Do More Cars Mean More Electricity? Investigating the Relationship Between Vehicle Energy Expenditure and Vehicle Density within an Urban Environment: An Agent-Based Modelling approach.

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Abstract

Electric Vehicle technology is slowly becoming the norm throughout the world. Given the disastrous impact Internal Combustion Engine Vehicles (ICEVs) have on people's health and the environment, there is a clear shift among governments to adopt these new technologies. The UK government announced its ambitious plans for a net-zero carbon future through investment in infrastructure for electric vehicles (EVs). This investment is estimated to cost over £1.8 billion and aims to increase access to zero-emission vehicles and promote a green economic recovery [37]. However, the literature on electric vehicle research mainly revolves around charging infrastructure and market penetration. This study will apply the agent-based modelling technique to quantify the electric fuel intake required to complete hypothetical drive cycle scenarios. The goal is to see if increased vehicle density leads to more or less electric fuel intake than lower densities. The study found that as density increases, electric fuel intake is lowered compared to scenarios where density is low, i.e., fewer vehicles are driving; thus, breaking speed limits has a higher effect on energy requirements as it is less likely to find constraints such as other vehicles ahead.

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1 Introduction

According to the World Health Organization (WHO), 55% of the world's population live in urban areas; this is set to increase to 68% in 2050. Ultimately, these statistics show that most

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of these electric vehicles will be driven in urban areas (cities). Many renewable energy sources can power electric vehicles, for example, wind turbines and solar; furthermore, the total energy use among these vehicles is 3.4 times lower than vehicles with internal combustion engines (ICEVs) that depend on petroleum. Similarly, CO_2 emissions are 4.5 times higher for internal combustion engine vehicles than electric vehicles (when the electricity comes from renewable sources) [25, 11]. Almost all vehicle manufacturing companies have started building and testing hybrid, and electric vehicles for the commercial market [38]. It is evident that governments welcome an economic and environmental benefit, and a push to replacing diesel with electric vehicles is on its way. However, not all countries have renewable technology to power these vehicles; some countries such as China still depend on coal to power the majority of their electric grid [40]. In their review of electric vehicles and their impact on the climate, [21] found that vehicles using electricity from sources with lower Global Warming Potentials [1] are better than ICEVs. A similar study shows that it was counterproductive to promote EVs in countries where electricity is produced from fossil fuels [22].

Many factors implicitly or explicitly cause an increase in greenhouse gasses (GHGs) in regards to EVs. However, it is clear that a net-reduction in greenhouse gasses is more likely with the adoption of these vehicles compared to the current norm as renewable energy technology becomes more globally accessible. This study aims to add to this debate and is concerned with the following hypothesis: the more EVs driving within an urban environment may lead to less impact on electric fuel intake globally as an increase in density leads to an increase in congestion, promoting slower speeds than usual. When vehicle density is lower, vehicles are more likely to travel at stable speeds with fewer intervals increasing electric fuel intake. Another important dimension inspected within this study is adherence to speed limits and their impact on electric fuel intake. A report on Vehicle Speed Compliance Statistics for Great Britain [6] found that on 30mph (miles per hour) roads, 54% of cars exceeded the speed limit in the first quarter of 2019. 6% of these cars exceeded the speed limit by over 10mph. This increased in the second quarter of 2019 to 56%. The statistics mentioned above show that people break speed limits in urban areas such as cities, and this should be taken into account when simulating the EV drive cycle to quantify electric fuel intake by these vehicles.

This study will attempt to quantify the relationship between vehicle density and speed limit adherence and its subsequent impact on electric fuel intake (the average amount of electricity required by the vehicles to complete their drive cycle) within an urban environment by employing agent-based modelling. The goal is to simulate multiple density and adherence levels within the environment and later analyse its impact on electric fuel intake. The agent-based model (ABM) adopted in this study [34] is still in its infancy; however, it does provide the means to simulate the phenomena mentioned above within a 3D environment giving access to granular vehicle features, for example, downforce, torque, drag, mass with some level of accuracy. We hope this study highlights the importance of individual-based modelling methods such as ABMs in quantifying these entities' individual-level behaviours to aid in policy-making.

The following section will introduce the agent-based modelling methodology, highlight its uses and describe other individual-based traffic simulators. Lastly, the section will outline the physics employed to calculate electric intake. The Model Description section will describe the agents, environment and processes utilised by the agent-based model adopted in the study [34]. The Experiment Analysis section will describe the experiments conducted for the study, the subsequent results from these experiments will be presented, and lastly, the findings will be conveyed. Finally, the Discussion and Conclusion section will delve into the results found and their relevance compared to empirical findings. The section will end with future research aims.

2 Background

The traffic system is characterised by multiple individual actors (drivers) and a street network made up of individual rules such as traffic lights and speed limits, to name but a few. Given the nature of this systems individual-level components, it is evident that these systems are perfectly poised to be studied using individual-based modelling methods. According to [27], individual-based modelling refers to simulation models that treat individual entities as unique and discrete components with at least one property, for example, age, height, position and these properties change during the life cycle of these entities. Therefore, in this study, vehicles can be thought of as individual heterogeneous entities with their own rules, while the urban street network is the environment in which these vehicle entities are observed from within.

Agent-based modelling (ABM) is an individual-based modelling method, it provides the means to plan, design and experiment with micro heterogeneous agents in an environment scenario. These models have been utilised in various domains to explain complex phenomena such as those that occur in crime [9, 31], ecology [23, 32, 17], economics [35, 14], sociology [39, 8] and geography [24, 12]. Furthermore, these methods represent a richer and more detailed set of alternatives than statistical models [13].

Several agent-based models within the literature have focused on electric vehicle research. [29] developed an agent-based model that measures consumer needs and decision strategies by policymakers to shift from internal combustion engine vehicles to electric vehicles. They found that effective policy requires a long-lasting implementation of a combination of monetary, structural and informational measures. Similarly, [16] developed a spatially explicit agent-based vehicles consumer choice model to identify the various influences that can impact plug-in hybrid electric vehicles (PHEVs) market penetration. The study found that providing consumers with ready estimates of expected lifetime fuel costs associated with other vehicle types, including the rise of petrol costs, can focus people's attention towards these new vehicles.

A sub-set of electric vehicle agent-based modelling research has focused on charging infrastructure. [33] developed a spatially-explicit agent-based model to calculate EV charging demand. In short, the model simulates each EV driver's model characteristics, mobility needs, and charging processes require to reach its destination. The study found that the voltages do not reach the minimum voltage allowed, but the medium and low voltage substations could exceed their capacities. These results were specific to the city of Barcelona.

The agent-based model utilised in this study does not explicitly calculate energy intake. Therefore, classical mechanics formulae are adopted alongside model outputs to calculate electric fuel intake. The second half of this section will describe these formulae.

To calculate electricity intake required to move the vehicles, the application of classical mechanics (newton's laws of motion) [30] including the drag equation from [7] were adopted for this study.

When a vehicle is moving at a constant velocity, the forces on it are balanced, i.e. the forces driving it forward are equal to those resisting. If a vehicle is moving at a constant velocity, v, up a ramp with angle θ, the following equation expresses this balance:

$$F = mg \times \sin(\theta) + \frac{1}{2}pC_DAv^2 \quad (1)$$

where:

- F is the force provided by the engine driving the vehicle forward,
- m is the mass of the vehicle (kilograms),
- g is the gravitational acceleration (9.81m/s),
- θ is the angle of the surface on which the vehicle is driving on,
- p is the density of air (1.225kg/m^3),
- C_D is the drag coefficient,
- A is the reference area (width $\times$ height),
- v is the velocity.

In the scenario where the road surface is flat, $\theta = 0$, Equation 1 becomes:

$$F = \frac{1}{2}pC_DAv^2 \quad (2)$$

which returns the force output by the car's engine to move the vehicle at a constant velocity v. Once the force, F, that is being exerted by the engine is known, and the distance of travel, d, over which it is being exerted, then the energy exerted by the engine can be calculated E:

$$E = F \times d \quad (3)$$

In this case, E is the energy output by the engine. To find the energy provided to the engine in the form of fuel, the engine efficiency is needed, k. Assuming that the efficiency of the engine is constant, i.e. that it has the same efficiency for all scenarios, the energy that needs to be provided to the engine can be found using the following equation:

$$E_{input} = \frac{E}{k} \quad (4)$$

These formulae will be referred to in the Experiment Analysis section where they will be utilised to calculate energy intake for each experiment scenario.

3 Model Description

This section describes the agent-based model adopted for this study. The Overview Design and Details (ODD) protocol will be utilised to explain all aspects of the model [19].

3.1 Purpose

The agent-based model used in this research is the 3D Urban Traffic Simulator in Unity [34]. The model was developed to provide researchers with the means to simulate hypothetical vehicle activity scenarios in a 3D urban environment. The model provides access to heterogeneous autonomous vehicle agents with granular features such as mass, velocity and traction control. Similarly, the road network is designed around a built-up environment that contains all the characteristics of a dense urban street network with varying speed limits and intersection rules adopted from the UK Speed Limits [3].

3.2 Variables

The model requires input parameters to run an experiment and output useful results that can later be analysed. The parameters that can be tuned are listed in Table 1.

Table 1 Model entities and parameter values.

Entity	Parameter	Values
Vehicle	Mass	[1000, 3000] (kg)
	Top Speed	[30, 45] (mph)
	Ray-cast Length	[1, 10] (m)
Environment	N. Of Vehicles	[1, 500]
	Speed Adherence	[0, N]
	Roads	1295
	Intersections	354

The model has two entities: the vehicle agents and model environment in which these agents are based. The vehicle parameters are:

- The vehicle mass parameter, the value of which is drawn from a random uniform distribution between 1000 and 3000 kilograms (inclusive); the model distributes vehicles arbitrarily across the environment with varying weights (source [2]).
- The top speed measure is between 30 and 45mph, and is only applied to the vehicles that do not adhere to speed limits. This measure is applied only if Speed Adherence is ≥ 1 (source [6]).
- The ray-cast length parameter can be between 1 to 10 for each vehicle. The variable assigns a distance between two vehicles in meters.

The environment specific parameters are:

- The number of vehicles generated in the model, N; this can be between 1 and 500.
- The speed adherence variable can be between $0 \leq x \leq N$. This quantifies the proportion of vehicles which will not adhere to the speed limits applied to the road which they are driving on.
- The urban road network consists of 1295 roads which vehicles drive on and 354 intersections which consist of traffic light rules. The road network has been designed to depict a small urban town.

The parameters above are used to produce output variables. These output variables observe various data points every time-step of the simulation run collecting individual level data from each vehicle. Table 2 describes the output variables that the model produces.

The model outputs thirteen variables that can be used for analysis (refer to Table 2). As the agent ID variable is present, this allows for a micro-level analysis of the agent behaviours during model execution (observing individual drive cycles). The collisions variable tracks the number of times a vehicle has collided with another. Top speed is the speed limit associated with the road that the vehicle is driving on, which in turn the vehicle is trying to match; however, in scenarios where some vehicles do not adhere, this would be a value between 30 and 45mph. The current speed value is the vehicle's speed at the current time step of the model. The distance of travel is in meters and tracks the vehicle's distance from the starting position on the road network each time step. The ray-cast length is the distance the vehicle is to keep from vehicles ahead. Traction control is set to either 1 (on) or 0 (off). If the traction control is on, the vehicle has full traction so that each wheel can adapt to

Table 2 Model output variables.

Variable	Output Type	Example Value
AgentID	Integer	-57648
xAxisPos	Float	75.98590
zAxisPos	Float	20.0907
collisions	Integer	10
topSpeed(mph)	Float	12.0
currentSpeed(mph)	Float	0.704907
distanceOfTravel(meters)	Float	0.003916
raycastLength	Integer	4
tractionControl	Integer	1
velocityMagnitude	Float	0.195808
vehicleMass	Integer	1000
downforce	Float	0.1
date-time	DateTime	15/01/2021 18:03:59

the surface; however, it is not within the scope of this study so is set to 0. The velocity magnitude is a scalar value indicating the rate of motion at that specific time-step. The vehicle mass variable assigns a weight to the vehicle between 1000 to 3000 in kilograms. The physics engine requires that every object have a mass assigned to it to ensure gravity is applied. Downforce coefficient is set to 0.1; for this research, it is left at 0.1 to have no impact on the vehicles. Lastly, date-time stamps are included in each row of data recorded such that time-series analysis can be applied.

3.3 Model Overview

The agent-based model was developed using the Unity development stack. Unity is a 3D development platform consisting of a rendering and physics engine and a graphical user interface called the Unity Editor. Unity has received wide-spread adoption in several industries, including gaming, automotive, and film [28].

The following workflow diagram describes the processes that the model [34] undergoes, during run-time.

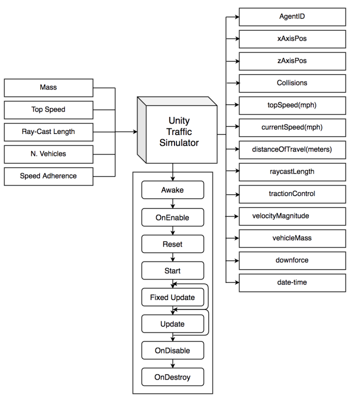


Figure 1 Workflow diagram depicting processes the Urban Traffic Simulator undergoes during run-time.

The Urban Traffic Simulator [34] workflow (refer to Figure 1) starts by taking input

Listing 1 Vehicle agent rules in pseudocode.

```
while(model_running){
    drive;
    if(not_adherence == true){
        accelerate to top speed [30, 45];
    }else{
        accelerate matching road speed limit;
    }
    if(vehicle_ahead == true){
        match speed of that vehicle;
    }else{
        continue at current speed;
    }
    if(at_intersection == true AND vehicle_present == false AND
    right_of_way == true){
        reduce speed and drive out of intersection;
    }elseif(at_intersection == true AND vehicle_present == true AND
    right_of_way == false){
        halt till intersection_clear == true;
    }elseif(at_intersection == true AND vehicle_present == false AND
    right_of_way == false){
        reduce speed and drive out of intersection;
    }else{
        halt till intersection_clear == true;
    }
}
```

values for the five variables described in Table 1. The software then resets all settings to launch the simulation scene where it renders the agents and environment. Once the reset process is complete, the model processes all agents, their starting locations, environment parameters, before the model run. Next, the model can run each frame, and every change that occurs is captured and stored with a time-stamp. Fixed Update is used to compute any physics elements such as vehicle wheels, mass, velocity. Update, on the other hand, computes variables each frame. The Urban Traffic Simulator uses Fixed Update due to the sheer number of physics components involved; therefore, these variables are tracked multiple times each frame. Once the user stops the model, the thirteen output variables are saved in a directory, and the model is destroyed (stopped).

3.4 Agent

The vehicles in the model are classed as autonomous agents; the vehicle population is heterogeneous; therefore, every vehicle will have varying features. These agents inherit similar characteristics as real-world vehicles; they have four wheels, steering angle, traction, mass and drag. Each agent applies the following set of rules during its drive cycle, refer to Algorithm 1.

The rules described in Algorithm 1 allow autonomous vehicle agents to navigate the environment and act as data collectors. Each vehicle follows the same condition-action rules. However, the parameters vary and depend on the input values from Table 1. These vehicle agents are a simplification of real-world vehicles. Therefore, it is not expected to perfectly mimic real-world vehicles, but does include the basic features that all vehicles possess.

If a vehicle is not adhering to the speed limits, it can increase its speed between 30 and 45mph. If vehicle A is ahead of B, then B should decrease speed to match vehicle A's speed. When a vehicle arrives at an intersection, if it has the right of way, i.e. on a horizontal lane and no vehicles are on the intersection, it drives through the intersection at 10mph. If the vehicle is at the intersection and does not have the right of way, it should wait until the intersection is cleared. If the vehicle is at an intersection, it is not right of way, and there are no vehicles at the intersection, the vehicle is free to reduce speed to 10mph and drive through the intersection. Lastly, all vehicles that adhere to the speed limit increase or decrease speed to match the road's speed limit.

3.5 Environment

The agents described in the last sub-section require an environment to function within. The Urban Traffic Simulator [34] deploys an urban street network that is described as a T-type network pattern in [20] which contains similar characteristics as downtown Philadelphia, PA [10] and San Francisco [36]. T-network patterns are like grid-shaped networks but include t-junctions. Several added features such as eight-lane intersections described in [18] also exist. The street network contains 1295 roads and 354 intersections which were arbitrarily generated to cover a small town. The individual roads, speed limits and intersection rules are described in the following Figure 2.

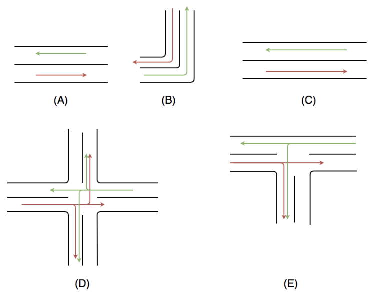


Figure 2 Urban Street Network roads and intersections.

The environment consists of three road types with varying speed limits and intersections with right of way rules. The model environment is a simplification of the real world. Therefore, it does not capture all intersection types. However, it does contain the basic characteristics of an urban street network which have also been observed in several cities across the United States [10, 36]. The following list describes each road and intersection in Figure 2:

- (A) two-way local road with a speed limit of 20mph.
- (B) a two-way corner road with a speed limit of 10mph.
- (C) two-way fixed road with a speed limit of 30mph.
- (D) an eight-way intersection, right of way is for traffic on horizontal lanes, speed limit 10mph.
- (E) a two-way t-junction, right of way is for horizontal lanes, speed limit 10mph.

The speed limits for the three types of roads (A, B and C) were derived from UK government sources such as [6], where, urban street networks consist of local 20mph and fixed 30mph zones; however, corner roads sometimes require lower speeds such as 10mph as vehicles require more room to turn. The "setting local speed limits" report by the UK Government's Department for Transport outlines that most urban streets (roads in built-up areas) have a fixed speed limit of 30mph. However, for dense areas — usually city centres — this may be designated 20mph by local councils to keep pedestrians safe from collisions [15].

3.6 Summary

The model description section describes the rules vehicle agents follow for every road type and intersection it finds it self driving on. Five rules govern the vehicle's movement; these broadly involve increased or reduce speed depending on road or adherence, interacting with intersections in a safe way to reduce the risks of collisions. The environment comprises three road types and two intersections, with varying local and fixed speed limits taken from empirical data via UK government sources. In the next section, the model is used to run nine hypothetical scenarios. The output data from these scenarios will be quantitatively analysed in several ways.

4 Experiment Analysis

In this section, the experiments designed to answer the earlier outlined hypothesis will be described. To recap, the hypothesis is *the more EVs driving within an urban environment may lead to less impact on electric fuel intake globally as an increase in density leads to an increase in congestion, promoting slower speeds than usual. When vehicle density is lower, vehicles are more likely to travel at stable speeds with fewer intervals increasing electric fuel intake.*

Due to the computational processes required to render 3D vehicles through space and time [34] and the hardware capacity at hand, nine experiments were designed which are computationally expensive yet just below the threshold of computability. The independent variables are adherence and vehicle density. The former is the number of vehicles that do **not** adhere to speed limits, while the latter is the number of agents in the environment. These experiments can be found in the following Table 3.

Table 3 Experiment conditions.

Variable	Low adherence	Mid adherence	High adherence
Low density	75 vehicles (25%) and 23 adherence (30%)	75 vehicles (25%) and 45 adherence (60%)	75 vehicles (25%) and 75 adherence (100%)
Mid density	150 vehicles (50%) and 45 adherence (30%)	150 vehicles (50%) and 90 adherence (60%)	150 vehicles (50%) and 150 adherence (100%)
High density	300 vehicles (100%) and 90 adherence (30%)	300 vehicles (100%) and 180 adherence (60%)	300 vehicles (100%) and 300 adherence (100%)

The density and non-adherence levels are categorised from low to high. Where low density = 75 vehicles (25% of 300) and low adherence = 23 vehicles (30% of 75). High density = 300 vehicles (100% of vehicles) and high adherence (100% of vehicles). It should be noted that low to mid adherence is the number of vehicles that **do not** comply with speed limits, i.e. driving over 30 to 45mph. In contrast, high adherence scenario is where all vehicles comply with the speed limits (10 to 30mph depending on the road being driven on).

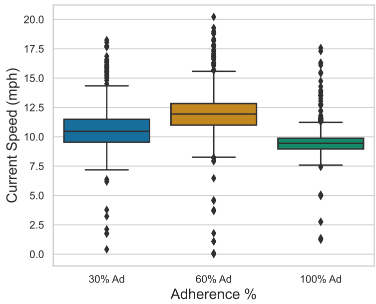
For all three vehicle density scenarios (75, 150 and 300), it becomes evident that the less the vehicles adhere (Figures 4a and 4b), i.e., more vehicles driving over the speed limit, this leads to a high energy intake compared to vehicles following the speed limits. However, over time the energy intake slowly converges with energy intake levels at 100% adherence.

For densities 75 (Figure 4a) and 150 (Figure 4b), the average energy intake is more erratic for both 30% and 60% adherence levels; this is expected as more vehicles are driving between 10 to 45mph over time while for 100% adherence, the speeds are between 10 to 30mph for all vehicles. However, for the scenario where density is 300 (Figure 4c), the adherence levels have less of an impact on energy intake. This is due to the local speeds becoming more regulated as vehicles that do not adhere to speed limits find slower-moving vehicles ahead more often due to the number of vehicles in the system.

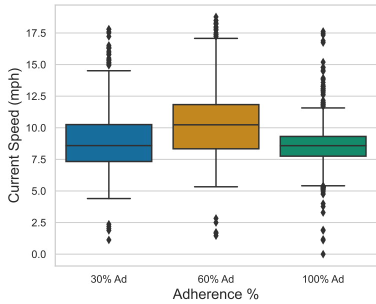
It should be noted that the Timesteps (simulation time) for all three scenarios vary as the number of vehicle densities vary. Thus, the number of data points captured are more for higher density scenarios compared to lower densities. However, all experiments were exactly 10 minutes long for each model-run. These preliminary results do support the hypothesis, where energy intake for higher density systems tend to be less over time (Figure 4c) compared to lower densities (Figure 4a) as vehicles are more likely to find slower-moving vehicles ahead, and the likelihood for congestion is higher.

To better understand the impact vehicle speed has on energy intake, the average speeds for all 9 scenarios will be compared. This will help identify scenarios where slower moving vehicles are the norm regardless of adherence levels.

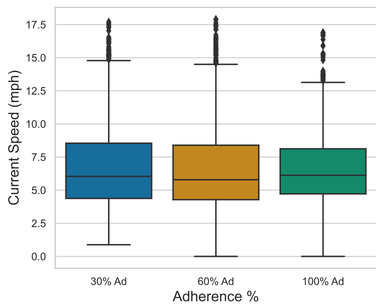
As expected, the average speeds for high density (Figure 3c) is lower (5.0 to 7.5mph) compared to low (Figure 3a) and mid (Figure 3b) density scenarios. These results add to the previously discussed energy intake comparison over all scenarios.



(a) Average speeds across all adherence levels for 75 vehicles



(b) Average speeds across all adherence levels for 150 vehicles



(c) Average speeds across all adherence levels for 300 vehicles

Figure 3 The average speeds over all adherence levels across all model-runs for each scenario.

4.1 Energy intake calculation

Equations (2, 3 and 4) were applied to the model outputs to calculate electricity intake:

- For Equation 2, F is calculated by using the following output variables from the model-run: $\theta = 0$ as the surface area is flat, $C_D = 0.1$ minimal drag, $A = 2.16$m (source [5], where height $= 1.46$m, width $= 1.475$m), lastly, $v =$ velocityMagnitude (refer to Table 2).

- For Equation 3, E is calculated by multiplying the output from Equation 2 with total_distance (d) travelled in meters for each agent using distanceOfTravel(meters) variable, Table 2.
- Lastly, Equation 4 is calculated by dividing the output from Equation 3 (E) with the engine efficiency $k = 0.88$ (source [4] where engine efficiency for electric vehicles is between 0.85 to 0.90). E_{input} is then divided by 3.6e+6 to convert energy to kilowatt hour (kWh).

4.2 Summary

The study found that higher density systems regulate speed compared to lower density systems. Ultimately, energy intake is lower on average for these high-density systems as vehicles are more constrained by the size of the environment and number of vehicles present, compared to lower density systems where vehicles have more space for navigating at preferred speeds. Lastly, these results show that the model is "good enough" at explaining energy intake by vehicles moving at various speeds in a hypothetical street network with simple traffic rules.

5 Discussion and Conclusion

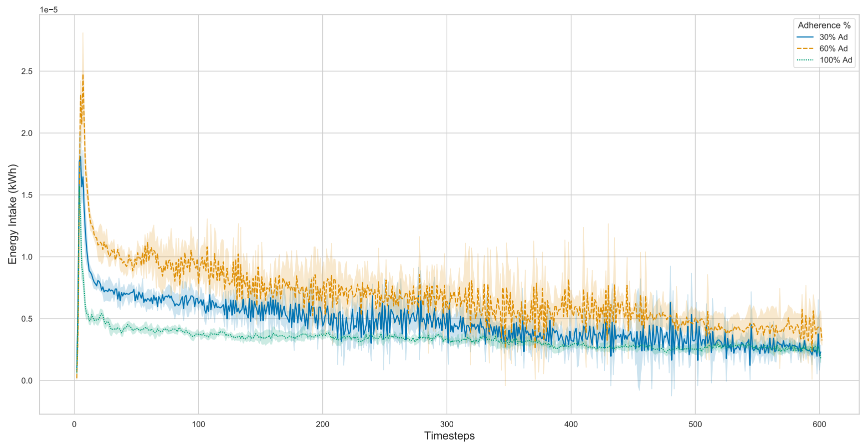
This study describes the relationship between vehicle density and the subsequent impact on electric energy intake. The study utilised a novel agent-based model (still in its infancy) to produce drive cycle data by running the model with varying input parameters leading to 9 scenarios to test the earlier outlined hypothesis. Given the configuration of the street network and simple traffic rules the model provides, it was found that as vehicle density increases, energy intake decreases as more vehicles travel at lower speeds. Conversely, it was found that as density is lowered, energy intake increases as more vehicles can roam at higher speeds with fewer instances of traffic control. Furthermore, as the number of vehicles not adhering to speed limits increases, this leads to higher energy intake for low to mid adherence, while for full adherence, energy intake is at its lowest, i.e. vehicles are all complying with speed limits (10 to 30mph).

[26] found that driver behaviour has a significant impact on fuel intake. They found that aggressive drivers can consume up to 30% more fuel than environmentally-friendly driving for electric vehicles. This study does support these findings; however, it should be noted that at this stage, aggressive behaviour is only parameterised by the non-adherence to speed limits parameter; the feelings/emotions of drivers is not captured in the agent-based model.

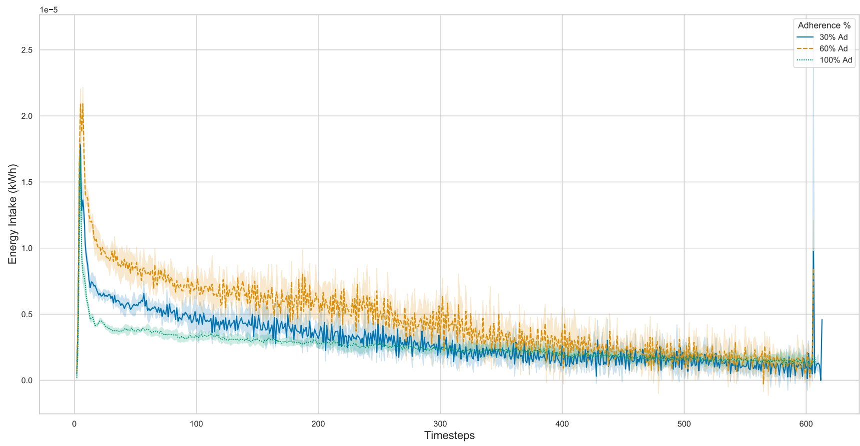
Furthermore, [26] highlights the gap in the literature regarding the impact of driving behaviours on electric vehicles' energy consumption in the real-world operation phase. They found no study that examined if a single standardised driving cycle can capture the dynamics encountered in real-world urban driving conditions as well as the heterogeneity among drivers. Therefore, this study will add to the literature by providing an agent-based modelling perspective to quantify energy intake among electric vehicles.

At this early stage, policy recommendations (given the results) would be:

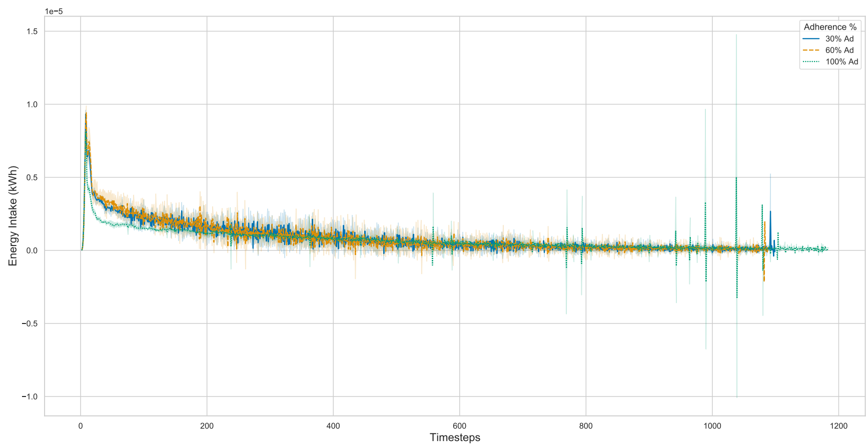
- Physical speed compliance measures should be increased, i.e. road humps to regulate speed among drivers where vehicle density is low.
- Congestion is not necessarily a bad thing when the entire driver fleet is electric; however, this is not recommended for countries where EV technology is yet to take afoot or electric production is reliant on fossil fuels.



(a) Average energy intake for 75 vehicles over all adherence levels



(b) Average energy intake for 150 vehicles over all adherence levels



(c) Average energy intake for 300 vehicles over all adherence levels

Figure 4 The average energy intake calculated using Equations 2, 3 and 4 over all 5 model-runs for each scenario.

- The benefits of electric vehicles far outweigh the drawbacks, especially in cities where congestion is ripe and electric energy is made from renewable sources.

For future studies, the model could be extended to cover real-world street networks with more complex traffic rules and a diverse range of road types to support empirical findings and aid in policy development for specific urban cities.

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