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THE EFFECTS OF THE PREFERENTIAL DRIVING STRATEGY TO FUEL CONSUMPTION AND GREENHOUSE GASSES

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Abstract. *This paper addresses the issue of personal driving preferences and how they affect fuel consumption and greenhouse gasses. The driving preference refers to the driver's attitude in driving – related to their preferential vehicle acceleration, braking deceleration, his time response for the relative change in the distance to the leading vehicle, and his thought on the safe distance. The vehicle movement is simulated by adopting an agent-based model where each agent represents a vehicle whose dynamic characteristics follow the intelligent driver model. To reveal the effects of the driving preferences on fuel consumption and greenhouse gasses, we focus on a simple interaction involving a follower vehicle and a leading vehicle. Both the vehicles are initially at rest and separated by 1 km. Then, the follower vehicle accelerates and then decelerates following the intelligent driver model to stop behind the leading vehicle. During the process, the fuel consumption and the amounts of emitted gasses of the follower vehicle are estimated by regression models. The results suggest that the driver preferences on the vehicle acceleration and braking deceleration seriously affect fuel consumption and the amount of the emitted greenhouse gasses. However, the driver preferences on the safe distance and time headway, both measured to the leading vehicle, are having negligible effects on the change of the fuel consumption and the emitted greenhouse gasses.*
Keywords: Fuel consumption, Greenhouse gasses, Intelligent driver model, Agent-based model, Driving preferences, Energy efficient driving, Vehicle dynamics

1. **Introduction.** Generally, we understand that the high level of air pollution has a detrimental effect on human health. According to the European Environment Agency (2011) [1], land transportation accounts for about 29% of the total emitted CO_2. The pollution is more visible in big cities where the number of vehicles is high. In October 2019, the Air Quality Index (AQI) reached the level of 160 in Jakarta, which is unsafe. According to the US Environmental Protection Agency [2], the AQI in the range of 151 and 200 is unhealthy. The citizen awareness about the air quality has been elevated with the emergence of the Airvisual website at https://www.airvisual.com/. The Jakarta government has implemented policies to improve traffic and air quality. The restriction on the operations of motor vehicles via even-odd license plate regulation was not effective, according to Airvisual.

[3] argued that with better traffic operations, including speed management, congestion mitigation, and traffic smoothing, as much as 30% CO_2 emissions could be reduced. The amount of the consumed fuel depends strongly on the velocity profile of the vehicles [4]. Unfortunately, the policymakers were primarily focused on introducing more efficient vehicles, alternative fuels, and reducing vehicle miles traveled, including building lighter and

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smaller vehicles, improving powertrain efficiency, and introducing alternative technologies such as hybrid and fuel-cell vehicles.

Several traffic management strategies for improving fuel efficiency have been studied including vehicle platooning where some vehicles are arranged in a row at a close range and the vehicle movement is controlled by using a wireless communication system. This strategy has many advantages, including reducing costs, reducing emissions, increasing safety in driving, reducing congestion, and using better road capacity. According to [5, 6] putting vehicles in one platoon can reduce fuel by 6% for the leading vehicle and 10% for the followers. The study of [7] found the use of an Air Conditioner (AC) in summer where the temperature is higher than 25 Celcius degrees accounts for an additional 1.3% of annual fuel consumption. On this basis, the authors argued that improving AC energy consumption can reduce CO_2 emission by 1.6-2.4 million tons annually in China. The fuel efficiency can also be improved by a good driving strategy [8]. A driving strategy is a pattern of someone regulating the speed when accelerating to reach the desired speed [9]. However, many factors affect a person's driving strategy, from habits to traffic conditions. An optimal driving strategy can lead to fuel savings by an amount of 5% to 35% [10]. Besides the driving strategy or behavior, [11] found certain aspects of socio-demographic characteristics and driving behavior correlated well with fuel efficiency. Based on the empirical data collected from a busy freeway in Austin, Texas, the authors found female drivers' fuel efficiency is worse during the peak period. Those who drove fast with a small velocity-variation (low acceleration) achieved the best fuel efficiency. A Cooperative Adaptive Cruise Control (CACC) could also improve fuel efficiency and emissions, according to [12]. They found CACC was better, as much as 20%, in fuel efficiency than manual driving on freeway traffic with a bottleneck. If CACC was entirely used, the improvement could reach 50%. As for the case of the aviation industry, [13] suggested that reducing NO_x is potentially better than reducing both NO_x and CO_2 simultaneously due to technical trade-off. However, how the driving strategy exactly affects fuel consumption and emissions is not completely clear.

Related to the fuel economy and emission, finding the most accurate method to measure fuel consumption and emissions on actual traffic conditions was also a subject of interest to many researchers. For example, [14] proposed a method so-called the grid engine map model to estimate fuel efficiency and emissions of a diesel engine. The method discretized the domain of engine torque and engine speed into smaller equal-sized domains. The method was evaluated by using a diesel Euro V bus under urban off-cycle conditions in Madrid, Spain, and found a total error of less than 5%.

In this paper, we quantify the effects of the driving strategy, namely, the driver's aggressiveness, on the fuel consumption and emissions of greenhouse gasses. We use a microscopic approach that allows us to observe the impacts of the driving behavior closely. We structure the paper as the following. Section 2, Research Method, describes the agent-based model simulating the interaction of two vehicles, and the four empirical formulas for estimating the fuel consumption and greenhouse gasses. Besides, we also provide data for the model parameters. In Section 3, Results and Discussion, we present the major findings of the effects of the driving strategy on the changes in fuel consumption and emissions. Finally, in Section 4, Conclusion, we conclude the most essential aspects contributed by this research and propose related areas for future investigation.

2. **Research Method.** In this research, we wish to understand how driving strategy affects fuel consumption and emissions of gasses. The driving strategy reflects individual preferences on the vehicle cruising speed, acceleration, braking deceleration, reaction time, and a safe distance to the leading vehicle. These personal preferences are microscopic and vary from individual to individual. The intelligent driver model is a mathematical model that relates the driving preferential to the vehicle dynamics. The model suggests

the driving strategy depending on the personal preference in the aspects of the vehicle acceleration and deceleration, the safe distance with the leading vehicle, and the driver reaction time. Those preferential driving parameters determine the vehicle dynamics by the equation:

$$a_i = a_{\max}\left[1 - \left(\frac{v_i}{v_0}\right)^{\delta} - \left(\frac{s^*}{s_0}\right)^2\right], \tag{1}$$

where $s^* = s_0 + v_i \cdot T + v_i \cdot \Delta v_i \big/ \left(2\sqrt{a_{\max} \cdot a_{\text{break}}}\right)$, $a_{\max}$ is the maximum vehicle acceleration, a_{break} is the driver comfortable breaking deceleration, v_0 is the desired velocity, δ is the velocity exponent, s_0 is the desired minimum net distance with the leading vehicle, and T is the desired time headway. The relative velocity is defined as $\Delta v_i = v_i - v_{(i-1)}$. The distance between vehicles is defined as $s_i = x_{(i-1)} - x_i - L_{(i-1)}$ where $L_{(i-1)}$ is the vehicle length. We assume the $(i-1)$-th vehicle leads the i-th vehicle. According to [15], the typical values of those parameters are presented in Table 1.

Table 1. The parameters and values of the Intelligent Driver Model (IDM) in this research [15]

No	IDM parameter	Values	Unit
1	The desired time headway (T)	1.50	s
2	The maximum vehicle acceleration ($a_{\max}$)	0.73	m/s^2
3	The driver comfortable breaking deceleration (a_{break})	1.76	m/s^2
4	The velocity exponent (δ)	4	
5	The desired minimum net distance (s_0)	2.00	m
6	The desired velocity (v_0)	30.00	m/s
7	The vehicle length (L)	5.00	m

As for fuel consumption and emissions of greenhouse gasses (GHG), we adopt the models proposed by [9]. The GHG consists of three types: carbon monoxide (CO), hydrocarbon (HC), and nitrogen monoxide (NO_x). According to the reference, the consumption and emission entirely depend on vehicle acceleration (a_i) and velocity (v_i). The equations to estimate the fuel consumption and emissions are provided as the following.

$$\begin{aligned}\log_e f = &-0.679439000 + 0.135273000 \cdot a + 0.015946000 \cdot a^2 - 0.001189000 \cdot a^3\\ &+ 0.029665000 \cdot v - 0.000276000 \cdot v^2 + 0.000001487 \cdot v^3\\ &+ 0.004808000 \cdot a \cdot v - 0.000020535 \cdot a \cdot v^2 + 5.5409285 \times 10^{-8} \cdot a \cdot v^3\\ &+ 0.000083329 \cdot a^2 \cdot v + 0.000000937 \cdot a^2 \cdot v^2 - 2.479644000 \times 10^{-8} \cdot a^2 \cdot v^3\\ &- 0.000061321 \cdot a^3 \cdot v + 0.000000304 \cdot a^3 \cdot v^2 - 4.467234000 \times 10^{-9} \cdot a^3 \cdot v^3 \end{aligned}\tag{2}$$

$$\begin{aligned}\log_e \text{CO} = &\ 0.887447 + 0.148841 \cdot a + 0.030550 \cdot a^2 - 0.001348 \cdot a^3\\ &+ 0.070994 \cdot v - 0.000786 \cdot v^2 + 0.000004616 \cdot v^3\\ &+ 0.003870 \cdot a \cdot v - 0.000093228 \cdot a \cdot v^2 - 0.000000706 \cdot a \cdot v^3\\ &- 0.000926 \cdot a^2 \cdot v + 0.000049181 \cdot a^2 \cdot v^2 - 0.000000314 \cdot a^2 \cdot v^3\\ &- 0.000046144 \cdot a^3 \cdot v - 0.000001410 \cdot a^3 \cdot v^2 - 8.41724008 \times 10^{-9} \cdot a^3 \cdot v^3 \end{aligned}\tag{3}$$

$$\begin{aligned}\log_e \text{HC} = &-0.728042 + 0.12211 \cdot a + 0.023371 \cdot a^2 - 0.000093243 \cdot a^3\\ &+ 0.024950 \cdot v - 0.000205 \cdot v^2 + 0.000001949 \cdot v^3\\ &+ 0.010145 \cdot a \cdot v - 0.000103 \cdot a \cdot v^2 - 0.000000618 \cdot a \cdot v^3\\ &- 0.000549 \cdot a^2 \cdot v + 0.000037592 \cdot a^2 \cdot v^2 - 0.000000213 \cdot a^2 \cdot v^3\\ &- 0.000113 \cdot a^3 \cdot v - 0.000003310 \cdot a^3 \cdot v^2 - 1.73972 \times 10^{-8} \cdot a^3 \cdot v^3 \end{aligned}\tag{4}$$

$$\log_e \text{NO}_\text{x} = -1.067682 + 0.254363 \cdot a + 0.008866 \cdot a^2 + 0.000951 \cdot a^3$$

$$
\begin{aligned}
&+ 0.046423 \cdot v - 0.000173 \cdot v^2 + 0.000000569 \cdot v^3 \\
&+ 0.015482 \cdot a \cdot v - 0.000131 \cdot a \cdot v^2 - 0.000000328 \cdot a \cdot v^3 \\
&- 0.002876 \cdot a^2 \cdot v + 0.000058660 \cdot a^2 \cdot v^2 - 0.000000240 \cdot a^2 \cdot v^3 \\
&- 0.000321 \cdot a^3 \cdot v - 0.000001943 \cdot a^3 \cdot v^2 - 1.257413 \times 10^{-8} \cdot a^3 \cdot v^3 \qquad (5)
\end{aligned}
$$

To use those equations, the acceleration should be in ft/s^2 and the velocity in ft/s. The estimated fuel consumption is in gallon/hour. For the reason, we use the following conversions: 1 m/s^2 = 3.2808399 ft/s^2, 1 m/s = 3.28084 ft/s, and 1 gallon/hour = 0.0010515 L/s. As for the gasses, the outputs are in mg/s.

In our opinion, the best approach to reveal the effects of the driving strategy to fuel consumption and emissions is to study the simplest but realistic interaction of vehicles. In the car following stage, interaction involving two vehicles where a leader vehicle is followed by a follower vehicle is the simplest (see Figure 1). Initially, we assume both vehicles are at rest and separated by a distance of one kilometer. The leader stays in place during the entire duration of the analysis. The follower accelerates and then decelerates before stoping behind the leader vehicle.

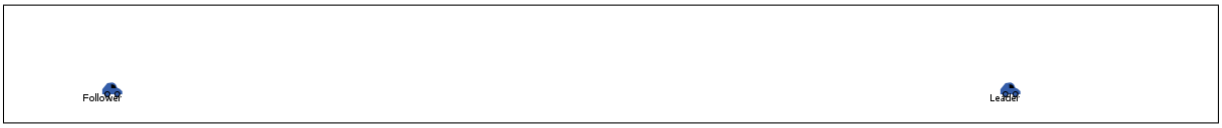

Figure 1. The simplest model of the car-following

We simulate the above interaction by using an agent-based model. For the simulation, we begin with creating and placing two vehicles (agents) one kilometer apart. Then, we set the IDM parameters as attributes to each agent. Finally, the vehicle velocity and position are updated with the procedure described in Table 2.

Table 2. The pseudo-code for NetLogo 'to-go' block. The variables a, v, and x denote the acceleration, velocity, and position of the vehicle, respectively

to go
  Compute the vehicle acceleation with Equation (1)
  Compute the change of speed: $\Delta v \leftarrow a \cdot \Delta t$
  Compute the change of position: $\Delta x \leftarrow v \cdot \Delta t + \frac{1}{2} \cdot a \cdot (\Delta t)^2$
  Update the vehicle speed: $v \leftarrow v + \Delta v$
  Update the vehicle position: $x \leftarrow x + \Delta x$
  Compute the fuel consumption and emissions with Equations (2)-(5)
end

3. **Results and Discussion.**

Most of the data presented in this section are the results of the computations in NetLogo, an agent-based simulation program. The agent, the vehicle, moves following the intelligent driver model with the values of the parameters presented in Table 1. We refer to this model with this set of values as the baseline and basic model.

Before using the NetLogo model to study the sensitivity of fuel consumption and the emissions of greenhouse gasses, we validate the NetLogo model by comparing its results with those by the Runge-Kutta algorithm, which is readily available in Python within the package `scipy.integrate`.

In Figure 2, we present the computed vehicle position, velocity, and acceleration by the NetLogo model. We also show the results of the Runge-Kutta algorithm. As for the

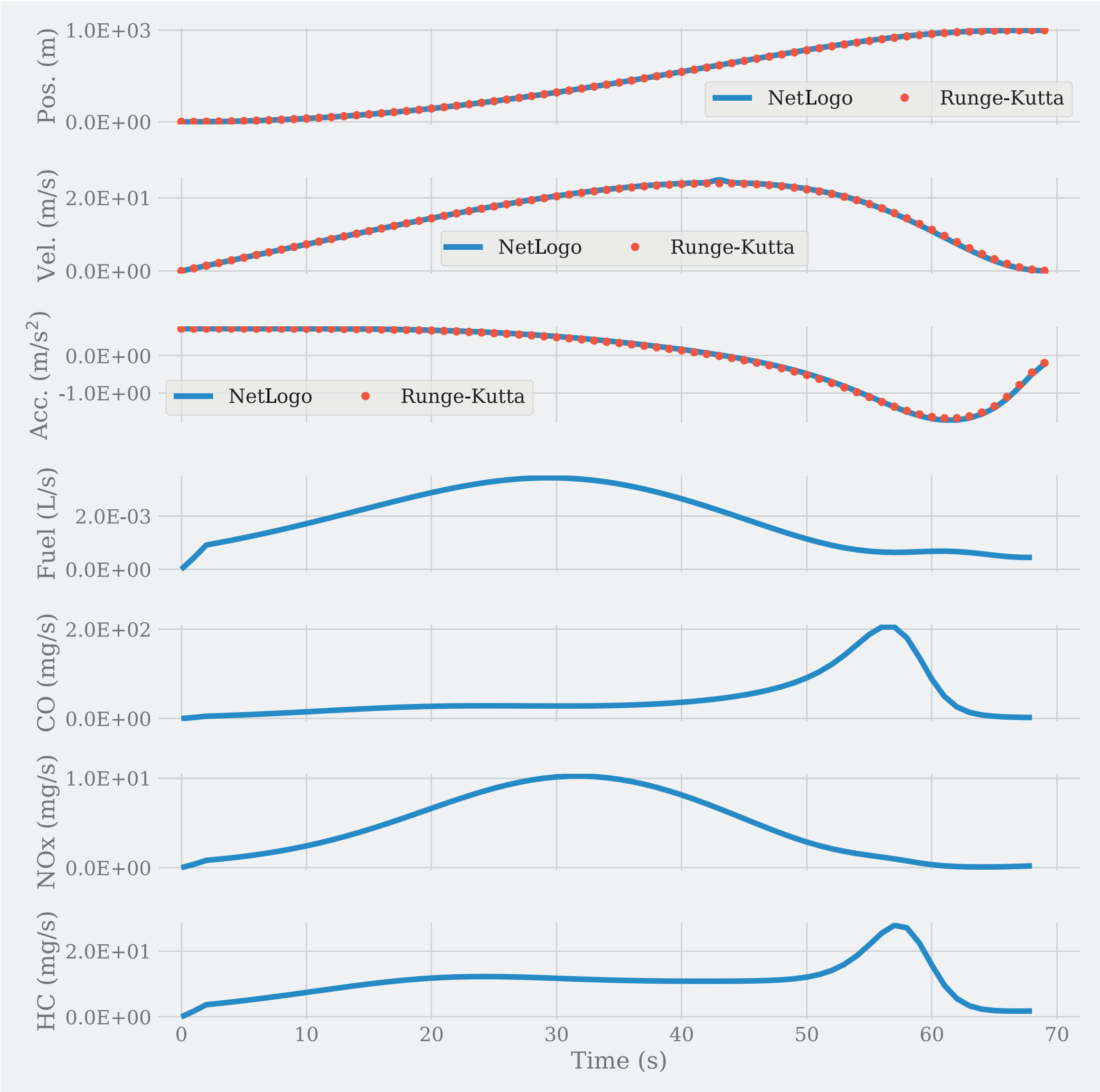

Figure 2. The dynamics of the follower vehicle from its initial position to its final destination and the fuel consumption rate and the rates of the emitted greenhouse gasses for the travel

vehicle position, it starts at $x = 0$ and ends at $x = 998$ m, or two meters behind the lead vehicle, and exactly matches the setting of the desired minimum net distance. As for the vehicle velocity, the highest value is 25 m/s, lower than the value sets for the desired velocity. The highest velocity is achieved at the time instant of 43 s, or 26 s before the vehicle reaches its final position. Clearly, from the velocity profile data, the vehicle has to slow down before reaching the top speed as the distance to the leading vehicle becomes too small. As for the vehicle acceleration, unlike the velocity, the vehicle can reach the values set to the model. The vehicle accelerates at 0.73 m/s^2 at the beginning of the simulation and decelerates at 1.76 m/s^2 at about 9 s before stopping.

We compare the results (vehicle position, velocity, and acceleration) of the NetLogo program with those of the Runge-Kutta algorithm. The figure shows that the NetLogo results agree well with the Runge-Kutta results. The differences between the two approaches for the three dynamic indicators are extremely small. Thus, we conclude the NetLogo model has been correctly implemented.

The figure also shows the histories of consumed fuel and emitted gasses (CO, NO_x, and HC). These results are rather interesting. The profile of fuel consumption is rather similar to the NO_x profile where the maximum values occur at around 30 s. Meanwhile, the profile of CO is similar to the HC profile where the maximum values occur just before the vehicle stops.

In the following, we discuss the effects of the driving strategy to fuel consumption and emissions of gasses. We vary the maximum vehicle acceleration by 5%, and we observe its effects on the change of the fuel consumption and emitted gasses. We also reduce the value by 5% and perform a similar observation. A similar procedure is also applied for the driver's comfortable breaking deceleration, the desired minimum net distance, and the desired time headway. The change is performed individually where the values of the other parameters are maintained at their baseline values as shown in Table 1.

The results in Figure 3 lead us to the following conclusions. In general, with more aggressive driving, associated with higher the maximum vehicle acceleration and braking deceleration but lower the desired minimum net distance and time headway, fuel consumption and emitted gasses tend to increase. From the four driving parameters, the change of the maximum vehicle acceleration seems to possess the largest impacts on fuel consumption and emitted gasses, followed by the breaking deceleration, and the time headway. The change of the desired minimum net distance has negligible effects on the change in fuel consumption and emitted gasses. However, the change of the breaking deceleration greatly influences the change of the amount of CO and NO_x.

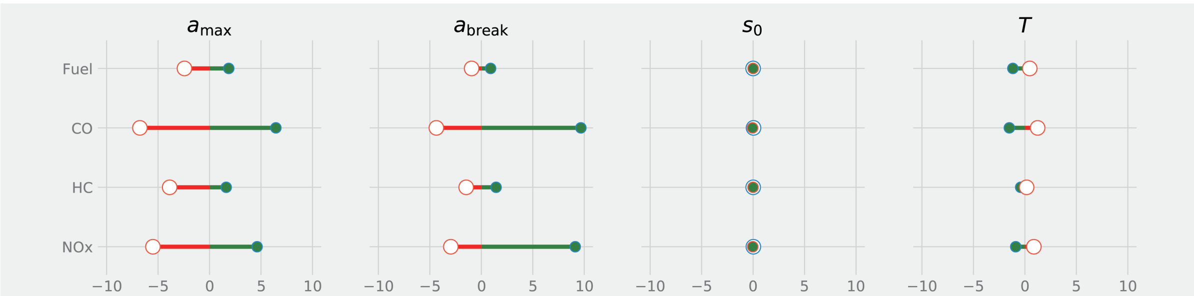

FIGURE 3. The effects of varying the maximum vehicle acceleration, the driver comfortable breaking deceleration, the desired minimum net distance, and the desired time headway to fuel consumption and emitted gasses. The marker '○' is associated with the results of increasing the parameter by 5%. The marker '•' is for 5% reduction. The changes in fuel consumption and emitted gasses are in percentage.

4. Conclusion.

When we drive a vehicle, we control the vehicle acceleration, deceleration, cruise velocity, and the distance to the leading vehicle. In this work, we study how these individual preferences affect fuel consumption and amount of the greenhouse gasses emitted by the vehicle. We simulate the vehicle dynamics by using an agent-based approach and estimate the consumed fuel and the amount of the emitted gasses. The results suggest that the changes in the vehicle's maximum acceleration and deceleration greatly affect both fuel and emitted gasses. As for a future study, we may explore many aspects of traffic characteristics, and associated emitted gasses, for example, we may look into the effects of a single aggressive driver on the entire traffic flow and the resulted gas emission.

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