research team
heading	262.0°	Direction of travel relative to true north
ignitionStatus	MID_JOURNEY	Indicator of vehicle state (e.g., key on or off, or within the journey)
Make, model, vehicleYear, bodyClass_NHTSA, fuelTypePrimary_NHTSA, fuelTypeSecondary_NHTSA, powerTrain	N/A	Vehicle information that became unavailable in later updates

The research team acquired a 15-day dataset covering Nevada and other states in the U.S. through Wejo. However, Wejo's business failure in June 2023 directly impacted this research, disrupting continuity in data availability and limiting opportunities to expand or validate analyses using the same data source.

The loss of Wejo led to increased uncertainty regarding long-term data access, licensing stability, and dataset comparability across vendors. As a result, this research must rely on existing archived Wejo datasets without the ability to obtain refreshed data or cross-check results against updated streams. More broadly, Wejo's exit highlights the volatility of the commercial ecosystem of vehicle telemetry data, implying the importance of developing analysis methods that remain adaptable to changing data providers, evolving data structures, and shifting market conditions.

Following Wejo's exit, StreetLight launched services in 2024, ensuring continuity of key portions of Wejo's data sources. The research team obtained datasets representing 7 days of data collected in May 2024 (sample data set provided by StreetLight) and another 7 days of data collected in April 2025.

FIGURE 3 exhibits an example of vehicle telemetry trajectory data provided by StreetLight using the data schema in 2025. And **TABLE 6** describes the data schema in detail.

```
"journey_id": "db835ff45e09eea8",
"capture_time": 1745022442,
"latitude": 39.567692,
"longitude": -105.046535,
"speed_mph": 55,
"heading_deg_north": 90.0,
"elevation_ft": 5332,
"ignition_status": "MIDTRIP",
"fuzzed_point": false
```


FIGURE 3: Example of Vehicle Telemetry Trajectory Data Provided by StreetLight (2025 Schema)

TABLE 6: StreetLight's Telemetry Data Schema Description

Data Attributes	Example Value	Description
journey_id	db835ff45e09eea8	Unique identifier linking all points belonging to the same trip; however, unique data point identifiers are no longer in use.
capture_time	1745022442	Timestamp in Unix epoch format indicating when the point was recorded.
latitude	2022-03-07T01:30:03.000-0800	Timestamp (ISO format) when the waypoint record was collected
longitude	39.567692	GPS latitude of the waypoint record. The decimal places are 6, implying geographic precision maintain at the same level compared to Wejo's data
longitude	-105.046535	GPS longitude of the waypoint record
speed_mph	55	Instantaneous speed when the waypoint was recorded. StreetLight provids speed in miles per hour directly
heading_deg_north	90.0°	Direction of travel relative to true north
elevation_ft	5332	New data attribute introduced by StreetLight. Useful for enhanced identification under various roadway grade and topography conditions
ignitionStatus	MID_JOURNEY	Indicator of vehicle state (e.g., key on or off, or within the journey)

fuzzed_point	false	Indicates whether the location was obfuscated for privacy, newly introduced by StreetLight

Vehicle telemetry trajectory datasets delivered in Apache Parquet format (used by both Wejo and StreetLight) poses challenges for many transportation agencies because the raw data packages can require advanced processing tools and specialized expertise to handle effectively. Unlike traditional CSV or visualizable data platform applications, the current vehicle telemetry trajectory datasets are often partitioned across hundreds of files and may contain hundreds of millions or billions of trajectory records. Processing them could demand distributed computing frameworks, along with strong data-engineering skills for tasks such as schema management, parallel I/O, timestamp normalization, and geospatial transformation. Many agencies lack the computational infrastructure and technical staff required to manage these workflows, making routine operations, such as reading, filtering, or aggregating the data, substantially more complex. As a result, this research developed a practical software tool capable of processing raw trajectory data and extracting performance measures on local computers. The tool is designed for accessibility, allowing general transportation analysts and practitioners to use it without significant training. The introduction of the software tool, Sysmatic Trajectory Extraction Program(STEP), is provided in this report.

Research Objectives

Facing the emergence of high-resolution vehicle trajectory data from vehicle telematics, both opportunities and challenges arise for transportation. To support data-driven decision-making and safety/operational performance management, this research establishes the following objectives:

1. Provide Nevada DOT and partner agencies with a comprehensive understanding of emerging vehicle telemetry trajectory data

This includes documenting data sources, coverage, resolution, accuracy, strengths, and limitations, as well as clarifying how these new data streams differ from traditional probe-vehicle datasets and sensor-based measurements.

2. Examine and explore the emerging vehicle telemetry trajectory data through applications in Nevada

The research applies trajectory data to mobility and safety analyses in several real-world projects across the state, demonstrating analytical capabilities and identifying conditions under which these data yield reliable and actionable insights.

3. Develop a practical, agency-ready tool to support vehicle telemetry trajectory data processing and

analysis within Nevada DOT and partner agencies

The tool enables data processing and measurements extraction, reducing big-data processing barriers and enabling staff to leverage high-resolution trajectory data for routine safety and operational assessments and performance monitoring.

Arterial Traffic Signal Performance Analysis

In this study, the UNR research team worked with the Regional Transportation Commission of Washoe County (RTC Washoe) to perform a comprehensive evaluation of 36 corridors timed and coordinated through the Regional Traffic Signal Operations Improvement Program (RTC Washoe Signal Timing Project). With a penetration rate of 3-5% of the total traffic in the Reno-Sparks region, a telemetry trajectory data set of 10 days (all weekdays selected from a 15-day consecutive calendar period) in March 2023 has been employed in this evaluation. The evaluation approach is exhibited in **FIGURE 4**.

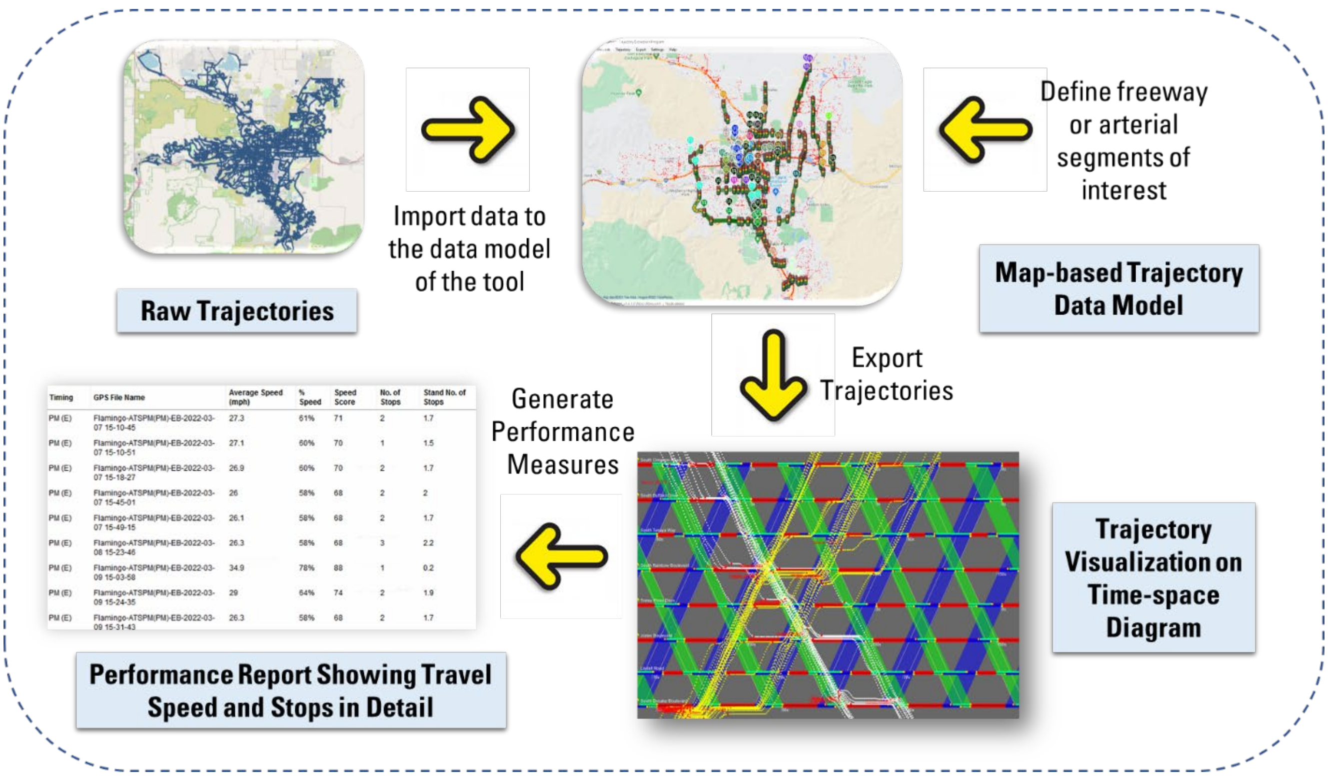


FIGURE 4: Approach to Using Vehicle Trajectory Data to Evaluate Traffic Signal Performance

Methodology

A methodology is adopted in this study, simplified based on prior Nevada DOT research [13], *Developing a Quality of Signal Timing Performance Measure Methodology for Arterial Operations*, called The *UNR Quality of Signal Timing Performance Index*. The index is calculated based primarily on speed and stop measures and adjusted based on cycle length and signal spacing.

The speed score is to evaluate the efficiency of signal timing plans refers to the percent speed of the posted arterial speed. Based on engineering judgment, it can be considered a good progression speed if the platoon travel speed reaches 90 percent of the posted speed. In this analysis, each of the performance scores is defined on a 0 to 100 scale. Therefore, with a 10-point addition, the percentage of the average actual travel speed over the posted link speed is used in the scoring. Although the actual travel speed may exceed the posted speed, the score is capped at 100. And the stop source focuses on vehicle stops at signals is an important evaluation criterion that can be perceived by road users. In this study, the standardized number of stops is defined to calculate the stop score. When a vehicle travels at a speed lower than 5 mph, it is considered idling. A standard stop at an intersection is defined as when the average idling time at an intersection equals 25 percent of the signal cycle length. For example, if the cycle length is 100 seconds, a 50-second stop is considered as 2 standard stops, while a 10-second stop is considered as 0.4 standard stops. The total standardized number of stops on a study arterial is calculated by summing up the standardized number of stops at all intersections. After obtaining the speed and stop scores, a weighted score is then calculated. It was determined that the number of stops is the dominant factor that affects drivers' perception of traffic efficiency.

In addition, designing arterial traffic signal coordination plans with the preference of favoring arterial through movements of traffic, and the delay of minor movements may not be fully considered. A common practice is extending green time to the coordinated movements to achieve a wider arterial progression bandwidth so the average arterial travel speed can be increased, and the total number of arterial stops can be reduced. However, this practice tends to result in longer cycle lengths and higher delays for the vehicles on minor movements. At an undersaturated intersection, a shorter cycle length usually results in less delay for all users and improves intersection level of service and user perceptions. Hence, an adjustment according to the cycle length is designed.

Another factor that can impact the traffic efficiency along an arterial is the spacing between adjacent signals. When designing arterial coordination plans, it is usually more difficult to achieve satisfactory two-way arterial progression if the intersections are closely spaced. On the contrary, if an arterial has larger intersection spacing, a good two-way progression is generally easier to achieve. Therefore, if two arterials have similar overall performance (e.g. number of stops), a bonus should be considered for the arterials with closer spaced signals.

Detailed methodology description can be found in the *2023 Regional Traffic Signal Coordination Performance Evaluation Report* prepared for RTC Washoe.

Enhancement with High-resolution Vehicle Telemetry Trajectory Data

This methodology was originally developed in 2020 based on manual collection of floating-car trajectory data along arterials, with a sampling design requiring more than five trajectories per travel direction for each signal timing plan. By leveraging vehicle telemetry trajectory data, stacked samples collected over

10 days now provide significantly richer and more representative datasets for all time-of-day timing plans.

For the 36 study corridors, focusing on the MDAM timing plan (approximately 10:00 AM to 11:30 AM, with slight variations across corridors), the average number of valid trajectory samples obtained from stacked daily datasets is illustrated in **FIGURE 5**, in which the number of trajectory samples was counted in both travel directions, and the continuity from the start to the end signals of each corridor was validated.

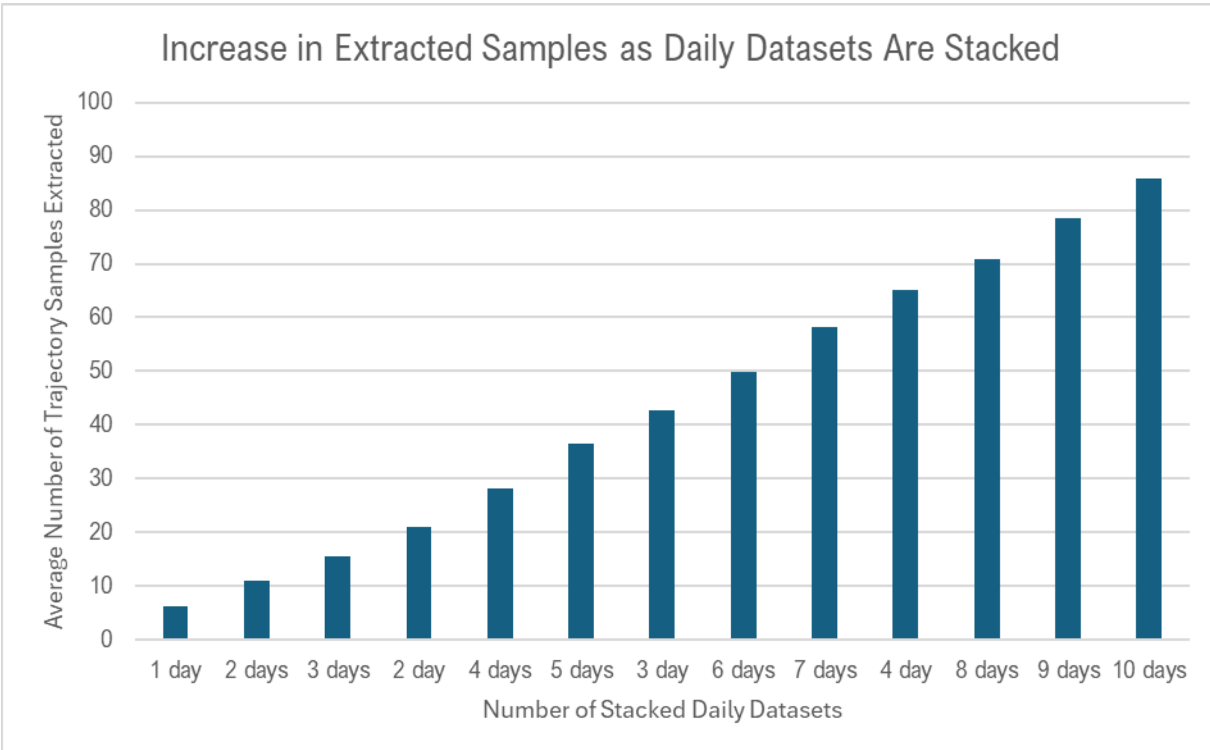


FIGURE 5: Trajectory Sample Size Growth with Stacked Daily Data

To evaluate the effect of stacking, one, two, three, and up to ten daily datasets were randomly combined to extract trajectory samples for the same signal timing plan operating period. The results indicate that even a single daily dataset provides more samples than traditional manual data collection, and across weekdays, the trajectory samples are generally evenly distributed.

This finding suggests that, provided traffic signals are not significantly retimed and traffic patterns remain stable during the analysis period, transportation agencies could acquire two weeks of vehicle telemetry trajectory data to conduct regional performance evaluations. The frequency of such evaluations can be adjusted based on seasonal traffic variations or changes caused by incidents, thereby enabling data-driven improvements to traffic signal timing rather than relying on fixed retiming cycles.

Another enhancement enabled by vehicle telemetry trajectory data is the ability to answer the question: *"How do traffic signals on a corridor perform overall?"* Traditionally, performance measurements are collected by time-of-day signal timing plans individually, but each plan serves different traffic demand levels. This makes it challenging to apply reasonable weighting and integrate all performance results into a single, comprehensive output for the corridor. However, such an overall result is essential in practice to inform signal timing project prioritization. A common-sense approach to producing an overall corridor performance measure is to weight results based on traffic volumes. However, hourly traffic volume counts are often unavailable and are generally expensive to obtain through ad-hoc data collection. Since vehicle telemetry trajectory data is crowdsourced from a known penetration rate of total traffic, the number of trajectories extracted during a given period can reasonably approximate hourly traffic volume distribution.

In this study, weights were determined using the Nevada DOT's TRINA database by selecting the nearest available dates with hourly counts corresponding to the two-week period between March 5 and March 20, 2023. The measured hourly traffic volume distribution was then compared with the hourly number of trajectories extracted from the dataset. The comparison results are presented in **TABLE 7**.

TABLE 7: Comparison of Traffic Volume Distribution and Trajectory Sample Distribution by Timing Plan Operating Times

Timing Plan	Operating Time	% of Total Traffic Volume in Signal Coordination Period*	% of Total Trajectory Samples in Signal Coordination Period**
AM Plan	6:00 AM – 10:00 AM	21%	19%
MDAM Plan	10:00 AM – 11:30 AM	12%	15%
Lunch Plan	11:30 AM – 1:15 PM	11%	14%
MDPM Plan 1	1:15 PM – 3:30 PM	17%	13%
PM Plan	3:30 PM – 6:00 PM	25%	22%
MDPM Plan 2	6:00 PM – 7:00 PM	8%	10%
Evening Plan	7:00 PM – 8:30 PM	6%	7%

** Since TRINA data only provides hourly volume counts, for timing schedules that break within an hour, traffic volumes of the timing plans are assumed and estimated to be evenly distributed across that hour.*

***The numbers of trajectory samples are directly extracted using the developed software tool, STEP.*

The findings indicate that the distributions of traffic volumes and trajectory samples are closely comparable, suggesting that traffic signal timing managers and practitioners can leverage several days of telemetry trajectory data to estimate weights across time-of-day plans and inform subsequent decisions.

In addition, visualizing large samples of vehicle telemetry trajectories on time–space diagrams (TSDs) integrated with traffic signal timing parameters can significantly facilitate timing diagnosis and fine-tuning during implementation. **FIGURE 6** illustrates an example where an error was detected during signal retiming by leveraging crowdsourced trajectories. Practitioners often face challenges in performing timing diagnosis due to limited resources for floating-car investigations. Access to vehicle telemetry trajectory data enables timing diagnosis to be conducted remotely, reducing costs and improving efficiency.

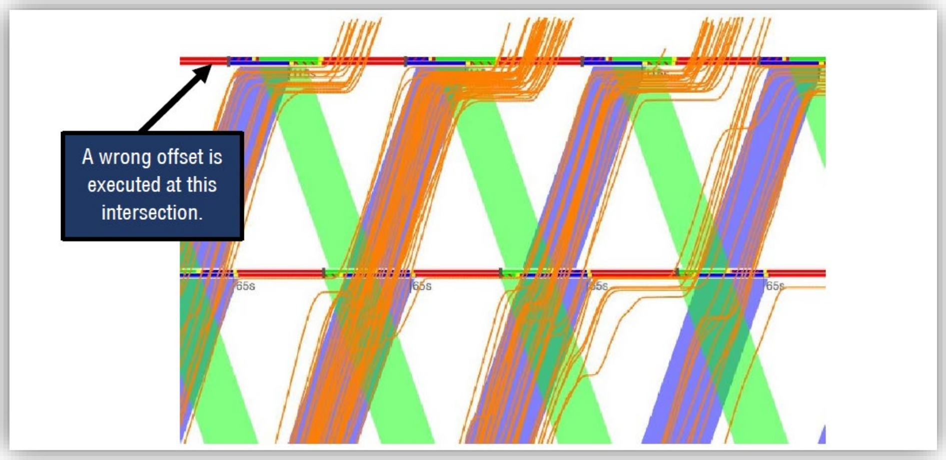


FIGURE 6: Timing Parameter Diagnosis Example Using Big Trajectory Data and TSD with Timing Displays

Study Results

High-resolution vehicle telemetry trajectory data enables scalable performance evaluation in several ways.

One key application is the development of a regional corridor traffic signal performance matrix using standardized evaluation criteria and uniform integration across corridors, which can potentially imply performance ranking and retiming urgency. **TABLE 8** shows an example without ranking information.

TABLE 8: Example of Regional Corridor Traffic Signal Evaluation Results

ID	Corridor Example	AM (0600-1000)	MDAM (1000-1130)	Lunch (1130-1315)	MDPM1 (1315-1530)	PM (1530-1800)	MDPM2 (1800-1900)	Evening (1900-2030)	Overall Corridor Score	Performance Quality Grade	Notes
1	Corridor A	61	66	54	59	54	59	68	60.1	D-	Connecting freeway under construction
2	Corridor B	94	100	99	95	95	97	97	98.0	A	
3	Corridor C	76	70	75	75	72	77	78	75.6	C+	
4	Corridor D	62	80	80	57	63	87	66	69.0	D+	Under construction
5	Corridor E	93	87	90	90	85	89	87	90.5	A-	

The performance evaluation results can also be visualized through map-based demonstrations, which enhance engineering communication and support public engagement. **FIGURE 7** presents a map-based visualization of corridor traffic signal performance, designed in a dashboard-like format to support intuitive interpretation and communication.

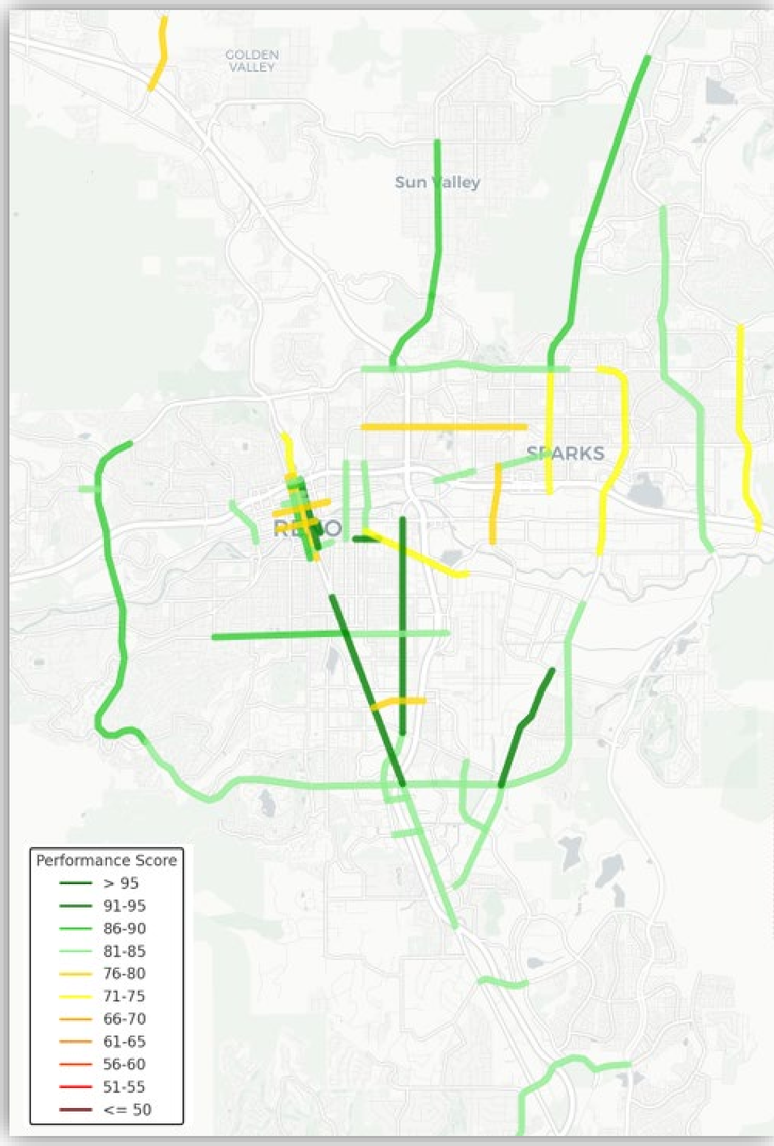


FIGURE 7: Regional Corridor Traffic Signal Performance Visualization (MDAM Plan)

Freeway Operational Performance Analysis

Freeway management can depend on accurate performance evaluation, which requires high-quality data. Freeway data has been collected using in-pavement and roadside detectors such as inductive loops, radar, and magnetometers. While these technologies provide valuable point-based measurements, they may be limited by deployment and maintenance, resulting in high investment and operational challenges.

Conventional probe data applications can estimate freeway performance metrics such as travel time and speed; however, aggregated speed values from probe vehicles naturally differ from those recorded by freeway detectors because they rely on fundamentally different measurement mechanisms. Therefore, direct cross-comparisons between probe-based aggregated speed measurements and detector-based speed measurements may not be appropriate.

High-resolution vehicle telemetry trajectory data provides meaningful opportunities to strengthen freeway performance evaluation by offering direct, point-based traffic observations rather than aggregated freeway segmentation averages. Because telemetry trajectories preserve the full time–location sequence of each vehicle, performance measures can be extracted at spatial resolutions that closely match the granularity of lane-level detectors. This alignment allows for reasonable comparisons between detector measurements and trajectory measurements, reducing uncertainty caused by mismatched segmentation or averaging effects. The ability to derive lane- or segment-specific speed, delay, and flow characteristics directly from raw trajectory points significantly enhances the fidelity of performance measurements.

Another advantage lies in the representativeness of telemetry trajectory-based speeds. Crowdsourced telemetry trajectories generate speed observations from sampled data across, even though limited percent of total traffic, a wide fleet of vehicles, producing large samples that reflect freeway performance. These speed measurements are directly from telematics of vehicles, not influenced by detector placement and sensor failures.

Applying vehicle telemetry trajectory data allows for extending beyond locations where sensors are installed, enabling freeway performance monitoring across transportation network with no infrastructure investment. Telemetry trajectories can validate areas where possible loop detectors malfunction, where possible microwave sensors drift, or where sensor placement does not capture lane-specific conditions effectively.

Without aggregation, multi-second sampling intervals allow for detailed reconstruction of performance influences by incidents. Sudden speed drops, abnormal acceleration patterns, and dense clusters of slow trajectories can identify incidents more quickly and characterize their duration and severity.

In this study, freeway detector data is analyzed using sample acquired through the Performance Measurement System (PeMS) managed by California Department of Transportation (Caltrans). The vehicle telemetry trajectory data is from the two-week data set between March 5th to March 20th in 2023. As for freeway detector data, hourly lane-by-lane and segment speeds as well as volumes with 100% observed in the same analysis period were exported from six detector stations in the PeMS. The six sites are selected on basic freeway segments following the definition of the basic segment and facility segmentation guidance in the Highway Capacity Manual. **TABLE 9** describes the profiles of the selected freeway detector stations in detail.

TABLE 9: Detector Station Profile

	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6
Freeway	I-80	US 101	I-5	I-15	I-880	US 101
Direction	SB	SB	SB	NB	NB	NB
Lane Use Type	Urban	Urban	Urban	Rural	Urban	Urban
Terrain	Flat	Flat	Flat	Rolling	Flat	Flat
Speed Limit (mph)	70	70	70	70	70	70
Number of Lanes	5	4	6	4	4	4
AADT	89,465	94,570	125,545	68,595	91,853	69,318
Managed Lane Existence	Yes	No	Yes	No	Yes	No
Detector Type	Radar	Dual Loops	Dual Loops	Magnetometer	Dual Loops	Dual Loops
Truck Proportion (%)	0.2	2.6	4.0	1.2	3.8	4.7
Segment Length (mile)	0.59	0.89	0.81	1.29	0.57	0.94

This study has been submitted and accepted by the 2025 Transportation Research Board Annual Meeting and the publication is under review by Transportation Research Record: Journal of the Transportation Research Board.

Methodology

The penetration of vehicle telemetry trajectory data was first validated. Penetration rates were calculated for entire freeway segments as well as at detector locations. Lower penetration at detector locations can occur because trajectory sampling intervals of three seconds may cause waypoints to skip over the exact detector position, resulting in potential data loss. **TABLE 10** summarizes vehicle trajectory data penetration rates at the selected six basic freeway segments in terms of the segment penetration rate and the segment penetration rate at the detector location.

TABLE 10: Vehicle Trajectory Data Penetration Rates at selected detector stations

	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6
Segment Penetration Rate (%)	3.0	2.4	2.8	4.3	2.2	3.4
Segment Penetration Rate at the Detector Location (%)	2.7	2.2	2.1	3.4	1.9	3.0

Extracting vehicle telemetry trajectory waypoints at a lane level according to the selected detector locations is required to obtain speed measurements. A polygon can be defined and drawn following the lane path to extract trajectory waypoints on each lane. **FIGURE 8** illustrates an example of extracted southbound lane-by-lane vehicle trajectory waypoints.

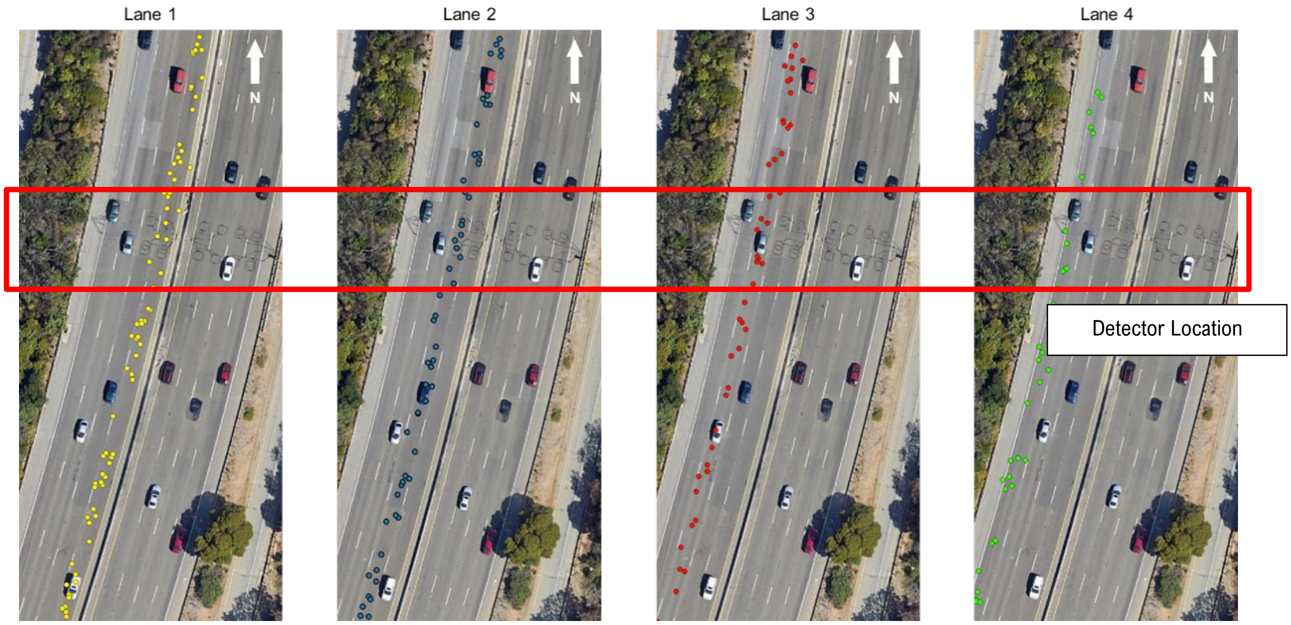


FIGURE 8: Lane-by-lane Vehicle Trajectory Waypoints on Freeway

As vehicle trajectory data in this study was only collected from passenger cars, the speed comparison between trajectory-based speeds at the detector location and detector speeds should be performed for lanes with trucks and no truck separately.

Both trajectory-based speeds and detector speeds represent time mean speeds, providing a consistent basis for comparison [14]. **FIGURE 9** illustrates an example of weekday hourly speed comparisons between trajectory-based speeds at the detector location and detector-measured speeds for all lanes at Station 2. Similar comparisons were conducted with other detector locations.

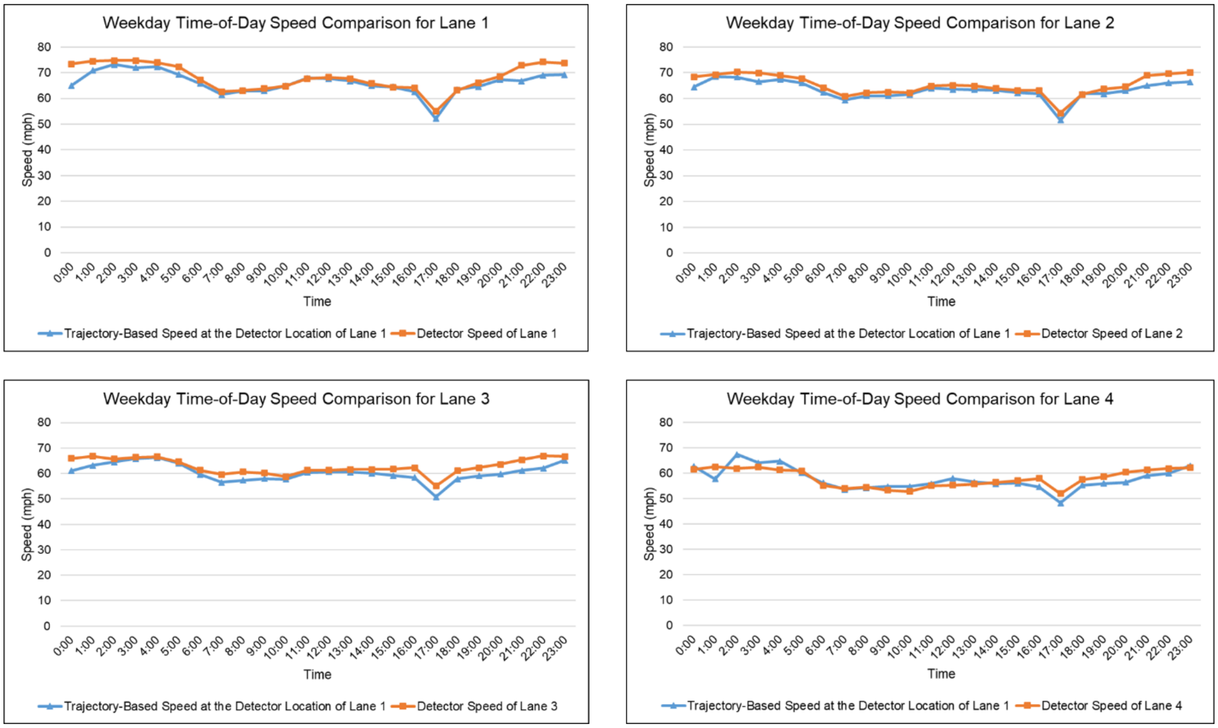
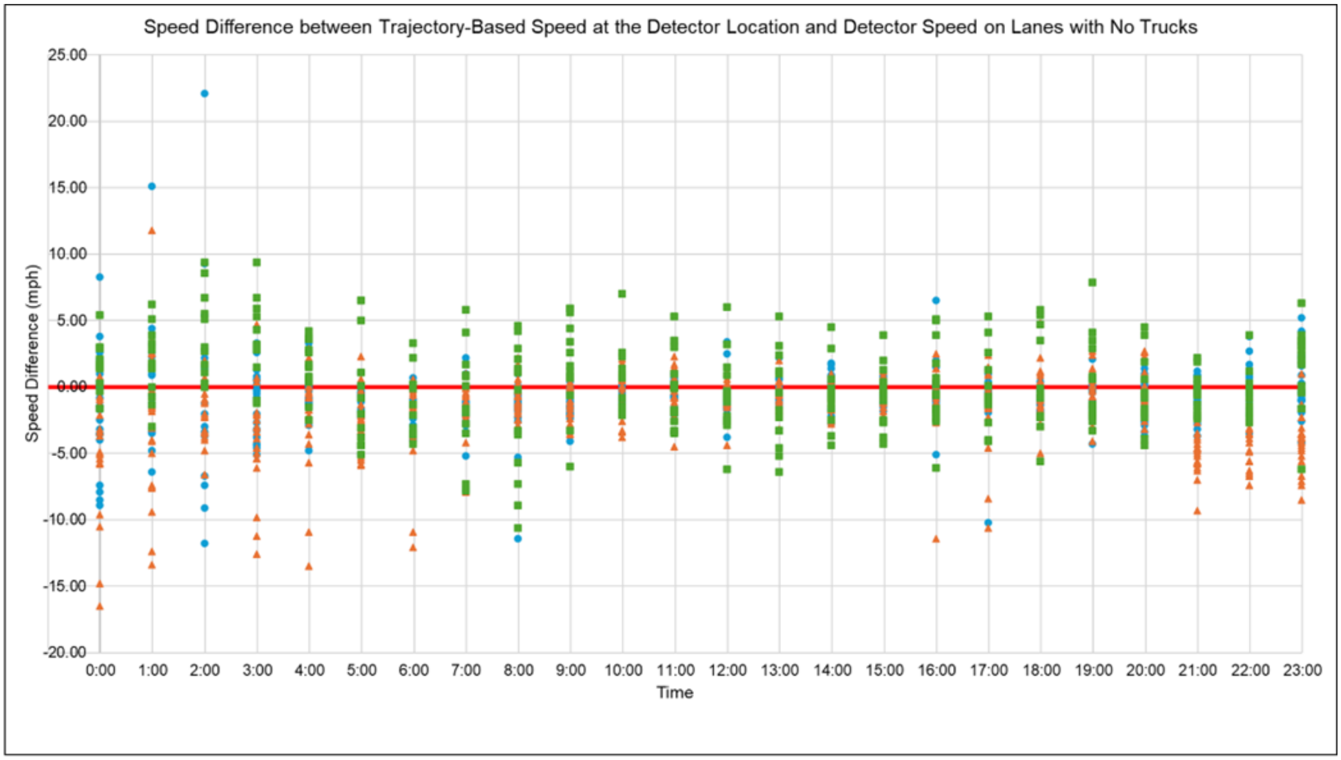


FIGURE 9: Weekday Hourly Speed Comparison between Trajectory-Based Average Speed and Detector Speed (Station 2)

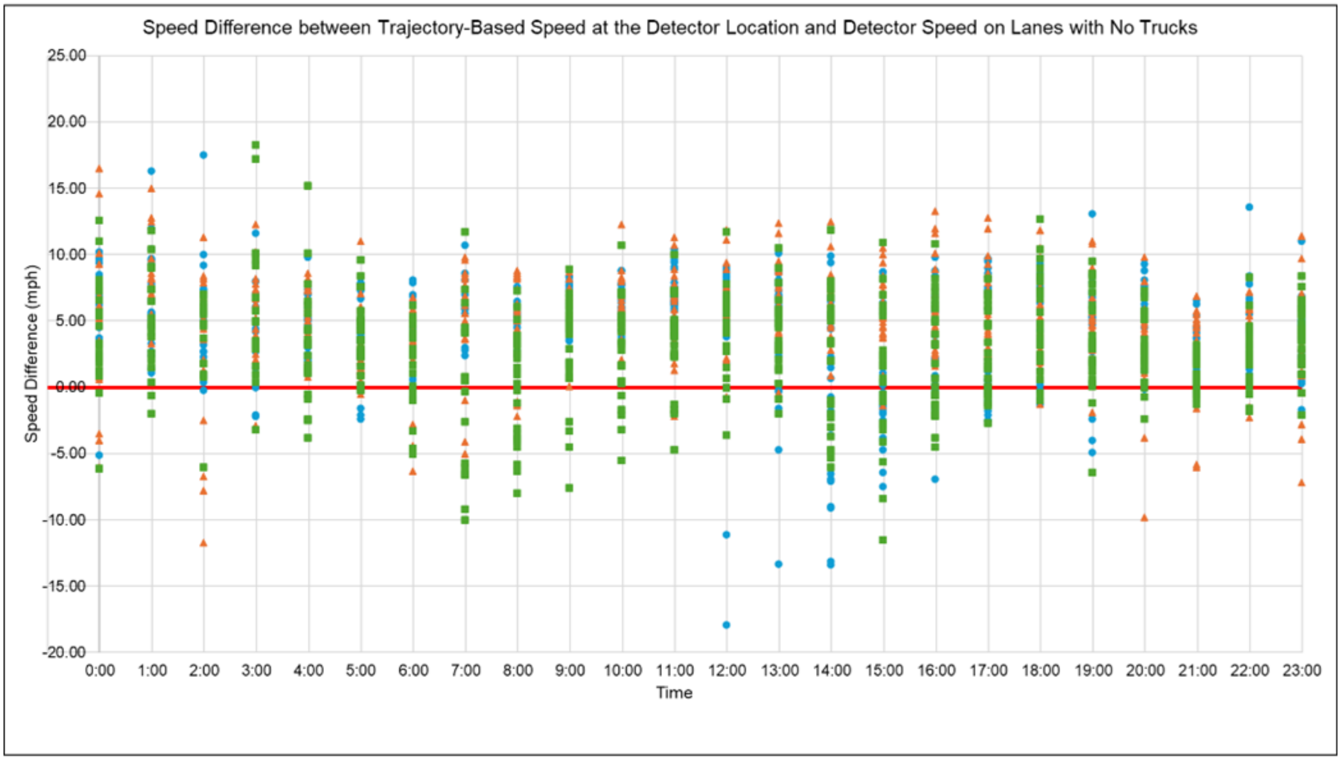
In **FIGURE 9**, the horizontal axis represents time, and the vertical axis represents speed. The blue curve shows trajectory-based speeds at the detector location, while the orange curve represents detector-measured speeds. Hourly speeds were aggregated from the same weekday hours during the analysis period.

Speed Measurement Comparison between Trajectory and Detector Data

The difference between trajectory-based speeds and detector-measured speeds was used as an indicator to examine the relationship between the two sources. By calculating these differences for lanes without trucks across all six stations, two distinct patterns emerged, as shown in **FIGURE 10**.



(a)



(b)

FIGURE 10: Speed Differences Between Trajectory-Based and Detector-Measured Speeds on Lanes Without Trucks: (a) Matched Patterns and (b) Unmatched Patterns

In **FIGURE 10**, the horizontal axis represents time, and the vertical axis represents the speed difference (trajectory-based speed minus detector-measured speed). A red horizontal line marks zero-difference reference. For each hour, points with the same shape and color correspond to the same site, aggregated from the two-week analysis period including both weekdays and weekends. For example, blue circles, orange triangles, and green squares represent speed differences at Station 1, Station 2, and Station 3, respectively, in **FIGURE 10(a)**. It is important to note that speeds from vehicle trajectory telemetry data were collected directly from vehicle telematics, potentially serving as a ground-truth reference for validating detector speed accuracy.

In **FIGURE 10(a)**, a relatively consistent speed difference pattern is observed at Stations 1, 2, and 3. Most points are distributed around the red horizontal line (zero difference reference), ranging from -5 mph to 5 mph, except during midnight and late-night periods (e.g., 00:00–03:00 AM and 11:00 PM). The correlation coefficients between trajectory-based speeds and detector-measured speeds were 0.89, 0.86, and 0.94 for Stations 1, 2, and 3, respectively.

As vehicle telemetry trajectory datasets only represent sampled observations, variations around zero can be expected, consistent with speed bias findings reported in a previous study [15]. Greater variation during midnight and late-night periods was attributed to the smaller number of vehicles captured compared with other times of day. Overall, the pattern in **FIGURE 10(a)** and the high correlation coefficients support the accuracy of detector speed measurements at these three detector locations.

In contrast, **FIGURE 10(b)**, shows a different pattern at Stations 4, 5, and 6, where most points cluster above the red horizontal line, ranging from 0 mph to 10 mph. Compared with **FIGURE 10(a)**, detector speeds at these stations were consistently lower than trajectory-based speeds, indicating potential inaccuracies in detector measurements.

For the scenarios where trucks should be taken into consideration, Figure 6 illustrates the speed comparison on lanes with trucks at Stations 1, 2, and 3.

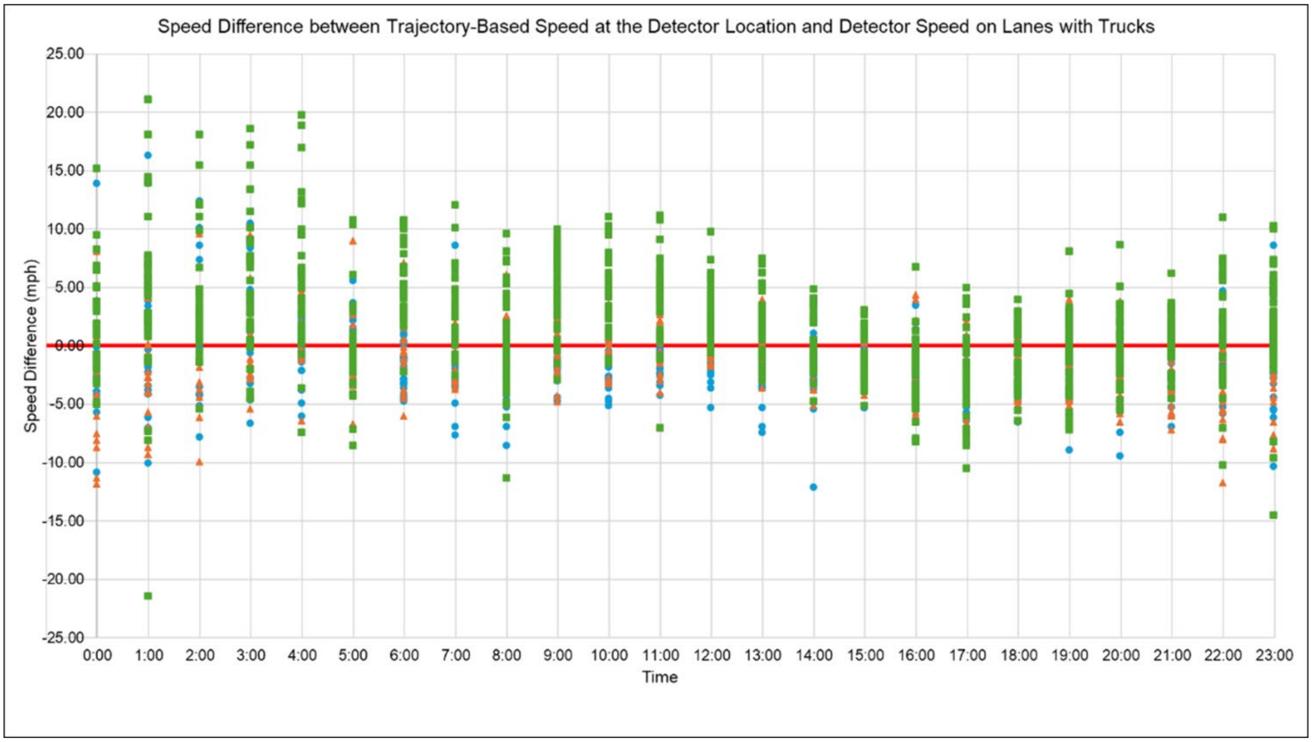
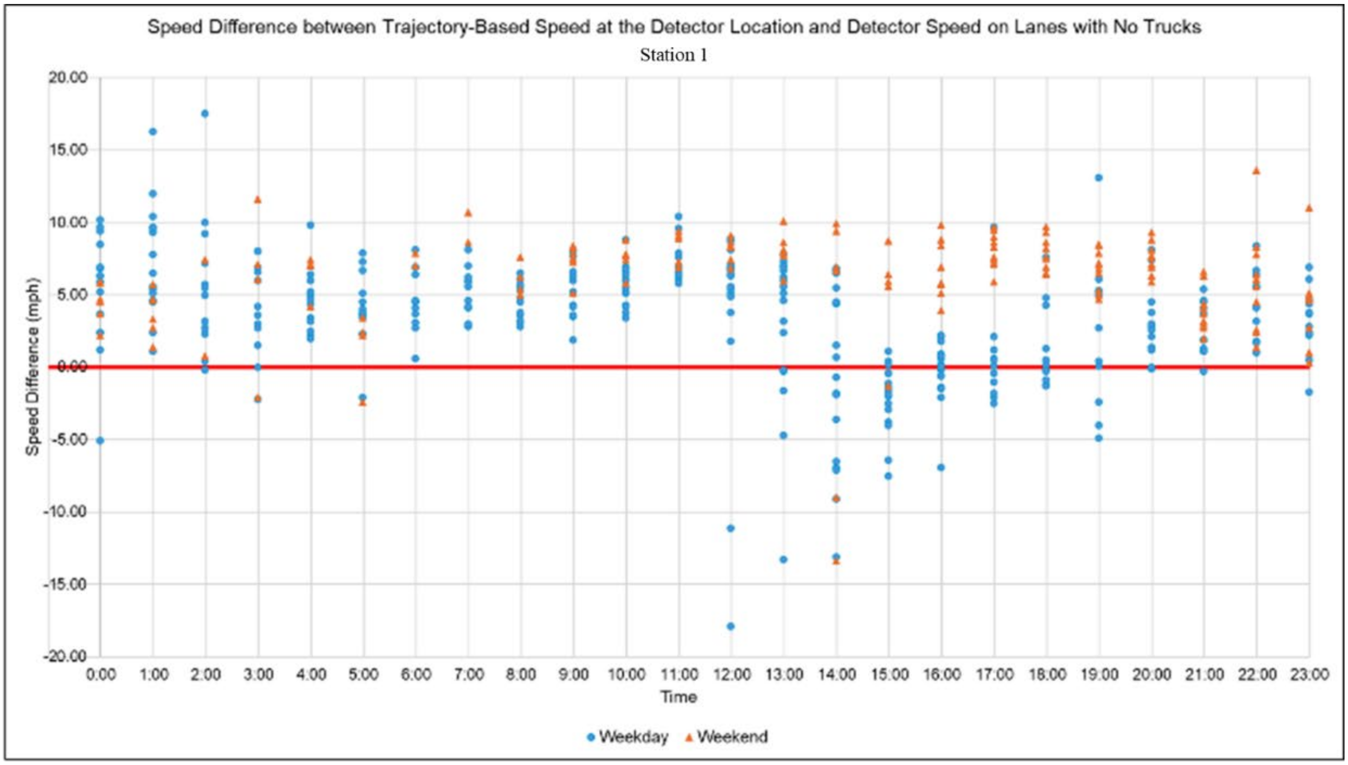


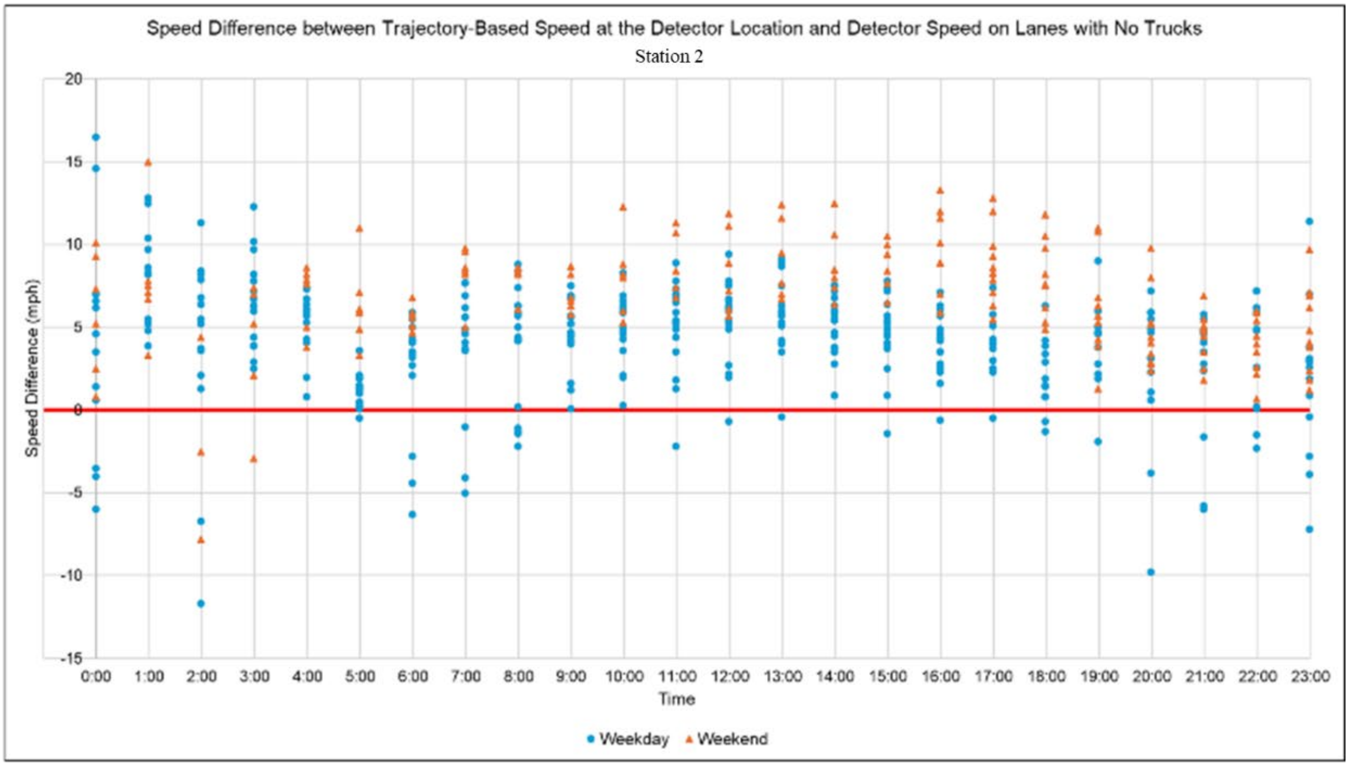
FIGURE 11: Speed Differences Between Trajectory-Based and Detector-Measured Speeds on Lanes with Trucks

Blue circles, orange triangles, and green squares represent speed differences at Stations 1, 2, and 3, respectively in **FIGURE 11**. Compared with **FIGURE 10(a)**, **FIGURE 11** shows that more points exceed a 5-mph difference, particularly during midnight and other non-congested periods (e.g., 00:00–11:00 AM). At these detector locations, a higher proportion of trucks traveled during nighttime, and trucks typically maintain lower speeds than passenger cars, as required by the speed limit regulation in California, which explains the significantly larger speed differences observed during midnight. During daytime (6:00–11:00 AM), speed differences between 5 mph and 10 mph were still evident, although the truck proportion decreased. This analysis indicates that the presence of trucks influences speed differences.

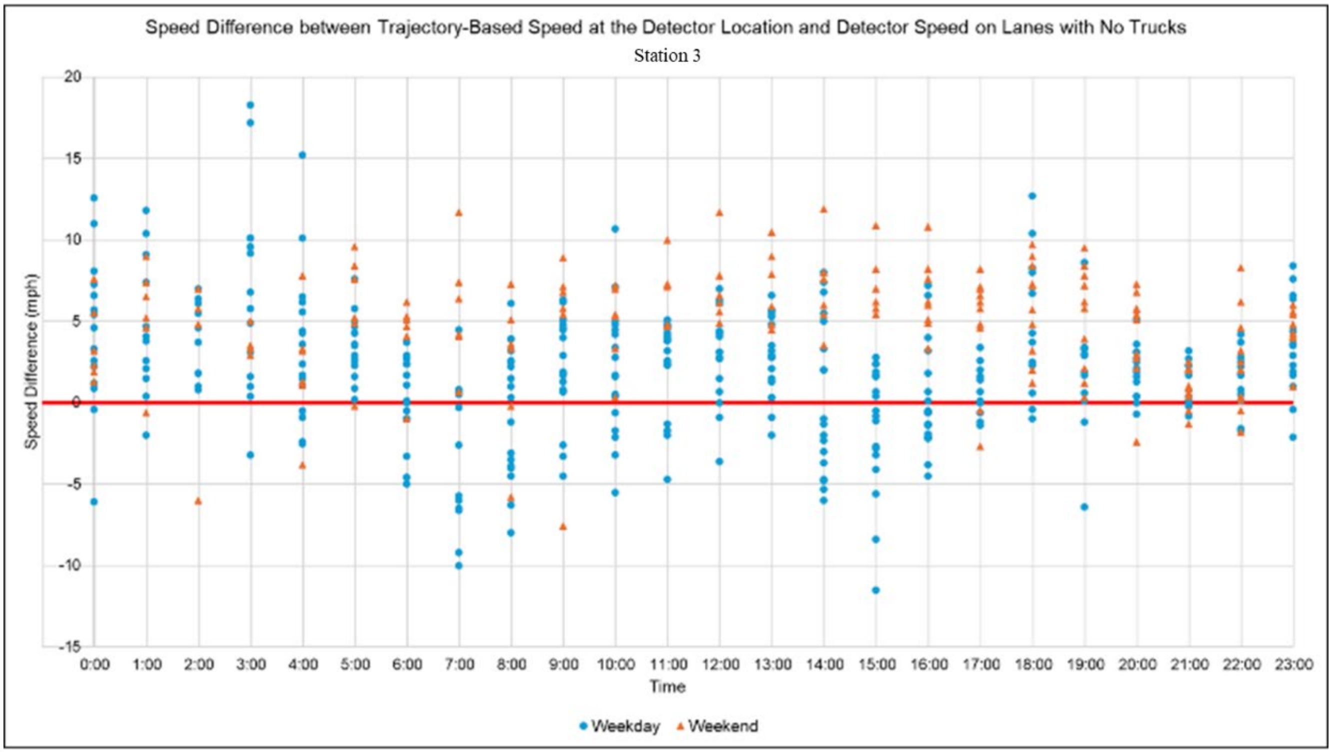
The significantly different detector speed measurements compared to trajectory data speed were found at three locations with different types of detection: Station 4 (magnetometer), Station 5 (dual loops), and Station 6 (dual loops). To better analyze the speed mismatch pattern at each station, **FIGURE 10(b)** is decomposed into three plots in **FIGURE 12** to display speed differences in lanes with no trucks. The blue circles and orange triangles represent speed differences on weekdays and weekends, respectively.


Speed Difference between Trajectory-Based Speed at the Detector Location and Detector Speed on Lanes with No Trucks
Station 1
Speed Difference (mph)
20.00
15.00
10.00
5.00
0.00
-5.00
-10.00
-15.00
-20.00
0:00 1:00 2:00 3:00 4:00 5:00 6:00 7:00 8:00 9:00 10:00 11:00 12:00 13:00 14:00 15:00 16:00 17:00 18:00 19:00 20:00 21:00 22:00 23:00
Time
Weekday
Weekend

(a)


Speed Difference between Trajectory-Based Speed at the Detector Location and Detector Speed on Lanes with No Trucks
Station 2
Speed Difference (mph)
20
15
10
5
0
-5
-10
-15
0:00 1:00 2:00 3:00 4:00 5:00 6:00 7:00 8:00 9:00 10:00 11:00 12:00 13:00 14:00 15:00 16:00 17:00 18:00 19:00 20:00 21:00 22:00 23:00
Time
Weekday
Weekend

(b)



(c)

FIGURE 12: Mismatched Speed Patterns on Lanes with No Trucks: (a) Station 4, (b) Station 5, and (c) Station 6

In **FIGURE 12(a)**, most points (blue circles and orange triangles) lie above the red horizontal line (speed difference = 0), except for a cluster of triangles between 2:00 and 7:00 PM. Both trajectory and detector speed data indicate that weekday PM congestion occurred during these hours, while weekends showed no congestion. At this location, the speed mismatch pattern appeared under uncongested conditions but did not exist under congestion. Common magnetometer detection errors include missed calls, false calls, dropped calls, and stuck-on calls. In this case, the mismatches likely result from improper detector configuration and inherent limitations of magnetometers for speed measurement. When vehicles pass at high speeds, magnetic changes may not be captured accurately, causing underestimation of speeds. Conversely, under congestion, magnetic changes are detected correctly, producing matched speed patterns in the PM peak. The correlation coefficient between trajectory-based and detector speeds for lanes without trucks was 0.99, indicating a strong linear relationship, though an adjustment factor may be needed for magnetometer calibration.

In **FIGURE 12(b)**, most points consistently fall above the red line, ranging from 0 mph to 15 mph on both weekdays and weekends at Station 5. The correlation coefficient of 0.7 suggests a weak linear relationship, pointing to potential loop configuration issues at this location.

In **FIGURE 12(c)**, the distributions of blue circles and orange triangles differ slightly at Station 6. Most triangles cluster above the 5-mph difference line, while circles are more evenly distributed around zero. This indicates that the mismatch pattern primarily occurred on weekends. Although both stations in **FIGURE 12 (b) and (c)** use the same type of detector, their mismatch patterns differ, likely due to variations in loop sensor configuration.

Overall, these analyses reveal that speed mismatch patterns can vary by location. Vehicle telemetry trajectory data provides a valuable resource for validating detector speed and identifying systematic issues.

FIGURE 11 indicates that the presence of trucks influences speed differences. Because Station 1 had very few trucks, additional speed and truck proportion data were obtained from Station 2 and Station 3. **FIGURE 13** is developed to examine the relationship between lane-by-lane speed differences, defined as trajectory-based speed at the detector location minus detector-measured speed, and corresponding truck proportions for Station 2, Station 3, and the combined dataset of Stations 2 and 3.

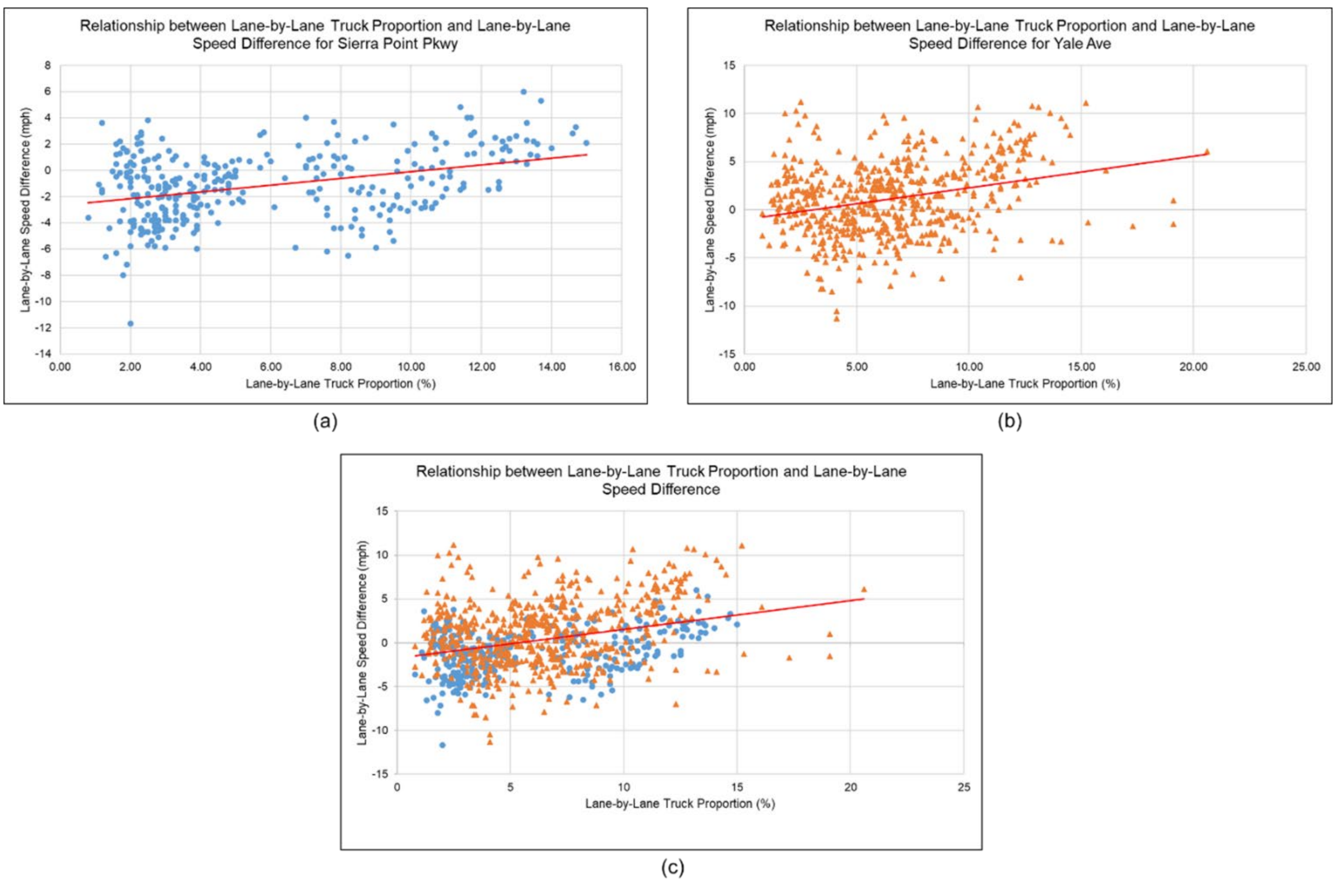


FIGURE 13: Relationship between Lane-by-lane Speed Difference and Truck Proportion: (a) Station 2, (b) Station 3, and (c) Stations 2 and 3 Combined

In **FIGURE 13**, the horizonal axis represents the lane-by-lane truck proportion, and the vertical axis represents the lane-by-lane speed difference. To reduce biased speed comparison, a minimum of 15 vehicles per hour per lane was used as a threshold to determine comparison periods. Each point was generated based on an hourly lane-by-lane truck proportion and the corresponding hourly lane-by-lane speed difference with blue circles and orange triangles for Stations 2 and 3, respectively. In **FIGURE 13(a)** and **FIGURE 13(b)**, it is clear to see that points cluster above and below 0 on the vertical axis because vehicle trajectory data was sampled data. The trendlines with positive slopes highlighted in red in both plots indicate that the lane-by-lane speed difference tends to increase as the lane-by-lane truck proportion increases. By aggregating all points from both spots, a similar trend can be captured in **FIGURE 13(c).**

Therefore, it was found that the lane-by-lane speed difference between trajectory-based speeds at the detector location and detector speeds cannot be ignored for lanes with trucks and tend to increase as the lane-by-lane truck proportion increases.

Findings

Based on comparisons between trajectory-based speeds and detector speeds, the following conclusions are drawn from this research:

- Freeway performance measurements, i.e., speeds, extracted from high-resolution vehicle telemetry trajectory data can serve as a valuable data source to validate freeway detection and provide insight into identifying speed mismatch patterns.
- The lane-by-lane speed difference between trajectory-based and detector measured speeds tends to increase as the lane-by-lane truck proportion increases.

Traffic Speed Analysis on Custom Roadway Segments (e.g., School Zones)

The UNR research team applied high-resolution vehicle telemetry trajectory data in a study, *School Zone Speed Study in Nevada (2024)*, to evaluate school zone speed characteristics in Nevada. This study is also sponsored by the Nevada Department of Public Safety Office of Traffic Safety. The full study report has been published by the office.

In this study, custom segmentation for extracting traffic speeds is explored, providing important advantages over pre-defined or aggregated segmentation that is typically applied in traditional probe-vehicle datasets. Defined segments often span long roadway sections that may not align with traffic safety performance analysis goals, such as specific intersection areas, subtle segments with lane drops, school zones, or locations where regulatory and warning devices influence driver behavior. As a result, aggregated speeds across these long segments can dilute or mask meaningful speed characteristics that are crucial for traffic engineering analysis.

Because high-resolution vehicle telemetry trajectory data preserves individual point-level observations, they allow transportation analyses to apply segmentation that follows specific logic of engineering design zones. Custom segmentation facilitates freeway and arterial traffic safety performance analyses by defining road segments precisely around meaningful features, enabling speed extraction that matches the functional profiles of the roadway.

For example, speeds typically decrease approaching intersections due to signal delay, queue formation, and turning movements. A pre-aggregated segment that spans both upstream free-flow conditions and the signalized intersection will average these conditions together, obscuring the magnitude and location of the speed reduction. Custom segmentation can minimize such under-estimations of speed when focusing on mid-block road speed characteristics.

Roadway locations, such as school zones, that often experience sharp speed reductions during specific time windows. Regular traffic message channels may be too long or misaligned with actual school zone boundaries, blending school zone speeds with adjacent normal-speed segments. Custom segmentation aligns the extraction boundaries exactly with the limits of the school zone, providing more accurate evaluation of compliance, speed variability, and effectiveness of school-zone controls. **FIGURE 14** illustrates trajectory waypoints over a broader school zone area captured in this study.

FIGURE 14: Vehicle Telemetry Trajectory Waypoint Extracted Near School

A finding is obtained through this study regarding school zone speed distribution. When comparing speed distribution between data from sensors of certain detection range and trajectories, significant differences can be observed if the school zone spans a relatively long distance, as illustrated in **FIGURE 15**.

FIGURE 15: Speed Distribution across a School Zone extracted from Vehicle Telemetry Trajectory Data

There is a noticeable increase in speeding maneuvers both upstream and downstream of the school zone. If the compliance rate is based on trajectories traversing the entire school zone, this pattern leads to a significant deterioration in overall compliance.

Safety Performance Screening for Passing Events

As high-resolution vehicle telemetry trajectory data features geographic precision of 10 feet, which implies the data can potentially be used to extract lane changing events. On rural highways in Nevada, passing events through overtaking maneuvers can be risky, resulting in traffic safety concerns. This study is conducted to explore the feasibility of using high-resolution telemetry trajectory data to identify passing events on two-way two-lane highways in Nevada. The study result has been accepted for presentation on the 2026 Transportation Research Board Annual Meeting.

In this study, telemetry trajectory data is extracted for the target road segments. A method using reference lines is developed to extract passing events, where the reference line is determined considering the telemetry trajectories and roadway features.

To identify lane change events, temporal and spatial stability of vehicle telemetry trajectories can be important. Specifically, whether waypoints within an individual trajectory exhibit a relatively consistent pattern or a structured lateral offset, rather than abrupt fluctuations or noise, is a fundamental question to be answered before identification of lane changes or passing events, as such identification is infeasible if a trajectory contains highly erratic or jittery waypoints.

FIGURE 16 illustrates the distribution of lateral offset variance across individual trajectories. Most trajectories exhibit very low variance values, indicating minimal fluctuation in lateral position over time. This concentration of low variance values suggests that, despite potential point noise and individual waypoint offsets, the trajectories maintain consistent lateral alignment within their respective lanes. Therefore, the spatial consistency observed across trajectories provides justification for using vehicle telemetry trajectory data as a viable approach to identifying passing events.

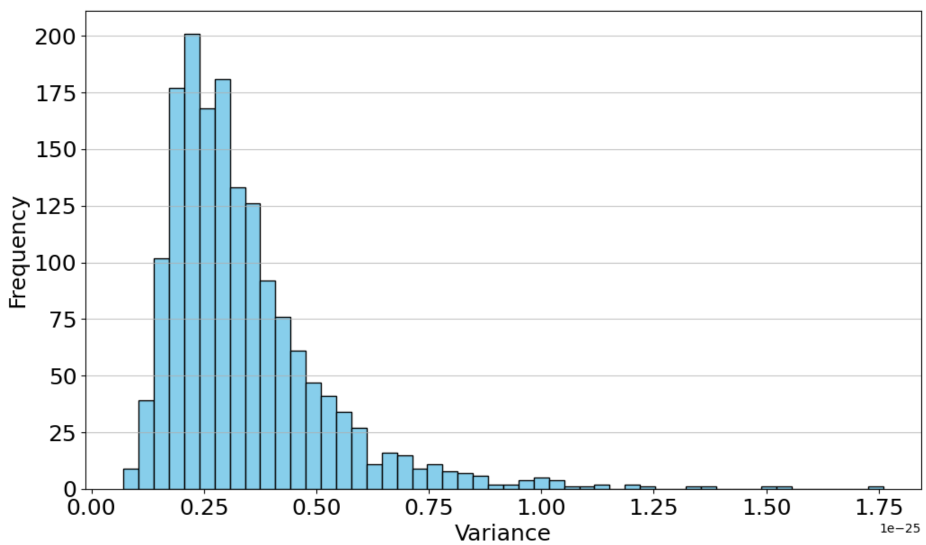


FIGURE 16: Distribution of Lateral Offset Variance Indicated by a Vehicle Telemetry Trajectory Sample

FIGURE 17 visually illustrates the stability of a randomly selected vehicle trajectory.

(a) (b) (c)

FIGURE 17: Visual Example of Vehicle Telemetry Trajectory Data Stability: (a) Spatial Distribution of Raw Data Waypoints (US-95, NV), (b) Example of an Individual Vehicle Trajectory, (c) Zoomed-In View of a Trajectory Segment from (b).

Along normal travel movements, waypoints are expected to indicate distinct clustering patterns, as vehicles typically remain within their designated travel lanes. To observe the data characteristics and examine this assumption, a journey ID that could be well-approximated by a straight-line fit-regardless of travel direction-was randomly selected as an initial baseline, as shown in **FIGURE 18**. The perpendicular distance from each waypoint to this baseline, defined as the lateral offset, as exhibited in **FIGURE 19**, where the blue arrows visually illustrate the offset.

The statistical distribution of these distances presented in **FIGURE 20** shows the cross-sectional distribution of waypoints on the roadway. The results reveal a bimodal distribution, with clusters corresponding to two lanes of directional traffic, indicating the assumption that the waypoints are concentrated within lane boundaries and supporting the use of a fitted approximate road centerline.

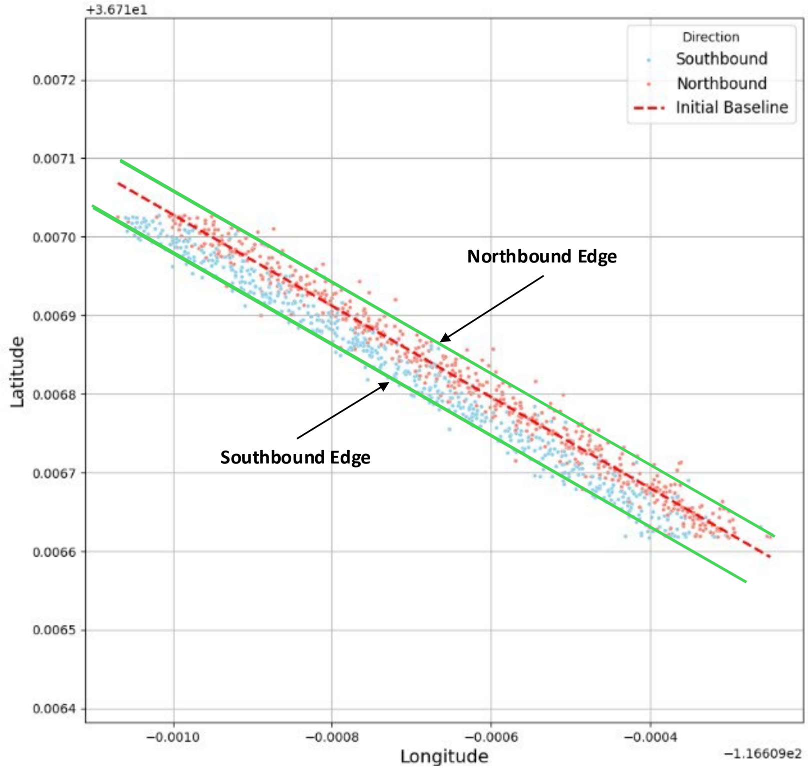


FIGURE 18: Trajectory Waypoints and the Initial Baseline

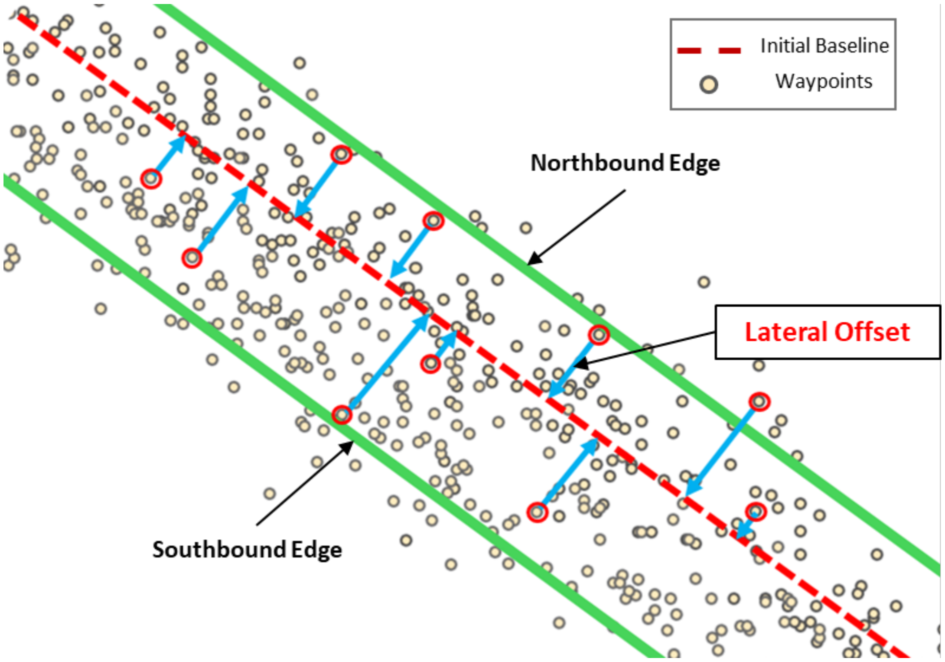


FIGURE 19: Lateral Offset of Waypoints

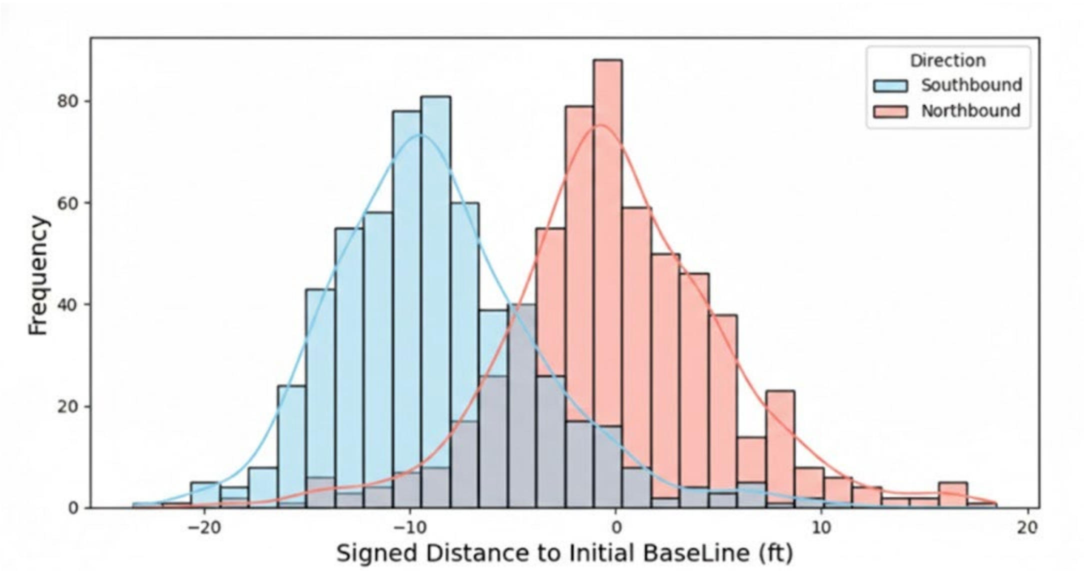


FIGURE 20: Directional Lateral Offset Distribution Relative to Initial Baseline

Telemetry trajectories on each directional lane are analyzed separately, and the lateral distance distribution for both travel directions generally follows a normal distribution as indicated in **FIGURE 21**.

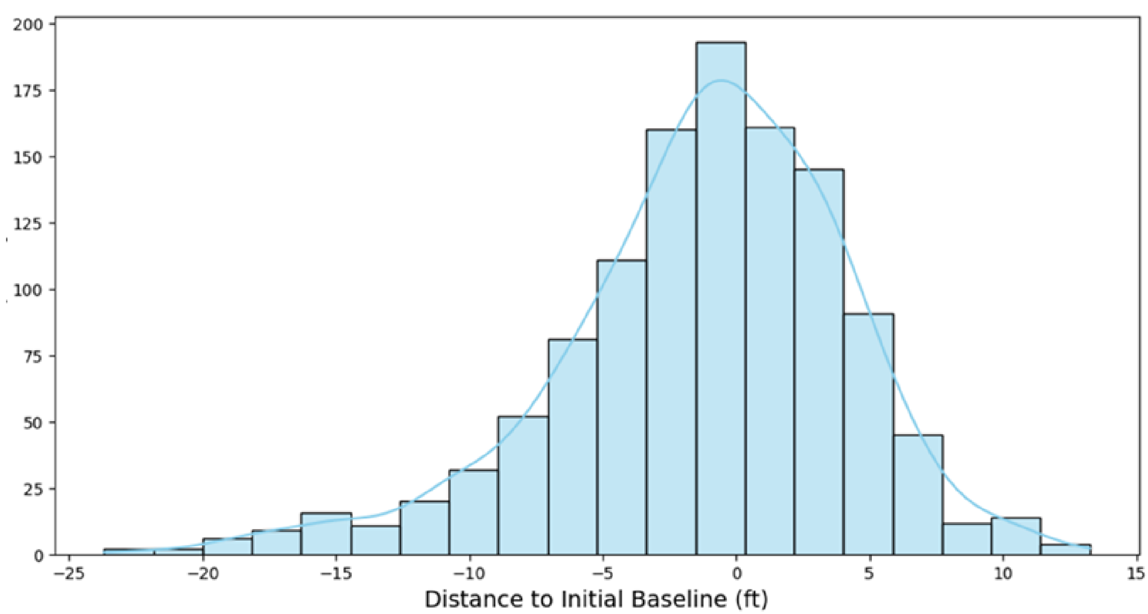


FIGURE 21: Lateral Distance Distribution of One Direction

Then, a passing event is identified according to the change of the lateral offset. When the lateral offset shows a consistent change crossing a lane boundary, it indicates a potential passing event.

Passing events can be categorized into three statuses: "Passing Start" points (colored in green to mark the start of a lane change), "Passing Process" points (colored in yellow to represent the ongoing lane change maneuver), and “Passing End” points (colored in red to indicate the end of the lane change and back to its initial lane). For example, as illustrated in **FIGURE 22**, the status of each waypoint is determined based on the change in lateral offset. The “No Passing” points (colored in grey) represent the trajectory waypoints recorded as a vehicle moving along the roadway within the lane of its direction. The lateral offsets between the “No Passing” points are generally within 4 feet along travel time. The “Passing Process” points can show significant lateral variations toward the lateral direction for the oncoming traffic by up to almost 10 feet, which is roughly a lane width observed in the field. Based on this vehicle telemetry trajectory, the duration of the overtaking lane passing is about 15 seconds.

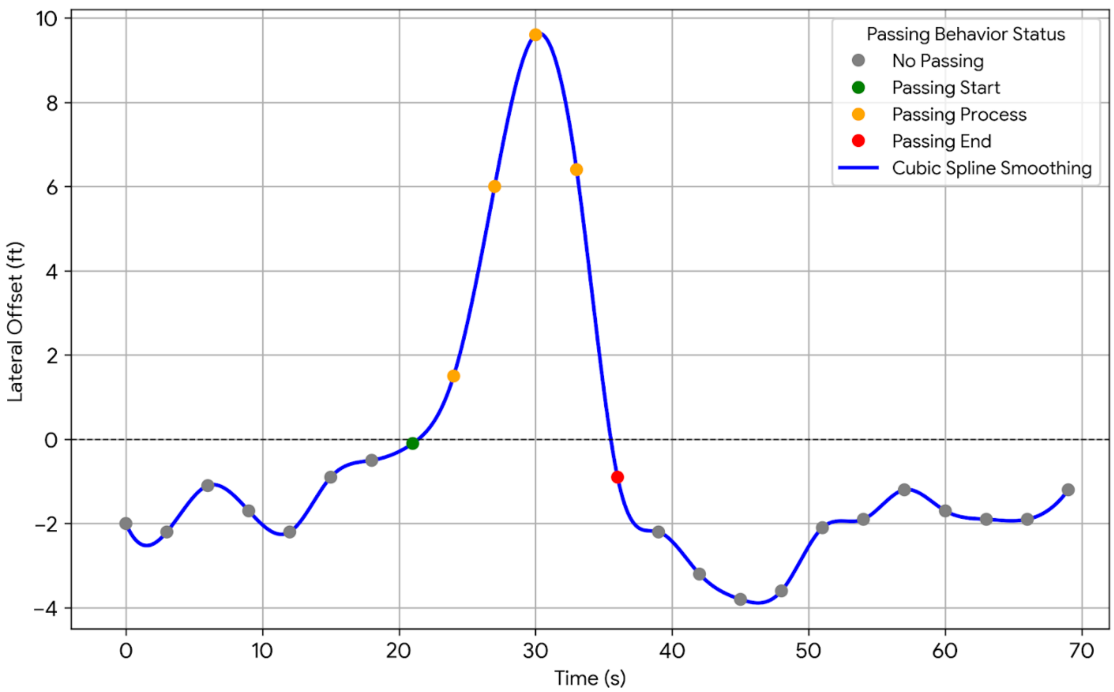


FIGURE 22: Passing Event Identification Based on Lateral Offset Variation

This method allows for scalable passing event identification using high-resolution telemetry trajectory data on roadways lacking performance monitoring infrastructure.

Systematic Trajectory Extraction Program (STEP)

A key deliverable of this research is a software tool that allows Nevada DOT users to access and process raw vehicle telemetry trajectory data and extract performance measurements for freeway and arterial analyses. This software application is currently named Systematic Trajectory Extraction Program (STEP).

The current software version is 3.0.11.0. The data schema support includes historical Wejo data and the latest StreetLight as of November 2025.

STEP Interface

To maximize the usability of the software, the user interface is mainly based on digital maps. Users can easily create freeway or arterial segmentation on the map background, and the geo-information will be automatically obtained.

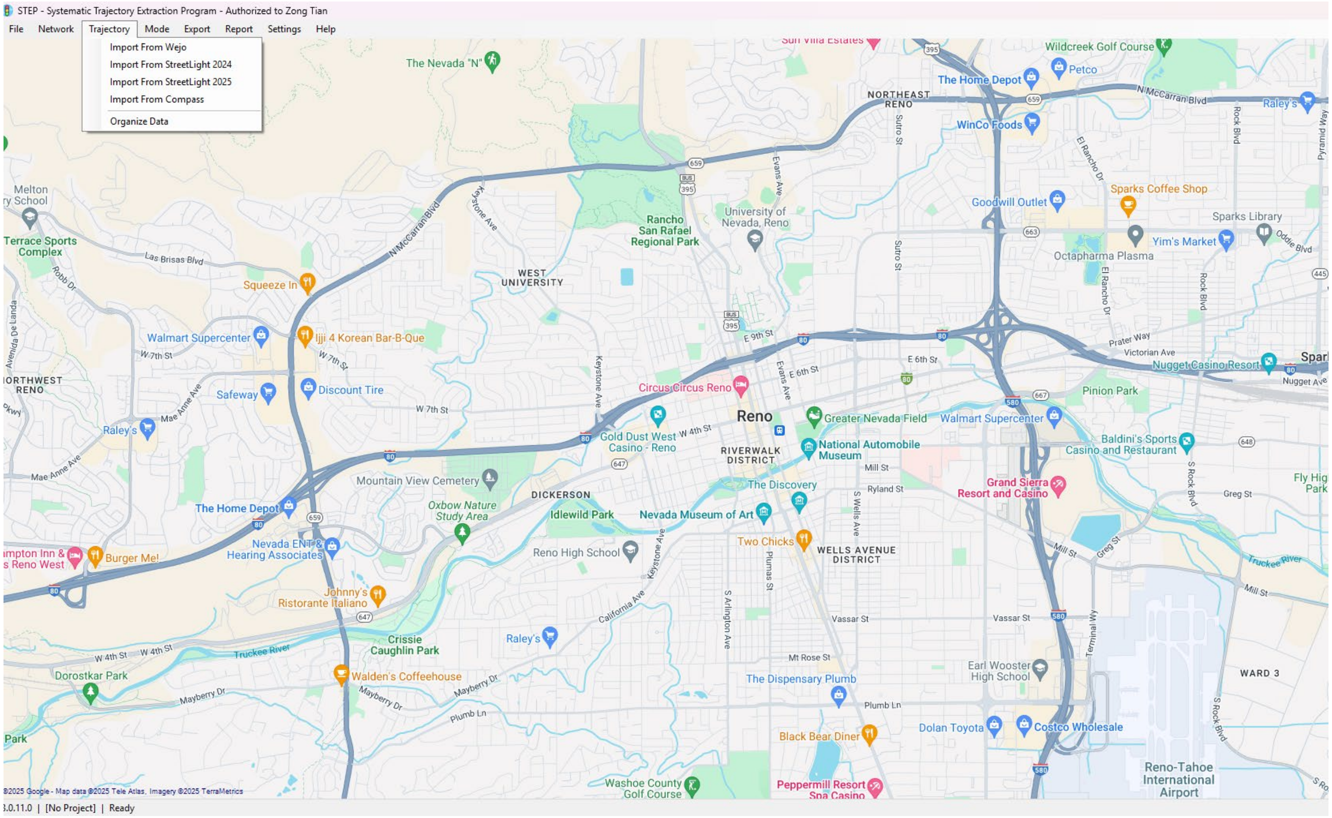


FIGURE 23: Map-based User Interface of STEP

Custom Segmentation

Users can establish points (e.g., individual intersections on arterials or access points of freeways) and subsystems (e.g., segments of signalized arterials or freeways) on the map-based interface. The established points and subsystems will be represented by visible icons, and users can easily manipulate them. Trajectory data processing, visualization, and performance measure generation will be based on the points and subsystems of interest. **FIGURE 24** presents several intersections and signalized corridors created in STEP. The “signal light” icons represent individual intersections, and the connections of “signal light” groups represent corridors that involve signal coordination.

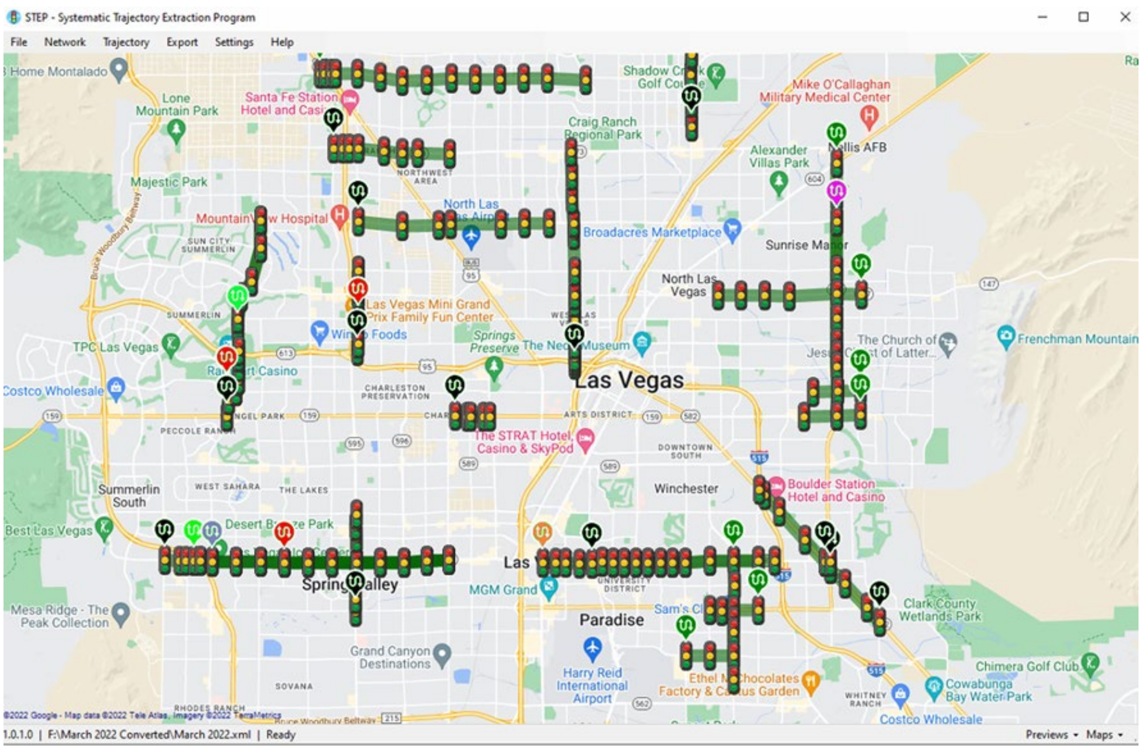


FIGURE 24: Custom Segmentation Established Using “Points” and “Subsystems”

Raw Data Processing

STEP can read a variety of trajectory data sources and extract needed information, which will be saved into a database.

The StreetLight (JSON) 2025 Data Import Module, as shown in **FIGURE 25**, enables users to efficiently load, manage, and filter high-resolution vehicle trajectory datasets packaged in StreetLight’s JSON-GZ format. The tool is designed for seamless integration of large-scale mobility data into traffic engineering, transportation analytics, and planning workflows.

With this module, users can:

1. Import Compressed StreetLight Trajectory Data

- Load folders containing StreetLight 2025 data in .gz format.
- Automatically decode JSON-formatted trajectory entries, including fields such as journey ID, timestamp, latitude, longitude, speed, heading, elevation, and ignition status.

2. Manage Data Conflicts

- Choose how to handle duplicate or previously imported datasets:
    - Ask for solution (manual decision per conflict)
    - Always take newly imported data
    - Always keep previously imported data

This ensures dataset integrity and flexibility for incremental imports.

3. Apply Location-Based Filters

- Import all available data or restrict imports to a customized rectangular geo-fence defined directly on the map interface.
- This allows users to focus on specific corridors, intersections, neighborhoods, or study areas.

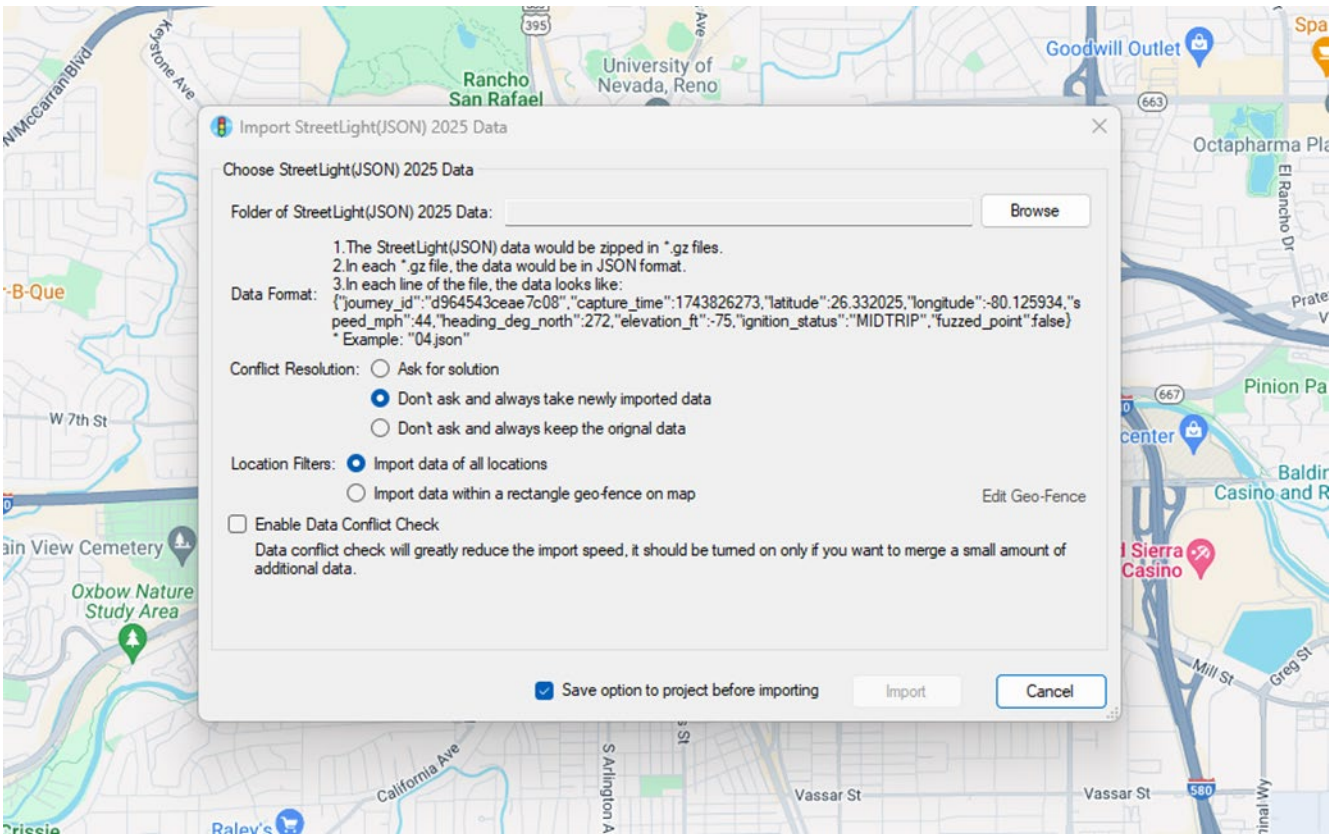


FIGURE 25: STEP Raw Data Processing Functions

Custom Time Extraction for Trajectory Data

STEO provides Custom Time Extraction functions that allow users to define precise time-of-day windows for extracting performance measurements from large-scale vehicle telemetry trajectory datasets, as shown in **FIGURE 26**.

With the functions, users can:

1. Create Flexible Time Windows

- Define custom time ranges such as AM Peak, PM Peak, Midday, Off-Peak, or any user-specified interval.
- Specify Start Time and End Time to the minute

2. Apply Custom Time Selection Across Subsystems

- Assign custom time selection to any points or subsystems
- The interface ensures each subsystem is assigned to at least one valid time window before extraction.

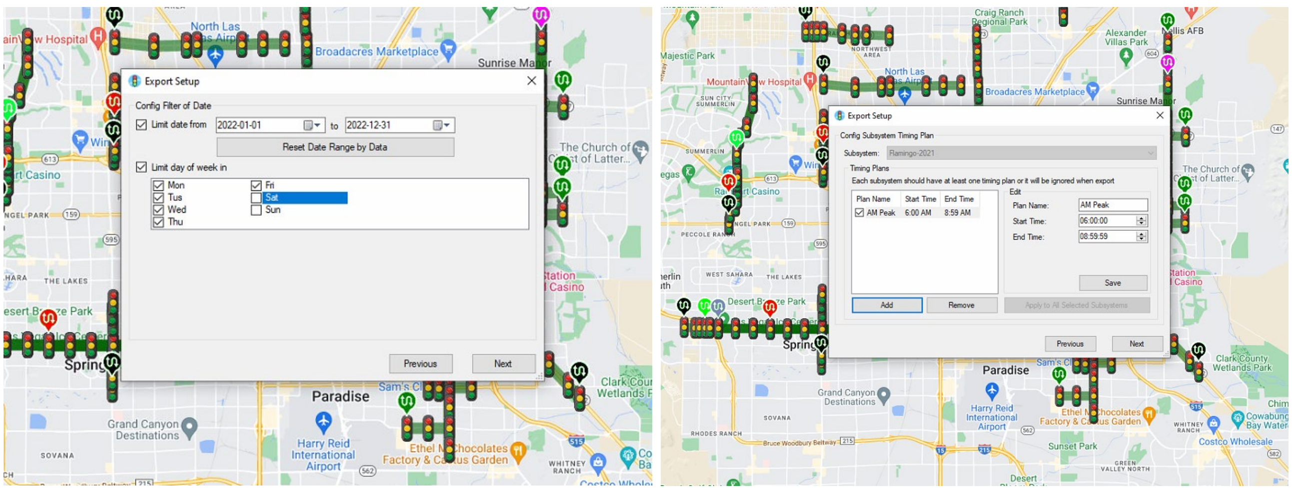


FIGURE 26: Custom Time for Trajectory Extraction

Performance Output

STEP outputs performance measurements in CSV files that can be directly accessible using Office Excel software, which can be convenient to Nevada DOT’s engineering practitioners.

Conclusions

This research confirms that high-resolution vehicle telemetry trajectory data can meaningfully enhance freeway and arterial performance analyses in Nevada. Compared with traditional point sensors and aggregated probe datasets, telemetry trajectories provide richer spatiotemporal detail, broader coverage, and the flexibility to perform custom segmentation aligned with engineering logic. These advantages are critical for evaluating complex roadway environments, such as regional coordinated signals on arterials, freeway mobility assessment and monitoring, school zones speed characteristics, and passing events on rural roads, where aggregated data may mask insights.

Across the arterial traffic signal performance study, multi-day stacked telemetry trajectories can be applied to generate performance scoring for 36 regional corridors, while also supporting diagnosis and performance monitoring of signal timing during implementation. The close alignment in distributions between number of trajectory samples and hourly traffic volumes demonstrated that telemetry data can serve as a reliable surrogate for developing weighting factors in regional traffic signal performance ranking and retiming project prioritization. Time–space diagram analyses further revealed signal timing errors, illustrating how trajectory-based diagnostics can relieve field investigation effort.

The freeway performance analysis showed that trajectory-based speeds can serve as an independent validation source for identifying detector malfunction, configuration errors, or technology limitations. Matched patterns across several stations confirmed detector accuracy, whereas systematic underestimation can be observed at some stations. The study also found that truck proportions significantly influence detector–trajectory speed differences, indicating a limitation of vehicle telemetry trajectory data that is solely sourced from passenger cars. These findings demonstrate the value of integrating trajectory data into routine detector health monitoring and freeway performance assessment.

In traffic safety applications, custom segmentation can improve the accuracy of school zone speed compliance analysis by capturing upstream and downstream speeding behavior that would be obscured in long predefined segments. With stable and sufficient geographic precision, telemetry trajectory data allows for the extraction of lane-consistent lateral offsets and identification of passing events on rural highways, which is not feasible using aggregated data or low-resolution probe data sources. These results highlight the potential of telemetry trajectories to support network-wide safety screening and traffic safety assessments for specific facilities across roadway networks.

The research offers a practical software tool to permit the use of telemetry trajectory data by Nevada DOT. The STEP software developed in this project, to streamline data ingestion, processing, and performance measure extraction.

In conclusion, high-resolution vehicle telemetry trajectory data offer significant value for Nevada DOT's operations and safety programs. Continued refinement of methods for applying high-resolution telemetry trajectory data will position Nevada DOT to leverage the full potential as a variety of trajectory data can become increasingly prevalent across the roadway network.

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