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Abstract

Vehicle driving behavior and traffic signal control operations influence energy consumption in road transportation. The former can be isolated, egoistic, or in groups or platoons. The latter determines how vehicles access intersections sequentially, parallelly, or synchronously. To optimize travel time and energy efficiency in mixed traffic involving autonomous vehicles powered by electricity and human-driven vehicles powered by gasoline, we introduce a framework called Software-Defined Intelligent Intersections (SDI). This framework leverages real-time traffic information to dynamically select the appropriate approach (synchronous or parallel) using a software-defined networking (SDN)-based controller. The comparison of the SDI2 framework with the synchronous approach shows a two-pronged improvement, reducing travel delays and minimizing energy waste. On the one hand, our proposed framework offers a significant reduction in waiting delays at intersections and travel delays of the road network with improvements of 79% and 47.45% over the synchronous approach. On the other hand, it also reduces the consumption of 0.27% electricity and 4.6% gasoline, as well as 8%PMx and 5.4%NOx emissions, respectively.

Energy Efficiency of Mixed Vehicles Influenced by the Driving Behavior and Traffic Signals

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***Abstract*—Vehicle driving behavior and traffic signal control operations influence energy consumption in road transportation. The former can be isolated, egoistic, or in groups or platoons. The latter determines how vehicles access intersections sequentially, parallelly, or synchronously. To optimize travel time and energy efficiency in mixed traffic involving autonomous vehicles powered by electricity and human-driven vehicles powered by gasoline, we introduce a framework called Software-Defined Intelligent Intersections (SDI^2). This framework leverages real-time traffic information to dynamically select the appropriate approach (synchronous or parallel) using a software-defined networking (SDN)-based controller. The comparison of the SDI^2 framework with the synchronous approach shows a two-pronged improvement, reducing travel delays and minimizing energy waste. On the one hand, our proposed framework offers a significant reduction in waiting delays at intersections and travel delays of the road network with improvements of 79% and 47.45% over the synchronous approach. On the other hand, it also reduces the consumption of 0.27% electricity and 4.6% gasoline, as well as 8% PM_x and 5.4% NO_x emissions, respectively.**

I. Introduction

According to the US Environmental Protection Agency, transport accounted for 28% of total global emissions in the US and is a significant source of air pollution [1]. As specified by the European Statistical Office [2], road transport consumed 74% of the total transportation energy. Furthermore, more than 80% of the urban population is exposed to higher concentration levels of PM_x and NO_x observed at traffic stations and intersections [3].

Electrification is expected to be one of the solutions to decarbonizing road transport by 2030 [4]. This includes the deployment of electric vehicles (EVs), such as battery electric vehicles (BEVs) and hydrogen fuel cell vehicles (HFCV) [5]. Recent estimates show that by 2050, electricity is expected to account for 75% of the total energy consumed by road transport [4]. Therefore, it becomes necessary to validate whether electrifying road transportation would benefit as projected or impose adverse effects.

Recent research has focused on the relationship between driving behavior, traffic signal control (TSC) operations, and fuel consumption [6]–[11]. For example, Al-Wreikat et al. [6] used the Nissan Leaf electric car model to establish factors influencing electricity consumption, such as driving behavior, travel distance, outside temperature, and traffic conditions. They observed that heavy traffic conditions and driving behavior increase energy consumption by 40% and 16%, respectively. On the other hand, the research by [7], [9]–[11] simulated various vehicle types to examine the impact of vehicle driving behavior and TSC operations on energy savings. Vehicle types include human-driven vehicles (HVs), such as internal combustion engine vehicles (ICEVs), and both human-driven (BEVs) and autonomous (BEAVs) electric vehicles (EVs).

As discussed in [12], TSC operations can be categorized as sequential, parallel, and synchronous based on how they permit vehicles to cross intersections. Sequential approaches allow a group of vehicles to cross intersections on one road while blocking vehicles on other roads [13]. Parallel approaches permit a group of vehicles to pass in opposite road lanes and move to the next pair of opposite lanes [14]. Synchronous approaches allow vehicles from all non-conflicting road lanes [15], [16]. However, the comparative study by [11] shows that the synchronous approach outperforms the sequential and parallel approaches.

Therefore, this work considers the synchronous approach as a foundation and presents a new hybrid model named the Software-Defined Intelligent Intersections (SDI^2) framework. The proposed framework uses software-defined networking (SDN) concepts that combine synchronous and parallel approaches. SDN decouples the control plane from the data plane, allowing centralized and real-time control of the network of intersections. When isolated vehicles are detected, the SDI^2 framework invokes the synchronous intersection management protocol - SIMP [15]. However, when groups of vehicles are detected that want to cross intersections in the same direction, the SDI^2 framework invokes a new acyclic and parallelly operating protocol called the Adaptive Intersection Management Protocol (AIMP), which is designed for maximum adaptability and efficiency. Our framework utilizes the SUMO simulator [17] and examines mixed vehicles comprising BEAVs and ICEVs. We evaluated the performance of the proposed framework in comparison to the base synchronous approach using a small road network consisting of four signalized intersections.

The key contributions of this paper are as follows.

- We propose a novel SDI^2 framework that integrates synchronous and parallel approaches, enabling the dynamic adaptation of operational modes based on real-time traffic conditions.
- To serve vehicle groups in parallel, we introduce the AIMP, which dynamically allocates green phases and adjusts their durations based on vehicle crossing directions.
- We study the influence of vehicle driving and TSC operations on delays, fuel wastage, and associated emissions.

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II. Related Work

This section discusses related work on the influence of vehicle driving behavior and TSC operations.

Regarding vehicle driving behavior, Jiang et al. [7] developed a safety-oriented eco-driving framework for connected EVs using *reinforcement learning* techniques. The framework optimizes both car-following and lane-changing maneuvers at intersections. Similarly, studies [8] and [10] examine eco-driving strategies for mixed traffic of EVs and ICEVs at intersections. Specifically, [8] introduced a *speed guidance model* aimed at reducing energy consumption and associated emissions, while [10] presented a *energy-efficient driving strategy* (EEDS), which includes a vehicle queue discharge predictor, an energy-efficient speed planner, and a speed tracker to avoid collisions. More information on eco-driving control strategies for connected and automated vehicles (CAV), considering different driving behaviors, such as single-vehicle, car-following, and multi-vehicle cooperation, is reviewed in [22]. This review highlights the concept of *cooperative eco-driving* as a means to significantly reduce global energy consumption and improve environmental sustainability through coordinated energy-efficient driving maneuvers.

Regarding the influence of TSC operations, Zhao et al. in [21] addressed emission reduction at intersections by analyzing mixed EV and ICEV traffic scenarios. Their approach involves developing a *signal timing optimization model* that prioritizes emission reduction, then evaluates its impact on vehicle control delay and stop rates. In light of the increasing adoption of EVs, Di et al. [9] introduced a traffic management model designed to minimize total travel time and energy consumption. Their study focuses on a network of intersections populated with fully connected vehicles, evaluating the model's effectiveness in optimizing mobility and energy efficiency.

Combining vehicle driving behavior with TSC operations, Reddy et al. investigated their joint impact on energy savings and emissions at isolated single-lane and multi-lane intersections [11], [23]. Their simulations involved mixed traffic of HVs and AVs, powered by gasoline or electricity. The results indicate that BEAVs facilitate smoother driving patterns, thus improving traffic flow, reducing delays, minimizing fuel wastage, and lowering emissions, even benefiting nearby ICEVs governed by the reactive SIMP protocol. These findings highlight that integrating AVs with advanced TSC strategies produces the most sustainable traffic outcomes.

In a similar yet more realistic context, Al-Wreikat et al. [6] examined the effects of driving behavior, TSC operations, traffic conditions, and external heat on energy consumption using the Nissan Leaf electric vehicle model. Their study demonstrates how these influencing factors significantly affect electricity usage.

Contrary to the aforementioned TSC methodologies, recent research, such as [24] and [25], has proposed SDN-based models that decouple the control and data planes. Specifically, Garg et al. [24] introduced a Software Defined Traffic Light Control System (SDTLCS) that integrates IoT devices with software-defined control principles to prioritize emergency vehicles. Similarly, Sachan et al. [25] presented SDN-QMPC. This SDN-enabled TSC framework enhances traditional max-pressure controllers by incorporating real-time vehicular dynamics, lane heterogeneity, and inter-intersection coordination via a cloud-based SDN controller.

In contrast to these conventional approaches, which typically deploy a single TSC system, we propose a novel hybrid model. This SDI^2 framework hosts two TSC systems: the synchronous SIMP and the adaptive AIMP. While SIMP is a well-established strategy for managing mixed HV and AV traffic, AIMP is a newly introduced mechanism that allocates green phases and durations based on the group of vehicles that intend to cross in the same direction. To the best of our knowledge, this is the first study to implement a hybrid TSC framework of this nature.

III. Software-Defined Intelligent Intersections

Figure 1 illustrates the proposed SDI^2 framework for a small road network of four signalized intersections (I_0,I_1,I_2,I_3). The proposed architecture is structured into three layers, viz *physical, control, and application*. Firstly, the application layer hosts intelligent intersection management (IIM) algorithms (SIMP and AIMP). Then, the control layer handles real-time traffic flow by detecting vehicles and their crossing directions, ensuring high responsiveness and low latency at the edge node. By decoupling the control layer from the physical layer, the SDI^2 framework centralizes the control interfaces of TSC systems across the road network. The functioning of each layer is discussed further.

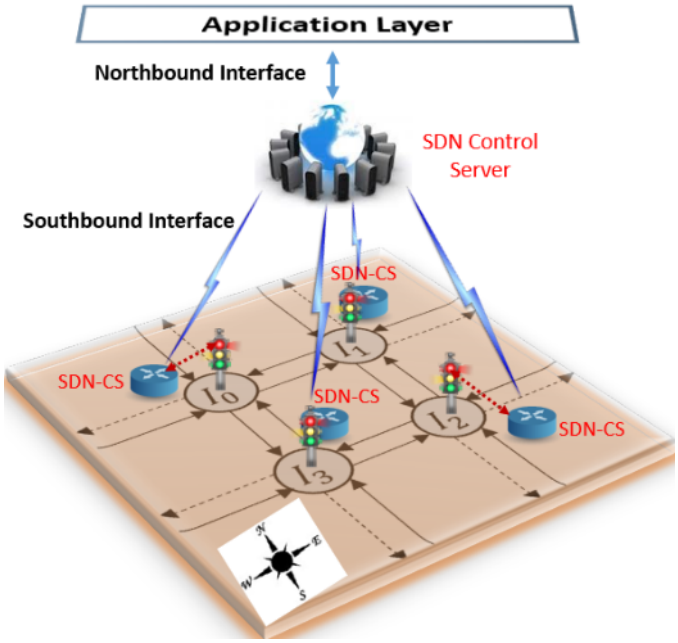


Fig. 1: SDN-based intelligent intersections for a small road network of four intersections.

The **physical layer** consists of the road infrastructure responsible for collecting traffic data through various components, including roadside sensors (e.g., induction loop detectors and cameras), roadside units (RSUs), connected vehicles, and edge devices equipped with TSC units and SDN Control Switches (SDN-CS) deployed at each intersection. The collected traffic data includes vehicle presence, count, speed, and lane occupancy, while cameras capture visual information on vehicle intersection crossing directions. The SDN-CS, which operates on the edge, interfaces with local physical devices to gather real-time traffic data and forward

it to the centralized SDN control server through the southbound interface. Additionally, it enables dynamic reconfiguration of TSC operations based on the TSC logic received from higher layers.

The **control layer** bridges the physical and application layers through the south and north interfaces. It maintains a global view of the state of the road network by collecting and aggregating real-time traffic data. Acting as the network operating system, it translates the high-level traffic control policies and strategies defined by the application layer into the low-level executable instructions for the physical layer. The useful information collected by the physical layer, including the number of vehicles and their details regarding intersection crossings, is used by the SDN control server to trigger appropriate TSC operations, ensuring low-latency responses. The decision could be either synchronous SIMP for isolated vehicles or parallel AIMP for serving a group of vehicles.

The **application layer**, as the high-level decision maker in TSC across the road network, functions in real-time. Operating above the control and physical layers, it uses abstracted network views and centralized intelligence to implement adaptive and optimized traffic policies. It encompasses advanced TSC applications within the SDN framework, including real-time monitoring, optimization algorithms, and policy enforcement. The TSC phases and timings are dynamically adjusted based on real-time traffic flow and contextual factors such as weather, incidents, or special events. The application layer relays decisions to the control layer, which issues executable commands to physical devices. As introduced earlier, the SDI^2 framework supports the TSC functionality through the synchronous SIMP and adaptive AIMP modules.

The **SIMP protocol** is a reactive cycle-based protocol designed to manage mixed AV/HV traffic. It uses a synchronous scheduling mechanism to grant intersection access to individual vehicles from each lane in conflict-free cycles, determined by a Conflicting Directions Matrix (CDM). Each cycle follows a circular order, admitting one vehicle per lane if there are no crossing conflicts. AVs communicate their intended direction via V2I technologies, while HVs are detected through roadside sensors. SIMP enforces a First-In-First-Out (FIFO) policy and makes real-time decisions based on vehicle presence, rather than relying on fixed or adaptive signal timings.

The **AIMP Protocol** is similar to SIMP in serving vehicles from all non-conflicting road lanes, but is acyclic in nature. Similarly to SIMP, the AIMP is designed to manage mixed AV and HV traffic. However, AIMP dynamically adjusts the TSC phases and their timing to serve groups of vehicles in parallel from opposite road lanes in response to real-time traffic conditions. Traffic conditions include the presence and count of vehicles in each lane of the road, and the count of vehicles is based on the number of vehicles that intend to cross the intersection in the same direction. AIMP represents an important step toward context-aware, traffic-responsive intersection management in urban mobility systems.

IV. Simulation Setup and Experiment Description

In our simulation, we consider a road network of four signalized intersections, as shown in Fig. 1. The inflow and outflow road lanes connect all four intersections (I_0, I_1, I_2, I_3), thus forming a grid. These lanes are 500 meters long and flat. The road network features homogeneous four-legged intersections, spanning 1540 m^2, including 20 m^2 intersection spaces. At each intersection, a TSC unit and an edge node host the SDN controller switch (SDN-CS).

We simulated a mixed AV (BEV) and HV (ICEV) traffic scenario to evaluate our proposed framework and compared it with the base approach, synchronous SIMP. In the simulated environment, the BEVs follow the adaptive cruise control (ACC) car-following model (CFM) [19], and ICEVs follow the Krauss CFM [18]. We consider a maximum speed of 30 km/h, a realistic representation of a typical low-speed urban area setting.

Considering different traffic arrival rates ($0.025, 0.05, 0.067, 0.1$) in veh/s, we compared waiting time at intersections and total travel time loss (s/veh), fuel consumption (electricity - Wh/veh and gasoline g/veh) and exhaust emissions (PM_x, NO_x, CO, CO_2, and HC) as performance indicators. We studied these performance indicators for 1000 vehicles each: BEAVs and ICEVs.

TABLE I: Simulation parameters and assigned values

Parameters	**Values**
Probability of vehicle injection	Poisson distribution
Vehicle length	5 meters
Safety distance (target)	5 meters
Fuel type	Gasoline (ICEVs) and Electricity (BEAVs)
Fuel consumption model	HBEFA3.1 (ICEVs) and Battery Electric (BEAVs)
Target speed	30 km/h, i.e., 8.33 m/s
Acceleration	2.6 m/s^2
Deceleration	-4.5 m/s^2
Emergency deceleration	-9 m/s^2
Minimum time headway	1 s
Drivers imperfection	0.5 (Human-driven) 0.0 (Autonomous)

Simulation of Urban Mobility (SUMO) [17] v1.21.0 is used to deploy the synchronous SIMP and SDI^2 frameworks in identical geographical settings of the road network. We ran simulations on Windows 11 OS with an AMD Ryzen 5 7520U processor (2.8 GHz, 4 Cores, and 8 Logical Processors) for the traffic scenario, which lasted more than 2.5 hours, considering the first 1000 vehicles of each type.

The simulation parameters, such as acceleration, deceleration, and emergency deceleration, are adopted from the default SUMO values[1]; they are 2.6 m/s^2,-4.5 m/s^2, and -9 m/s^2, respectively. Table I summarizes the relevant simulation parameters and their associated values.

TABLE II: Parameters specific for BEAVs.

Parameters	**Values**
Max. battery capacity	64 kWh
Max. power	150 kW
Constant power intake	100 W
Internal moment of inertia	0.01 $Kg.m^2$
Air drag coefficient	0.35
Radial drag coefficient	0.5
Roll drag coefficient	0.01
Propulsion efficiency	0.98
Recuperation efficiency	0.96
Stopping threshold	0.1 km/h

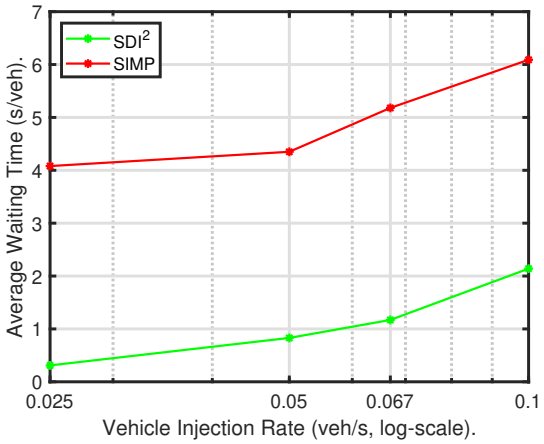
The simulation parameters specific to BEAVs are presented in Table II. These values are adopted, representing a commonly used electric passenger car [11], [20].

[1] https://sumo.dlr.de/docs/Vehicle_Type_Parameter_Defaults.html

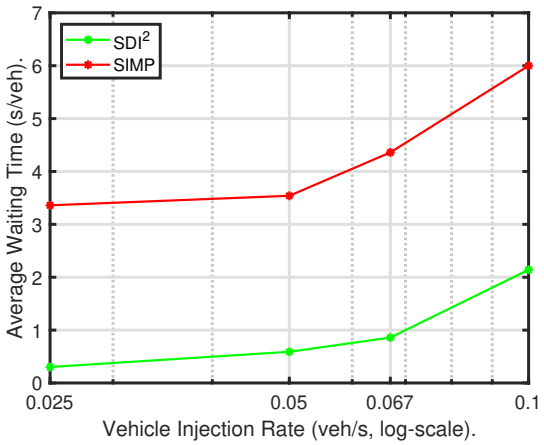
V. Results Discussion

In this section, we present the performance results indicating the waiting delay (s/veh), travel time loss (s/veh), fuel consumption (electricity - Wh/veh and gasoline - g/veh), and associated emissions (g/veh or mg/veh) for the experiments detailed in section IV.

Waiting delay occurs due to TSC operations at intersections. The average waiting delay of AVs and HVs, 1000 vehicles each, is presented in Figs. 2a and 2b, respectively.



(a) AVs waiting time (s/veh).

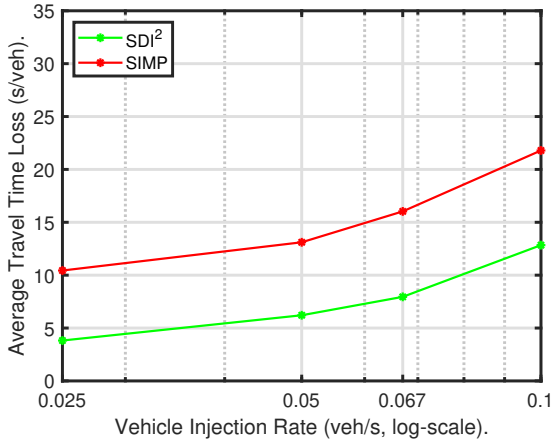


(b) HVs waiting time (s/veh).

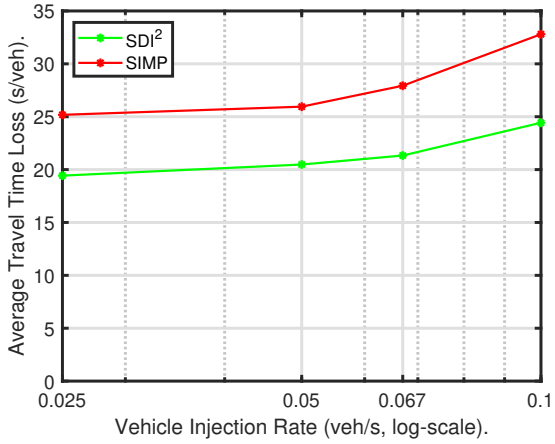
Fig. 2: Average waiting time (s/veh) of 1000 vehicles at $30km/h$.

The overall waiting time results for the AVs and HVs in both the SIMP and SDI^2 frameworks exhibit similar behavior, with a negligible difference of up to 0.8 s. This slight difference can be attributed to the driving behavior of vehicles; that is, AVs strictly adhere to smooth driving rules, while HVs have a fast throttle response, as they are egoistic and jerky [11]. However, a significant performance difference between the SIMP and SDI^2 frameworks is observable from the individual graphs. The SDI^2 framework outperforms SIMP by up to 4 s at all traffic injection rates tested. This performance gap is more significant with higher vehicle injection rates, indicating the SDI^2 framework's efficient TSC operations. A performance improvement of 79% was achieved thanks to AIMP, which allocates green time to the opposite lanes in parallel according to the number of vehicles crossing the intersection in the same direction. In contrast, SIMP allows only one vehicle from each non-conflicting lane, without taking into account the crossing direction of subsequent vehicles.

Travel time loss is a combination of waiting time at intersections (shown in Fig. 2) and delays due to traffic congestion, acceleration, and deceleration. Figure 3 presents the average travel time loss results for 1000 vehicles each, i.e., AVs (Fig. 3a) and HVs (Fig. 3b). The primary observation is that AVs exhibit lower travel time loss than HVs.



(a) AVs travel time loss (s/veh).

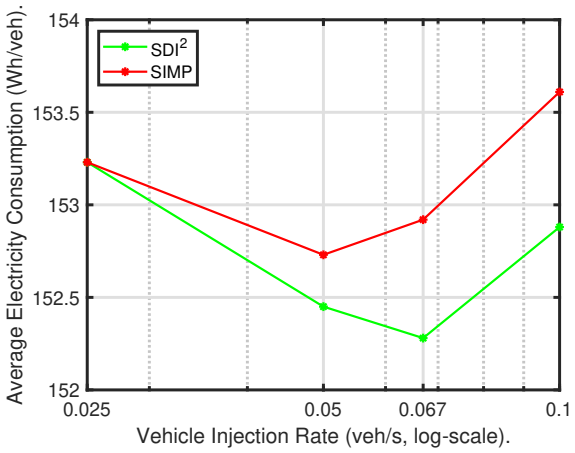


(b) HVs travel time loss (s/veh).

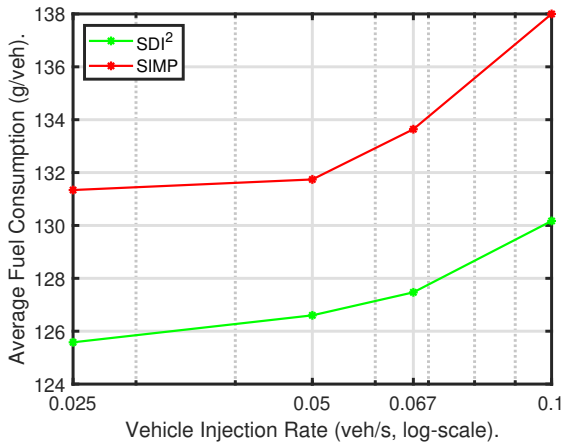
Fig. 3: Average travel time loss (s/veh) of 1000 vehicles at $30km/h$ maximum speed.

For both AVs and HVs, the SDI^2 framework consistently results in lower travel time loss than the SIMP protocol for all vehicle injection rates. As expected, the travel time loss for increased traffic injection rates also increased for both strategies. Concerning AVs, the gap between SDI^2 and SIMP increases at higher vehicle injection rates of about 9 s, indicating that SDI^2 performs significantly better in higher traffic conditions. It is interesting to note that for HVs, at higher injection rates, the difference between SDI^2 and SIMP reduces slightly, reaching 8.4 s due to erratic driving behavior of HVs. Consequently, by employing AVs and the SDI^2 framework, it is possible to save 47.45% travel time at 0.1 veh/s against the SIMP protocol.

Energy consumption indicates the amount of energy (electricity or fuel) consumed by a vehicle (AV or HV) in the actual simulation step. Figures 4a and 4b show the average consumption of electricity (Wh/veh) and gasoline fuel (g/veh).



(a) Electricity consumption (Wh/veh).



(b) Fuel consumption (g/veh).

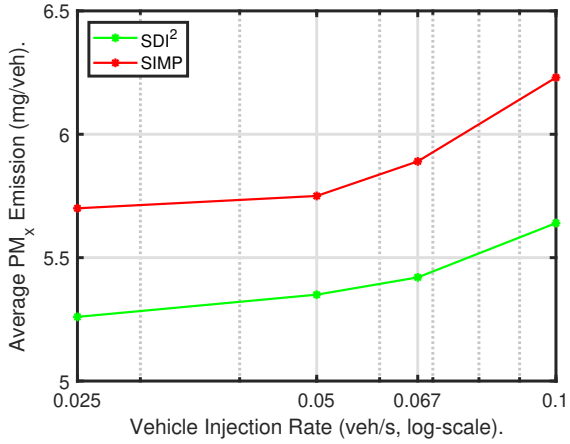
Fig. 4: Average fuel consumption results of 1000 vehicles.

Firstly, both SIMP and SDI^2 exhibit a dip-and-recover pattern, with electricity consumption dropping initially and then increasing as the vehicle injection rate increases. Except for 0.025 veh/s, the SDI^2 framework consistently consumes less electricity than SIMP at all injection rates. The performance gap between the two approaches becomes more significant at higher injection rates of 0.05 and $0.1veh/s$. At $0.067veh/s$, SDI2 achieves its lowest energy consumption, clearly establishing it as an energy-efficient approach. On average, the SDI^2 framework improves electricity consumption by 0.27% over the SIMP.

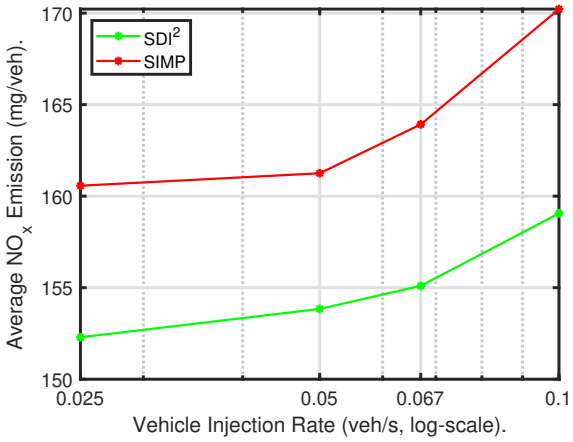
The trend in gasoline consumption correlates with the waiting time results shown in Fig. 2b. This means that the fuel consumption increases as the vehicle injection rate increases. The SDI^2 exhibits significantly lower fuel consumption than SIMP at all traffic injection rates. The gap between the two methods increases as the injection rate increases, indicating that SDI^2 is more fuel efficient at higher traffic volumes. This can be attributed to the amount of time vehicles spend idling at intersections, indicating TSC operations.

The analysis of energy consumption underscores the superiority of the SDI^2 framework over the SIMP protocol. SDI^2 achieves 4.66% lower fuel consumption than SIMP, indicating better fuel efficiency. Importantly, SDI^2 demonstrates greater consistency in fuel consumption, making it a more stable and reliable solution under varying traffic conditions.

Emissions were recorded for the same simulations discussed above. Figure 5 presents the average emissions of PM$_x$ and NO$_x$, measured in mg/veh.



(a) PM$_x$ emissions (mg/veh).



(b) NO$_x$ emissions (mg/veh).

Fig. 5: Average emission of PM$_x$ and NO$_x$ for 1000 ICEVs.

One can observe that both the PM$_x$ and NO$_x$ emissions correlate with the fuel consumption shown in Fig. 4b. The SIMP protocol consistently shows higher PM$_x$ emissions compared to SDI^2. At the highest vehicle injection rate of 0.1 veh/s, SIMP reaches 6.2 mg/veh, while SDI^2 remains below 5.6 mg/veh, showing a lower PM$_x$ emission profile. A similar NO$_x$ emission behavior can be observed. At the highest vehicle injection rate of 0.1 veh/s, SIMP reaches approximately 170 mg/veh, while SDI^2 remains below 160 mg/veh. Furthermore, the correlation coefficient between the two approaches is 0.98, suggesting a strong positive correlation between vehicle injection rate, fuel consumption, and associated PM$_x$ and NO$_x$ emissions.

Discussion: The average results show that our proposed hybrid model, which combines both SIMP and AIMP, is more efficient than the well-established synchronous SIMP. It improves travel efficiency by significantly reducing waiting times at intersections and the total travel time loss for both AVs and HVs. This is because of the efficient invocation of SIMP (to serve isolated vehicles) and AIMP (to serve groups of vehicles) based on the number of vehicles and their intersection crossing information. Furthermore, the travel time loss results shown in Fig. 3 indicate that AVs benefit more from SDI^2 than HVs, highlighting their greater responsiveness to TSC operations.

Consequently, the effect of the SDI^2 framework is notable, and improvements in electricity consumption can be observed, although BEAVs employ regenerative braking, particularly after $0.05\ veh/s$. Concerning gasoline consumption, the superiority of the SDI^2 framework becomes even more evident at all traffic arrival rates tested, making it a more sustainable option for urban mobility.

The PM_x and NO_x emission results align with the gasoline consumption results, revealing a direct correlation. However, for SIMP, the sharper increase in NO_x emissions compared to PM_x suggests that NO_x is even more sensitive to traffic congestion due to increased stop-and-go driving and prolonged engine operation at inefficient speeds. In contrast, the SDI^2 strategy demonstrates robust emission control, attributed to SIMP and AIMP, which reduces emissions toward sustainable urban mobility.

VI. Conclusions

This paper comprehensively studies the hybrid SDI^2 framework for managing dynamic incoming traffic involving isolated and group vehicles. This hybrid framework combines the synchronous SIMP for serving isolated vehicles and the AIMP for vehicle groups. Incoming traffic is divided into isolated or groups based on the intersection crossing directions. The study aims to understand the influence of vehicle driving behavior and TSC operations on travel delays and energy consumption. Consequently, we employed mixed autonomous BEVs and human-driven ICEVs, simulating them in the SUMO simulator.

The results show that the newly proposed hybrid SDI^2 framework outperforms the synchronous approach measured in waiting delays at intersections, total travel delays, fuel consumption (electricity and gasoline) and associated emissions (PM_x and NO_x). The maximum improvements of the SDI^2 framework in numbers are 79%, 47.45%, 0.27%, 4.6%, 8%, and 5.4%, respectively.

The presented results are exploratory toward a promising future of smart mobility. We intend to further investigate the applicability of the SDI^2 framework to a wide range of traffic scenarios, including platoons and more complex road networks.

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