Trajectory-based Performance Ranking System of Low-level Automated Vehicles*

Chengyuan Ma, Xiaopeng Li*, Ke Ma, Peng Zhang, Keke Long, Sikai Chen

Abstract—**This study introduces a comparative evaluation and ranking system for low-level automated vehicles (LAVs) using real-world trajectory data. In the framework of the proposed evaluation system, different LAVs' behaviors are first modeled based on their trajectory data. Test scenarios are designed according to the specific test goals. Subsequently, simulation tests are then conducted using extracted vehicle behavior models in the designed traffic scenario. Several measurements in terms of safety, environmental impact, and mobility efficiency are used to evaluate and rank the performance of different types of LAVs. In numerical studies, the Long Short-Term Memory (LSTM) models are used to extract LAVS' behavior features from the OpenACC dataset, demonstrating high accuracy in vehicle motion prediction and specificity among different types of LAVs. Simulation tests on a real-world road corridor validate the applicability of the proposed framework. As more data sources on LAVs become available, the proposed evaluation and ranking system has the potential to inform customers and government agencies during decision-making.**

I. INTRODUCTION

Automated vehicles (AVs) have garnered significant attention in recent years as a transformative technology with the potential in reducing environmental impact and improving driving experience by minimizing human error and optimizing vehicle operation. Particularly, low-level automated vehicles (LAVs), which are equipped with Level 1-2 automation features as defined by the Society of Automotive Engineers (SAE), are becoming increasingly common. Nowadays, 92% of new cars have Adaptive Cruise Control (ACC; Level 1 automation), and 50% of new cars have lateral lane control (Level 2 automation). The market penetration rate of Advanced Driver Assistance Systems (ADAS)-equipped vehicles is projected to increase from 2% in 2015 to 40% in 2040 [1].

With the gradual emergence of LAVs on road networks, conducting thorough evaluations of these vehicles has become crucial [2]. Extensive simulations and field tests have been conducted in both the research and industry fields in terms of safety [3], mobility efficiency [3, 4], and environmental impact [5, 6]. One common method is to conduct experiments in specific, controlled scenarios, which allows for a large amount of repeatable testing [7]. These evaluation methods select representative driving conditions of various category and test the passability and detailed performance of the AVs during the testing process [7, 8]. These methods focus on a limited selection of scenarios with specific parameters, fail to reflect the comprehensive evaluation results under various real-world conditions [10]. Another method is to test AVs in comprehensive public road scenarios for long-term continuous random testing [9, 10]. However, due to the spatiotemporal complexity and high interactivity of real-world naturalistic driving environments, sometimes hundreds of billions of miles would need to be tested. Recent studies have made significant progress in addressing this challenge utilizing technologies including important sampling and dense reinforcement learning [13]. In addition to testing under various driving scenarios, sub-system failure risk assessment is also investigated to evaluate the reliability and robustness of AVs [11, 12].

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However, existing studies usually focus on developing tests for individual types of AVs, lacking a comparative evaluation across different types of AVs. A major challenge of the comparative evaluation lies in the limited availability of detailed control logic for different types of AVs. Existing scenario-based test methods typically require precise knowledge of a certain AV's driving strategies [15]. However, in comparative evaluations, the exact control strategies of all types of AVs may not always be accessible due to commercial secrecy concerns [16].

Furthermore, the behavior of AVs during controlled tests may differ from real-world driving conditions due to various factors such as the test environment, the conditions of AVs, or the interaction between AVs and other road users. This discrepancy between controlled tests and real-world conditions could potentially undermine the credibility of the test results, as they may not accurately represent the performance of AVs in everyday driving scenarios.

Thanks to the increasing number of AVs in road networks, the availability of extensive vehicle trajectory data provides a novel avenue for a comprehensive evaluation of different AV types. By extracting driving behavior models based on trajectory data recorded when AVs are operating in ADAS mode, it becomes possible to build simulations that accurately represent their behavior. These simulations can then be employed to test and evaluate various AV types, enabling comparison and ranking of their performance across multiple dimensions.

The objective of this paper is to propose a methodology for the comprehensive and fair evaluation of different types of LAVs, without relying on prior knowledge of their specific control logic. First, we construct behavior models of different types of LAVs leveraging their trajectory data. Next, we develop realistic driving scenarios according to the test goals. Finally, we evaluate and rank the performance of different types of LAVs in these scenarios, using various measurements.

The remainder of this paper is organized as follows. Section II proposes the model framework. Section III provides the detailed process of trajectory construction, simulation scenario development, and evaluation processes. Section IV presents the results of numerical studies. Section V provides concluding remarks and future research directions.

II. FRAMEWORK

This section states the trajectory-based LAV performance ranking problem and introduces the proposed model framework. This study aims to evaluate and rank different types of LAVs in terms of safety, efficiency, and eco-performance, using their real-world trajectory data as input. As shown in Figure 1, the proposed trajectory-based LAV performance ranking system can be divided into 3 key modules: trajectory construction, scenario development, and performance evaluation.

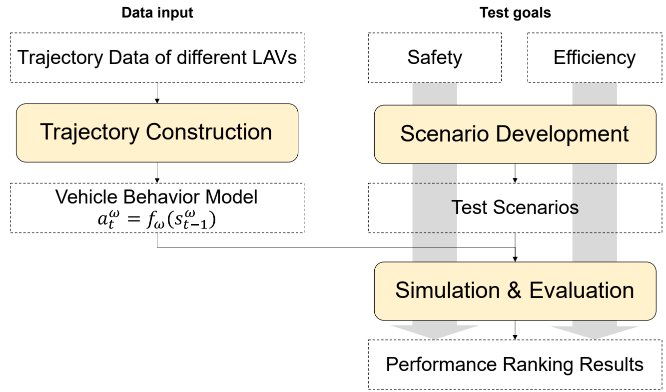

Figure 1. The model framework of the trajectory-based performance ranking system of LAVs.

The trajectory construction module aims to derive vehicle behavior models for different types of LAVs based on their trajectory data. Let t be the index of the time step. Let a_t^ω and s_t^ω be the action and the states of LAV ω at time step t. The output of the trajectory construction module is a certain type of LAVs' action function f_ω, as shown in Figure 1. In this study, only car-following behaviors are modeled for simplification. A long short-term memory (LSTM) model [17] is adopted to capture LAVs' acceleration rate at the next time step a_t, based on the real-time speed of the ego vehicle, its leading vehicle, and the distance between them. The lane-changing choice and vehicles' driving strategies during lane-changing are simulated with default models. The trajectory construction does not need any prior information on LAV's control logic.

The scenario development module designs simulation scenarios for LAV performance evaluation according to the test goals. For instance, comprehensive scenarios can be used for long-term efficiency and eco-performance tests. Critical scenarios can be designed for safety tests to reduce the computational costs of evaluation. The scenario development module provides parameters about road elements, traffic demands, and traffic control strategies for the simulation scenarios. In this study, all vehicles are assumed to be replaced by one type of LAV in simulation to avoid the comprehensive effects of the background vehicles' behaviors.

Finally, the performance of different types of LAVs is tested in simulation, where vehicles' driving behaviors are modeled by the extracted action functions. Quantitative measurements are designed to examine the performance of different types of LAVs under simulation scenarios in terms of safety, mobility, and other aspects. From this, comparison and ranking conclusions can be drawn.

III. METHODOLOGY

A. Trajectory construction

First, we need to capture the driving behaviors of LAVs. In this study, we focus on car-following behavior to demonstrate the evaluation framework. There are various types of models to depict car-following behaviors in the existing literature. In this study, an LSTM model is adopted to model LAVs' longitudinal driving behavior at discrete time steps. The structure of the LSTM model is illustrated in Figure 2. The input of the LSTM model at time step $t-1$ is the traffic states of a LAV over historic time steps in $[t-h, t-1]$, including the speed of the ego vehicle v_t its leading vehicle, and the distance between them d_t at each time step. And the output is the LAV's acceleration rate at the next step, i.e., a_t.

Some commonly used configurations are implemented in the LSTM model. A normalization layer is incorporated prior to the LSTM layers to standardize the input data, while a denormalization layer is applied after the LSTM layers to revert the output data to its original scale. The last hidden state in the sequence of the LSTM is used as the model's prediction.

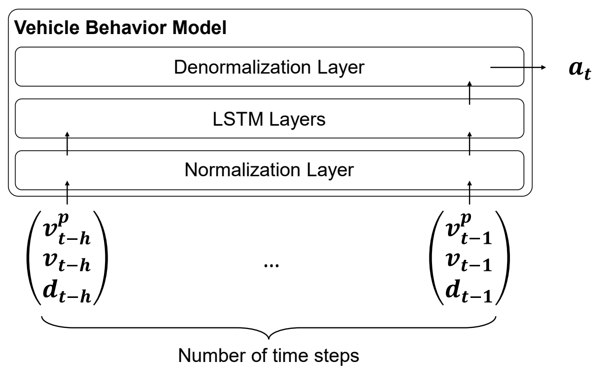

Figure 2. The structure of the LSTM model.

The advantage of the trajectory-based vehicle behavior modeling approach is that it does not require any prior information of vehicle control logic. This makes the framework applicable for comparing a variety of vehicle types. In addition, the proposed framework is flexible and can accommodate other types of models based on specific requirements.

B. Scenario development

The design of test scenarios for LAV evaluation is a critical aspect of the ranking system, providing a series of parameters that describe the test road segments, traffic control strategies [2], and so forth. Typically, the action mode of vehicles is also included in the scenario design. However, in this study, vehicles operate according to the extracted behavior model.

The design of test scenarios is highly dependent on the specific test purpose. For safety testing of LAVs, a large number of different test experiments are required if only normal traffic scenarios are adopted due to the rarity of safety-critical events [18]. A potential solution to this challenge is to choose safety-critical scenarios with artificial intelligence-based importance sampling [19]. This approach shows great potential to accelerate the evaluation process by multiple orders of magnitude, making it feasible to conduct comprehensive safety evaluations despite the rarity of safety-critical events.

For evaluating the mobility and environmental cost of LAVs, adopting more comprehensive scenarios can provide a better representation of real-world conditions. In this case, we can design scenarios based on real-world road networks and traffic demand. These scenarios would simulate a wide range of driving conditions and situations, allowing us to assess the overall performance of LAVs. Besides, using real-world road networks and traffic demand in the test scenarios allows the comparison of the different LAVs' performances in different cities, and the identification of the best suited type of LAV to the unique conditions of each city. Further, it provides insights into the relationship between vehicle performance and the structure of the road network.

C. Simulation and evaluation

Following the extraction of the vehicle motion model and the design of test scenarios, the corresponding simulations are conducted to assess the performance of the LAVs. The vehicle behavior models are trained to predict vehicles' actions at the next time step. They are used in the simulation in a recursive approach for multiple time step prediction, which means the predicted vehicle behaviors at each time step become the basis for future predictions of vehicle behaviors. This "open-loop" approach can lead to larger prediction errors compared to one-step predictions due to the cumulative effect of these errors over multiple time steps. To mitigate this, the feedback effect in the extracted car following model (i.e., vehicles tend to accelerate when the headway to the lead vehicle is too far, and vice versa) is utilized to maintain realistic vehicle trajectory prediction over long durations.

A series of measures are developed to evaluate various aspects of LAV performance, quantifying the performance of various types of LAVs in a consistent and comparable way. Surrogate measures can be used for safety evaluation. Finally, we aim to integrate these different aspects into a single overall result, e.g., to convert the performance measures into a monetary value, which provides a common unit of measurement for comparison. This approach allows us to rank different types of LAVs based on their overall performance, providing a comprehensive and comparative evaluation of different types of LAVs.

IV. EXPERIMENTS

A. Trajectory construction

The OpenACC dataset, collected by the Joint Research Centre, is adopted to extract LAVs' behavior models in this study [5]. This dataset includes trajectories from several different types of LAVs with ACC engaged on a ring road. Vehicles' position and speed are collected at 0.1-second intervals. LSTM models are developed as described above. The length of a time step is set at 0.1 s, and the horizon length of the data input is set as 15, i.e., 1.5 s. The Adam optimization algorithm [20] is utilized in the training process. The initial learning rate, set at 0.005, is designed to decrease during the training process. The test results demonstrate the promising accuracy of the proposed LSTM model in the "open-loop" prediction of LAVs' longitudinal positions, achieving a root mean square error (RMSE) of less than 3 m.

In addition to prediction accuracy, it is crucial to demonstrate the specificity of the trained LSTM models for different types of LAVs, which indicates that a model trained for one type of LAV may not be suitable for predicting the behavior of other types of LAVs. The specificity of the vehicle behavior model is essential for comparing the performance of different types of LAVs in the performance evaluation. Therefore, we employ four LSTM models, each trained on data from a distinct type of LAV, to predict the behaviors of the corresponding LAV and the other LAVs. As shown in Figure 3, the matrix below presents the RMSEs in the predictions made by different models for various LAVs. The results affirm that the proposed LSTM model can not only accurately predict the behavior of the corresponding LAV but also discern the behavioral differences among various LAVs.

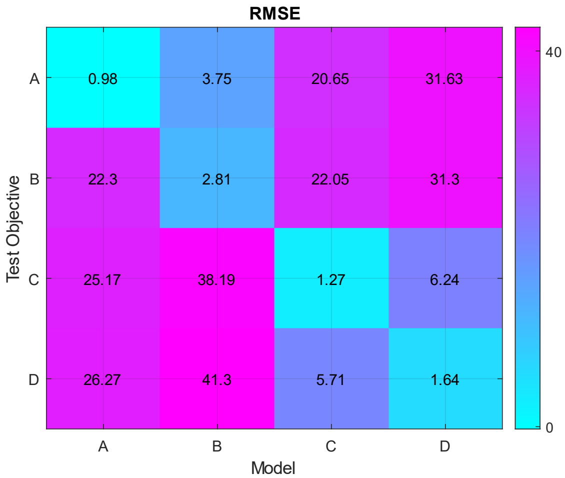

Figure 3. Model specificity for different types of LAV.

B. Simulation development

Traffic simulation is further developed in Simulation of Urban MObility (SUMO) [21] based on a part of University Avenue in front of our university in Madison, Wisconsin, as shown in Figure 4. The configuration of the road network is established with assistance from the OpenStreetMap [22].

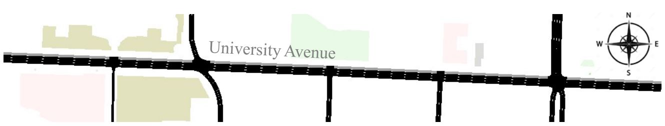

Figure 4. Simulation scenario in SUMO.

The test corridor encompasses six signalized intersections, which provide a comprehensive environment with traffic shock waves for the test LAVs. Fixed signal timings are applied at these intersections, and the test focuses on three westward lanes on the main line. The traffic demand is set at 3,600 passenger car units per hour (pcu/h) across the three lanes. In each experiment, all vehicles are set as the same type of LAV, and their behaviors are simulated with the extracted LSTM model. Five random seeds are used in the simulation for each type of LAV, considering the stochastic traffic environment.

C. Results

This section evaluates the performance of the 4 types of LAVs mentioned in terms of mobility, safety, and environmental effects.

Figure 5 shows the distribution of LAVs' travel time in the simulation experiments for 4 different types of LAVs. The distribution is presented at intervals of 10 s ranging from 60 s to 150 s. The vertical axis in Figure 6 represents the proportion of LAVs whose travel times fall within the corresponding intervals. And a smooth curve is used to connect the distribution bars for ease of comparison. The results indicate that a larger proportion of vehicles exhibit shorter travel times in the experiments for LAVs of type C and D, demonstrating their potential in mobility performance.

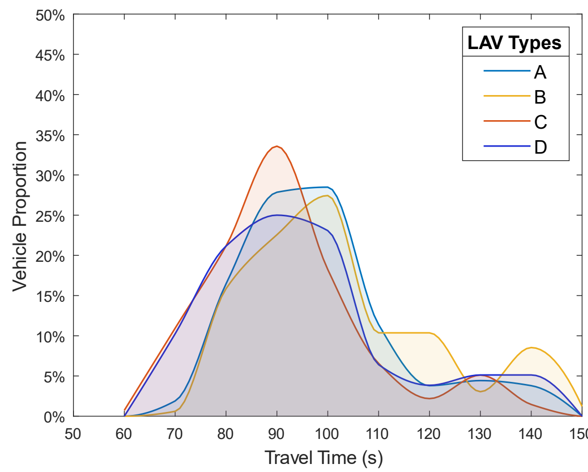

Figure 5. Distribution of different types of LAVs' travel time.

For the safety test, we extract the minimum time-to-collision (TTC) [23] for each LAV with its leading vehicle during the simulation experiment, which represents its most critical safety condition. Figure 6 illustrates the distribution of these minimum TTC values across different LAVs. The plotting principle for this distribution is similar to that in Figure 5, with intervals of 1 s ranging from 0 to 20 s. The results indicate that LAVs of type B and C may maintain larger gaps with their leaders. In contrast, the driving models of LAVs of type A and D are more likely to result in vehicles falling into conditions with shorter TTC.

Note that the vehicle behavior models are extracted based on limited data in this study, without any input regarding LAV behavior under dangerous conditions, such as crashes. Therefore, these models may not fully simulate safety-critical behaviors that rarely occur. The experiment primarily demonstrates the applicability of the proposed framework in safety testing. It can be seen in Figure 6 that even in the most dangerous conditions, the TTC remains larger than 2 seconds. Additional data and experiments are necessary for more dependable safety evaluations.

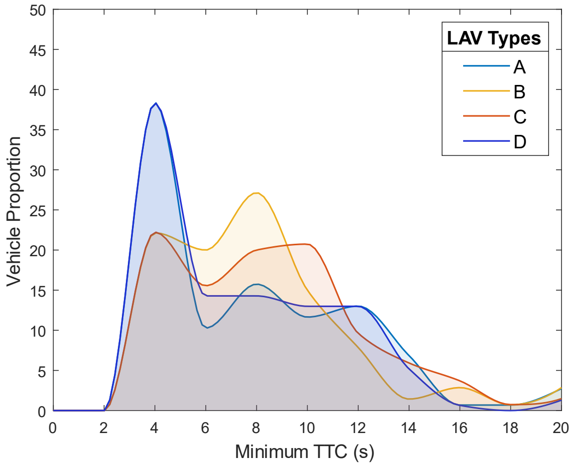

Figure 6. Distribution of different types of LAVs' minimum time-to-collision (TTC).

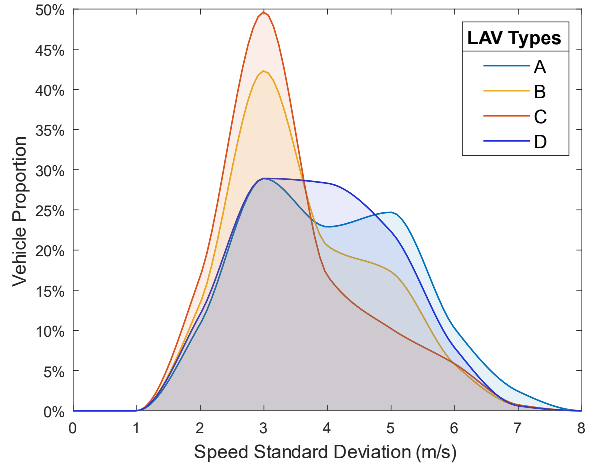

Figure 8. Distribution of different types of LAVs' speed standard deviation.

Figure 7 shows the distribution of LAVs' fuel consumption efficiency in the simulation experiments for 4 different types of LAVs. The fuel consumption model for the passenger car in reference [21] is applied for the estimation of fuel economy. The distribution is calculated with intervals of 1 L/100km ranging from 0 to 18 L/100km. The results indicate that LAVs of type B and C have significant advantages in terms of fuel consumption efficiency than LAVs A and D. More LAVs of type B and C can traverse the corridor with lower energy consumption.

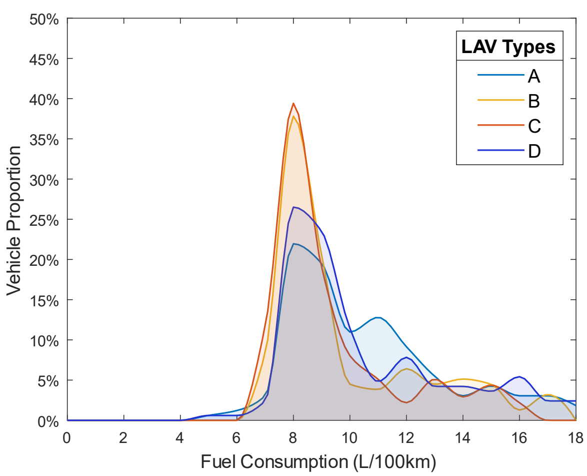

Figure 7. Distribution of different types of LAVs' fuel consumption efficiency.

To further evaluate the driving experience of different LAVs, we use the standard deviation of vehicle speeds to represent the fluctuation in driving conditions. Figure 8 shows the distribution of these speed standard deviations, with intervals of 1 m/s ranging from 0 to 8 m/s. The results reveal a trend similar to that observed in the fuel economy evaluation. Specifically, LAVs of type B and C are able to maintain a more stable speed along the signalized corridor, contributing to a smoother driving experience.

In summary, LAVs of types B and C show significant advantages over A and D in terms of both safety and environmental effects. C and D have a slight edge in terms of mobility efficiency. LAVs of type C have the best overall performance in the simulation.

V. CONCLUSION

This study presented a comprehensive evaluation and ranking system for LAVs based on their real-world trajectory data. The behavior models of different LAVs are extracted from their trajectory data using an LSTM model. Test scenarios for the LAVs are designed based on specific test goals. Subsequently, the extracted vehicle behavior model is employed in a simulation constructed based on the designed scenario in an "open-loop" mode. A range of performance measurements is utilized to evaluate the performance of different LAVs in terms of mobility efficiency, safety, and environmental impact. The conducted simulation experiments validate the applicability of the proposed framework.

Our study introduces an evaluation and ranking framework for LAVs, serving as a starting point and paving the way for several potential avenues for future research. Firstly, there is potential for the development of more sophisticated models for vehicle behavior modeling than the LSTM model used in this study. One promising approach is to construct a physical-aware artificial intelligence (AI) model since the physical nature of the control logic of ACC. The AI model could enhance the precision of the physical model under various conditions [24]. Other than model type, the data inputs in this study are also limited. Better models could be captured with the enriched trajectory dataset including LAVs' behaviors under various conditions [25, 26, 27]. In addition to the model type, the data inputs used in this study are limited. As the trajectory dataset expands to include LAV behaviors under a broader range of conditions, more accurate and comprehensive models could be developed.

Secondly, more sophisticated test scenarios could be developed for more dependable evaluations of LAVs. For mobility testing, more comprehensive scenarios could be designed, such as simulating the network of an entire city. For safety testing, scenarios that generate crucial or safety-critical situations could be developed to provide a more rigorous evaluation of LAV performance.

Finally, future work could investigate the integrated performance measurements that capture multiple aspects of LAV performance in a single number, such as a monetary value. This would provide a more comprehensive understanding of LAV performance and further enhance the utility of the evaluation and ranking system for customers and government agencies.

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