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Assessing EV energy consumption for real word trips based on origin and destination: proof-of-concept in Lisbon, Portugal

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Summary

With the growing concern towards the environmental problems associated with climate change, an energy transition is inevitable. This work aims at evaluating the energy and environmental performance of different vehicle propulsion technologies in real routes through the creation of speed profiles for specific routes. The information given by the Google Maps and OpenStreetMap APIs is used to build the speed profile on specific routes, considering 3 different driving styles – eco, normal and aggressive. The simulated vehicle dynamics were validated by comparing the dynamic parameters of the real profiles in that same route, with good validation result enabling deviations inferior to 3% for the average acceleration. After the creation of the speed profile, it is possible to estimate the energy and environmental performance of the different technologies using the Vehicle Specific Power (VSP) methodology. The results show that the type of route affects both the energy consumption (at about 25% in Diesel vehicles and 20% in electric vehicles) and the driving style (25% increase in average from eco to aggressive driving with the difference increasing for electric vehicles). In terms of vehicle technology, the energy consumption of an electric vehicle is 43%, 46.5% and 52% lower than the Diesel vehicle energy consumption for a hilly, urban and extra-urban route, respectively.

Keywords: vehicle dynamics; speed profile; driving profile; vehicle technologies

1 Introduction

The interest in electric vehicles has been growing, although it only reflects on 3.5% of new vehicles registered in 2019 [1], and the trend is that it keeps growing in the next decade due to the advantages relative to conventional vehicles that will only increase with changes in legislation. However, electric vehicles still face some challenges related to batteries. There is still a high initial cost, a reduced range and a high recharging time [2]. Another technology that is finally gaining traction is fuel cells technology. Its high energy density of hydrogen enables a much higher range without compromising the weight and performance of the vehicle and the refueling time (5-8 minutes compared to a minimum of 1 hour and generally 6-8 hours of electric vehicles) [2]. The big challenge of fuel cell vehicles is still the high costs associated with the production of hydrogen by electrolysis and fuel cell production primarily due to the lack of infrastructure and the lack of mass production. It is expected a 70% drop in the cost of fuel cell and hydrogen tanks production with mass production [3]. The other problem is that nowadays 95% of hydrogen production comes from natural gas through methane steam reforming (STM), that produces 14.14 kg CO_2/kg H_2, but continues using fossil fuels, requiring the shift to green H_2 produced using renewables.

Transportation systems are always in transformation, so simulation is extremely important to allow companies and people to quantify the savings associated with a shift from a technology to another. In line with this, it is necessary a model that keeps valid through the years that allows the quantification of energy consumptions to different vehicle technologies in specific routes. The way to do it is through the simulation of driving conditions using driving cycles that try to emulate them. Several driving cycles have been developed trying to characterize vehicle emissions, energy consumption and autonomy.

To avoid the need for specific engine operating data such as speed, torque and throttle position, less computationally intensive and more adjusted backward models were developed to be used by traffic microsimulators. Their main input is dynamic data such as speed profiles, acceleration and elevation profiles or road gradient which enables them to estimate the power required to the wheels using engine efficiency maps or power models such as the VSP. The Comprehensive Modal Emission Model (CMEM) [4] is a microscopic model that estimates energy consumption second by second. Through the PARAMICS simulator, it uses a physical approach considering several inputs: three dynamic variables (acceleration, equivalence ratio and fuel rate), the second-by-second speed, the road gradient angle and the use of auxiliaries such as air conditioning and returns instantaneous emissions. Its biggest limitation is not being able to estimate heavy vehicle emissions for both goods and passengers.

In order to avoid the need to develop dynamic engine maps, other approaches were taken, such as power models. The VT-micro was developed by Rakha et.al at the beginning of the century, estimating consumptions with a difference of less than 3% of the road tests, and later it was adapted to electric vehicles and the VT-CPEM (Virginia Tech Comprehensive Power-based Electric Vehicle Energy Consumption) [5]. These models are based on wheel power as a variable of acceleration, road gradient, aerodynamic drag coefficient and rolling resistance parameters that depend on vehicle speed. Finally, the software MOVES [6] (Motor Vehicle Emission Simulator), a microscopic model, was adopted in 2010 in the United States based on the VSP methodology. MOVES defines 14 VSP modes chosen so that they all have different consumptions, and none are dominant over the others. The quantification of energy consumption is done through the temporal distribution of each VSP mode to which emission or consumption factors are attributed based on empirical data for each vehicle. [7] developed a model based on the VSP capable of estimating energy consumption of an electric or hybrid vehicle using a braking energy regeneration model that adds to the existing literature by using a function that limits the power in the regeneration phase that best describes the energy flow.

Other commercially used microscopic models have been developed to estimate energy consumption using both linear regressions based on collected data and physical models based on vehicle dynamics [8]. More recently, taking into account the differences of an electric vehicle in the estimation of its consumption, studies that are based on physical models have also tried to develop battery modulation [9]. [10] opted for a method based on a database collected from driving in real conditions, an electric vehicle consumption database, a climate database and geographic information. These data are used to train a Neural Network (NN) that estimates the velocity profile and builds the energy consumption model using linear regression. The disadvantage of using an NN is that the data processing is complex and the universality of the data is difficult to prove.

Taking into account the approach of physical models in the estimation of energy consumption in electric vehicles, [11] addressed the influence of driving style, climate variables and road infrastructure. The results indicate that on urban routes the forces of rolling resistance and acceleration are dominant while on highways it is the aerodynamic drag force that dominates. As for the climate, it mainly affects the auxiliary systems having also its influence on the aerodynamic resistance and rolling resistance that increase with decreasing temperatures [12]. In a winter scenario, the amount spent on auxiliary systems can increase by up to 40% when compared to another period of the year with higher temperatures.

Over the last few decades, driving cycles have been developed in order to characterize vehicle emissions, consumption and autonomy. However, this approach has the limitation of only comparing the consumption of vehicles in the region where the cycle was developed, which is why there is a huge variety of driving cycles. The WLTC cycle is currently used for car emissions certification, which represents an improvement in terms of approximation to the values of real consumption compared to the one previously used (NEDC), however, like the other cycles, it does not take into account the specificity of a private trip.

To add to the existing literature in speed profiles construction using maps features [12], the is work will seek to develop a tool, that creates a representative speed profile of a route for 3 different types of drivers based only on origin- destination coordinates given by Google Maps and OSM APIs, considering the influence of elements of road infrastructure such as roundabouts, traffic lights, intersections, etc. and road gradient. Furthermore, the quantification of consumption by applying VSP approach to the created speed profiles will also be achieved. The great advantage of this model is the possibility of quantifying energy consumption and environmental performance for different vehicle technologies in real and specific routes through the creation of representative speed profiles of a route of choice by the user.

2 Methodology

Taking into account the main objectives of this work, a speed cycle of a specific route defined initially is developed, taking into account the information available in the APIs of Google Maps and Open Street Maps (OSM) for the defined route. Figure 1 presents the developed methodology regarding the construction of the speed profiles and the energy consumption estimation of that profile for a particular vehicle technology.

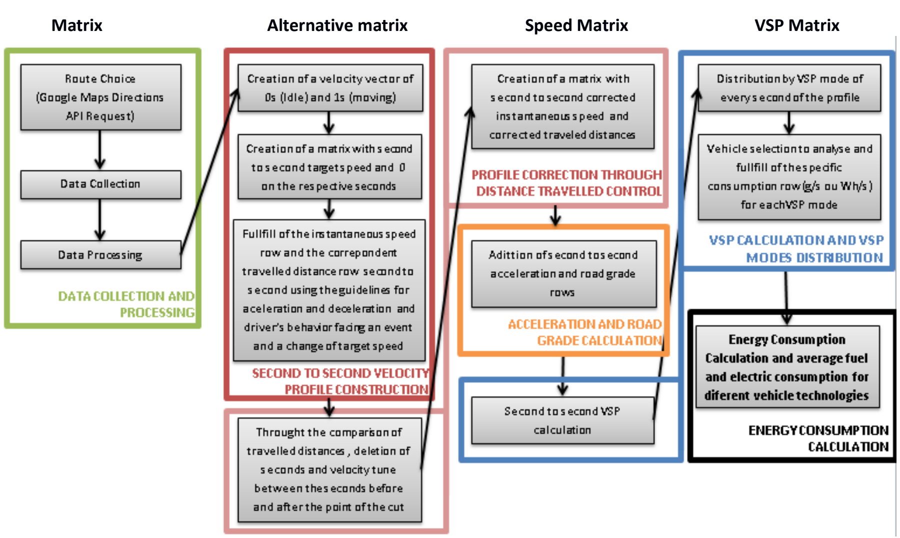


Figure 1: Stage by Stage Methodology scheme description

2.1 Data collection and processing

The first step is collecting information from the route for which the energy consumption is to be determined, organizing the route data in a matrix that will later be the basis for the creation of the cycle of speeds. To obtain the route information, a request is first made to the Directions API do Google Maps that returns the expected duration, distance and n structures, being n the number of steps which represent a segment between two maneuver. Each one of these sub-structures has the duration and distance of the step that allows the determination of the average speed, the maneuver that marks the start of the step, and the step polyline, which is a coded version of the latitude/longitude pairs of the step. The polyline is used to make the request to the Elevations API to obtain the values of elevation, latitude and longitude of every second of the route. All the information is organized in a matrix where the rows are consecutively: time (second to second); average speed on the step; distance traveled; the number of the step; maneuver between steps; latitude; longitude and; elevation. The information is complemented by a row of corner radius second to second determined using latitude and longitude values as developed by Beckers et al [13].

To add more useful information to the matrix, like maximum legislated speed, the presence of crossings, traffic lights or STOP signs, a request is made to OSM API. However, the information needs to be mapped to the route in question so that only the nodes that are part of the route are considered. The information of maximum allowed speeds may be limited and the mapping may be imperfect due to the presence of viaducts or tunnels for example. Therefore, the information collected must be cleaned and completed using some assumptions and approximations for the maximum speed taking into account the road type and the average speed of the step.

2.2 Second by Second velocity profile construction

The velocity profile is built second by second taking into account the previous matrix information:

a) Find the points of the route where the vehicle will stop. The vehicle can stop at traffic lights, crossings, roundabouts, STOPs, and intersections, being random to all events although with different probabilities for each one and for each driving style. The exceptions are STOPs and turn lefts where the vehicles always STOP except for the aggressive driving. The time that the vehicle is idling at any event is also variable and random within an interval of time defined for each event. With this, a vector containing 0s (stopped) and 1s (running) is obtained.

b) Creation of the alternative matrix that will copy the necessary information of the initial matrix adding the seconds the vehicle is stopped after each maneuver. It is also created a row of target speeds second by second based on the maximum allowed speed by law or, if the maximum possible speed in the segment is lower, a target speed defined by the distance between two zeros or a maneuver and a zero or by a limited speed driving a corner, based on the maximum lateral acceleration (a_lat) comfortable for the driver, different for each driving style, and the corner radius (R) determined using equation (1):

$$\sqrt{a_{lat} * R} = v \tag{1}$$

The distances traveled until each maneuver or in a change of target speeds are kept and written in a row of the new matrix. These distances will work as guides in the construction of the profile since they will have to always verify, apart from some exceptions to smooth the profile (in correcting it in 2.3 and 2.4 for example in non-stopping traffic lights and crossings and in target speeds differences lower than 20 km/h).

c) The profile is finally built on a second by second basis, using the information of the matrix and values of acceleration and deceleration for each driving style adapted from the literature and taking into consideration the influence of each event on driving. Deligianni et al. [26] studied the influence of different events in driving, concluding that braking behavior changes based on the motive for braking, showing that deceleration values are higher facing a dynamic obstacle like an erratic behavior of other drivers rather than a signalized event. This study also stated that the most used deceleration profile implies an early aggressive brake and then the deceleration gets smoother. Rakha et.al [27] studied the behavior in the approximation of traffic light changing to yellow, while [28] state the maximum recommended speed at roundabouts and [29] the behavior of drivers at roundabouts considering different exits. The profile is then built following:

- Initial acceleration until target speed;
  - For each second there are two options: 1) a maneuver exists: creates a deceleration until the defined velocity for the maneuver (might be 0, the new target speed or a velocity defined for that specific maneuver) starting from the velocity of the previous second. The deceleration is built backward so that the velocity at the second of the maneuver is achieved. After that, if the target speed is higher than the velocity of the maneuver, acceleration is built from that second onward until achieving the target speed; 2) a maneuver does not exist and the velocity is not filled by a previous maneuver: creates acceleration or deceleration if there is a difference in target speeds or if there is not, keeps the same velocity adding a small random value of acceleration or deceleration.
- Final braking until the last zero.

When a velocity is written in the instantaneous speed row also a distance traveled value is written in the corresponding row according to equation (2).

$$d_i = d_{i-1} + (v_i + v_{i+1})/7.2 \tag{2}$$

From 24 km/h the acceleration and deceleration behaviors are based on the light blue curve in Figure 2 obtained in a road test in the city of Lisbon [30]. For the eco driver, values 20% inferiors to that line were used, and for aggressive drivers 50% superiors.

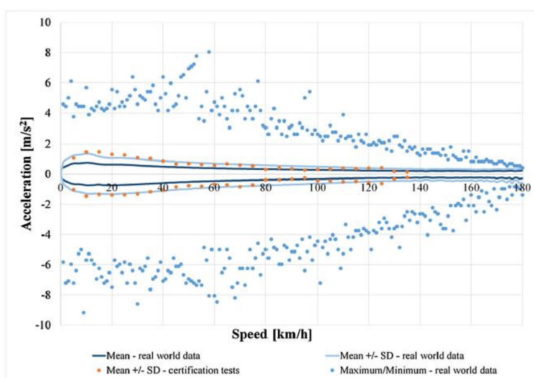


Figure 2 – Average acceleration/deceleration at different speeds (N = 28.9 million seconds) [30]

2.2.1 Driving style

The driving style is the dynamic behavior of a driver on the road. Aggressive driving includes driving over the speed limit, aggressive accelerations and decelerations (with high values of jerk that represents an aggressive use of the pedals) and higher values of lateral acceleration in corners. Also, the anticipation of events is considered in the driving style. The values of Table 1 were used in this work, based on values from the literature [14] as guides in acceleration and deceleration maneuvers bearing into account that jerk is variable throughout the maneuvers and these are maximum values. Note that all the maneuvers are different due to the randomness used in the creation of the maneuvers.

Table 1 – Driving style guiding parameters

	Eco	Normal	Aggressive
jerk (m/s^3)	± 0.4 - 0.6	± 0.6 - 0.8	± 1 - 1.4
a_{max} (m/s^2)	1.2-1.5	1.5 - 2	2.2 – 3
d_{max} (m/s^2)	-1.8 - -2.1	-2.5 - -3.2	-4 - -4.8
a_{lat} (m/s^2)	1.5 - 4	1.5 - 4	3 - 6
v_{target}	0.9	1	1.2

2.3 Profile correction through distance travelled control

Analyzing every second of the matrix allows us to evaluate situations when appears a distance smaller than the previous one. In that case, the seconds immediately before are deleted until the second with a distance smaller than that of the start of the cut point. After deleting some lines of the matrix, it is imperative to correct the velocities around the cut to guarantee that Eq. (2) always verifies. To guarantee that unreal accelerations or decelerations appear:

- If the difference of velocities between the second in which the cut started and the new previous one is superior to the maximum acceleration of the driver: acceleration from the value of the second before the cut until the second which the velocity difference to the previous one is smaller than the maximum acceleration.
- If the difference of velocities between the second in which the cut started and the new previous one is superior to the maximum deceleration: deceleration in the previous seconds starting from the second that originated the cut until the velocity difference between consecutive points is smaller than the deceleration distance.
- If the speed difference is within the maximum values of acceleration and deceleration of the driver: run the matrix backward and forwards until we find a new event or until the velocity is inferior to 20 km/h or the velocity difference between that second and the second of the cut is larger than 25 km/h. This creates an interval of seconds with the point of the cut somewhere in the middle in which the distance and velocity of the first (l) and last (j) point of the interval will be used as control points since before and after that point (2) will verify. The average velocity in that interval is determined guaranteeing that the velocities in the first and last point verify using equations (3)(4)(5).

$$v_{med_{pre}} = (d_j - d_l)/(t_j - t_l) \quad (3)$$

$$v_{alt} = (v_j + v_l)/2 \quad (4)$$

$$v_{med} = (v_{med_{pre}} * (t_j - t_l) - v_{alt})/(t_j - t_l - 1) \quad (5)$$

After that process, the velocities of the interval are summed except the first and last one and it is determined a pre-processed average velocity. The difference between the two average velocities will be subtracted for the velocities of every second of the interval except the first and last one. This process is also done to the first two points after the accelerations and decelerations. On the other hand, the differences between two consecutive seconds might as well be too large, since the method builds the profile onwards and backward from the maneuvers. It is then necessary to add seconds. To do this a new matrix (matriz velocidade) is created with the corrected seconds of the previous matrix adding the new seconds needed to close out those distances differences. The process of adding seconds works similar to the explained to the erasing of seconds and the adjustments made afterward.

2.4 Acceleration and road grade calculation

The new matrix has 3 rows: time of the trip, second to second, starting in t=0s; velocity (in km/h) and distance traveled (in m). From the time and speed the acceleration is determined second by second as the slope of three consecutive points. Based on the distances traveled and the information of the first matrix, the values of the altitude are mapped to this new matrix. From the altitude and the instantaneous speed and acceleration the road grade (m/m) is determined.

2.5 VSP calculation and VSP modes distribution

The information from the matrix will be used in Vehicle Specific Power (VSP) methodology to estimate energy consumption. The advantage of this methodology is that it allows estimating the consumptions based only on the dynamic of the vehicle in the route. VSP is defined as the power per unit mass (W/kg) and is calculated second by second according to the vehicle velocity and acceleration, rolling and aerodynamic resistances and road grade. The instantaneous power is used to overcome the rolling and aerodynamic forces and to increase the kinetic and potential energy of the vehicle. The mathematic expression was created in 1999 [15]:

$$VSP = \frac{\frac{d}{dt}\left(E_{kin} + E_{pot}\right) + F_{roll} \times v + F_{aero} \times v}{m} \quad (1)$$

$$= v \times [a \times (1 + \varepsilon_i) + g \times i + g \times C_{rr}] + \frac{\rho}{2} \times \frac{C_d \times A}{m} \times v^3 \quad (2)$$

Where C_{rr} depends on the pavement type and tire type and pressure. Typical values vary from 0.0085 and 0.016 and it is used 0.0135 for every vehicle in this work. $\rho_{ar} = 1.207\ kg/m^3$ at T=20ºC; $\frac{C_d \times inhaA}{m}$: varies for each vehicle class and it is selected to use 0.0005 (m^2/kg); v (m/s) is the velocity of the vehicle; a (m/s^2) the acceleration and $\varepsilon_i = 0.1$ a mass factor relative to the mass translation of rotating components; g=9.81 m/s^2 is the acceleration of gravity and I the road grade (m/m). Eq. (3) is obtained:

$$VSP = v * (1.1 * a + 9.81 * i + 0.132) + 0.000302 * v^3 \quad (3)$$

For the application of the VSP methodology in light-duty vehicles, VSP values are grouped in 14 modes, as defined in the literature [16]. The goal is to attribute to each mode a specific consumption (g/s for Diesel and hydrogen and Wh/s for electric vehicles) determined in vehicle tests or using numerical simulations.

2.6 Energy consumption calculation

Knowing the specific consumption value (from the VSP curve), tc_m, and the time spent in each mode, t_m, the total consumption of the trip (in kg of fuel or kWh of electricity) can be determined:

$$E_m = (t_m * tc_m)/1000 \rightarrow E_{Total} = \sum_{m=1}^{nm} E_m \quad (4)$$

To compare the different technologies, the energy consumption for all vehicles in MJ/km is calculated. The low heating value (LHV) of diesel and hydrogen, respectively, LHV_{diesel}=42.5 MJ/kg and LHV_{H2}=120 MJ/kg are used to obtain MJ/km, according with $E_c = E_{Total} * LHV/d_{total}$ For the electric vehicle the only conversion needed is from kWh to MJ (1 kWh=3.6 MJ):$E_c = E_{Total} * 3.6/d_{total}$. The emissions for the Diesel vehicle were also calculated using a factor of 3.16 kg_{CO_2}/kg_{fuel} based on the combustion reaction of $C_{12}H_{23}$.

2.7 Case Study definition

To compare the effect of the route in different vehicles technologies, energy consumption was analyzed on two case studies:

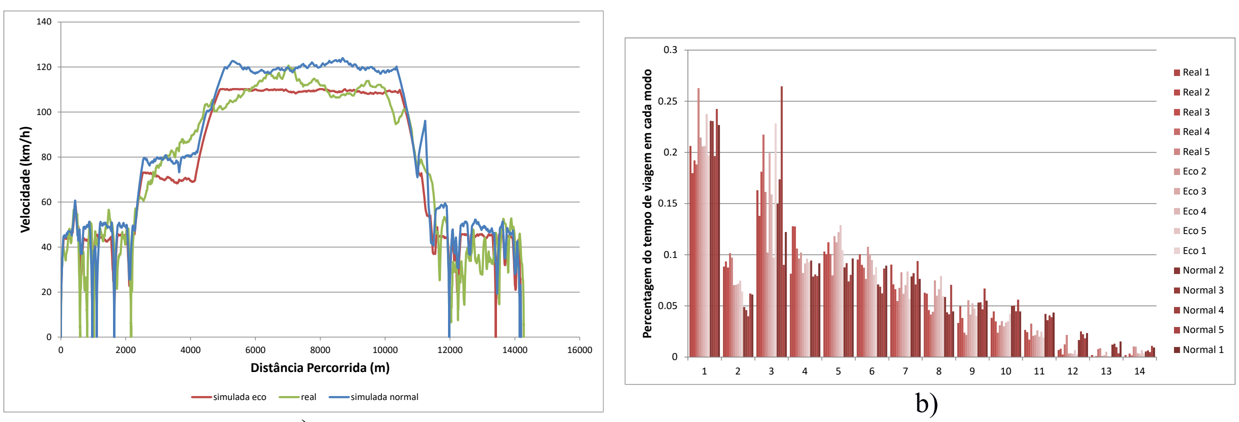
1) Loures-Lisbon: connection with more trips and higher vehicle utilization between two AML municipalities [17]. The destination chosen was Saldanha because it is a crowded work zone in the city. The trip includes a small highway course, a steep climb and a typical urban course with several traffic lights and crossings. It represents well the typical Lisbon circulating conditions.
2) Parque das Nações (Lisbon) – Albufeira: long distance trip that allows the comparison between using the highway or the national road and the effect of vehicle choice.

These case studies were analyzed using 4 VSP curves one for each technology: for the Diesel vehicle it was used the curve of a VW Golf Variant 1.6 TDI 110 cv (average of 4 l/100km, 3.8 l/100km extra-urban and 4.4 l/100km urban with 101 gCO_2/km emissions WLTP [18]); for the hybrid vehicle, a Hyundai Ionic (average 4l/100km, 3l/100km in urban driving and 4l/100km in the highway); for the electric, a Nissan Leaf (14 kWh/100km WLTP and 19.7kWh in road tests [19]); and finally a curve for a fuel cell vehicle (1.11 kg/100km [20] or 1.33 MJ/km) whose last two VSP modes had to be extrapolated because the vehicle simulation for the creation of the curve never achieved those modes. This implies that the consumption for higher powers might be over-estimated for the hydrogen vehicle.

3 Results and discussion

3.1 Speed profile validation

The validation of the velocity profiles is made through the comparison of dynamic parameters of the simulated trips for the three modeled drivers with trips performed by a real driver, collected using a GPS device on the road in the same course with exception of some meters in the start of the trip. The route chosen was a work-to-home trip (ISEL – Povoa Santa Iria) with highway and urban driving. The distances at which the events occur in the simulated runs correspond to the distances of the real course what validates the corrections made in 2.3. These corrections and distances control makes all the simulated trips have the same distance, the one given by the Maps API request (14189 m) while the real trips have slightly different distances due to the spot where GPS started to work (14275m±60m). Figure 2 a) shows the comparison between a real speed profile and profiles simulated for the eco and normal drivers for every meter of the trip where we can see a good match between events.



a) b)

Figure 2 – Comparison of the speed profiles for real (green) eco (red) and a normal (blue) driver (a) and of VSP distribution for real trips (on the left) with simulated trips for an eco-driver (in the middle) and a normal driver (right) (b)

One of the most important factors validating the tool is that the dynamic of the simulated runs respects the dynamic of the real trips. A good agreement can be seen in Figure 2 b) where, in every mode, the VSP distribution of the real driver is between the eco and the normal simulations. The variability in mode 3 for the same driver is well simulated. This variability relates to the fact that mode 3 represents idling conditions and depends on the number of stops and time stopped in the trip.

The dynamic parameters used to validate the tool were the average speed, average acceleration and average positive VSP. For average speed, the tool overestimates it in 16% for eco and 18.9% for normal driving simulation. The major difference happens between]0-65[km/h. This is in an urban environment where it is probable that the real driver caught traffic in some of their runs accounting for an overestimate of the average speed of 21.1% for the eco simulations and 25.3% for the normal ones. In the high speed part of the trip (over 85 km/h) the differences were only 3.2% and 3.5% respectively. For the average acceleration, the values were very close between the real trips and the simulated to a normal driver (deviation of -2.3%). The eco driver had a smaller average acceleration since it is modeled to avoid any aggressive acceleration and anticipate every event (deviation of -25.6%). The average positive VSP is influenced by the velocities as well as the accelerations (the difference of the road grade is not very important because it is the same route). The lower average speeds will cause this value also to be below the simulated ones. Another influencing factor can be seen in Figure 2 b), since the normal driver simulations reach the higher VSP modes while the real driver rarely reaches them.

3.2 Case study results

3.2.1 LOURES-SALDANHA (URBAN DRIVING)

From Figure 3 it is understood that the time of the trip in urban circulation is very often out of the driver's control. However, and despite not influencing the travel time, aggressive behavior will have a big impact on consumption. The increase in consumption from eco to aggressive driving is 23.6% and 29.2% for the Diesel and electric Vehicle respectively.

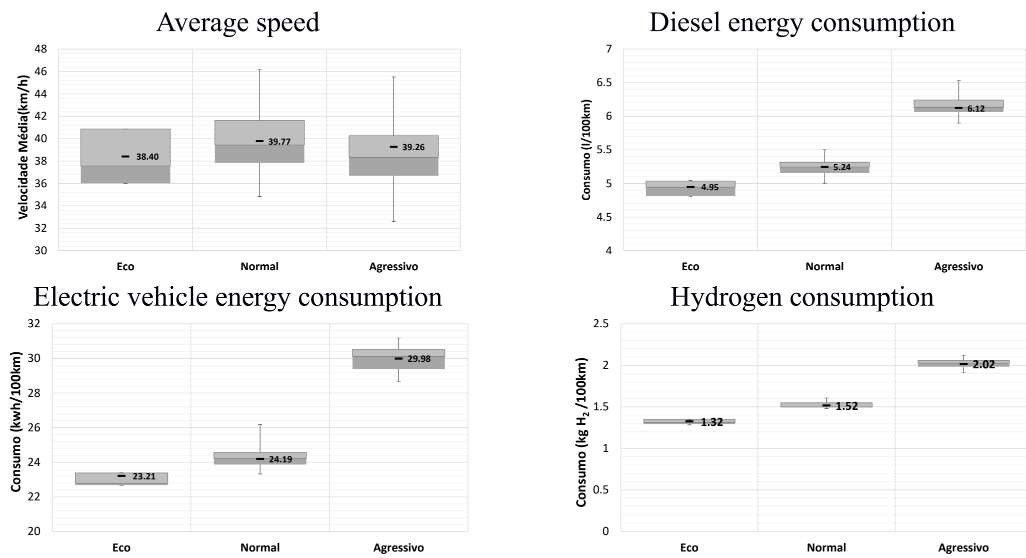


Figure 3 – Average speed, diesel, electricity and hydrogen consumption for the Loures-Saldanha simulations

3.2.2 LISBON-ALBUFEIRA

From Figure 4, compared to urban driving, extra-urban driving presents a very different shaped VSP distribution with much fewer stops and inferior stoppage time (percent wise), resulting in modes 1 and 3 having much less influence on the trip. These differences in dynamics related to the route will affect the energy consumption after applying the vehicle's VSP curves over each distribution.

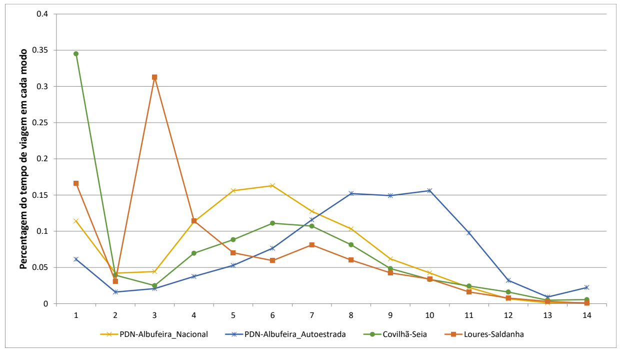


Figure 4 – VSP modes time distribution for the different case studies: Urban (red); Extra-Urban (yellow); Highway (blue); Hilly (green)

Comparing the extra-urban case with the urban one, we observe a reduction in energy consumption of -26.74% for Diesel, -25% for hybrid and -17.4% for electric. The reduction in consumption of electric vehicles is inferior since the advantage of regenerating energy is lost when the vehicle circulates always at the same speeds. For the highway case, we can observe from the VSP distribution in Figure 4 that the vehicle spends more time in higher modes leading to higher consumption when compared to the same origin-destination points using the national roads (+19.7% Diesel; +20% for hybrid, +25.3% for electric vehicles and +37.23% in fuel cell vehicles). This extra energy consumption added to the cost of the toll saves the drive 4km and about 48 minutes of travel time.

For the electric vehicle analyzed in this work, Nissan Leaf, the battery capacity is 40 kWh (144 MJ). With the energy consumptions estimated by this tool, this allows the vehicle to run 162 km of the highway course and 203km on the national road insufficient in either case to complete the journey. The recharging time is never less than 1 hour so this vehicle in particular is not usable in this kind of trip and this is still a major barrier for most electric vehicles. The lack of range and the time for recharging does not allow its usage on long trips. Fuel cell vehicles, whose hydrogen tank has the capacity for 4.5-6 kg of hydrogen, are a viable option for long trips. Even calculating with the smaller tank, 4.5kg of stored hydrogen allows 287km on the highway and 394 km on the national road more than enough to finish this journey.

4 Conclusions

This work aimed to evaluate the energy and environmental impacts of different vehicle technologies through the creation of route representative speed profiles. By considering the particular conditions of each specific route, the limitation of driving cycles like NEDC and WLTC to provide average energy values to represent real world conditions is strongly reduced. For this, a tool was developed in MATLAB that uses route information given by the Google Maps and OSM APIs for a pair of origin-destination points and curves of acceleration and deceleration as a function of the velocity taken from the literature. The validation results show a good agreement between the VSP distributions between the real and simulated dynamics for the same route. For the dynamic parameters used for validation an 18% deviation was verified for the average speed (23% in urban conditions), a -2.5% for average speed and an average positive VSP deviation of 27% for normal driver simulations and 5% for the eco driver simulations. These values can be improved in the future if traffic information can be taken into consideration in the tool.

The tool also considers the variability in speed profiles based on driving styles. It is concluded that as it is increased the electrification level of the vehicle (Diesel-hybrid-electric) the influence of aggressive driving on energy consumptions increases (percent wise). With the shift from conventional to electric vehicles an aggressive driver will face 1.29 times the consumption of an eco-driver in urban regime instead of 1.24, 1.35 instead of 1.26 on highways and 1.15 instead of 1.06 on hilly terrain. Those values for the hilly terrain show that when it is the characteristics of the course that imposes the velocity of circulation and power applied due to the road grade, the influence of the driving style in consumption is inferior.

In terms of emissions and considering only the tank-to-wheel stage shifting from the Diesel vehicle to either the electric or fuel cell vehicle, saves the environment 150 gCO_2/km in hilly terrain, 139 gCO_2/km in urban routes, 122 gCO_2/km in highway trips and 100 gCO_2/km in the extra-urban course. However, these values are cut by more than half if we consider the emissions associated with electricity production and battery construction, and grey hydrogen production. The electric vehicle is worst for the environment until it reaches the 20000-30000km mark. Only after that mileage does the electric vehicle become better in terms of emissions. Fuel cell vehicles only represent a better solution than conventional vehicles if the hydrogen is produced through electrolysis and using renewable power (usually from the wind) and not electricity from the grid.

As it is understood, due to enormous variability and randomness of a car trip associated with the route and the driver, different routes originate different energy consumptions, as well as the influence of shift in propulsion technology and aggressiveness. With this in mind, this tool assumes its importance in filling the gap in literature allowing the estimation of energy consumption on specific routes.

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