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INCORPORATING ELEVATION IN TRAFFIC-VEHICLE CO-SIMULATION: ISSUES, IMPACTS, AND SOLUTIONS

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ABSTRACT

Traffic-vehicle co-simulation couples microscopic traffic simulation with full-body vehicle dynamics to assess system-level impacts on mobility, energy, and safety with greater realism. Incorporating elevation is critical for accurately modeling vehicle behavior and energy use, especially for gradient-sensitive vehicles such as electric and heavy-duty trucks. However, raw elevation data often contain noise, discontinuities, and inconsistencies. While such issues may be negligible in traditional traffic simulations, they significantly affect traffic-vehicle co-simulations where vehicle dynamics are sensitive to road grade variations. This paper investigates the impact of unprocessed elevation data on vehicle behavior and energy consumption using a 42-mile simulation along Interstate 81. We propose an elevation processing workflow that can mitigate the effects stem from elevation data issues, improving the realism and stability of traffic-vehicle co-simulation. Results show that the method effectively removes noise and abrupt elevation transitions while preserving roadway geometry.

1 INTRODUCTION

Traffic-vehicle co-simulation has emerged as a powerful tool for analyzing transportation systems with enhanced physical realism. By coupling microscopic traffic simulation with detailed vehicle dynamics models, co-simulation frameworks enable researchers and practitioners to more accurately evaluate the system-level impacts of vehicle behavior on mobility, energy consumption, and safety.

One critical but often overlooked factor in traffic-vehicle co-simulation is road elevation. Elevation changes significantly influence vehicle dynamics, powertrain load, and regenerative braking behavior, especially for gradient-sensitive vehicle types like electric vehicles and heavy-duty vehicles. Accurately modeling these effects is essential for reliable evaluation of energy efficiency, emissions, and mobility under realistic roadway conditions. Despite its importance, elevation is frequently excluded or simplified in co-simulation workflows due to difficulties in data integration.

Raw elevation data, typically sourced from digital elevation models (DEMs), map APIs, or GPS recordings, often contain various artifacts such as noise, abrupt discontinuities, and inconsistent resolution. These issues can propagate into the co-simulation environment, causing unstable vertical dynamics, artificial vehicle crashes, or unrealistic spikes in energy consumption. As a result, failure to properly process elevation inputs undermines the accuracy and reliability of simulation outcomes.

To address these limitations, this paper focuses on developing and validating an elevation data processing workflow to support realistic traffic-vehicle co-simulation. The key contributions of this paper are as follows:

- The negative impacts of raw elevation data on traffic-vehicle co-simulation stability and vehicle behavior are demonstrated using a simulation of a 42-mile corridor along Interstate 81 built with real-world elevation and traffic data.
- A novel three-step elevation processing workflow consisting of outlier filtering, elevation smoothing, and grade smoothing is proposed to produce realistic elevation and grade profiles.

- The effectiveness of the proposed workflow is validated through improved simulation behavior and energy consumption under various payload conditions.

2 LITERATURE REVIEW

2.1 Traffic and Vehicle Simulation

Traffic simulation is a modeling approach used to replicate the movement and interaction of vehicles on a transportation network. It is often applied to analyze traffic operations (Xu and Gayah 2023), evaluate safety interventions (Xu et al. 2025), and test traffic and vehicle control technologies such as signal control, eco-driving, and connected and automated vehicles (Yuan et al. ; Zhou et al. 2022; Yu et al. 2020). Some commonly used traffic simulation software includes AIMSUN, PTV VISSIM, CORSIM, TransModeler, Simulation of Urban Mobility (SUMO), and Paramics (Saroj et al. 2024). These simulators, particularly at the microscopic level, model each vehicle as an individual agent governed by driver behavior models such as car-following and lane-changing models. However, they generally do not simulate internal vehicle dynamics (e.g., drivetrain behavior, braking force, traction control) and thus are limited in evaluating in-vehicle control and operation technologies.

By contrast, vehicle simulators are used to model detailed vehicle physics and control responses. These simulators are essential for studying technologies related to Advanced Driver Assistance Systems (ADAS), Connected and Autonomous Vehicles (CAVs), and Connected Vehicles (CVs) systems (Zhou et al. 2022). In such simulations, control modules send commands—such as throttle, brake, and steering—through a virtual controller area network (CAN) bus to replicate vehicle responses in a virtual environment. As highlighted in (Zhou et al. 2022), high-quality vehicle simulators require accurate sensor models, advanced vehicle dynamics, and photo-realistic environments. Popular vehicle simulators include CarSim (CarSim 2025), IPG CarMaker™ (IPG 2025), LGSVL (Rong et al. 2020), MATLAB/Simulink (MathWorks 2025), and PreScan (Siemens 2025). These platforms are commonly used to study driver responses (Zhang et al. 2025), evaluate new technologies, and test features such as eco-driving strategies (Huang et al. 2018), automated braking, and adaptive cruise control (Zhou et al. 2022).

2.2 Co-simulation Framework for Vehicle Technology Studies

To create virtual testbeds for realistic traffic movement and control environments, co-simulation frameworks are often employed. These frameworks enable the evaluation of technologies such as ADAS and CAVs at scale by combining a traffic simulation environment for modeling the road network and background traffic with a vehicle simulator for high-fidelity vehicle dynamics (Shi et al. 2022; Azfar and Ke 2024). For example, Shao et al. (Shao et al. 2023) demonstrated a co-simulation setup for CAVs using an everything-in-the-loop (XIL) framework (Shao et al. 2023), integrating traffic simulation with software, hardware, and vehicle simulators such as CARLA and IPG CarMaker™ to evaluate CAV control strategies. Detailed vehicle dynamics in these simulators provide accurate estimations of the impacts of emerging vehicle technologies on fuel efficiency and energy consumption. While these frameworks successfully combine realistic ambient traffic with physics-based vehicle models, to the best of the authors' knowledge, no existing studies have discussed the impact of elevation on vehicle motion and energy consumption within this co-simulation framework.

2.3 Role and Challenges of Elevation Data in Traffic and Vehicle Simulation

In recent years, the effects of elevation and road grade on vehicle motion and energy consumption have been examined in several studies (Perrotta et al. 2020; Ferreira et al. 2020; Liu et al. 2019; Liu et al. 2017; Wood et al. 2015). Traditionally, microscopic traffic simulation models are used to generate realistic vehicle speed profiles along specific routes in a network (Ferreira et al. 2020). These speed profiles are then input into emission and energy models such as PHEM (Lejri et al. 2018), CMEM (Kan et al. 2018), and VT-Micro (Wang and Rakha 2017) to estimate fuel consumption or emissions. However, these simulations typically do not account for detailed vehicle dynamics, which can limit the accuracy of energy and emissions estimates.

However, the traffic-vehicle co-simulation framework enables more accurate evaluation of fuel consumption and emissions, as it considers both detailed vehicle dynamics and interactions with surrounding traffic in realistic simulation environments. For such evaluations, incorporating road elevation data is essential, as elevation has a direct influence on vehicle load, power demand, and regenerative braking behavior.

Elevation data are available from a variety of open-source and commercial sources, including the Shuttle Radar Topography Mission (SRTM) (Farr et al. 2007), USGS National Elevation Dataset (NED) (U.S. Geological Survey 2013), Google™ Maps Elevation API (Google Developers 2023), Mapbox API (Mapbox 2023), HERE™ API (HERE Technologies 2025), and LiDAR-based datasets such as the USGS 3D Elevation Program (3DEP) (U.S. Geological Survey 2021). Although terrain elevation data is widely available, it often does not accurately represent the elevation of the road surface itself. Some services, such as the HERE™ API (HERE Technologies 2025), provide elevation data along roadway centerlines, but this data is often sparse and must be smoothed to produce realistic road grades for simulation purposes. Additionally, road elevation data frequently contains noise, outliers, or discontinuities that can result in unrealistic vehicle behavior in simulations and inaccurate assessments of vehicle energy consumption (Fisher and Tate 2006). Existing research on elevation data processing and smoothing focuses on improving terrain data quality for geographic or visualization purposes (Hofer et al. 2006; Gallant 2011; Arrell et al. 2008; Chen et al. 2017), without considering its impact on traffic or vehicle simulation. This paper uniquely highlights how unprocessed elevation data can degrade traffic-vehicle co-simulation by affecting vehicle dynamics, and proposes a workflow to mitigate these issues and enhance simulation accuracy. The proposed method can be applied across vehicle simulation, traffic simulation, and integrated traffic-vehicle co-simulation to ensure realistic and reliable elevation inputs.

3 TRAFFIC-VEHICLE CO-SIMULATION OF A CORRIDOR

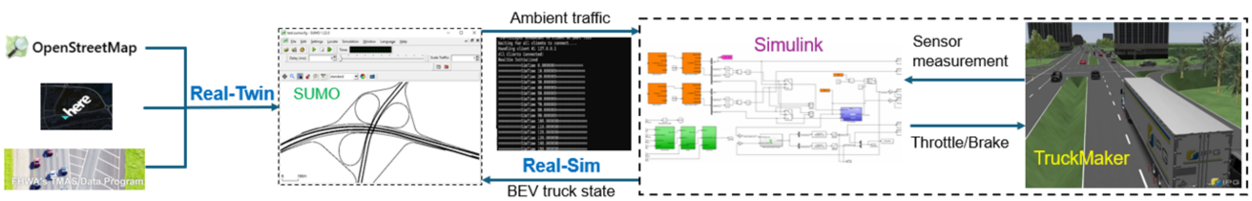


Figure 1: Co-simulation framework between SUMO and IPG TruckMaker™

To investigate vehicle behavior and energy consumption in a realistic traffic environment, a traffic-vehicle co-simulation is developed for a 42-mile highway segment along Interstate 81 (I-81) following the framework shown in Figure 1. This corridor is selected due to its notable elevation variation, ranging from 945 ft to 1860 ft, which provides a representative terrain profile for testing elevation-sensitive vehicle dynamics. The simulation scenario models a battery electric vehicle (BEV) truck traveling through the corridor while interacting with surrounding traffic. Throughout the simulation, the vehicle dynamics and energy consumption are continuously recorded.

For the traffic simulation, we use the Simulation of Urban Mobility (SUMO), a microscopic traffic simulator capable of modeling detailed vehicle-level interactions. The traffic simulation here is to provide realistic surrounding vehicle behavior, enabling the ego BEV truck to respond as it would in real-world traffic. These interactions—such as accelerating, braking, or changing lanes in response to other vehicles—directly influence the ego truck's dynamics. Elevation further compounds this effect by altering the required power, braking effort, and traction depending on the road grade. Note that although SUMO has models that consider impact of elevation, it does not capture detailed longitudinal vehicle dynamics such as traction limitations, or regenerative braking, necessitating the use of a high-fidelity vehicle simulator. We utilize *Real-Twin* (Wang et al. 2025; Xu et al. 2025), a tool for automatic scenario generation for microscopic traffic simulation developed by Oak Ridge National Laboratory, to generate the simulation network for this corridor based on road network data from OpenStreetMap (OSM), elevation data collected at 10-meter intervals along the road centerline of I-81 from HERE™ Maps, and traffic volume data from the Federal

Highway Administration's Traffic Monitoring Analysis System (TMAS) as well as Highway Performance Monitoring System (HPMS). Specifically, HPMS Annual Average Daily Traffic (AADT) data along highway segments and ramp exits are combined with hourly traffic data from the nearest TMAS stations to estimate hourly traffic volumes across the network. As a preliminary step, this paper uses traffic generated by SUMO's tool *randomTrips.py* to easily create diverse traffic scenarios. Future work will incorporate more realistic traffic estimates based on HPMS and TMAS data.

For the vehicle simulation, we use the vehicle simulator IPG TruckMaker™ which provides a high-fidelity 3D simulation environment capable of accurately modeling detailed vehicle dynamics (including drivetrain, steering system, trailer, tires, chassis, body shell, and sensors). Additionally, Simulink is integrated into the simulation loop to implement a customized speed planner and throttle/brake controller for the ego vehicle. The speed planner is formulated using a model-free controller (Wang et al. 2023) that can estimate the gradient variations of vehicle speed and acceleration based on past trajectories, and adaptively adjusts the planned speed profile to enable desired car-following and cruising performance. The throttle/brake controller is built upon a proportional-derivative-feedforward control mechanism, where the proportional and integral terms seek to mitigate the impacts from operational disturbances (e.g., wind, slope, friction) and the feedforward term devotes to maintain a consistent speed level. The controller parameters are empirically tuned to ensure desired balance among travel time, energy consumption, and speed tracking performance. Finally, to integrate traffic and vehicle simulation, the *Real-Sim* (Shao et al. 2023) tool is utilized. *Real-Sim* enables multi-resolution, everything-in-the-loop co-simulation, synchronizing SUMO and IPG TruckMaker™ in real time. This setup allows the ego BEV truck in TruckMaker™ to interact dynamically with the traffic flow generated by SUMO, creating a tightly coupled simulation that reflects both traffic behavior and high-fidelity vehicle dynamics mimicking real-world conditions.

4 POTENTIAL EFFECTS OF UNPROCESSED ELEVATION ON SIMULATION

Unprocessed elevation can exert negative impacts on traffic-vehicle simulations. First, the raw elevation data is excessively choppy due to measurement limitations, leading dramatic variations in road grade. This will then translate to a non-smooth road surface profile with multiple bumps, exaggerating trucks' vertical motions, creating immensely choppy and unreasonably large acceleration/deceleration in the z direction (as shown in Figure 2), and even sending the truck into the air (as shown in Figure 3, the truck body also experiences dramatic movements). These phenomena differ significantly from real-world I-81 operations, reducing the realism in vehicle-traffic simulation.

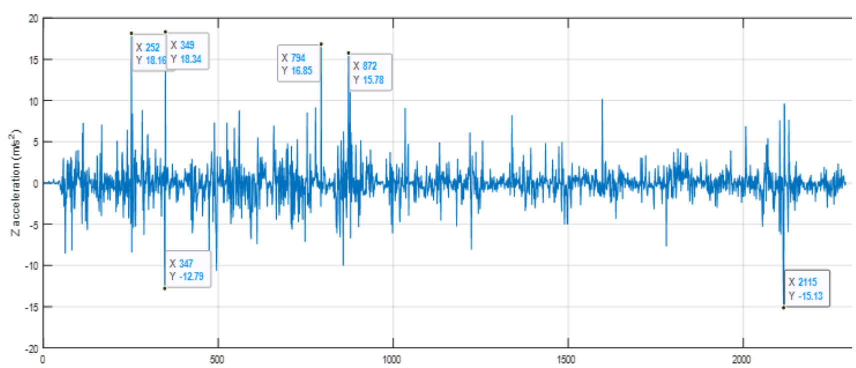


Figure 2: Acceleration/deceleration in Z axis

More importantly, critical road bumps from unprocessed elevation can destabilize truck lateral movements and create safety hazards that can disrupt simulations. This is because the truck can experience tire traction variations (unbalanced traction force of left and right tires) and center-of-gravity shift after landing from a road bump, triggering a rotational moment that can swing the truck to deviate from the target lane. The

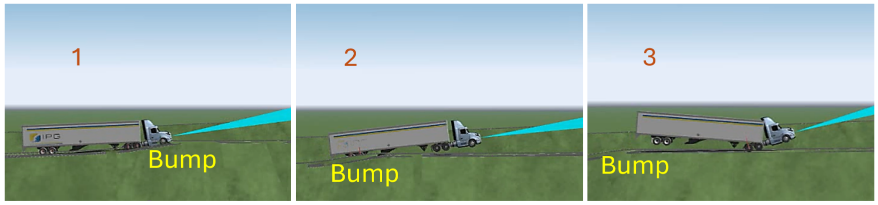


Figure 3: Screenshots of truck experiencing a bump

large weight and length of the truck further increase the challenges of steering the truck back to the target lane and stabilizing the chassis motion. Figure 4 shows that the truck cannot center itself in the target middle lane after experiencing the bump, producing a weaving motion and ultimately running off-road. This undesired phenomenon can become more severe if lane-change maneuvers are involved.

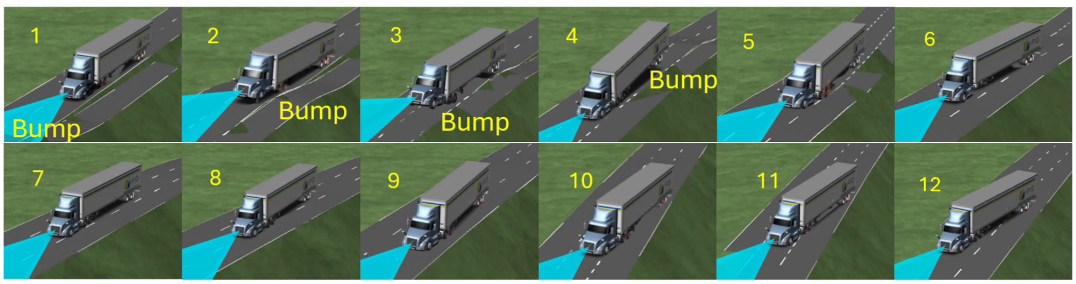


Figure 4: Screenshots of truck running off road after experiencing a bump

5 WORKFLOW OF PROCESSING ELEVATION DATA

Based on the above observations, it is clear that to ensure realistic traffic-vehicle co-simulation, raw elevation data must be preprocessed to remove noise, outliers, and abrupt variations that can distort vertical vehicle dynamics. Therefore, this paper proposes a workflow for processing elevation data, shown in Figure 5, which consists of three steps: outlier filtering, elevation smoothing, and grade smoothing. Once processed, the elevation data are integrated into the traffic simulation network using the tool *Real-Twin* (Wang et al. 2025) and synchronized into the vehicle simulation network through the tool *Real-Sim* (Shao et al. 2023).

Figure 5: Workflow of processing elevation data

Step 1: Outlier Filtering

Raw elevation profiles sometimes contain abnormal values such as sudden spikes, dips, or discontinuities, often caused by GPS drift, data stitching artifacts, or mismatches in terrain data resolution. These outliers can significantly affect downstream elevation smoothing and grade computation, leading to unrealistic slopes and unstable simulation behavior. To address this, several outlier detection methods could be used, e.g., z-score filtering, Hampel filters, and percentile-based trimming (Iglewicz and Hoaglin 1993; Aguinis et al. 2013; Pearson et al. 2016). The interquartile range (IQR) method was selected due to its ease of use and robustness to non-Gaussian distributions and its ability to isolate extreme values without assuming normality (Liu et al. 2007). IQR-based filtering is especially effective for elevation data with skewed distributions or embedded noise. The IQR method identifies outliers as data points falling below:

$$\text{Outliers} < Q_1 - 1.5 \times \text{IQR} \quad \text{or} \quad \text{Outliers} > Q_3 + 1.5 \times \text{IQR} \tag{1}$$

where Q_1 and Q_3 are the first and third quartiles, and IQR = Q_3 - Q_1. Points outside this range are replaced via linear interpolation using neighboring inlier values to preserve data continuity.

Step 2: Elevation Smoothing

After outlier removal, the elevation profile may still exhibit high-frequency noise or step changes that do not correspond to the actual grade. These variations can lead to unrealistic vehicle vertical movement, especially on road segments that should be relatively flat or gradually changing. To reduce this noise while preserving the real-world roadway shape, several data smoothing techniques can be applied, such as moving average (Smith, Steven W and others 1997), Savitzky-Golay filtering (Savitzky and Golay 1964), or Butterworth filtering (Butterworth et al. 1930). In this paper, a moving average smoothing method is applied. Moving average provides a simple yet effective way to reduce small fluctuations without introducing significant shifts or over-smoothing.The moving average filter replaces each point in the elevation profile with the average of its neighboring values over a defined window size. Mathematically, for a sequence of elevation points $e_1, e_2, \ldots, e_n$, the smoothed elevation $\bar{e}_i$ at position i, using a moving average with a window size of $2k+1$, is computed as:

$$\bar{e}_i = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} e_j \tag{2}$$

The window length is chosen based on a trade-off between reducing high-frequency noise and preserving meaningful elevation transitions. In this study, elevation data are sampled at 10-meter intervals, and a window length corresponding to 200 meters (i.e., 20 points) was applied for smoothing.

While a simple moving average applies equal weights across the window, a weighted moving average, which gives more importance to central points, could be explored in the future to better preserve local elevation features while still reducing noise.

Step 3: Grade Smoothing

Grade is the first derivative of elevation with respect to horizontal distance. As a result, even mildly noisy elevation profiles can lead to unrealistic and erratic grade values. Therefore, realistic roadway grade for simulation requires an additional smoothing step beyond elevation smoothing. In this paper, the Savitzky-Golay filter is used to smooth the grade after calculating it from the smoothed elevation data. This filter performs a local polynomial regression within a sliding window to smooth the signal. For a window centered at index i, it fits a polynomial of the form

$$f(x) = a_0 + a_1 x + \cdots + a_p x^p \tag{3}$$

by minimizing the least-squares error:

$$\min_{a_0,\ldots,a_p} \sum_{j=-k}^{k} (g_{i+j} - f(j))^2 \tag{4}$$

where g_{i+j} denotes the raw grade value at position $i+j$. The smoothed value at the center of the window is then given by $f(0)$. A polynomial order of $p = 2$ is used in this study.

This filter is particularly well-suited for preserving the shape and local features of the signal (e.g., grade transitions) while reducing noise. Unlike moving average, which may flatten peaks or inflection points, the

Savitzky-Golay filter preserves local features by fitting a polynomial to the data within a sliding window, maintaining the shape of transitions while reducing noise.

Stopping Criteria

In this paper, smoothing is performed using fixed parameters rather than iterative refinement. We rely on visual inspection to ensure the smoothed elevation profile maintains the overall shape of the raw data. Additionally, the smoothed data are compared directly to the original elevation to verify minimal distortion. Grade smoothing is further evaluated against design constraints: maximum allowable grade values recommended by the American Association of State Highway and Transportation Officials (AASHTO) "Green Book" (Hancock and Wright 2013) are incorporated to ensure physical realism of highway conditions.

6 RESULTS

This section presents the results of applying the proposed elevation processing workflow and its effects on traffic-vehicle co-simulation. First, the impact of elevation smoothing is analyzed to determine how well it preserves the original roadway shape while eliminating unrealistic variations. Second, the corresponding grade profiles are evaluated to assess the effectiveness of smoothing in generating smooth and realistic slope transitions. Finally, simulation results illustrate how the processed elevation and grade improve vehicle behavior in the traffic-vehicle co-simulation and the corresponding impact on energy consumption.

6.1 Elevation after elevation processing

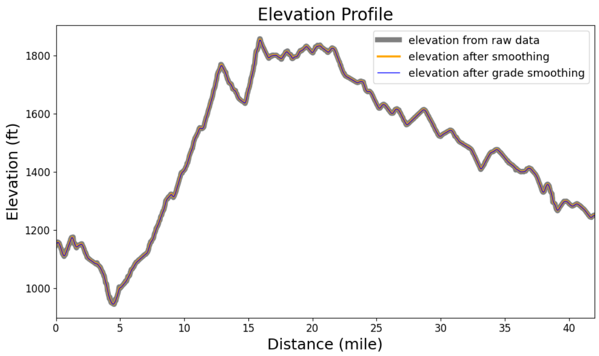
Figure 6 presents the elevation profiles after applying the proposed smoothing steps. Specifically, Figure 6a shows the elevation profile of the entire simulation corridor before and after smoothing, while Figure 6b focuses on the first mile (5,280 ft) to highlight local geometric features. As shown in Figure 6a, the smoothing process preserves the overall shape and trend of the original elevation profile, indicating that major topographic features (vertical alignment) are retained. In Figure 6b, each sag or crest corresponds to a vertical curve commonly found in roadway design. The raw elevation data exhibits frequent and sharp sags and crests that are unrealistic for highway geometry. After elevation smoothing, these transitions become more gradual, eliminating abrupt changes while maintaining the general terrain contour. When grade smoothing is also applied, the resulting elevation profile displays even smoother vertical transitions.

Figure 6c and Figure 6d display the change of elevation after the smoothing process. It can be seen that smoothing operations introduce only minimal deviations from the original data. Both elevation and grade smoothing yield elevation changes generally within ± 5 ft, with all changes within ± 10 ft. This indicates that the smoothing workflow effectively reduces noise and abrupt changes from the raw elevation data while preserving the overall shape and characteristics of the elevation profile, making it suitable for integration into traffic-vehicle co-simulation while maintaining real-world roadway conditions.

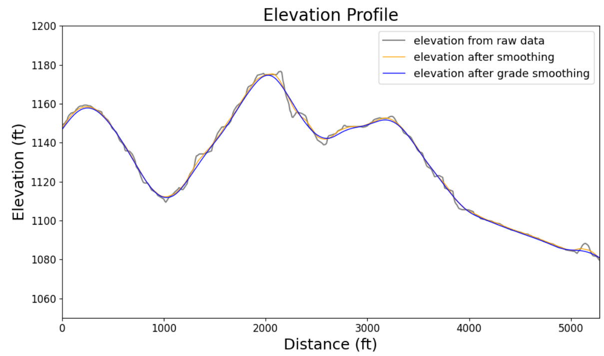
6.2 Grade after elevation processing

Figure 7 compares grade calculated from the raw elevation data, grade after elevation smoothing, and grade after both elevation and grade smoothing. Figure 7a shows the grade profile of the entire 40-mile corridor, while Figure 7b focuses on the first 5 miles to better illustrate local fluctuations. As shown in Figure 7a, elevation smoothing significantly reduces the large, random fluctuations present in the raw grade profile. The grade computed from the smoothed elevation generally falls within the range of -5% to 5%, aligning with the maximum road grade limits recommended by the "Green Book" (Hancock and Wright 2013). For highways such as I-81, where the posted speed limit is typically 65–70 mph (with a design speed of 70–75 mph), AASHTO recommends a maximum grade of 5%. The results demonstrate that raw elevation data can produce unrealistic slope estimates exceeding these limits, and that elevation smoothing helps preserve geometric consistency with actual road design standards.

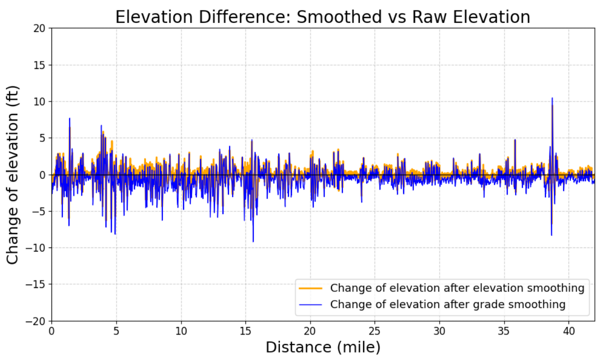
Moreover, from both Figure 7a and Figure 7b, it is evident that applying grade smoothing after elevation smoothing further reduces smaller, localized fluctuations. This is particularly important because



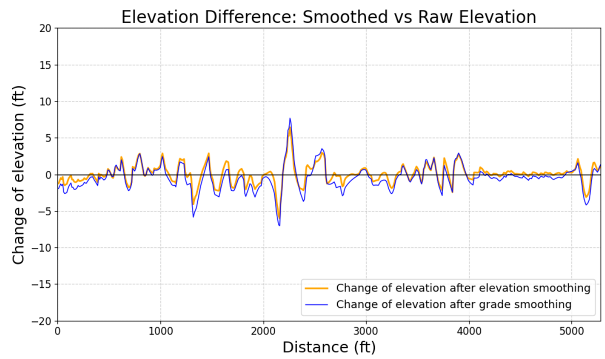
(a) elevation profile of entire corridor



(b) elevation profile of first 1-mile (5280-ft) segment



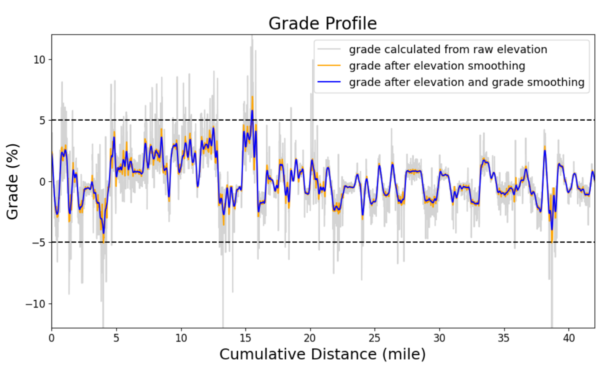
(c) elevation difference of entire corridor



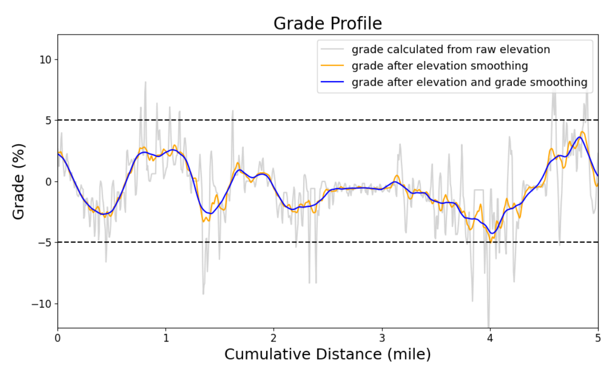
(d) elevation difference of first 1-mile (5280-ft) segment

Figure 6: Elevation before and after smoothing

road grades should change gradually as vertical alignment in roadway design follows smooth curvature to ensure drivability and safety. Sudden reversals (i.e., where a grade abruptly increases after a decrease or vice versa) are physically unrealistic. The final smoothed grade profile reflects the continuous and smooth nature of real-world road geometry, enhancing the reliability of simulation for gradient-sensitive vehicle.



(a) entire corridor



(b) first 5-mile segment

Figure 7: Grade before and after smoothing

6.3 Simulation after elevation processing

Figure 8 compares truck motions: the truck experiences substantially grade variations and dramatic chassis motion before smoothing, while the chassis motion in the environment with elevation smoothing remains steady and stable. This further removes the potential hazards of destabilizing truck lateral motions (recall Figure 4), enhancing simulation reliability.

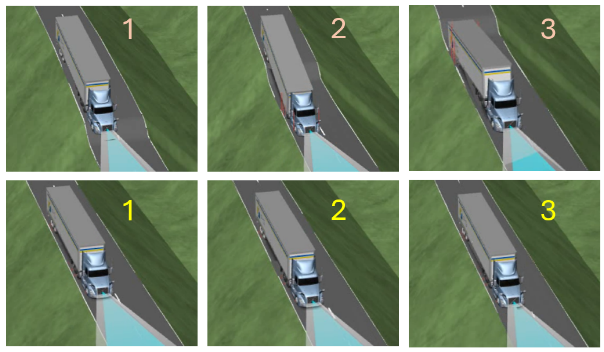


Figure 8: Truck vertical motions: the first (second) row shows simulation before (after) elevation smoothing

Next, we simulate the truck operations on the first 4.1 miles of the selected I-81 segment to compare the energy consumption with and without elevation smoothing. Note that we do not use the entire corridor in this comparison, as the truck would run off road (recall Figure 4) in the environment without proper elevation smoothing. Table 1 demonstrates the negative impact of unprocessed elevation on energy consumption under different trailer payloads. This is attributed to the road bumps associated with the unprocessed elevation, which produce more tire rolling resistance and induce the truck to execute more irregular throttle/brake actions. Interestingly, the truck without any payload suffers from the most dramatic increase in energy consumption. This is because the truck controller behaves more aggressively when the overall weight is reduced and the truck can be maneuvered more freely to stay close to the desired operating speed. The vehicle controller adapts to different payloads through a parsimonious model whose parameters are adaptively updated at each time step to capture the dynamics of vehicle motions. The model can maintain agnostic to characterize vehicle dynamics due to varying payloads, grade, air drag, and tire frictions, so that the controller can recognize the dynamics and properly respond to disturbances and manage desired car-following and speed-tracking performance. Under the impacts of payloads and grade, the controller learns the vehicle motions differently: requiring greater (smaller) reference acceleration to achieve desired desired maneuver when confronting an uphill (downhill) and heavier (lighter) payload. Correspondingly, the truck controller reacts even more aggressively to counteract the additional resistance from road bumps. By contrast, when this is payload onboard, controller will leverage the induced inertial to maneuver the truck, leading to reduced variations in energy consumption.

Table 1: Energy consumption comparison

Trailer payload (tons)	0	10	20	30
Energy consumption w/o elevation smoothing (kWh/mi)	1.54 (38.67%↑)	2.83 (17.74%↑)	3.41 (17.79%↑)	4.03 (18.41%↑)
Energy consumption w/ elevation smoothing (kWh/mi)	1.11	2.41	2.89	3.40

7 CONCLUSION

In summary, this paper demonstrates the significant role of elevation processing for traffic-vehicle co-simulation. Unprocessed elevation data can severely compromise simulation stability, realism, and energy estimation, particularly for gradient-sensitive vehicle types such as electric vehicles and heavy-duty vehicles operating on roads with frequent elevation changes. By implementing a structured workflow consisting of outlier filtering, elevation smoothing, and grade smoothing, we successfully mitigate vehicle vertical instability and artificial energy fluctuations while preserving realistic roadway geometry in the traffic-vehicle co-simulation. The results validate the effectiveness of the proposed approach in enabling a more reliable assessment of vehicle performance in a high-fidelity simulation environment.

Future research points to improving grade smoothing techniques by incorporating principles from roadway vertical alignment design. Current smoothing methods primarily target noise reduction without fully considering geometric design standards. A more refined approach would involve identifying key vertical alignment points such as the Point of Vertical Curvature (PVC) and Point of Vertical Intersection (PVI) to better preserve the structure of real-world vertical curves. Additionally, the smoothing algorithm should consider constraints such as the minimum vertical curve length and the minimum distance between adjacent reversal vertical curves to reflect design practices used in road geometric design. In addition, future work should consider incorporating more refined stopping criteria, such as curvature-based thresholds, localized slope continuity checks, or constrained smoothing that preserves elevation at surveyed control points or critical infrastructure locations. Finally, future work will explore and compare the performance of different smoothing techniques on elevation smoothing.

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