

Original Research

GHG Emissions Management in Urban Areas by Interactive Road Traffic Control: Application of Artificial Intelligence

Carlos Armenta-Déu *

Dpt. of Matter Structure, Thermal Physics and Electronics, Faculty of Physics Sciences, Complutense University of Madrid, 28040 Madrid, Spain; E-Mail: cardeu@fis.ucm.es

* **Correspondence:** Carlos Armenta-Déu; E-Mail: cardeu@fis.ucm.es

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Abstract

The rising pollution levels in congested urban areas pose a serious threat to human health. Many solutions have been proposed to control and reduce gas emissions from road traffic, with results that are not entirely satisfactory. The adoption of new techniques and methodologies for early detection of pollutant emissions may enable effective management and control of road traffic contamination. The proposed method introduces an interactive protocol that facilitates communication between the traffic control center and a vehicle speed recognition system. This protocol autonomously adjusts vehicle speeds to align with traffic control center limits, correlating maximum velocity with greenhouse gas (GHG) concentrations in designated urban areas. The paper examines the environmental impacts of road traffic emissions in urban areas and explores strategies to mitigate them through speed limit management based on pollution levels. To implement this strategy, we suggest installing pollution detection sensors and interactive speed signage. GHG mitigation hinges on specific sensors that measure emissions from vehicle exhaust pipes strategically positioned along roads or pedestrian walkways. The integration of Artificial Intelligence enhances the protocol's effectiveness, reducing significant deviations in vehicle performance and associated emissions. Simulation results indicate a potential reduction in GHG emissions of



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21.8% when vehicles operate at 45 km/h, following a 15 km/h decrease from typical velocities and maintaining no acceleration. Additionally, vehicle speed, the extent of speed reduction, and acceleration rates influence the reductions in GHG emissions, yielding reference emission reductions of 12.4% and 15.2% for average speeds of 70 km/h and 45 km/h, respectively. Conversely, the maximum increase in GHG emissions can reach 66.7% when experiencing an acceleration of 3.6 m/s^2 , with a 15 km/h speed reduction. Theoretical predictions have demonstrated a high accuracy of 98.5% for speeds exceeding 57.5 km/h, regardless of the engine type. However, this accuracy diminishes at lower speeds (below 55 km/h), ranging from 69.5% to 98.5%, depending on engine type and acceleration rate. The proposed methodology improves the current state of the art in managing pollution levels and helps achieve early control of urban contamination from road traffic.

Keywords

Environmental impact; people health affection; GHG emissions; detection and management; urban area; road traffic; control protocol; artificial intelligence

1. Introduction

Currently, urban pollution from road traffic is a significant issue, leading to health complications and economic losses from the corrective measures implemented needed to address it. Greenhouse gases (GHG), among other factors, are responsible for the increasing pollution, climate change, and global warming [1-8]. GHG emissions come from industrial processes, commercial activities, residential heating, fossil fuel power plants, and road traffic [9-21]. Greenhouse gas emissions from urban road traffic depend on engine and car type and dynamic driving conditions, speed, and acceleration. For non-electric vehicles (n-EVs), four types are available: diesel, gasoline, compressed natural gas (CNG), liquefied gas (LPG), and hybrid. Among the GHG, combustion engine cars emit carbon dioxide (CO_2), nitrous oxides (NO/NO_2), Sulphur dioxide (SO_2), carbon monoxide (CO), and solid particles (PMs). The most relevant emitted gas is carbon dioxide because of its highest emission rate, although other GHGs also affect people's health. While the carbon dioxide and nitrous oxide emission rates from an internal combustion engine (ICE) are a function of vehicle speed, sulphur dioxide does not depend directly on vehicle speed but on fuel consumption, which is related to vehicle speed. Sulphur dioxide emissions only affect diesel and gasoline engines, with CNG and LPG showing only traces [22].

Road traffic represents one of the most challenging problems local authorities must face due to the continuous population growth in urban areas and the need for public or private transportation for house-to-work commuting and vice versa, as peri-urban zones expand [23-26]. Traffic congestion produces high GHG emissions into the atmosphere without benefiting the population with a better transportation system [27-29]. Traffic congestion is widely studied through developed metrics for congestion measures [30-32]. The two most-cited reports are the Texas Transportation Institute's Urban Mobility Study [33] and the National Cooperative Highway Research Program Report 398 [34].

Political measures aimed at regulating GHG emissions seek to mitigate environmental contamination, particularly in urban areas where high population density [35-43] and traffic

congestion [44-46] lead to unacceptable pollution levels, impacting human health [47-51]. Local authorities propose the public transportation model as the solution for urban traffic congestion [52-54]; however, this policy confronts people's reluctance to use public transportation [55, 56] due to overcrowding, irregular service, low frequency, access difficulties for disabled people, and delays derived from breakdowns and service problems [57-60], resulting in massive private car use. Cities use different measures to reduce pollution from mobility: improvements to public transport, infrastructure, pedestrian and bicycle facilities, restrictions on private vehicles, traffic and parking management, changes to vehicles, speed limits, and land use, promoting eco-driving, defining low-emission zones, tolls, and so on.

There are two ways to reduce traffic emissions: reducing the total number of kilometers traveled by vehicles (vehicle-km) or reducing vehicle emission rates. The first way depends on citizens' willingness to switch from private to public transportation or leave vehicles. A comparative analysis of Copernicus Sentinel data (Figure 1) shows the impact of reducing the vehicle-km rate on the environmental pollution [61, 62]. The vehicle emissions rate depends on the vehicle type and on changes in speed. Some GHG emissions, like nitrous oxides (NO_x), increase with engine temperature and vehicle speed; the faster the vehicle runs, the higher the NO_x emissions rate. Nevertheless, modern engines are more sensitive to increased GHG emissions during acceleration than at average high speed. Private transportation in urban areas suffers from drivers' attitudes and variable driving modes. Continuous vehicle acceleration and speed changes provoke sudden braking and traffic congestion. Irregular maneuvers, such as unexpected lane changes or lateral movements without using blinkers, also generate sudden braking and accelerations, and consequently, traffic congestion. Some studies argue that variable speed systems are better than lowering the speed limit because they reduce traffic congestion. Furthermore, similar vehicle speeds are more important for environmental pollution and fuel consumption than the absolute level of average traffic speeds [63]. Another study shows that no optimal speed reduces fuel consumption and emissions, but a range of speeds with lower GHG emissions values [64]. Complementing the previous study [65], this paper proposes an interactive method between the urban traffic control system and vehicles based on a protocol assisted by Artificial Intelligence. The protocol uses road traffic density in any metropolitan area, adjusts vehicle speed limits to traffic conditions, and avoids excessive GHG emissions. The protocol adapts to the city's pollution levels, setting speed limits to keep carbon emissions within healthy limits.

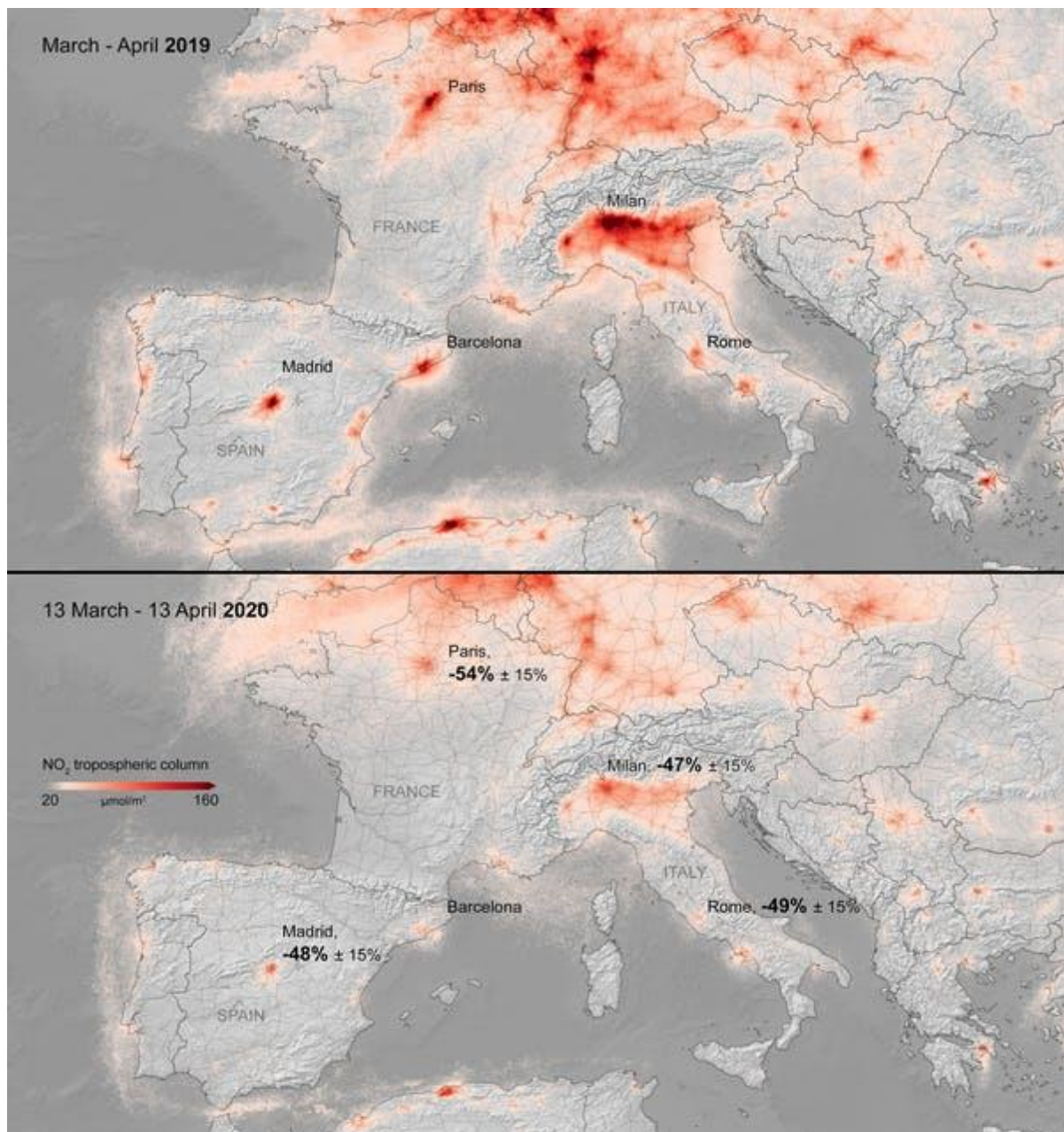


Figure 1 Impact of reducing the vehicle-km rate on the environmental pollution [61].

The main contribution of the present paper is the application of Artificial Intelligence to road traffic gas emissions in urban areas, providing advanced methods to local authorities to manage GHG emissions control and pollution levels.

The paper is structured as follows:

- A short description of greenhouse emissions, principal components, and the influence of road traffic on the GHG emissions by type of car engine.
- A brief description of the influence of road traffic on the pollution problem.
- Measures taken by authorities to face the increasing pollution levels in urban areas due to road traffic.
- A description of the two principal ways to reduce traffic emissions, including relevant studies and works concerning this issue.
- Short explanation of the main contribution of the paper to the state of the art.

2. Theoretical Foundations

Based on previous premises, we may define the GHG emission rate as a function of the vehicle speed, as presented in Equation 1:

$$\dot{m}_{GHG} = f_{eng} r_{eng} \quad (1)$$

f and r are the emission factor and fuel consumption rate for any specific engine type. The subscript eng indicates the engine type.

Because fuel consumption rate depends on the dynamic driving conditions, we may express it as a function of vehicle speed as in Equation 2.

$$r_{eng} = \frac{\sum_{i=1}^n F_i v_i}{\dot{Q}_{fuel} \rho_{fuel} \eta_{eng} \bar{v}} \quad (2)$$

$\dot{Q}_{fuel}$ and ρ_{fuel} are the fuel combustion power and density. η_{eng} is the engine efficiency, $\bar{v}$ is the average vehicle speed in a daily journey, and F_i and v_i are the propelling force and vehicle speed for every i -segment of the daily journey.

Applying dynamic laws to the vehicle driving conditions (see Equation 3), we have:

$$F_i = m_{veh} a_i + \kappa \bar{v}_i^2 + \mu m_{veh} g + m_{veh} g \sin \alpha_i \quad (3)$$

m_{veh} is the vehicle mass, a_i and v_i are the vehicle acceleration and speed in the i -segment, κ and μ are the drag and rolling coefficients, and α_i is the road slope in the i -segment.

Considering a uniform acceleration for the i -segment, we define the acceleration as in Equation 4:

$$a_i = \frac{v_i - v_i^o}{t_i} \quad (4)$$

v_i^o and v_i represent the initial and final vehicle speed in the i -segment, and t_i is the time interval for the i -segment.

Combining Equations 2, 3, and 4, we express the fuel consumption rate as presented in Equation 5:

$$r_{eng} = \frac{\sum_{i=1}^n \left(m_{veh} \frac{v_i - v_i^o}{t_i} + \kappa \bar{v}_i^2 + \mu m_{veh} g + m_{veh} g \sin \alpha_i \right) v_i}{\dot{Q}_{fuel} \rho_{fuel} \eta_{eng} \bar{v}} \quad (5)$$

Considering the engine efficiency and pavement rugosity constant in a daily journey, the fuel consumption rate expression is defined by Equation 6:

$$r_{eng} = C_o \frac{\sum_{i=1}^n \left(\frac{v_i - v_i^o}{t_i} + C_1 \bar{v}_i^2 + C_2 + g \sin \alpha_i \right) v_i}{\bar{v}} \quad (6)$$

With coefficients C_o , C_1 , and C_2 defined in Equation 7:

$$C_o = \frac{m_{veh}}{\dot{Q}_{fuel}\rho_{fuel}\eta_{eng}}; C_1 = \frac{\kappa}{m_{veh}} = \frac{1}{2}\rho_{air}C_x\frac{S}{m_{veh}}; C_2 = \mu g \quad (7)$$

ρ_{air} is the air density, C_x is the vehicle aerodynamic coefficient, and S is the vehicle cross section front area.

Since the final vehicle speed in the i -segment matches the initial speed of the $i+1$ segment, Equation 6 transforms into Equation 8:

$$r_{eng} = \frac{C_o}{\bar{v}} \left(\sum_{i=1}^n \frac{v_i^2}{t_i} - \sum_{i=1}^n \frac{v_i^2}{t_{i+1}} + \sum_{i=1}^n C_1 \bar{v}_i^3 + \sum_{i=1}^n C_2 v_i + \sum_{i=1}^n g v_i \sin \alpha_i \right) \quad (8)$$

Because C_1 and C_2 are much lower than one, and the road slope in urban pathways is currently low, we may neglect terms affected by these coefficients, transforming Equation 8 into Equation 9:

$$r_{eng} = \frac{C_o}{\bar{v}} \left(\sum_{i=1}^n \frac{v_i^2}{t_i} - \sum_{i=1}^n \frac{v_i^2}{t_{i+1}} \right) \quad (9)$$

Comparing two driving conditions with vehicle speed, v_{i1} and v_{i2} , where $v_{i2} = f_v v_{i1}$, being f_v the vehicle speed correction factor, we have the fuel consumption rate ratio as shown in Equation 10:

$$\frac{r_{eng,1}}{r_{eng,2}} = \frac{\bar{v}_2}{f_v^2 \bar{v}_1} \quad (10)$$

Combining Equations 1 and 10, we obtain the ratio of GHG mass emissions rate, defined by Equation 11:

$$R_{GHG} = \frac{\dot{m}_{GHG,2}}{\dot{m}_{GHG,1}} = \frac{f_v^2 \bar{v}_1}{\bar{v}_2} \quad (11)$$

If we express the average car velocity ratio as in Equation 12:

$$\bar{f}_v = \frac{\bar{v}_1}{\bar{v}_2} \quad (12)$$

Equation 11 transforms into Equation 13:

$$R_{GHG} = \bar{f}_v f_v^2 \quad (13)$$

Equation 13 provides a simple and valuable tool for evaluating the reduction in GHG emissions achieved by slowing vehicle speed.

If we develop a similar analysis focused on acceleration rather than vehicle speed variation, Equation 6 adopts the form of Equation 14:

$$r_{eng} = C_o \frac{\sum_{i=1}^n (a_i + C_1 \bar{v}_i^2 + C_2 + g \sin \alpha_i) v_i}{\bar{v}} \quad (14)$$

Considering only kinetic effects, Equation 14 transforms into Equation 15:

$$r_{eng} = \frac{C_o}{\bar{v}} \left(\sum_{i=1}^n a_i v_i \right) \quad (15)$$

Comparing the two cases for vehicle speed, v_{i1} and v_{i2} , we have the final expression for R_{GHG} as presented in Equation 16:

$$R_{GHG} = \bar{f}_v f_v f_a \quad (16)$$

Where f_a is the acceleration factor defined as $a_{i2} = f_a a_{i1}$.

3. Methodology

We divide the methodological process into the following sections:

- A simulation process, including the following issues:
 - a) Evaluation of the influence of neglecting drag, rolling, and weight forces on the ratio of GHG mass emissions rate (R_{GHG}), expressed in Equation 13, for variable initial vehicle speed; therefore, operating with only kinematic conditions, which simplifies the study development and analysis.
 - b) Determination of the GHG mass emissions rate reduction as a function of variable kinematic driving conditions, initial vehicle speed, vehicle speed reduction, and acceleration.
 - c) An analysis of simulated results for the GHG mass emissions rate evolution for the defined kinematic driving conditions.
- Description of the control system to ensure vehicle speed and acceleration are in line with traffic regulations and road conditions. The description includes a detailed explanation of the operational mode.
- A section describing the benefits of the Artificial Intelligence implementation on the control process.
- Validation of the proposed methodology through experimental tests. The experimental results for the different tests conducted under variable kinematic driving conditions, as dictated by the simulation process, are presented in this section. Tests are developed for different car engine types (gasoline, diesel, CNG, LPG). This section also includes the analysis of the experimental evaluation.

4. Simulation

The values derived from Equation 13 are approximate because the mathematical development neglects the dynamic terms associated with drag, rolling, and weight. We evaluate the deviation introduced by neglecting these terms by running a simulation for specific vehicle characteristics and driving conditions. We run a simulation under variable driving conditions to assess the reduction in the GHG emissions rate as vehicle speed lowers. The first simulation runs with an initial average vehicle speed of 45-70 km/h and a 15 km/h speed reduction; the second runs with a 10 km/h speed reduction. The speed reduction corresponds to the vehicle speed lowering to reduce GHG emissions.

Figure 2 shows the deviation from the simulation results for the two analyzed cases. Table 1 shows the vehicle characteristics and driving conditions.

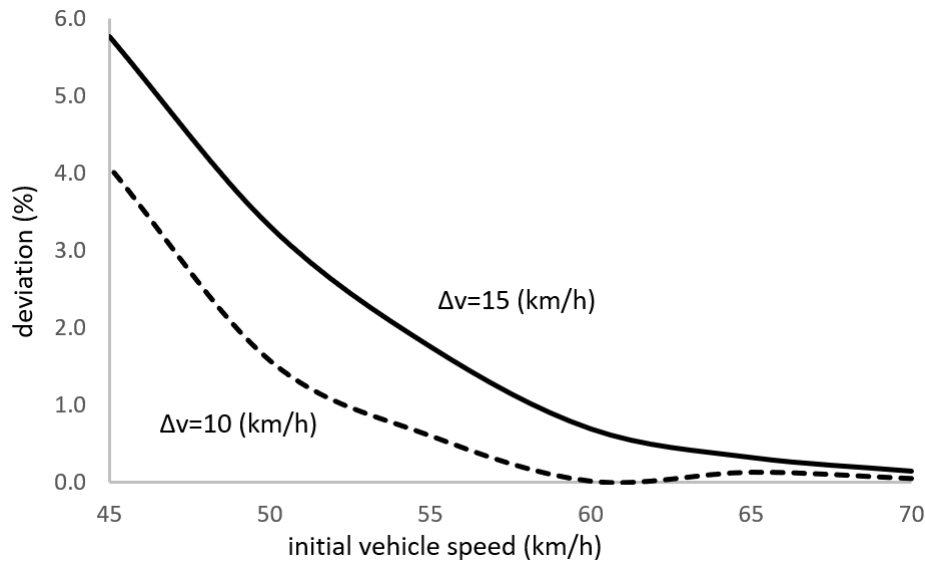


Figure 2 Deviation in the estimation of the GHG reduction coefficient when considering only kinematic driving conditions.

Table 1 Vehicle characteristics and driving conditions.

	m_{veh} (kg)	C_x	S (m ²)	μ	ρ_{air} (kg/m ³)
Value	1500	0.29	2.59	0.015	1.225

We observe that the deviation increases as the average vehicle speed decreases. Nevertheless, it is within an acceptable range, with a maximum value of 5.8% and an average of 1.67%. Therefore, we operate without considering drag, rolling, and weight forces to determine the GHG emissions rate reduction.

Using Equation 13, we can determine the GHG emissions rate reduction for the driving conditions mentioned above. Figure 3 shows the calculation results.

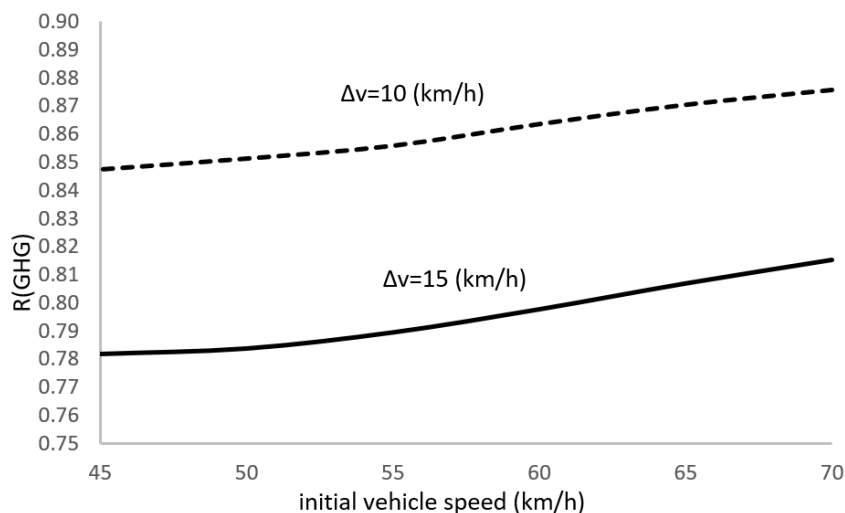


Figure 3 GHG emissions rate reduction for variable kinematic driving conditions.

Repeating the calculation for accelerations, 1.2 m/s^2 , 2.4 m/s^2 , and 3.6 m/s^2 , we obtain the data shown in Figure 4 for the GHG emissions rate.

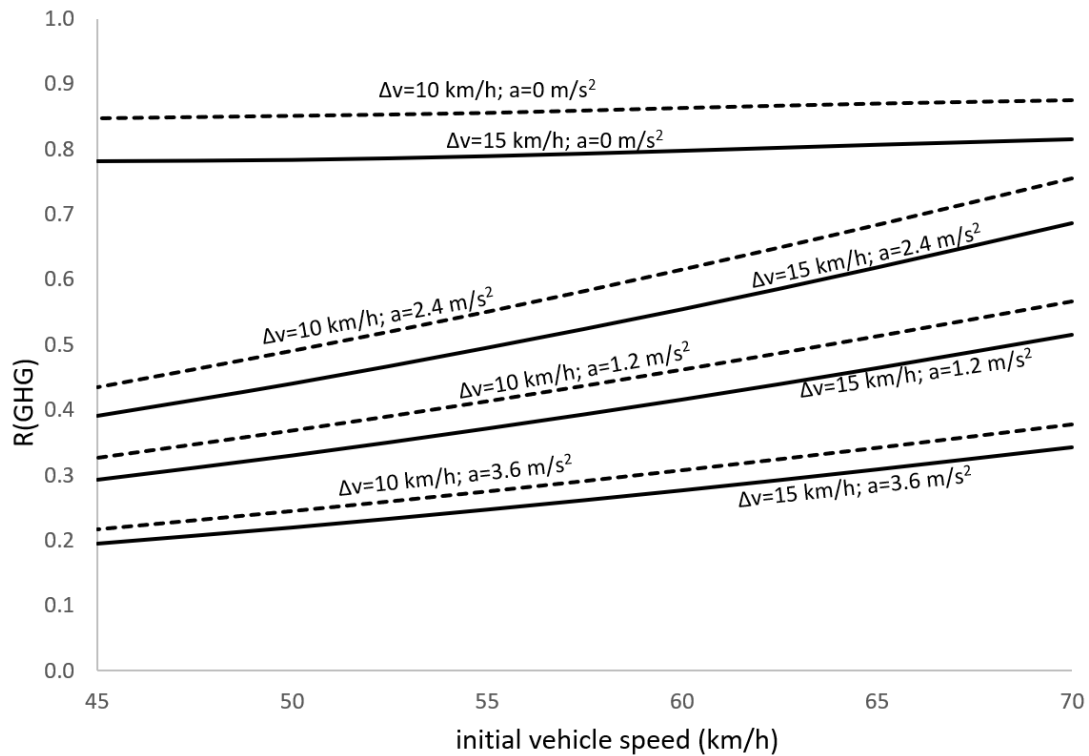


Figure 4 Evolution of the GHG emissions rate coefficient in a daily journey for variable initial vehicle speed, vehicle speed reduction, and acceleration.

We observe that the GHG emissions rate coefficient, R_{GHG} , lowers as the acceleration increases. Comparing the average value of the R_{GHG} coefficient for identical vehicle speed reduction but different acceleration rates, we obtain the following results (Table 2).

Table 2 Evolution of the average GHG emissions rate coefficient in a daily journey for variable acceleration rate.

Speed variation: 10 km/h							
Reference vehicle speed (km/h)		70	65	60	55	50	45
$a \text{ (m/s}^2\text{)}$	0	0.876	0.870	0.864	0.856	0.851	0.848
	1.2	0.755	0.684	0.615	0.551	0.491	0.435
	2.4	0.566	0.513	0.462	0.413	0.368	0.326
	3.6	0.378	0.342	0.308	0.275	0.245	0.218
Speed variation: 15 km/h							
Reference vehicle speed (km/h)		70	65	60	55	50	45
$a \text{ (m/s}^2\text{)}$	0	0.815	0.807	0.798	0.789	0.784	0.782
	1.2	0.687	0.619	0.555	0.496	0.441	0.391
	2.4	0.515	0.464	0.416	0.372	0.331	0.293
	3.6	0.344	0.310	0.277	0.248	0.220	0.196

Comparing the data in Table 2, we can determine the influence of vehicle acceleration on the GHG emissions rate. Figure 5 shows the comparative analysis results. The drawn lines in Figure 5 represent the increase in GHG emissions rate due to car acceleration, as indicated in the adjacent label for non-acceleration driving.

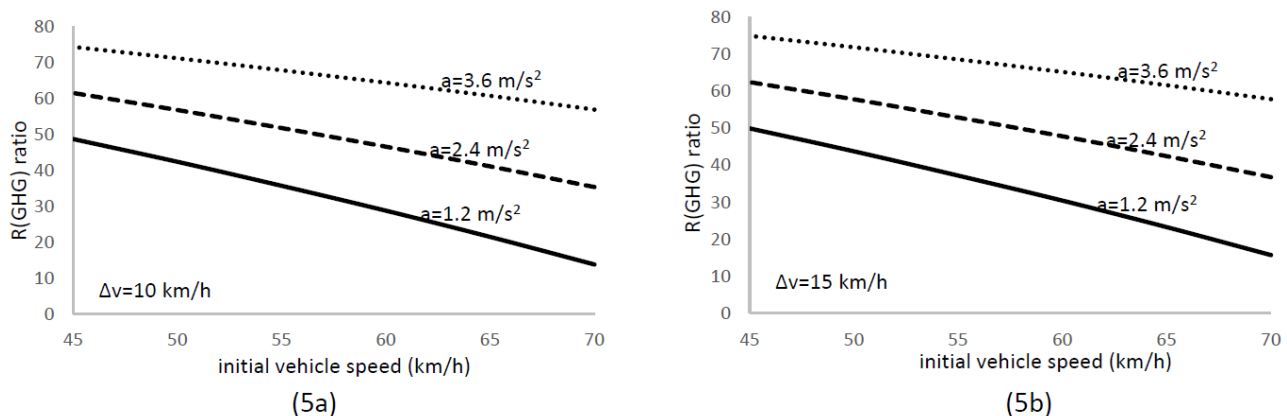


Figure 5 Evolution of the GHG emissions coefficient ratio for various acceleration rates and vehicle speed reduction, 10 km/h (5a), and 15 km/h (5b).

We observe that the acceleration influence on the GHG emissions rate increases as the vehicle speed lowers, which is in close agreement with the expected results since the engine power demand is higher at low velocities when compared with non-acceleration driving, requiring more fuel consumption and a higher GHG emissions rate. On the other hand, the acceleration's influence on the GHG emissions rate increases with acceleration, confirming that acceleration is more relevant than velocity.

Analyzing data from Figure 5, we evaluate the comparative evolution in GHG emissions when the vehicle runs at different speeds and accelerations. Table 3 summarizes the analysis and presents the average value for each case.

Table 3 Average increase in GHG emissions at different vehicle speeds, speed reduction, and acceleration.

Speed variation: 10 km/h		
Acceleration (m/s^2)	ΔR_{GHG}	σ
$a = 0 \rightarrow a = 1.2$	31.8	11.9
$a = 0 \rightarrow a = 2.4$	48.8	8.9
$a = 0 \rightarrow a = 3.6$	65.9	6.0
Speed variation: 15 km/h		
Acceleration (m/s^2)	ΔR_{GHG}	σ
$a = 0 \rightarrow a = 1.2$	33.4	11.7
$a = 0 \rightarrow a = 2.4$	50.0	8.8
$a = 0 \rightarrow a = 3.6$	66.7	5.8

Table 3 shows that driving the vehicle in acceleration mode means an average increase in the GHG emissions rate from a minimum of 31.8% for 1.2 m/s^2 acceleration to a maximum of 65.9% for

an acceleration of 3.6 m/s^2 , in the case of vehicle speed lowering of 10 km/h. For the case of vehicle speed reduction of 15 km/h, the GHG emissions rate increase varies in the range from 33.4% for the lowest acceleration, 1.2 m/s^2 , to 66.7% for the highest, 3.6 m/s^2 . The high standard deviation values indicate that we should use the average data as a reference over a daily journey, but not as an accurate value for GHG emissions evaluation.

The above analysis supports the statement in the Introduction section that acceleration is more significant for GHG emissions than vehicle speed or speed reduction.

5. Control System

The vehicle's driving performance is managed by a control system that ensures speed and acceleration comply with traffic regulations and road conditions. A traffic sign recognition system is integrated directly with the control unit to support this function. Additionally, the car features cruise control, which allows the driver to set the speed to their preferred level. Acceleration is determined by the selected driving mode, with specific values set at 1.2 m/s^2 for ECO mode, 2.4 m/s^2 for NORMAL mode, and 3.6 m/s^2 for SPORT mode. To achieve zero acceleration, the driver should choose super-ECO mode. This driving mode requires a specific installation in the vehicle driving mode configuration; the driver should activate it in ECO mode by pressing a button on the car dashboard. However, it is critical to note that while the driving mode establishes an acceleration limit, the actual acceleration value depends on how the driver manages the vehicle's operation.

To ensure security in urban driving, the control system operates with a front detector linked to the control system, which reduces the vehicle's speed if the distance to the car ahead is too close. The distance control system operates by calculating the time the vehicle would collide with the front car at the current driving speed in case of sudden braking; if the estimated time is above a setup threshold, the vehicle control system interacts with the cruise control and automatically sets up a lower speed to fulfill the expected security collision time, and activates the super-ECO mode, blocking the acceleration option, and limiting the velocity.

Figure 6 shows the system operating flowchart. The control system operational mode works as follows:

- The vehicle's front camera detects speed limit traffic signs.
- The recognition system collects the information and sends it to the control system, which sets up the vehicle speed according to traffic regulations.
- Once the vehicle speed is established, the control system activates the cruise control unit and opens the driving mode configuration.
- The driver selects the wishing driving mode, ECO, NORMAL, or SPORT, and the control system automatically sets up the acceleration value. If the driver wants to circulate in zero-acceleration mode, he should select ECO mode and press the super-ECO button.
- The control system measures vehicle speed and acceleration, comparing the current with the setup velocity. If the values do not match, the control system reconfigures the acceleration value until the running velocity matches the setup value. At this moment, the control system collects information from the detection sensor and calculates the recommended velocity to maintain the security distance. If the vehicle runs at the security speed, the control system takes no further action; otherwise, it adjusts the setup velocity and restarts the checking protocol.

- Concerning the acceleration determination, the control system continuously evaluates the vehicle speed and applies the classical dynamic expression shown in Equation 4. The acceleration value is averaged over the testing time period.
- The vehicle weight is considered constant over the entire testing period.
- Although ambient temperature changes along the testing period, we consider its influence not significant on the vehicle performance, especially compared to the car speed and acceleration changes.

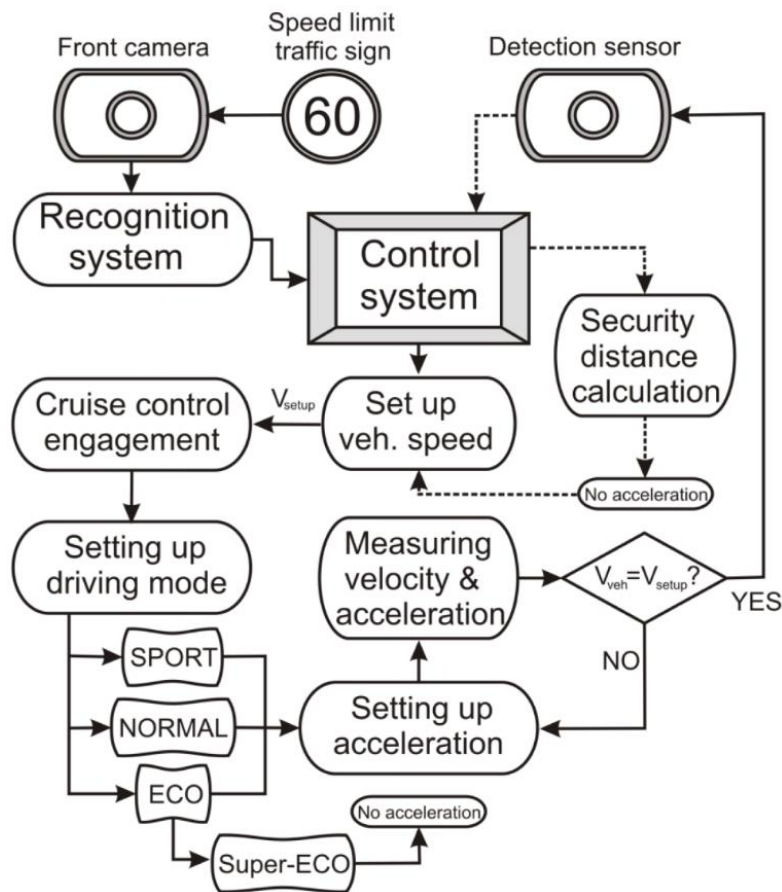


Figure 6 Control system operational flowchart.

Although the control system guarantees accurate data around established values with a narrow error margin, the driver should pay attention to the dashboard; unexpected changes in driving conditions may prompt the control system to modify the predicted setup values. In this case, the driver should operate the vehicle in manual mode, disabling the control protocol. Under these conditions, determining the GHG emissions is invalid.

6. Artificial Intelligence Assistance

Because the daily journey mostly follows a defined pattern, with similar or identical pathways and driving conditions, Artificial Intelligence (AI) is extremely useful in helping the control system manage vehicle driving conditions by anticipating actions it should take. Indeed, speed limit traffic signs do not change along specific urban pathways unless unexpected road conditions occur, such as maintenance labor or programmed repairs. In such a case, since the road work may last for a

prolonged time, the control protocol may be adapted to the new driving conditions, operating as usual with the new setup values. These new values should be adapted to the road conditions, limiting vehicle speed and acceleration. The results from the developed study in this paper no longer match, requiring new calculations for the new setup parameter values.

Artificial Intelligence requires a learning period to establish the specific protocol to be used by the control system; therefore, the AI application is useless if the urban pathway and the driving conditions change frequently. In such a case, the AI uses a learning protocol based on the error function and additional test data to obtain accurate predictions used by the control system to manage vehicle driving conditions. Figure 7 shows the AI protocol flowchart.

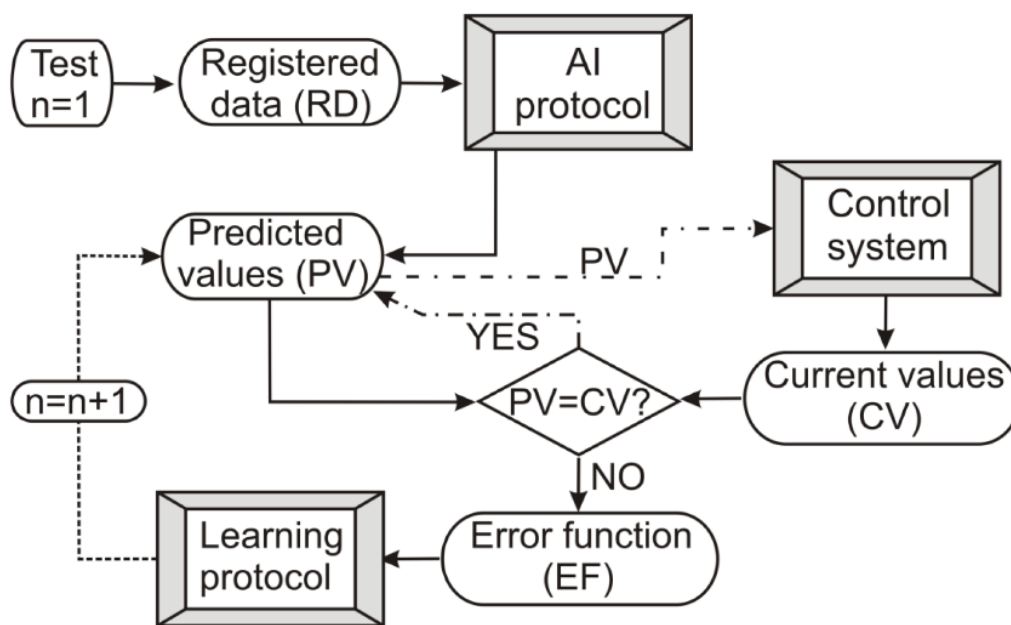


Figure 7 AI protocol flowchart.

The AI protocol operates as follows:

- AI collects information from registered data at the initial test ($n = 1$).
- According to the setup protocol, AI predicts values for driving conditions at the selected urban zone (PV).
- AI protocol compares the predicted and current values (CV) supplied by the control system; if both match, the AI protocol sends PV values to the control system to manage driving conditions under these operating conditions.
- If predicted and current values do not match, the AI runs the error function, entering data into the learning protocol. It collects data from the following test ($n = n + 1$) and recalculates the predicted values until the error function reaches zero. At this point, the control system uses the most recent predicted values from the AI protocol to manage driving conditions.

The most relevant section of the AI protocol operation is the value prediction for vehicle speed and acceleration for driving conditions at the selected urban zone. In current practice, the AI protocol predicts values based on the control system's reference database. Nevertheless, if driving conditions change, according to the standard values stored in the database, the AI applies a sub-protocol for safer driving conditions and improved energy efficiency. The AI sub-protocol considers

traffic conditions based on the distance to the front driving car, calculated from the classical expression:

$$t_c = d/v_s \quad (17)$$

where t_c is the collision time, d is the distance to the front car, and v_s is the current vehicle speed. The control system calculates the distance using the camera sensor on the car's front.

AI classifies the traffic conditions in four categories:

- a) Traffic congestion (red zone) indicates that a collision may occur in less than 1.0 seconds, considering the distance and the current vehicle speed.
- b) Traffic speed restriction (yellow zone) if a collision may occur between 1.0 and 1.6 seconds.
- c) Traffic precautions (blue zone) if the collision may occur in the 1.6 to 2.5 second time range.
- d) Standard traffic (green zone) when the system does not expect any collision risk for 2.5 seconds.

Applying the error function definition:

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^{\Delta v} e^{-t^2} dt \quad (18)$$

Δv represents the difference between the current and expected value for the vehicle speed, defined by the expression:

$$\Delta v = \frac{P}{m} (t_{ref}^{max})^2 \quad (19)$$

P and m are the vehicle driving power and mass, and t_{ref}^{max} is the limit for the time range corresponding to the traffic conditions category.

The expected vehicle speed corresponds to the predicted value under conventional driving conditions, and it is the value determined by the AI protocol when applying the new traffic conditions.

The AI protocol applies the algorithms described by Equations 18 and 19 to minimize the error function iteratively until the most suitable car velocity that maintains a safe vehicle speed is reached.

The vehicle speed values obtained under the new traffic conditions are stored in the control system database and used by the AI protocol to learn from variable traffic conditions; therefore, the AI protocol is adaptive to changes in driving behavior driven by traffic conditions.

7. Experimental Validation

Because measuring GHG emissions in running cars is almost impossible, we validate theoretical predictions from the simulation process through fuel consumption. To this goal, we drive cars powered by different engine types: gasoline, diesel, CNG, and LPG. Tests run in a daily round-trip distance of 25 km. The test duration is eight consecutive months, with four tests daily, one for each engine type. We repeat the test under identical driving conditions five times to ensure consistent results. Daily tests for specific engine types rotate to ensure that city driving conditions are tested

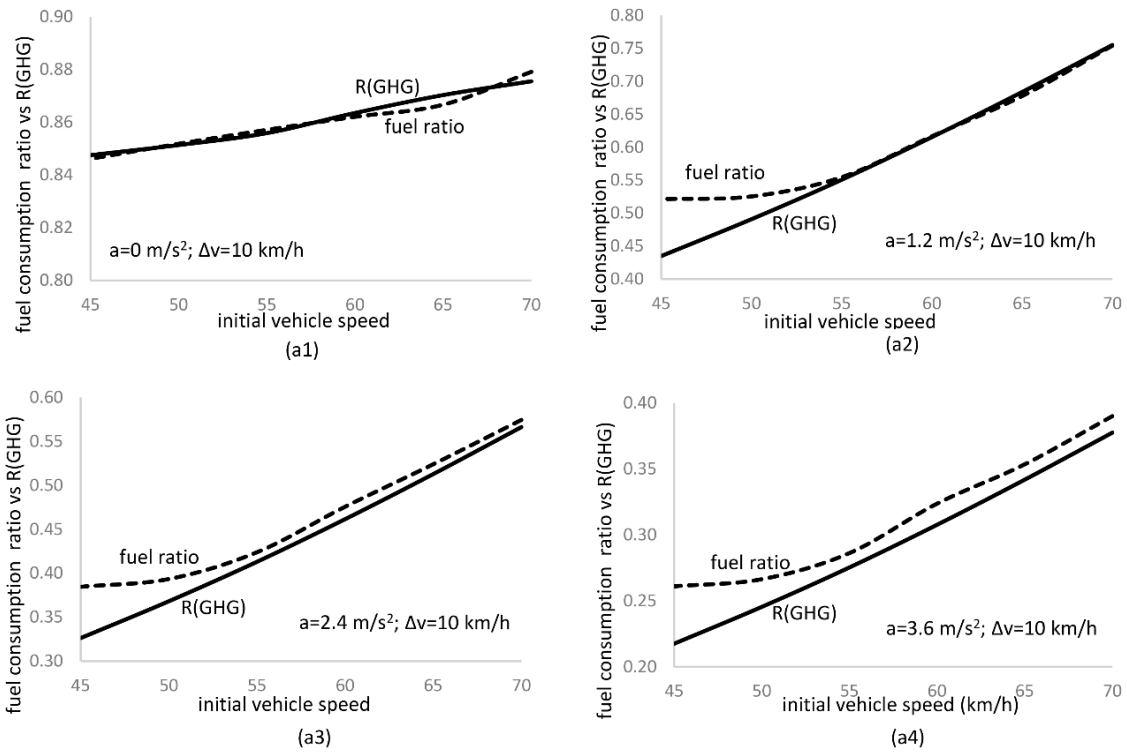
identically; therefore, the engine test sequence is as shown in Table 4. The test sequence order warrants that all engines run on the same day hours during the four-day testing cycle.

Table 4 Daily sequence order for engine test.

Day	Gasoline	Diesel	CNG	LPG
1	First	Second	Third	Fourth
2	Fourth	First	Second	Third
3	Third	Fourth	First	Second
4	Second	Third	Fourth	First

We control the vehicle speed through the cruise control system and the acceleration value, and measure the initial and final velocity in the time interval during which the vehicle accelerates. Figure 8 and Figure 9 show the results from the experimental tests.

Case a: Gasoline engine



Case b: Diesel engine

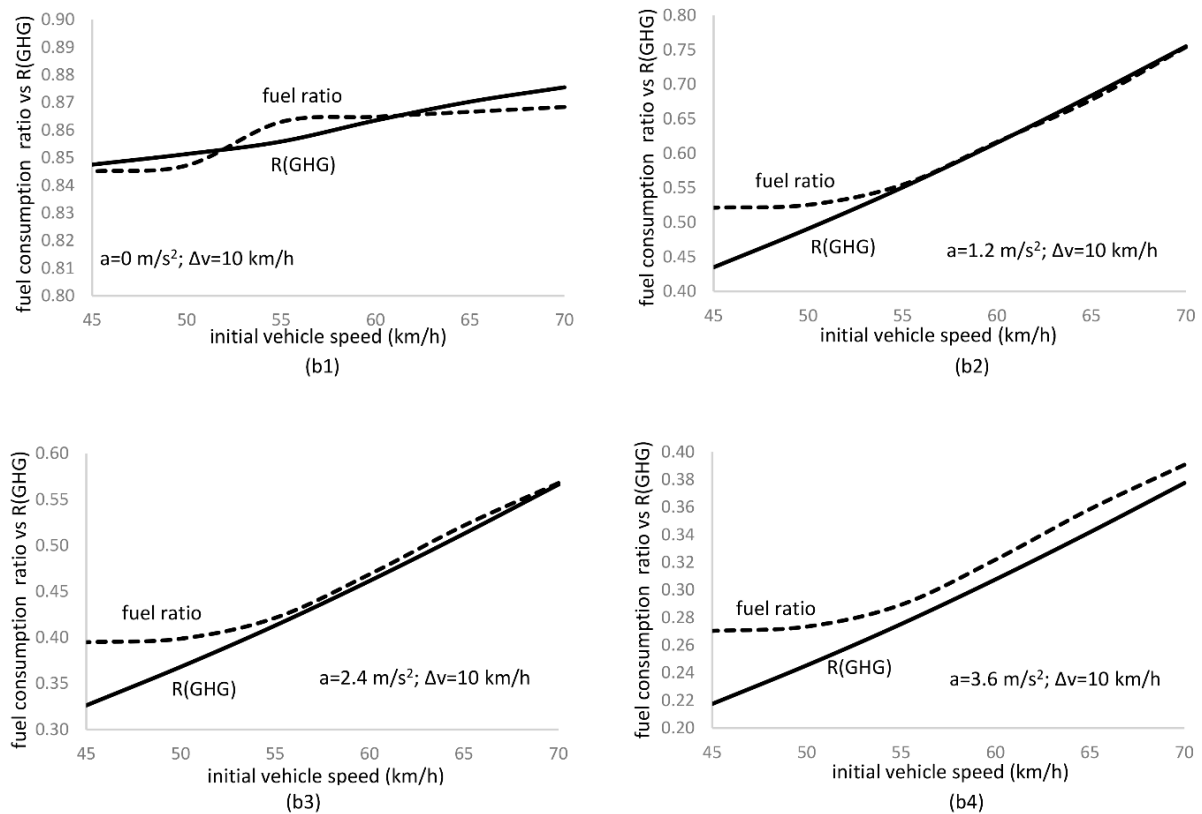
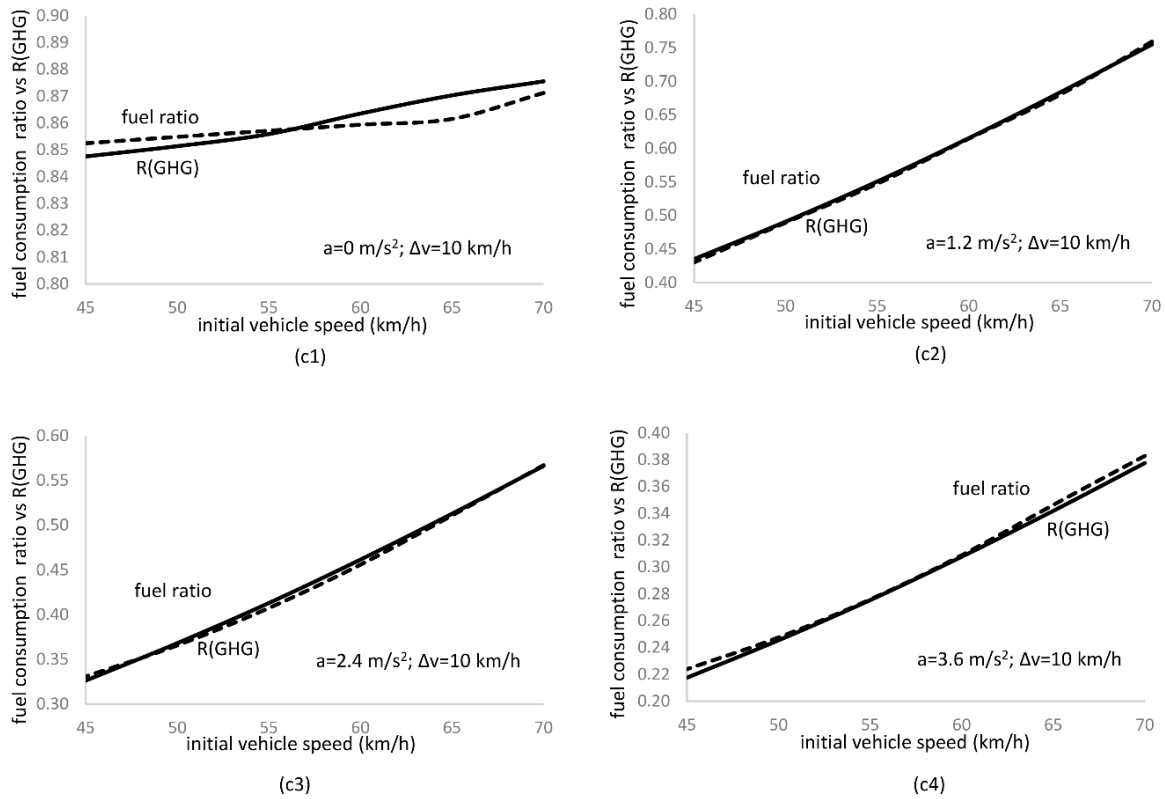


Figure 8 (Case a and Case b) Correlation between theoretical values (R_{GHG}) and experimental data (fuel ratio) for gasoline and diesel combustion engine types, vehicle speed, and acceleration rate at vehicle speed reduction: 10 km/h. (1: $a = 0$ m/s²; 2: $a = 1.2$ m/s²; 3: $a = 2.4$ m/s²; 4: $a = 3.6$ m/s²).

Case c: CNG engine



Case d: LPG engine

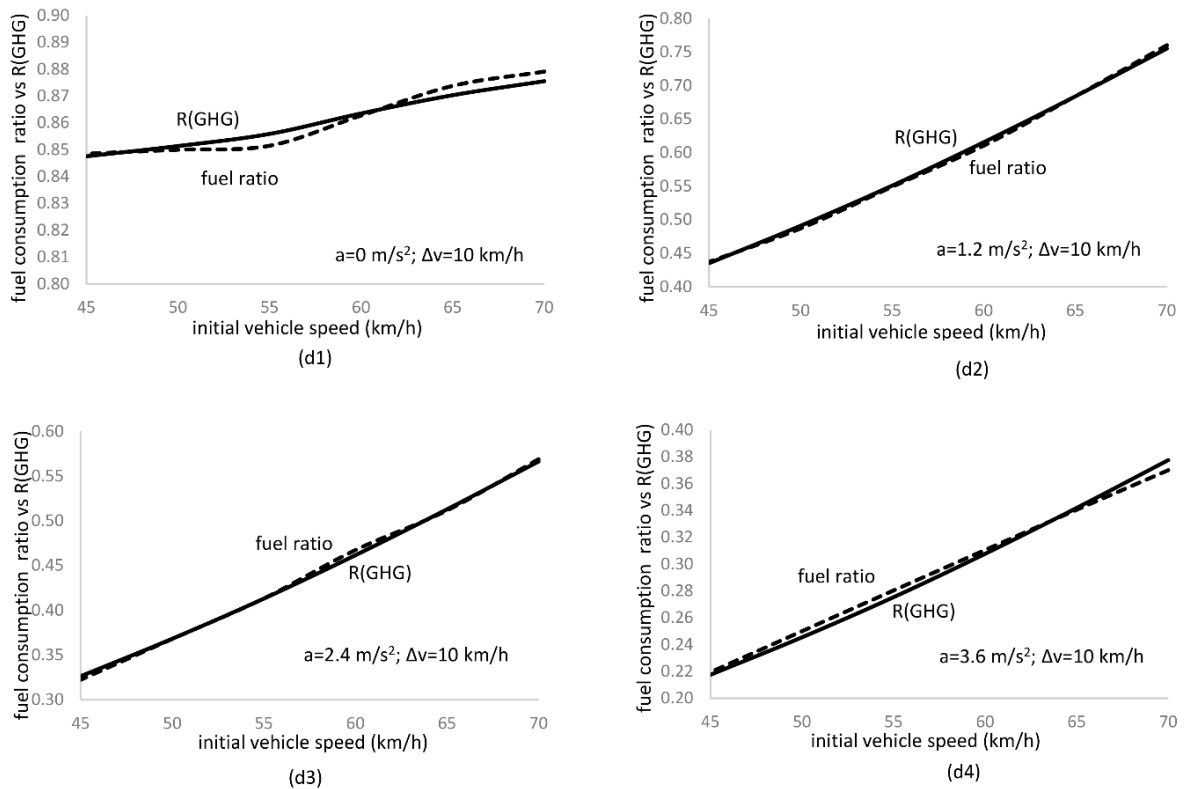


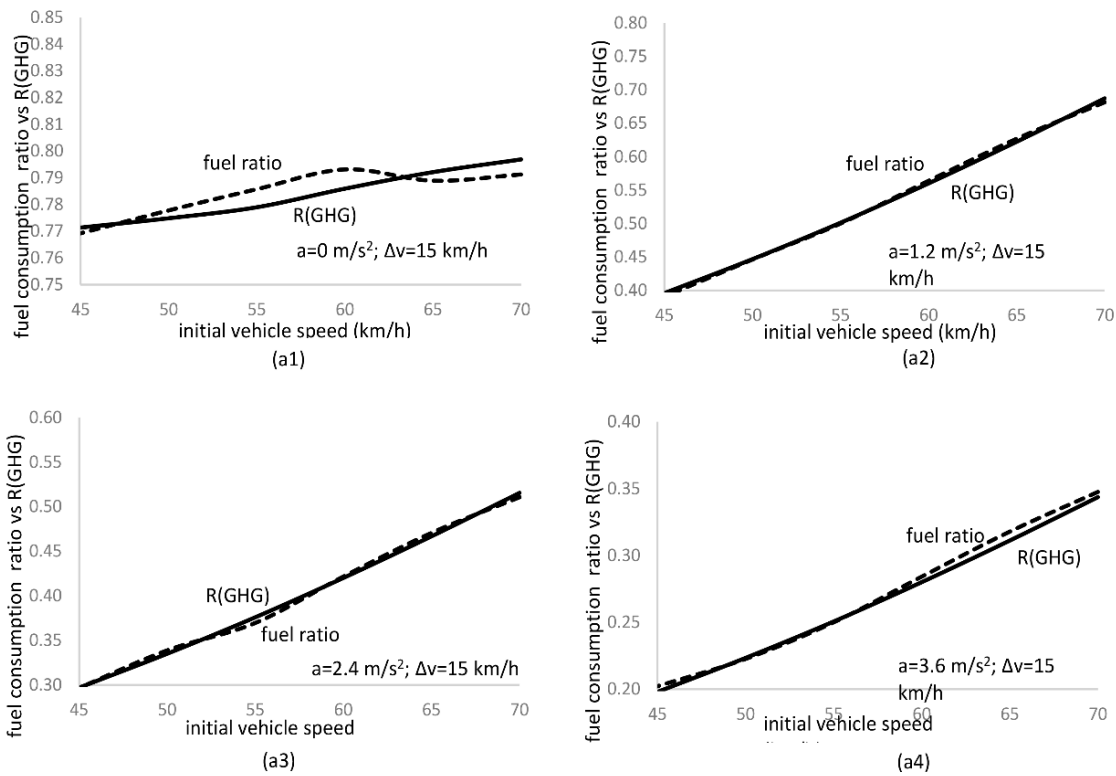
Figure 9 (Case c and Case d) Correlation between theoretical values (R_{GHG}) and experimental data (fuel ratio) for CNG and LPG combustion engine types, vehicle speed, and acceleration rate at vehicle speed reduction: 10 km/h. (1: $a = 0 \text{ m/s}^2$; 2: $a = 1.2 \text{ m/s}^2$; 3: $a = 2.4 \text{ m/s}^2$; 4: $a = 3.6 \text{ m/s}^2$).

The continuous line in Figure 8 and Figure 9 show the predicted evaluation of the GHG emissions rate coefficient evolution as a function of the initial vehicle speed for different acceleration rates. The values shown in Figure 8 and Figure 9 correspond to the theoretically predicted R_{GHG} coefficient. Since GHG emissions are directly related to fuel consumption, we can assume that the fuel ratio represents the relationships between GHG emissions at the initial and reduced vehicle speeds; therefore, the correlation between the fuel ratio and the R_{GHG} coefficient is expected.

We observe close agreement between theoretical values and experimental data across all engine types, initial vehicle speed ranges, speed variations, and acceleration rates, with low deviations at low vehicle speeds, and acceleration modes for gasoline and diesel engines. The deviation vanishes when we deal with gasified fuels, CNG, and LPG, meaning that the model's theoretical predictions work more accurately with these fuel types. On the other hand, the low deviation does not preclude validation of the proposed methodology for evaluating fuel consumption and GHG emissions.

We observe the experimental tests under identical driving conditions except for the vehicle speed reduction, set to 15 km/h for this second test group. Figure 10 and Figure 11 show the correlation between theoretical predictions and experimental data for the new driving conditions.

Case a: Gasoline engine



Case b: Diesel engine

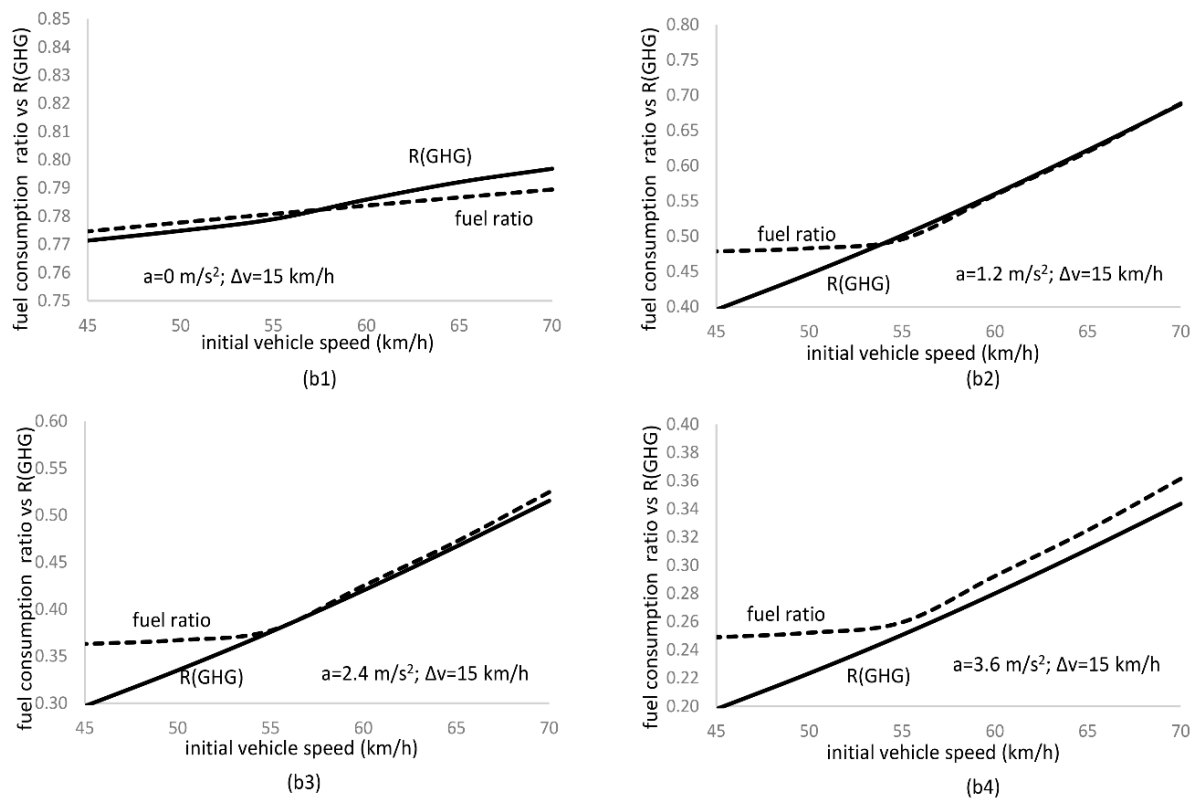
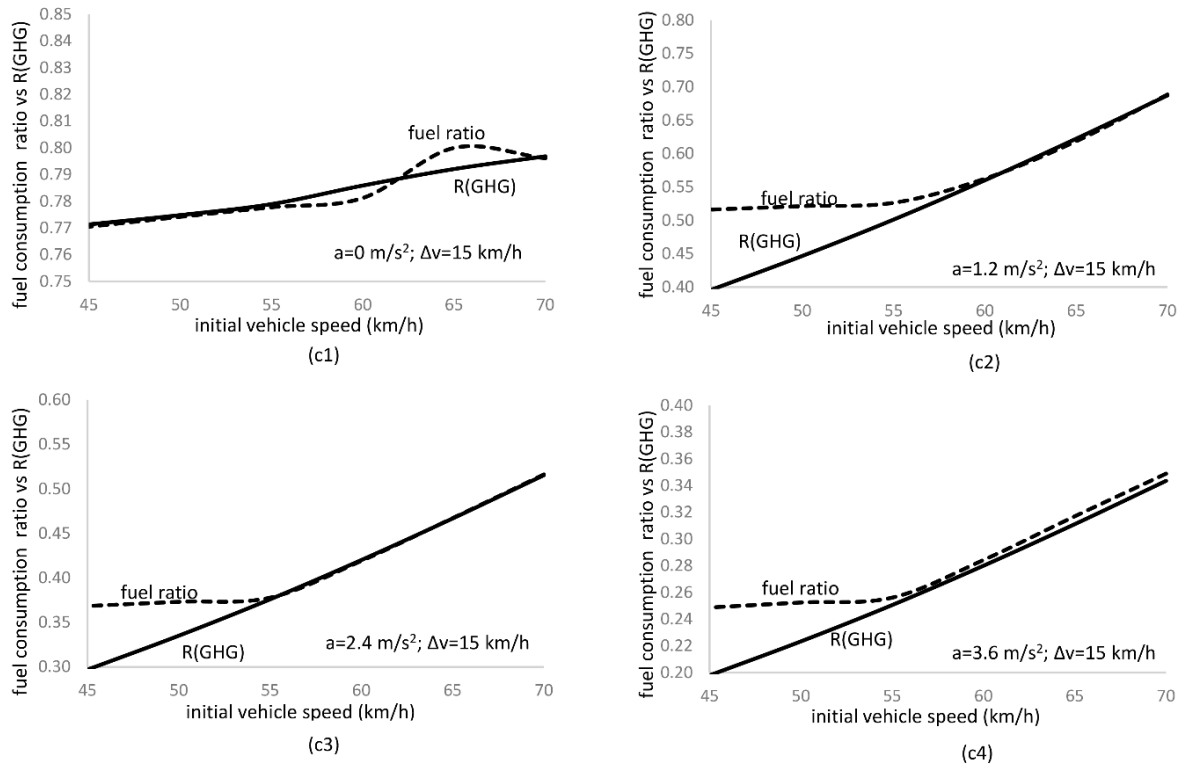


Figure 10 (Case a and Case b) Correlation between theoretical values (R_{GHG}) and experimental data (fuel ratio) for gasoline and diesel combustion engine types, vehicle speed, and acceleration rate at vehicle speed reduction: 15 km/h. (1: $a = 0 \text{ m/s}^2$; 2: $a = 1.2 \text{ m/s}^2$; 3: $a = 2.4 \text{ m/s}^2$; 4: $a = 3.6 \text{ m/s}^2$).

Case c: CNG engine



Case d: LPG engine

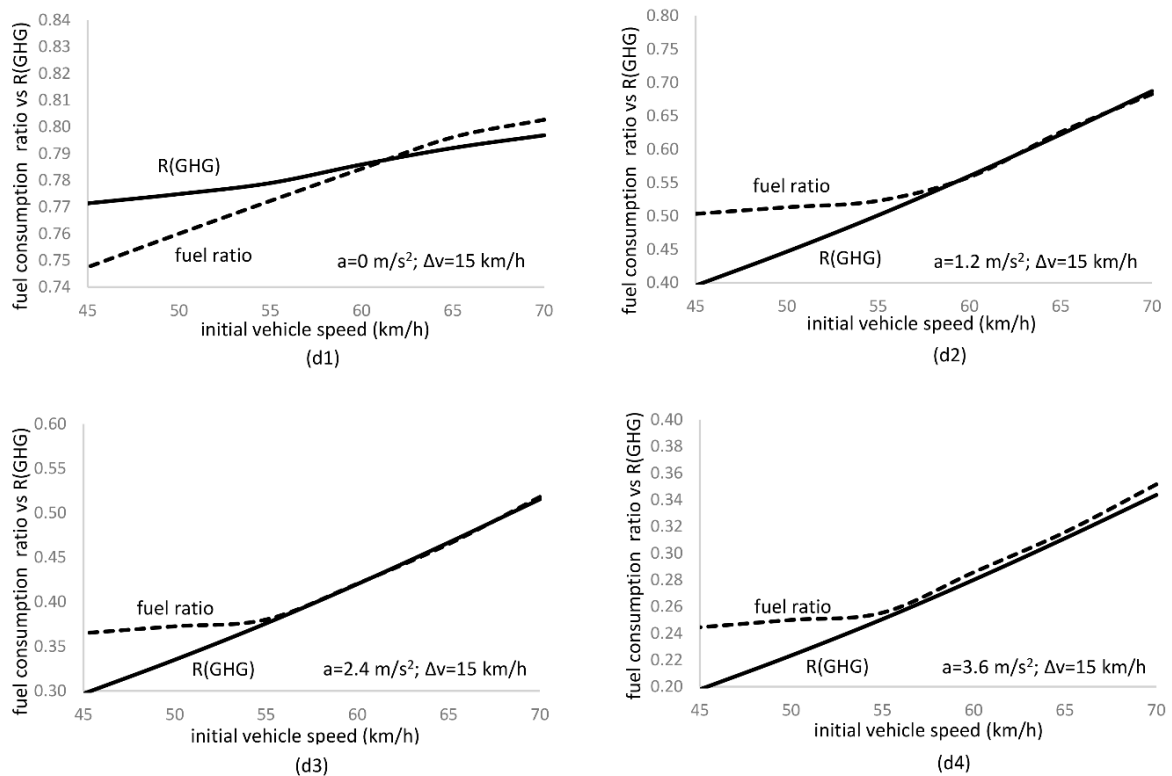


Figure 11 (Case c and Case d) Correlation between theoretical values (R_{GHG}) and experimental data (fuel ratio) for CNG and LPG combustion engine types, vehicle speed, and acceleration rate at vehicle speed reduction: 15 km/h. (1: $a = 0 \text{ m/s}^2$; 2: $a = 1.2 \text{ m/s}^2$; 3: $a = 2.4 \text{ m/s}^2$; 4: $a = 3.6 \text{ m/s}^2$).

We observe that the correlation for vehicle speed reductions of 10 and 15 km/h shows a similar behavior, with close agreement between theoretical prediction (RGHG) and the experimental data (fuel ratio). We also notice that the experimental data diverge from the theoretical prediction for an initial vehicle speed lower than 50 km/h, probably due to the control system's inaccuracy in calculating the fuel consumption under current driving conditions. Nevertheless, we evaluate the standard deviation for every initial vehicle speed to determine how significant the deviation is between the theoretical prediction and the experimental data. Table 5 shows the calculation results.

Table 5 Standard deviation for the correlation between theoretical data and experimental values for various engine types and acceleration rate.

Engine type	Acceleration rate (m/s ²)			
	0	1.2	2.4	3.6
Gasoline	0.012	0.010	0.010	0.010
Diesel	0.011	0.091	0.074	0.065
CNG	0.009	0.144	0.081	0.060
LPG	0.030	0.128	0.078	0.055

We observe an excellent match for the gasoline engine at any acceleration rate. For diesel, GNC, and LPG, the standard deviation increases for vehicle acceleration, although the values remain low; therefore, we can validate the accuracy of the prediction method.

The higher deviation in diesel and gas-fueled engines may be due to the different performance of these types of engines compared to a gasoline motor. A gasoline engine accelerates faster than a diesel engine due to a quicker combustion process and a higher rev range. While gasoline engines use a spark to ignite, which is a faster process, diesel engines rely on high compression for self-ignition, a slower process that generates more torque at low revs but limits acceleration. Analyzing the GHG emissions rate evolution with engine type for variable average vehicle speed and acceleration rate, we obtain (Figure 12):

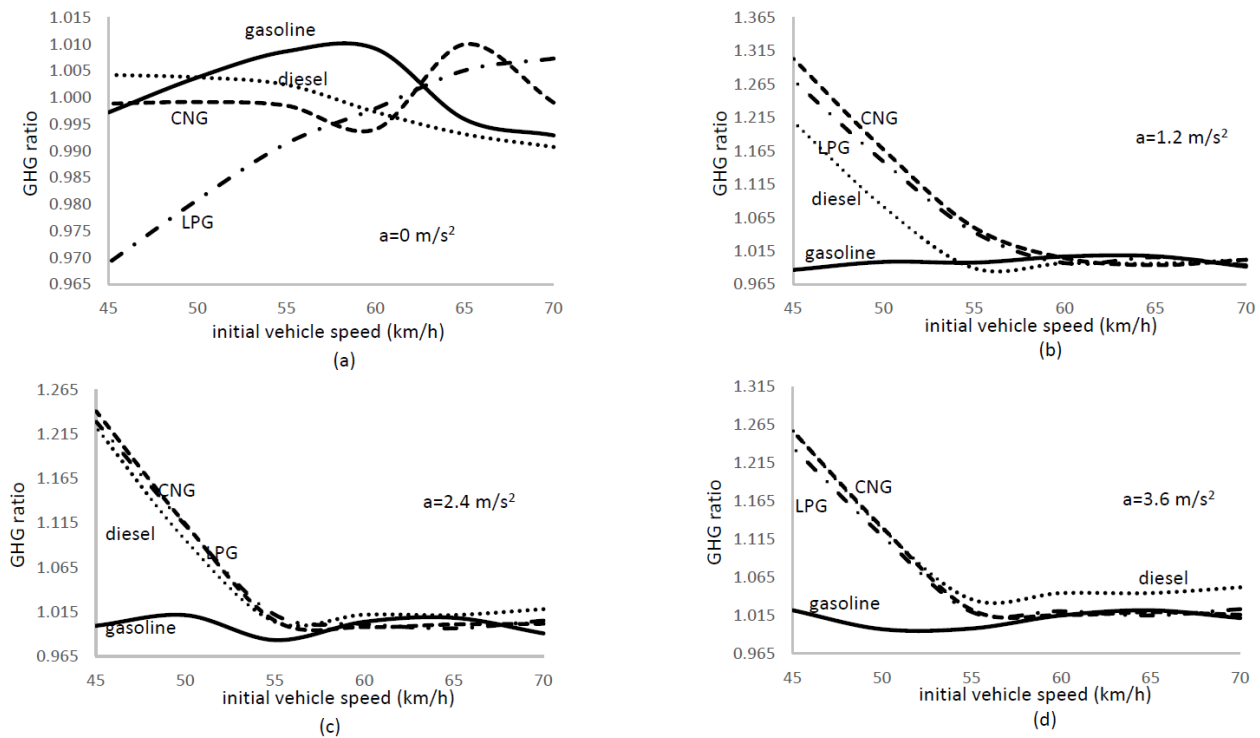


Figure 12 GHG emissions rate evolution with engine type for variable average vehicle speed and acceleration rate. (a: $a = 0 \text{ m/s}^2$; b: $a = 1.2 \text{ m/s}^2$; c: $a = 2.4 \text{ m/s}^2$; d: $a = 3.6 \text{ m/s}^2$).

Data in Figure 12 illustrates the GHG ratio between experimental values and theoretical predictions. We observe that the GHG emission ratio decreases as average vehicle speed increases, reaching a point of stabilization at 57.5 km/h, where it maintains its lowest value. This trend is consistent across all acceleration situations, except for the case of null acceleration, which displays a different pattern. When examining gasoline and CNG engines, the GHG ratio fluctuates around an average value. In contrast, the diesel engine experiences a slight decrease with rising average vehicle speed, while the LPG engine demonstrates a rapid increase in GHG emissions as car velocity increases.

GHG ratio decreases linearly with increasing average vehicle speed until 57.5 km/h; from this point on, the ratio remains constant at 1.015. This situation is only applicable to the acceleration mode because when the acceleration is null, the GHG ratio evolves differently for every engine type, as mentioned before. The linear decrease in the GHG ratio indicates that theoretical prediction accuracy increases with average vehicle speed up to 57.5 km/h, after which it remains constant at its highest value, 98.5%.

8. Conclusions

Theoretical simulation predicts an increase in the GHG emissions rate due to the higher fuel consumption. The increase depends on the engine type, average vehicle speed, speed reduction, and acceleration rate. For null acceleration and speed reduction of 10 km/h, the GHG emissions rate reduction varies from a minimum of 12.4% for an average speed of 70 km/h to a maximum of 15.2% for an average car velocity of 45 km/h. The reduction is higher if the speed reduction increases to

15 km/h, with a decrease of 18.5% for 70 km/h and 21.8% for 45 km/h. Averaging over the vehicle speed range, the reduction for a 10 km/h decrease in vehicle speed is 14.9%, while for a 15 km/h decrease is 20.4%.

For higher acceleration values, the GHG emissions rate increases from a minimum of 31.8% at 1.2 m/s^2 to a maximum of 65.9% at 3.6 m/s^2 , in the case of a vehicle speed lowering of 10 km/h. For the case of vehicle speed reduction of 15 km/h, the GHG emissions rate increase varies in the range from 33.4% for the lowest acceleration, 1.2 m/s^2 , to 66.7% for the highest, 3.6 m/s^2 .

Experimental tests, run under identical driving conditions to the simulation cases, show a close agreement with theoretical prediction, with the standard deviation of 0.010-0.144, resulting in a global average deviation of 0.054. The low standard deviation supports the theoretical prediction with an accuracy greater than 98.2%.

The GHG emissions ratio between experimental values and theoretical predictions reduces linearly with increasing average vehicle speed up to 57.5 km/h. From this point on, the ratio remains constant at its minimum value of 1.015, corresponding to a prediction accuracy of 98.5%.

Future work focuses on applying Artificial Intelligence to the automatic vehicle speed control using the car front camera and traffic signs to adapt the vehicle speed to the traffic speed limit, and sensors in the front side of the car to regulate vehicle acceleration by means of the distance between the vehicle in question and the one traveling just in front.

Author Contributions

The author did all the research work of this study.

Competing Interests

The author has declared that no competing interests exist.

References

1. Ramanathan V, Feng Y. Air pollution, greenhouse gases and climate change: Global and regional perspectives. *Atmos Environ*. 2009; 43: 37-50.
2. Vanderheiden S. Globalizing responsibility for climate change. *Ethics Int Aff*. 2011; 25: 65-84.
3. Bessou C, Ferchaud F, Gabrielle B, Mary B. Biofuels, greenhouse gases and climate change. In: *Sustainable Agriculture Volume 2*. Dordrecht: Springer; 2011. pp. 365-468.
4. Hertzberg M, Siddons A, Schreuder H. Role of greenhouse gases in climate change. *Energy Environ*. 2017; 28: 530-539.
5. Lashof DA, Ahuja DR. Relative contributions of greenhouse gas emissions to global warming. *Nature*. 1990; 344: 529-531.
6. Kweku DW, Bismark O, Maxwell A, Desmond KA, Danso KB, Oti-Mensah EA, et al. Greenhouse effect: Greenhouse gases and their impact on global warming. *J Sci Res Rep*. 2018; 17: 1-9.
7. Mohajan HK. Greenhouse gas emissions, global warming and climate change. *Proceedings of the 15th Chittagong Conference on Mathematical Physics*, Jamal Nazrul Islam Research Centre for Mathematical and Physical Sciences (JNIRCMPS); 2017 March; Chittagong, Bangladesh. Chittagong, Bangladesh: University of Chittagong.

8. Mohajan H. Greenhouse gas emissions increase global warming. *Int J Econ Polit Integr.* 2011; 1: 21-34.
9. Wadanambi RT, Wandana LS, Chathumini KK, Dassanayake NP, Preethika DD, Arachchige US. The effects of industrialization on climate change. *J Res Technol Eng.* 2020; 1: 86-94.
10. Le Menestrel M, Le Menestrel M, De Bettignies HC. Processes and consequences in business ethical dilemmas: The oil industry and climate change. *J Bus Ethics.* 2002; 41: 251-266.
11. Ng AK, Wang T, Yang Z, Li KX, Jiang C. How is business adapting to climate change impacts appropriately? Insight from the commercial port sector. *J Bus Ethics.* 2018; 150: 1029-1047.
12. Sussman FG, Freed JR. Adapting to climate change: A business approach. Arlington, VA: Pew Center on Global Climate Change; 2008.
13. Pinkse J, Kolk A. International business and global climate change. London, UK: Routledge; 2009.
14. Mancini F, Lo Basso G. How climate change affects the building energy consumptions due to cooling, heating, and electricity demands of Italian residential sector. *Energies.* 2020; 13: 410.
15. Olonscheck M, Holsten A, Kropp JP. Heating and cooling energy demand and related emissions of the German residential building stock under climate change. *Energy Policy.* 2011; 39: 4795-4806.
16. Ranson M, Morris L, Kats-Rubin A. Climate change and space heating energy demand: A review of the literature. Washington, D.C.: U.S. Environmental Protection Agency; 2014.
17. Soeder DJ. Fossil fuels and climate change. In: *Fracking and the environment: A scientific assessment of the environmental risks from hydraulic fracturing and fossil fuels.* Cham: Springer International Publishing; 2020. pp. 155-185.
18. Krane J. Climate change and fossil fuel: An examination of risks for the energy industry and producer states. *MRS Energy Sustain.* 2017; 4: E2.
19. Stanley JK, Hensher DA, Loader C. Road transport and climate change: Stepping off the greenhouse gas. *Transp Res Part A Policy Pract.* 2011; 45: 1020-1030.
20. Chapman L. Transport and climate change: A review. *J Transp Geogr.* 2007; 15: 354-367.
21. Mansour AI, Aljamal HA. Investigating the effect of traffic flow on pollution, noise for urban road network. *IOP Conf Ser Earth Environ Sci.* 2022; 961: 012067.
22. Zhou X, Wang H, Huang Z, Bao Y, Zhou G, Liu Y. Identifying spatiotemporal characteristics and driving factors for road traffic CO₂ emissions. *Sci Total Environ.* 2022; 834: 155270.
23. Cohen B. Urban growth in developing countries: A review of current trends and a caution regarding existing forecasts. *World Dev.* 2004; 32: 23-51.
24. Güneralp B, Reba M, Hales BU, Wentz EA, Seto KC. Trends in urban land expansion, density, and land transitions from 1970 to 2010: A global synthesis. *Environ Res Lett.* 2020; 15: 044015.
25. Kabisch N, Haase D. Diversifying European agglomerations: Evidence of urban population trends for the 21st century. *Popul Space Place.* 2011; 17: 236-253.
26. Ford T. Understanding population growth in the peri-urban region. *Int J Popul Geogr.* 1999; 5: 297-311.
27. Barth M, Boriboonsomsin K. Traffic congestion and greenhouse gases. *Access Mag.* 2009; 1: 2-9.
28. Bharadwaj S, Ballare S, Chandel MK. Impact of congestion on greenhouse gas emissions for road transport in Mumbai metropolitan region. *Transp Res Procedia.* 2017; 25: 3538-3551.
29. Rosca E, Costescu D, Rusca FV, Burciu S. Assessing the effect of traffic congestion on greenhouse gas emissions. *Proceedings of the International Conference on Traffic and Transport*

- Engineering; 2014 November 27-28; Belgrade, Serbia. Belgrade, Serbia: City Net Scientific Research Center Ltd.
30. Pattara-Atikom W, Pongpaibool P, Thajchayapong S. Estimating road traffic congestion using vehicle velocity. Proceedings of the 2006 6th International Conference on ITS Telecommunications; 2006 June 21-23; Chengdu, China. New York, NY: IEEE.
 31. Rao AM, Rao KR. Measuring urban traffic congestion-A review. Int J Traffic Transport Eng. 2012; 2: 286-305.
 32. Rahman MM, Najaf P, Fields MG, Thill JC. Traffic congestion and its urban scale factors: Empirical evidence from American urban areas. Int J Sustain Transp. 2022; 16: 406-421.
 33. Texas A&M Transportation Institute. Urban Mobility Report [Internet]. College Station, TX: Texas A&M Transportation Institute; 2006. Available from: <https://mobility.tamu.edu/umr/>.
 34. Lomax STT, Shunk G. Quantifying Congestion [Internet]. Washington, D.C.: National Cooperative Highway Research Program; 1997. Available from: https://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_398.pdf.
 35. Dietz T, Frank KA, Whitley CT, Kelly J, Kelly R. Political influences on greenhouse gas emissions from US states. Proc Natl Acad Sci. 2015; 112: 8254-8259.
 36. Lægreid OM. Political and economic effects on greenhouse gas emissions-A quantitative study. World Polit Sci. 2014; 10: 313-341.
 37. Feiock RC, Bae J. Politics, institutions and entrepreneurship: City decisions leading to inventoried GHG emissions. Carbon Manage. 2011; 2: 443-453.
 38. DeCanio SJ. The political economy of global carbon emissions reductions. Ecol Econ. 2009; 68: 915-924.
 39. Liu Y, Gao C, Lu Y. The impact of urbanization on GHG emissions in China: The role of population density. J Clean Prod. 2017; 157: 299-309.
 40. Timmons D, Ziogiannis N, Lutz M. Location matters: Population density and carbon emissions from residential building energy use in the United States. Energy Res Soc Sci. 2016; 22: 137-146.
 41. Lee S, Lee B. The influence of urban form on GHG emissions in the US household sector. Energy Policy. 2014; 68: 534-549.
 42. Kumar S, Sen R. Are larger or denser cities more emission efficient? Exploring the nexus between urban household carbon emission, population size and density. Appl Energy. 2025; 377: 124500.
 43. Dodman D. Urban density and climate change. Analytical review of the interaction between urban growth trends and environmental changes [Internet]. 2009. Available from: [https://www.semanticscholar.org/paper/United-Nations-Population-Fund-\(UNFPA\)-Analytical-1-Dodman/1dc49bbbfc07e5af525d3a9e4b2f22e5306d34bf](https://www.semanticscholar.org/paper/United-Nations-Population-Fund-(UNFPA)-Analytical-1-Dodman/1dc49bbbfc07e5af525d3a9e4b2f22e5306d34bf).
 44. Lei H, Zeng S, Namaiti A, Zeng J. The impacts of road traffic on urban carbon emissions and the corresponding planning strategies. Land. 2023; 12: 800.
 45. Grote M, Williams I, Preston J, Kemp S. Including congestion effects in urban road traffic CO₂ emissions modelling: Do local government authorities have the right options? Transp Res D Transp Environ. 2016; 43: 95-106.
 46. Yang Y, Takase T. Spatial characteristics of carbon dioxide emission intensity of urban road traffic and driving factors: Road network and land use. Sustain Cities Soc. 2024; 113: 105700.

47. Stepanova NV, Rashitovich SR, Valeeva ER, Raifovna IA, Fomina SF, Vagizovich SN. The impact of traffic density on population health in the city of Kazan. *Arch Venez Farmacol Ter.* 2020; 39: 890-898.
48. Godec R, Jakovljević I, Davila S, Šega K, Bešlić I, Rinkovec J, et al. Air pollution levels near crossroads with different traffic density and the estimation of health risk. *Environ Geochem Health.* 2021; 43: 3935-3952.
49. Levy JI, Buonocore JJ, Von Stackelberg K. Evaluation of the public health impacts of traffic congestion: A health risk assessment. *Environ Health.* 2010; 9: 65.
50. Khreis H, Warsow KM, Verlinghieri E, Guzman A, Pellecuer L, Ferreira A, et al. The health impacts of traffic-related exposures in urban areas: Understanding real effects, underlying driving forces and co-producing future directions. *J Transp Health.* 2016; 3: 249-267.
51. Wjst M, Reitmeir P, Dold S, Wulff A, Nicolai T, von Loeffelholz-Colberg EF, et al. Road traffic and adverse effects on respiratory health in children. *Br Med J.* 1993; 307: 596-600.
52. Stopher PR. Reducing road congestion: A reality check. *Transp Policy.* 2004; 11: 117-131.
53. Nguyen-Phuoc DQ, Young W, Currie G, De Gruyter C. Traffic congestion relief associated with public transport: State-of-the-art. *Public Transp.* 2020; 12: 455-481.
54. Dabbour DI, Tarabieh KH. Traffic congestion sustainable solutions: Mass transportation (Railway Upgrade). In: *Global Climate Change, Biodiversity and Sustainability: Challenges and Opportunities.* 2013. pp. 325-335.
55. Ramos S, Vicente P, Passos AM, Costa P, Reis E. Perceptions of the public transport service as a barrier to the adoption of public transport: A qualitative study. *Soc Sci.* 2019; 8: 150.
56. Beirão G, Cabral JS. Understanding attitudes towards public transport and private car: A qualitative study. *Transp Policy.* 2007; 14: 478-489.
57. Carrel A, Halvorsen A, Walker JL. Passengers' perception of and behavioral adaptation to unreliability in public transportation. *Transp Res Rec.* 2013; 2351: 153-162.
58. Park J, Chowdhury S. Investigating the barriers in a typical journey by public transport users with disabilities. *J Transp Health.* 2018; 10: 361-368.
59. Van Exel NJ, Rietveld P. Public transport strikes and traveller behaviour. *Transp Policy.* 2001; 8: 237-246.
60. Ronan WJ. Public transportation problems in urban areas [Internet]. Washington, D.C.: Transportation Research Board Special; 1974. Available from: <http://onlinepubs.trb.org/Onlinepubs/sr/sr144/sr144-003.pdf>.
61. CDSE. Sentinel-5P—Monitoring our atmosphere. Copernicus Sentinel data (2019-20) [Internet]. KNMI/ESA. Available from: <https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-5p>.
62. Zehner C. Using copernicus sentinel measurements to monitor covid-19 impact on the environment. *Proceedings of the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*; 2021 July 11-16; Brussels, Belgium. New York, NY: IEEE.
63. Arce-Ruiz RM. ¿Reducen las limitaciones de velocidad la contaminación atmosférica? [Internet]. Carlton, Australia: The Conversation; 2021. Available from: <https://theconversation.com/reducen-las-limitaciones-de-velocidad-la-contaminacion-atmosferica-151391>.
64. Arce-Ruiz RM. Por qué conducir más lento no sirve para contaminar menos el aire de tu ciudad [Internet]. Guayaquil, Ecuador: El Español; 2021. Available from:

https://www.elespanol.com/ciencia/medio-ambiente/20210121/conducir-lento-no-sirve-contaminar-aire-ciudad/552695975_0.html.

65. Olusanya GS, Eze MO, Ebiesuwa O, Okunbor C. Smart transportation system for solving urban traffic congestion. *Rev Comput Eng Stud*. 2020; 7: 55-59.