

Adaptive GLOSA with Queue Estimation, Driver Behavior Sensitivity, and Signal Timing Uncertainty: A Simulation Study

Bonigala Sandhya Rani¹, Gopiseti Anusha², Mallidi Bheemeswara Reddy³, Alapati Madhu Babu⁴, Sanam Subrahmanyam⁵, Anil Kumar Gurrapusala⁶

^{1,2,3,4}Undergraduate Students, Department of Electrical and Electronics Engineering, Bapatla Engineering College, Bapatla, Andhra Pradesh, India

^{5,6}Assistant Professors, Department of Electrical and Electronics Engineering, Bapatla Engineering College, Bapatla, Andhra Pradesh, India

Abstract - Signalized intersections often lead to unnecessary speed variations, delayed vehicle movement, and increased energy consumption during the approach phase. This paper presents an adaptive Green Light Optimal Speed Advisory (GLOSA) framework developed in MATLAB/Simulink for a signalized intersection with queue-aware and uncertainty-sensitive operation. The proposed model integrates a traffic signal controller, queue estimation module, advisory speed generation logic, driver response model, and vehicle dynamics. To improve the realism of the simulation, queue evolution is updated using the actual simulation time, and the advisory logic accounts for remaining distance, vehicle speed, signal phase, remaining signal time, and queue clearance delay. Driver behavior sensitivity is also examined by considering cautious, normal, and aggressive response characteristics, while signal timing uncertainty is incorporated to study advisory behavior under non-ideal timing information. The model is evaluated through queue evolution, advisory and vehicle speed behavior, near-stop-line distance response, driver-response variation, and comparative fuel and CO₂ estimation. The results show that the developed framework provides a structured and realistic basis for evaluating adaptive GLOSA behavior under practical operating conditions. The study highlights the influence of queue dynamics, driver compliance, and signal timing uncertainty on advisory tracking and overall approach performance at signalized intersections.

Key Words: Green Light Optimal Speed Advisory (GLOSA), queue estimation, signalized intersection, driver behavior sensitivity, signal timing uncertainty, MATLAB/Simulink, fuel and CO₂ analysis.

1. INTRODUCTION

Signalized intersections are critical control points in urban traffic networks, but they often introduce unnecessary deceleration, stopping, idling, and delayed vehicle movement during the approach phase. These effects not only reduce traffic flow efficiency but also contribute to increased fuel consumption and exhaust emissions, particularly when vehicles fail to adapt their speed appropriately to the upcoming signal condition [4]. In recent years, Green Light Optimal Speed Advisory (GLOSA) has emerged as a

promising approach for improving intersection approach behavior by providing speed guidance that helps vehicles pass through signalized intersections more smoothly. By reducing unnecessary stopping and aggressive speed changes, GLOSA-based strategies can support more efficient, economical, and environmentally conscious driving behavior [1]-[3].

Green Light Optimal Speed Advisory (GLOSA) has been widely studied as an intelligent transportation strategy for improving vehicle movement near traffic signals by recommending an appropriate approach speed. By using signal timing information, a GLOSA system can help reduce unnecessary stopping, smooth the vehicle trajectory, and improve energy-efficient driving behavior. However, practical implementation is influenced by several factors such as queue formation near the stop line, imperfect driver response, and uncertainty in available signal timing information. Therefore, the performance of a GLOSA system depends not only on advisory generation itself, but also on how realistically surrounding traffic and driver behavior are represented in the model.

Although GLOSA has shown strong potential for improving signalized-intersection approach behavior, realistic implementation requires more than basic speed guidance. In practical conditions, vehicle movement is influenced by queue formation near the stop line, non-uniform driver response, and uncertainty in the available signal timing information. If these factors are ignored, the advisory strategy may appear effective in simulation while not accurately representing actual approach behavior. Therefore, a more meaningful GLOSA evaluation should account for queue-induced delay, driver-following sensitivity, and non-ideal timing conditions within the same simulation framework.

In this work, an adaptive GLOSA framework is developed in MATLAB/Simulink for a signalized intersection by integrating queue estimation, queue-aware advisory generation, driver response modeling, and signal timing uncertainty analysis within a single simulation environment. The proposed study includes queue evolution based on actual simulation time, advisory logic influenced by queue clearance delay and signal phase information, driver behavior sensitivity under cautious, normal, and aggressive

conditions, and uncertainty analysis using modified remaining signal time. The objective of the paper is to provide a structured simulation-based evaluation of adaptive GLOSA behavior under more practical operating conditions and to examine its effect on advisory tracking, approach behavior, and comparative fuel and CO₂ performance.

2. LITERATURE REVIEW

Green Light Optimal Speed Advisory (GLOSA) has been studied as an intelligent transportation strategy for improving vehicle movement at signalized intersections by recommending an appropriate approach speed based on signal timing information. Existing studies have shown that GLOSA can reduce unnecessary stopping, smooth vehicle approach trajectories, and improve fuel-efficient driving behavior under controlled conditions. Many simulation-based studies have focused on advisory speed generation using signal phase and timing information to help vehicles pass through intersections more efficiently. As a result, GLOSA has become an important research topic in the broader area of eco-driving and intelligent traffic management [1], [4]–[6].

Recent studies have also recognized that the practical performance of GLOSA depends on more than advisory generation alone. Factors such as queue formation near the stop line, variations in driver compliance, and uncertainty in signal timing information can significantly influence the actual response of the vehicle during the approach phase. Therefore, simulation-based GLOSA evaluation becomes more meaningful when these non-ideal conditions are included in the model. In this context, the present work focuses on integrating queue estimation, queue-aware advisory logic, driver behavior sensitivity, and signal timing uncertainty within a single MATLAB/Simulink framework for a more structured and practical assessment of adaptive GLOSA behavior [5], [6].

3. METHODOLOGY / SYSTEM MODEL

3.1 System Architecture / Model Overview

The proposed adaptive GLOSA framework is developed in MATLAB/Simulink to represent vehicle approach behavior at a signalized intersection under queue-aware and uncertainty-sensitive conditions. The overall model consists of a traffic signal controller, a queue estimation module, an advisory speed generation block, a driver response model, and a vehicle dynamics section. These components operate in a closed-loop manner, where the signal and queue information are used to generate advisory speed, the driver model responds to that advisory, and the updated vehicle motion is fed back to the advisory block through the remaining-distance calculation. This structure allows the model to represent not only advisory generation, but also the practical response of the vehicle under changing signal and queue conditions.

The traffic signal controller provides the current signal phase and remaining phase time, while the queue estimation logic determines queue length and the corresponding queue clearance delay. These signals are supplied to the adaptive GLOSA advisory block, which computes the target and applied advisory speed based on the current approach condition. The driver response model then follows the advisory according to the selected driver behavior parameters, and the resulting vehicle speed is used to update travelled distance and remaining distance to the stop line. The overall signal flow of the proposed framework is presented through the system flowchart, which summarizes the interaction between signal control, queue estimation, advisory generation, driver response, vehicle dynamics, and performance evaluation.

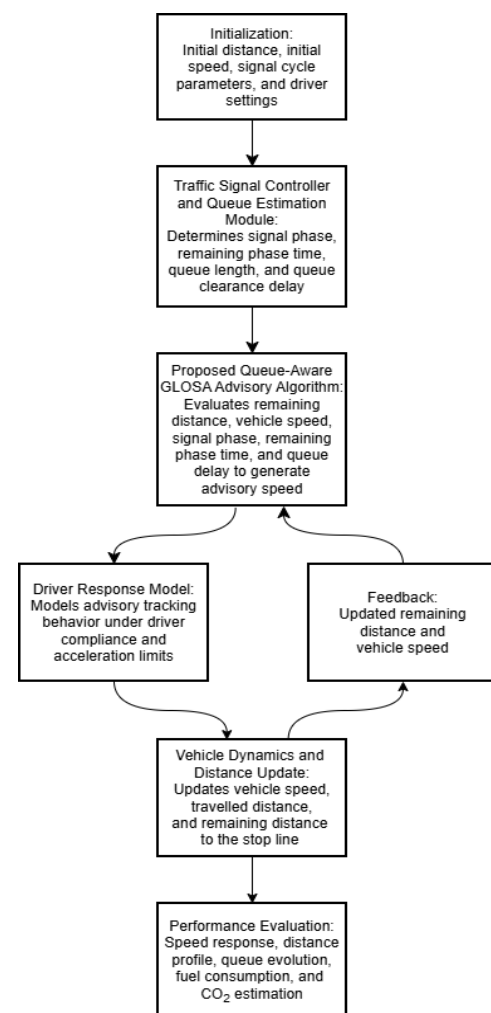


Fig -1: Overall signal flow and functional structure of the proposed adaptive GLOSA framework.

Figure 1 illustrates the overall signal flow and functional structure of the proposed adaptive GLOSA framework. The model begins with initialization of the main simulation conditions, including vehicle state, signal cycle parameters, and driver settings. The traffic signal controller and queue

estimation module determine the signal phase, remaining phase time, queue length, and queue clearance delay, which are then supplied to the queue-aware GLOSA advisory block. Based on these inputs, the advisory algorithm generates an appropriate speed recommendation for the approaching vehicle. The driver response model follows the advisory subject to driver compliance and acceleration limits, and the vehicle dynamics block updates speed, travelled distance, and remaining distance to the stop line. These updated motion variables are fed back into the advisory logic, forming a closed-loop simulation structure. The final outputs are used for performance evaluation in terms of approach behavior, queue evolution, and comparative fuel and CO₂ estimation.

3.2 Queue Estimation Model

Queue estimation is included in the proposed framework to represent the influence of vehicles accumulated near the stop line during blocked signal phases. In the model, queue behavior is described using queue length and queue clearance delay so that the advisory logic can account for the additional time required before the stop line becomes usable. The queue length is updated using the actual elapsed simulation time instead of a fixed assumed time step, which ensures physically consistent behavior under both fixed-step and variable-step simulation. During red and yellow phases, the queue grows according to the arrival rate of vehicles, while during the green phase it evolves according to the difference between arrival and discharge rates. The corresponding queue clearance delay is then estimated through a headway-based formulation and supplied to the advisory block for queue-aware speed guidance.

The queue evolution and queue clearance delay used in the model are expressed as follows:

$$(1) N_{\text{queue}}(k) = N_{\text{queue}}(k-1) + \Delta N(k)$$

$$(2a) \Delta N(k) = \lambda \Delta t, \text{ during red or yellow}$$

$$(2b) \Delta N(k) = (\lambda - \mu) \Delta t, \text{ during green}$$

$$(3) T_{\text{queue}} = N_{\text{queue}} \times t_{\text{headway}}$$

In the above formulation, $N_{\text{queue}}(k)$ represents the queue length at the current simulation step, while $N_{\text{queue}}(k-1)$ denotes the queue length from the previous step. The term $\Delta N(k)$ gives the change in queue length during the elapsed simulation interval. During red and yellow phases, the queue increases according to the vehicle arrival rate λ , whereas during the green phase the queue evolves according to the difference between the arrival rate λ and discharge rate μ . Here, Δt denotes the actual elapsed simulation time, which allows the queue update to remain physically consistent under both fixed-step and variable-step simulation. The queue clearance delay T_{queue} is then estimated using the queue length and the discharge headway t_{headway} , representing the expected time required for the queued vehicles to clear before the stop line becomes effectively available for the approaching vehicle.

3.3 Adaptive GLOSA Advisory Algorithm

The adaptive GLOSA advisory algorithm is responsible for generating a speed recommendation for the approaching vehicle based on the current traffic signal condition, remaining phase time, queue clearance delay, remaining distance to the stop line, and current vehicle speed. The objective of the advisory logic is to avoid unnecessary stopping, reduce abrupt speed variation, and guide the vehicle toward a smoother and more efficient approach. In the proposed framework, the advisory is not based only on the nominal signal phase, but also on whether queued vehicles ahead are expected to delay the effective usability of the stop line. As a result, the generated speed recommendation becomes sensitive to both signal timing and queue conditions.

The target advisory speed is fundamentally determined using the ratio of remaining distance to an effective arrival time, scaled by a conservative margin factor. This can be expressed as follows:

$$(4) v_{a,\text{target}} = \eta d / T_{\text{arrived}}$$

where $v_{a,\text{target}}$ is the target advisory speed, η is the advisory margin factor, d is the remaining distance to the stop line, and T_{arrive} is the effective arrival time considered by the advisory logic. In the proposed model, the effective arrival time depends on the current signal phase and queue condition. During the red phase, the advisory is influenced by the sum of the remaining red time and queue clearance delay. During the green phase, if the queue is not yet cleared, the vehicle approach is guided more conservatively so that the stop line is not reached prematurely. During the yellow phase, a conservative policy is applied to avoid unrealistic or unsafe passage attempts near the phase transition.

To improve the practical behavior of the advisory near the intersection, the final model also includes stop-line handling logic. A small standstill gap before the stop line is considered in order to avoid unrealistic exact-zero stopping behaviour, and the advisory is constrained so that the vehicle does not accelerate aggressively toward the stop line when queue delay is still present. Therefore, the proposed GLOSA advisory algorithm performs as a queue-aware and phase-aware speed guidance mechanism, rather than a simple free-flow speed recommendation based only on signal timing.

3.4 Driver Behavior Model

The driver behavior model is included in the proposed framework to represent the practical response of the vehicle to the generated advisory speed. Instead of assuming perfect advisory tracking, the model considers that the actual vehicle speed follows the advisory with a finite response determined by driver compliance and acceleration limits. This allows the simulation to capture more realistic approach behavior and makes the advisory evaluation meaningful under different

driver conditions. In the present work, driver sensitivity is examined using cautious, normal, and aggressive response settings, which differ in compliance gain and allowable acceleration and deceleration limits.

The driver response is formulated using the speed-tracking error between the advisory speed and the actual vehicle speed. The control effort generated by the driver model is proportional to this error and is then constrained by acceleration saturation limits to avoid unrealistic motion. This can be expressed as follows:

$$(5) e_v = v_{\text{advisory}} - v_{\text{actual}}$$

$$(6) a_{\text{cmd}} = K_d e_v$$

$$(7) a = \text{sat}(a_{\text{cmd}}, a_{\text{min}}, a_{\text{max}})$$

where e_v is the speed-tracking error, K_d is the driver compliance gain, a_{cmd} is the commanded acceleration, and a is the final acceleration after applying the acceleration and deceleration limits. The updated acceleration is then integrated in the vehicle dynamics section to obtain the actual vehicle speed. Through this formulation, the model captures the effect of driver-following behavior on advisory tracking performance and enables comparative analysis under different driver-response conditions.

3.5 Simulation Setup

The proposed adaptive GLOSA framework is simulated in MATLAB/Simulink for a single-vehicle approach to a signalized intersection. The simulation is carried out using a fixed signal cycle with red, green, and yellow phases, and the vehicle is initialized with a predefined distance from the stop line and an initial speed condition. The traffic signal controller, queue estimation logic, advisory speed generation block, driver response model, and vehicle dynamics are integrated within the same closed-loop environment so that the effect of signal timing, queue delay, and driver-following behavior can be evaluated consistently during the approach phase.

The simulation settings are selected to represent practical intersection approach conditions while maintaining a clear and interpretable model structure. The advisory logic is bounded by speed limits and influenced by a conservative margin factor, while the queue model uses arrival and discharge rates together with a headway-based queue clearance delay formulation. Driver response is represented through compliance gain and acceleration limits, and the model is further evaluated under cautious, normal, and aggressive driver settings to study driver behavior sensitivity. In addition, signal timing uncertainty is examined by modifying the remaining signal time in order to observe its influence on advisory generation and vehicle response.

The overall simulation setup is therefore designed to support the evaluation of queue-aware advisory behavior, driver-following sensitivity, and uncertainty-aware GLOSA performance within a unified MATLAB/Simulink framework.

4. RESULTS AND DISCUSSION

The proposed adaptive GLOSA framework is evaluated in MATLAB/Simulink to examine its behavior under queue-aware and uncertainty-sensitive operating conditions. The analysis focuses on queue dynamics, advisory speed generation, vehicle response during the approach phase, driver behavior sensitivity, and the effect of signal timing uncertainty. In addition, comparative fuel consumption and CO₂ emission estimates are used to study the energy-related implications of the modeled approach behavior. The discussion in this section first explains the core behavior of the improved model and then examines its sensitivity under different driver and signal conditions.

4.1 Core Model Behavior

The core behavior of the proposed model is first examined using the queue evolution, advisory response, vehicle speed behavior, and distance profile during the approach to the signalized intersection. The queue length and queue clearance delay plots verify that the queue estimation logic evolves consistently with time and shows time-varying queue behavior consistent with the operation of the proposed queue estimation model. The advisory-related plots show that the generated speed guidance remains responsive to both signal timing and queue conditions, while the driver response and vehicle speed plots indicate that the vehicle follows the advisory with a practical lag rather than instantaneous tracking. The distance remaining profile further shows a conservative near-stop-line approach behavior, indicating that the queue-aware advisory prevents premature arrival at the stop line.

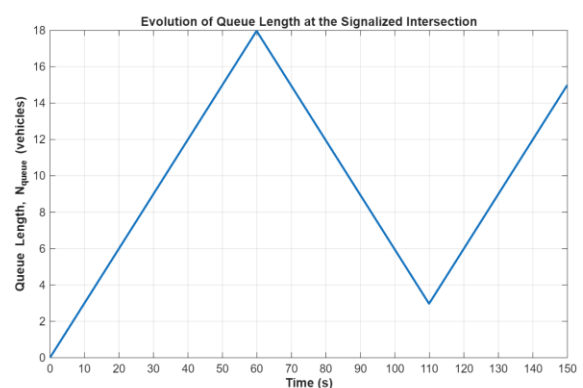


Fig -2: Evolution of queue length at the signalized intersection

Figure 2 shows the variation of estimated queue length with time, indicating the expected buildup of vehicles during blocked phases and discharge during green phases.

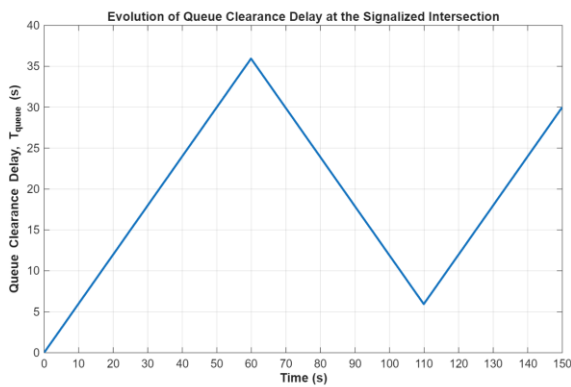


Fig -3: Evolution of queue clearance delay at the signalized intersection

Figure 3 presents the corresponding queue clearance delay derived from the estimated queue length and discharge headway, representing the additional time before the stop line becomes effectively usable.

The advisory-response behavior of the proposed model is further examined using the target advisory speed, applied advisory speed, and actual vehicle speed during the intersection approach. These plots help illustrate how the generated advisory is translated into practical vehicle motion through the driver response and vehicle dynamics blocks.

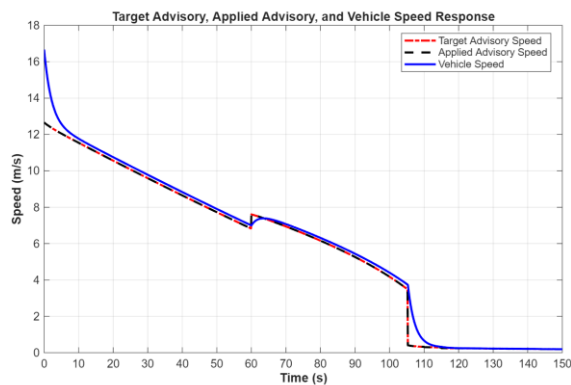


Fig -4: Target advisory, applied advisory, and vehicle speed response

Figure 4 shows the relationship between the target advisory speed generated by the control logic, the applied advisory speed, and the actual vehicle speed followed by the vehicle during the approach phase.

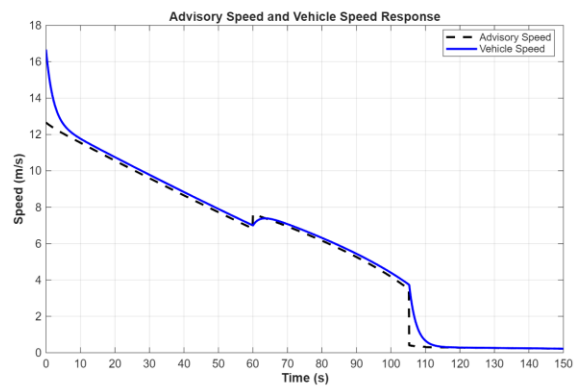


Fig -5: Advisory speed and vehicle speed response

Figure 5 presents the advisory-following behavior of the vehicle, highlighting the practical lag between advisory generation and actual speed response

To further interpret the approach behavior of the vehicle, the response is also observed with explicit signal phase background and through the remaining-distance profile during the approach to the stop line. These plots help explain how the vehicle motion evolves with respect to changing signal conditions and how the final advisory logic influences the near-stop-line behavior.

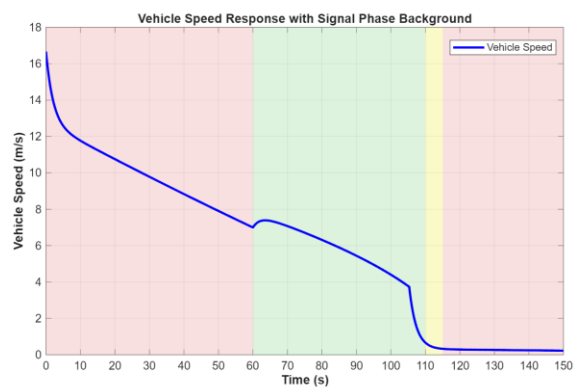


Fig -6: Vehicle speed response with signal phase background

Figure 6 shows the vehicle speed variation together with the corresponding signal phase background, allowing the approach behavior to be interpreted with respect to red, green, and yellow phases.

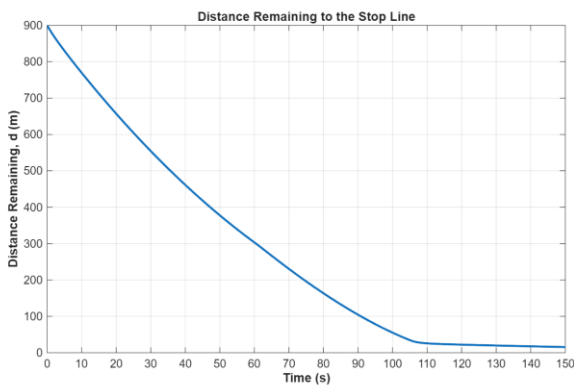


Fig -7: Distance remaining to the stop line during the vehicle approach

Figure 7 shows the variation of remaining distance during the vehicle approach and indicates a conservative near-stop-line response under the final queue-aware advisory logic.

The distance profile shows that the vehicle approaches the intersection smoothly without aggressively targeting the stop line under queue-aware conditions. However, the final model does not include a dedicated exact stop-position controller near the stop line, and therefore a residual stopping distance remains in the final part of the approach. This behavior is treated as a known simplification of the current model and is interpreted as conservative near-stop-line handling rather than an exact stop-line capture mechanism.

4.2 Driver Behavior Sensitivity

Driver behavior sensitivity is examined in the proposed framework by considering cautious, normal, and aggressive response settings. These cases differ in driver compliance gain and acceleration limits, which influence how closely the vehicle follows the advisory speed during the approach phase. The comparison is useful for understanding how advisory-following behavior changes when the driver is more conservative or more responsive. In the simulation results, the cautious driver responds more gradually, while the aggressive driver follows the advisory more quickly, and the normal driver provides an intermediate response.

The vehicle speed comparison under different driver settings is shown through the driver-type response plot, while the advisory and driver-response comparison plot highlights how each driver category tracks the generated advisory speed. These results indicate that the driver response model has a direct influence on the practical realization of the advisory logic, even when the same queue-aware GLOSA strategy is used. Therefore, the driver behavior analysis confirms that advisory performance should be evaluated together with driver-following characteristics rather than through advisory generation alone.

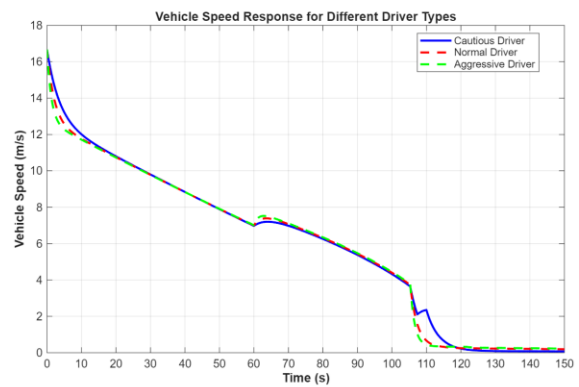


Fig -8: Vehicle speed response for different driver types

Figure 8 compares the vehicle speed response under cautious, normal, and aggressive driver settings during the approach phase.

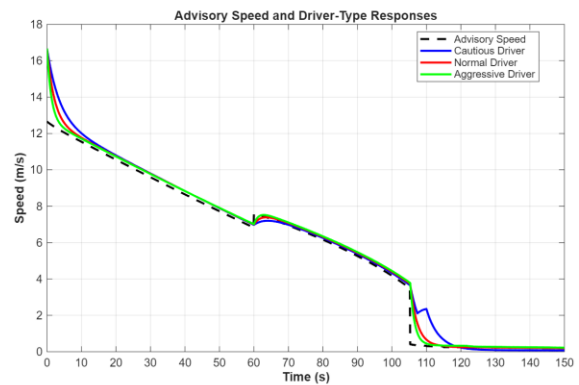


Fig -9: Advisory speed and driver-type responses

Figure 9 illustrates how the generated advisory speed is followed under different driver-response characteristics.

In addition to advisory-following behavior, the driver sensitivity study is also examined through comparative fuel consumption and CO₂ emission estimates. These results help indicate how different driver-response characteristics influence the modeled energy and emission behavior during the approach phase.

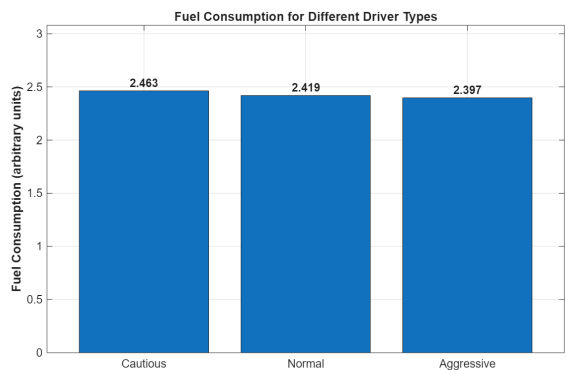


Fig -10: Fuel consumption for different driver types

Figure 10 compares the estimated fuel consumption under cautious, normal, and aggressive driver-response settings.

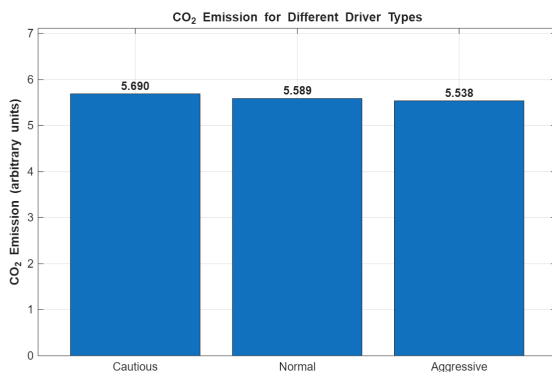


Fig -11: CO₂ emission for different driver types

Figure 11 compares the estimated CO₂ emission under cautious, normal, and aggressive driver-response settings.

Table -1: Driver behavior tracking results

Driver Type	Compliance Gain (K _a)	Max Acceleration (m/s ²)	Max Deceleration (m/s ²)	Mean Tracking Error (m/s)
Cautious	0.3	1.5	-2.0	1.2558
Normal	0.5	2.0	-3.0	0.89662
Aggressive	0.8	2.5	-4.0	0.72593

The driver behavior results indicate that the tracking performance of the advisory is strongly influenced by the selected driver response characteristics. The cautious driver shows the largest tracking error due to slower response and lower acceleration capability, while the aggressive driver exhibits the lowest tracking error because of faster advisory-following behavior. The normal driver provides an intermediate response between these two cases. These observations confirm that advisory performance should be interpreted together with driver sensitivity, rather than assuming ideal or identical tracking behavior for all drivers.

4.3 Signal Timing Uncertainty

Signal timing uncertainty is considered in the proposed framework to examine how advisory behavior changes when the remaining phase time is not assumed to be exact. In practical traffic conditions, the timing information available to the approaching vehicle may not always remain perfectly fixed, and therefore the advisory strategy should be studied under such non-ideal timing conditions. In the present work, uncertainty is introduced by modifying the remaining signal time using additional timing offsets, and the resulting advisory and vehicle responses are compared with the exact-timing case.

The comparative uncertainty analysis shows that increasing timing uncertainty makes the generated advisory more conservative. As the uncertainty level increases, both the initial advisory speed and the mean advisory speed during the approach are reduced, while the advisory-following error increases slightly. At the same time, the comparative fuel and CO₂ estimates also decrease gradually, indicating that a more conservative speed guidance profile can smooth the vehicle approach and reduce the modeled energy/emission proxy. These observations demonstrate that the final model is capable of representing uncertainty-sensitive GLOSA behavior in a structured manner.

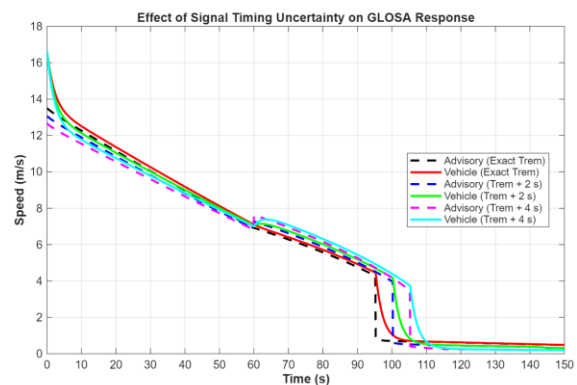


Fig -12: Effect of signal timing uncertainty on GLOSA response

Figure 12 compares the advisory and vehicle speed responses for the exact-timing case and the uncertainty-modified signal timing cases.

Table -2: Signal timing uncertainty results

Case Type	Initial Advisory Speed (m/s)	Mean Advisory Speed up to 75 s (m/s)	Mean Tracking Error (m/s)
Exact Trem	13.5000	9.3571	0.21450
Trem + 2 s	13.0645	9.2395	0.21924
Trem + 4 s	12.6562	9.1263	0.22877

The uncertainty results indicate that increasing the remaining-time uncertainty causes the advisory to become progressively more conservative. This is reflected by the reduction in both initial and mean advisory speed, together with a slight increase in tracking error. Therefore, the uncertainty analysis confirms that timing inaccuracies influence both advisory generation and the practical response of the vehicle during the approach phase.

4.4 Comparative Fuel Consumption and CO₂ Emission Analysis

The energy-related behavior of the proposed framework is examined using comparative fuel consumption and CO₂ emission estimates obtained from the simulated vehicle

response. In the present study, these values are used as relative performance indicators derived from the modeled speed and acceleration behavior rather than as exact real-world consumption measurements. Therefore, the fuel and CO₂ results should be interpreted as comparative simulation-based estimates that help distinguish how different driver-response and uncertainty conditions influence the overall approach behavior.

For the driver sensitivity analysis, the comparative fuel and CO₂ plots indicate how cautious, normal, and aggressive driver-response characteristics affect the modeled energy and emission behavior during the approach phase. In addition, the uncertainty study also produces comparative fuel and CO₂ estimates for the exact-timing and uncertainty-modified cases. To summarize these results in a compact manner, the combined comparative values for both driver behavior sensitivity and signal timing uncertainty are presented in Table -3.

Table -3: Comparative fuel consumption and CO₂ emission results

Case Category	Case Name	Fuel Consumption (arb. units)	CO ₂ Emission (arb. units)
Driver Sensitivity	Cautious	2.4631	5.6899
Driver Sensitivity	Normal	2.4194	5.5887
Driver Sensitivity	Aggressive	2.3972	5.5375
Signal Uncertainty	Exact Trem	2.4738	5.7145
Signal Uncertainty	Trem + 2 s	2.4438	5.6451
Signal Uncertainty	Trem + 4 s	2.4194	5.5887

The combined fuel and CO₂ results show that the comparative energy/emission behavior changes with both driver sensitivity and signal timing uncertainty. In the driver-response study, the estimated values vary only moderately across cautious, normal, and aggressive settings, while in the uncertainty study the estimates decrease gradually as the advisory becomes more conservative. These results indicate that the final queue-aware and uncertainty-sensitive advisory framework not only affects advisory tracking behavior, but also influences the comparative energy and emission profile of the simulated vehicle approach.

5. LIMITATIONS OF THE MODEL

The present model is developed as a structured simulation-based framework for evaluating adaptive GLOSA behavior under queue-aware and uncertainty-sensitive conditions; however, certain simplifications remain. The study considers a single-vehicle approach at a signalized intersection and does not include multi-vehicle interaction, lane-changing behavior, or network-level traffic effects. In addition, the final near-stop-line response is represented through simplified queue-aware stopping behavior rather than a

dedicated exact stop-position controller, which results in a residual stopping distance in the final approach stage. The fuel consumption and CO₂ results are also interpreted as comparative simulation-based estimates rather than exact real-world measurements. These limitations do not reduce the usefulness of the model for comparative analysis, but they indicate the directions in which the framework can be extended further.

6. CONCLUSION

The present work developed and evaluated an adaptive GLOSA framework in MATLAB/Simulink for a signalized intersection under queue-aware and uncertainty-sensitive operating conditions. The model integrated traffic signal control, queue estimation, advisory speed generation, driver response, and vehicle dynamics within a single closed-loop simulation environment. The results showed that queue-aware advisory behavior, driver sensitivity, and signal timing uncertainty all influence the practical response of the vehicle during the approach phase. The driver behavior analysis confirmed that advisory-following performance changes with driver compliance and acceleration capability, while the uncertainty analysis showed that increasing timing uncertainty makes the advisory progressively more conservative. The comparative fuel consumption and CO₂ estimates also indicated that the proposed framework affects not only tracking behavior but also the modeled energy and emission profile of the vehicle approach. Overall, the study provides a structured simulation-based basis for evaluating adaptive GLOSA behavior under more practical operating conditions than a purely signal-timing-based advisory model.

REFERENCES

- [1] T. Wágner, T. Ormándi, T. Tettamanti, and I. Varga, "SPaT/MAP V2X communication between traffic light and vehicles and a realization with digital twin," *Computers and Electrical Engineering*, vol. 106, 2023, Art. no. 108560.
- [2] M. N. Ahangar, Q. Z. Ahmed, F. A. Khan, and M. Hafeez, "A survey of autonomous vehicles: Enabling communication technologies and challenges," *Sensors*, vol. 21, no. 3, 2021.
- [3] E. Zadobrischi and M. Dimian, "Vehicular communications utility in road safety applications: A step toward self-aware intelligent traffic systems," *Symmetry*, vol. 13, no. 3, 2021.
- [4] M. Papageorgiou, "Overview of road traffic control strategies," *IFAC Proceedings Volumes*, vol. 37, no. 19, pp. 29-40, 2004.
- [5] K. Katsaros, R. Kernchen, M. Dianati, and D. Rieck, "Performance study of a green light optimized speed advisory (GLOSA) application using an integrated

cooperative ITS simulation platform,” in 2011 7th International Wireless Communications and Mobile Computing Conference, 2011, pp. 918–923.

- [6] A. Coppola, L. D. Costanzo, L. Pariota, S. Santini, and G. N. Bifulco, “An integrated simulation environment to test the effectiveness of GLOSA services under different working conditions,” *Transportation Research Part C*, vol. 134, 2022, Art. no. 103455.
- [7] H. Chen and H. A. Rakha, “Developing and Field Testing a Green Light Optimal Speed Advisory System for Buses,” *Energies*, vol. 15, no. 4, Art. no. 1491, 2022.
- [8] J. Ma, F. Zhou, Z. Huang, C. L. Melson, R. James, and X. Zhang, “Hardware-in-the-Loop Testing of Connected and Automated Vehicle Applications: A Use Case for Queue-Aware Signalized Intersection Approach and Departure,” *Transportation Research Record*, vol. 2672, no. 22, pp. 36–46, 2018.
- [9] S. Stebbins, M. Hickman, J. Kim, and H. L. Vu, “Characterising Green Light Optimal Speed Advisory Trajectories for Platoon-Based Optimisation,” *Transportation Research Part C: Emerging Technologies*, vol. 82, pp. 43–62, 2017.
- [10] P. Typaldos and M. Papageorgiou, “Modified Dynamic Programming Algorithms for GLOSA Systems with Stochastic Signal Switching Times,” *Transportation Research Part C: Emerging Technologies*, vol. 157, Art. no. 104364, 2023.
- [11] L. Simchon and R. Rabinovici, “Real-Time Implementation of Green Light Optimal Speed Advisory for Electric Vehicles,” *Vehicles*, vol. 2, no. 1, pp. 35–54, 2020.
- [12] M. Xu, D. Zuo, and J. Li, “Adaptive Frequency Green Light Optimal Speed Advisory Based on Deep Reinforcement Learning,” *Journal of Transportation Engineering, Part A: Systems*, 2024.