

**Analyzing the real-world fuel and energy consumption of conventional and electric cars in  
Europe**

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# **Analyzing the real-world fuel and energy consumption of conventional and electric cars in Europe**

## **Overview:**

The mass market rollout of Electric Vehicle (EV) technologies has been a central challenge in the debate on how we can reach our net zero emissions target by 2050 or sooner. Despite continued innovations in battery manufacturing and favorable market conditions making electric vehicles (EVs) more accessible to consumers, reaching our ambitious target to phase out the sale of fossil fuel-powered vehicles by 2030 will depend a great deal on several variables – including the provision of alternative fuel and transport sources, and the capacity of distribution network operators (DNOs) to accommodate shifting patterns of electricity consumption.

## **Introduction:**

This case study describes an analyzing the real-world fuel and energy consumption of conventional and electric cars in Europe to project the European Union (EU) Climate law sets the target of climate neutrality by 2050. Passenger cars and vans are responsible for 15 % of the total European Union (EU) CO<sub>2</sub> emissions, and the emissions reduction pace in transport is the slowest among all the sectors contributing. According to current regulations, the EU fleet-wide CO<sub>2</sub> emissions of new car sales will have to be reduced by 15 % by 2025 and 37.5 % by 2030 compared to the 2021 reference. The path to achieving these objectives is to create incentives

for investments in new technologies and increase the diffusion of zero- and low-emissions vehicles in the EU market.

The study focuses on three scenarios: average European conditions, the best and worst case for assessing the extremes, and a Monte Carlo-based scenario to determine the impact of warm and cold periods.

The study consists of 3 steps: model validation to simulate modern European passenger cars and quantification of the certification procedure impact; review and quantification of the impact of different factors in the gap; and finally, fleet data collection and scenarios applications to understand the variability reported by previous studies for the European fleet.

### **Methods and Result:**

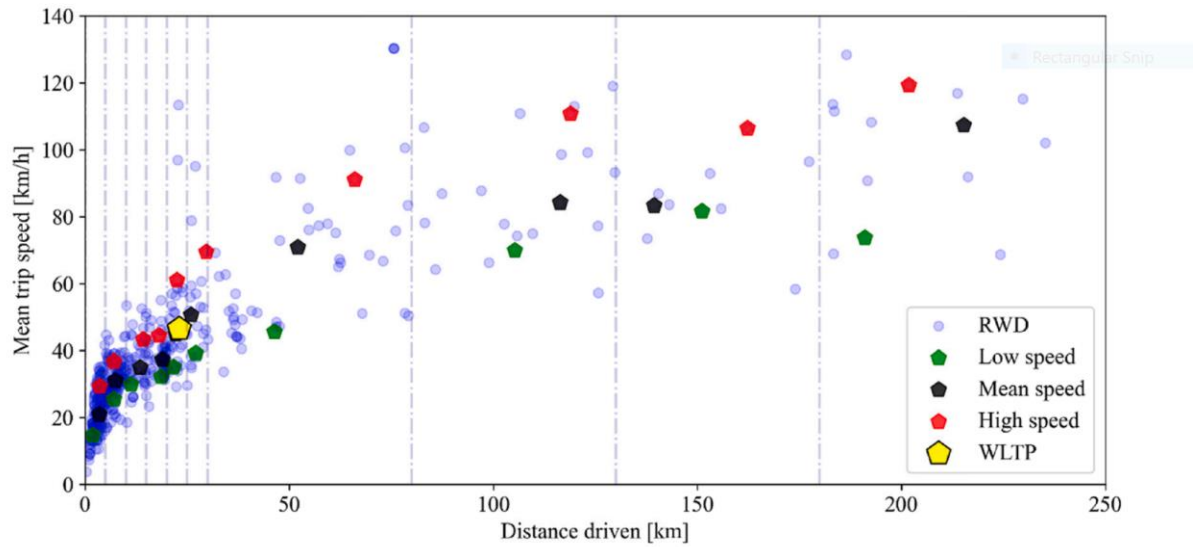
The data performed by the EU Joint Research Centre (JRC) in the period between 2018 and 2021. EU Member States use a standard secure electronic exchange system for sharing information about motor vehicles, trailers, and systems, certified in the EU [ETAES n.d. <https://www.etaes.eu/> (accessed December 10, 2021)]. The JRC has collected technical characteristics, the manufacturers' declared CO<sub>2</sub> emission values (for the ICEVs), and the battery-electric energy consumption (for BEVs), for 1,500 vehicle variants type-approved in EU during the first year of the WLTP introduction (August 2017 to December 2018).

The study provides a detailed description of the materials collected and the methodological steps proposed to study the CO<sub>2</sub> and energy consumption gap and its variability.

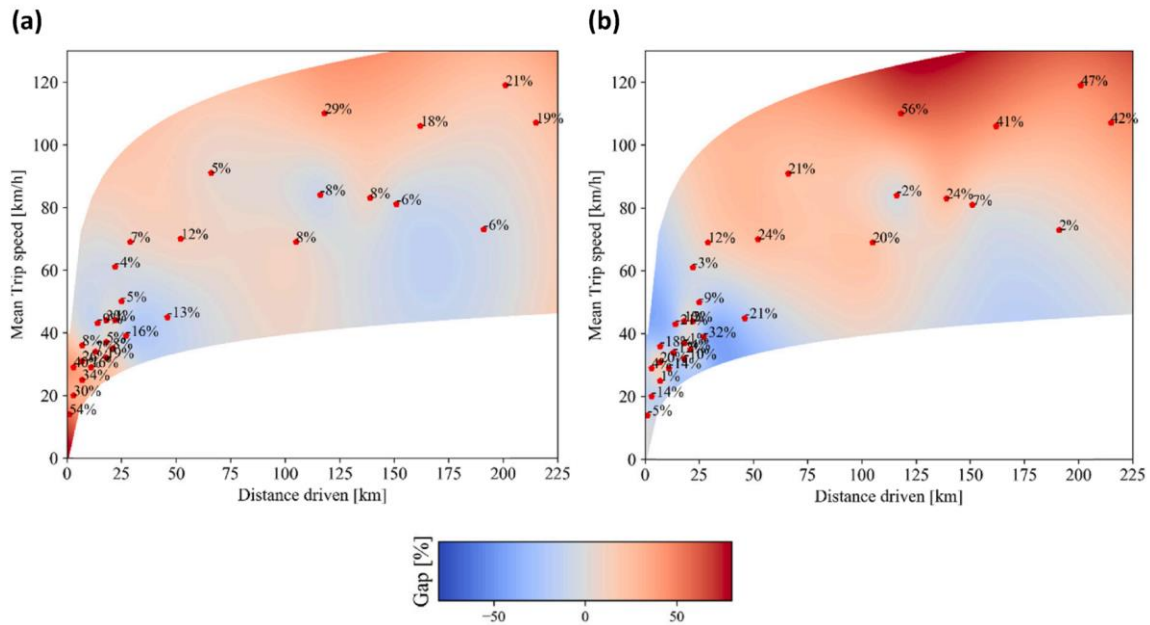
In this study author used K-means algorithm in each distance to form the group to solve the problems.

In order to maximize the representativeness of all the trips, the authors adopted a method to select 3 trips per segment. The selection criteria to identify the subset are the following:

1. The data were grouped in 10 distance clusters (vertical blue dashed lines in below figure).
2. Trip distance and mean vehicle speed were used to characterize the complete set of recordings (light blue points in below figure).
3. The K-means algorithm was applied in each distance cluster to form 3 groups: low, mean, and high speed.
4. The trips falling closer to the center of each K-means cluster were selected, resulting in 3 trips per segment (green, black, and red hexagons in below figure), thus 30 trips in total.
5. The yellow pentagon represents WLTC



Above figure RW trips selection. Blue dots present the distance and average speed pairs of each recorded RWD trip in the campaign described. Pentagons present the 30 selected trips. Their colors characterize the trip speed categories they fall into low, mean, and high are colored with green, black, and red, respectively. The yellow pentagon represents WLTP. The light blue vertical dashed lines separate the distance clusters.



Above figure simulated average gap from the vehicles tested by the JRC: (a) CO<sub>2</sub> gap for ICEVs; (b) battery-electric consumption gap for BEVs. Red dots depict the 30 actual trips simulated.

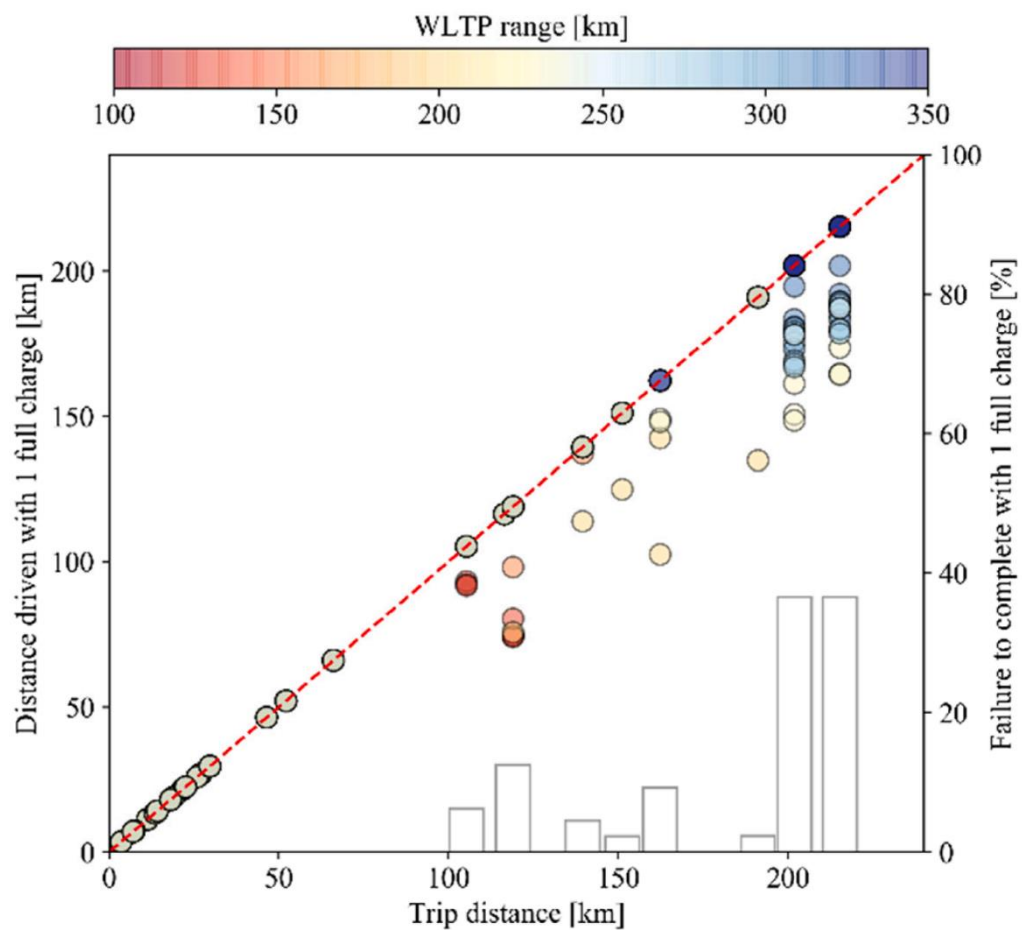
The background coloring represents the map produced by fitting in the simulated CO<sub>2</sub> gap on the trips. Red shades represent a positive gap, blue shades represent a negative one.

Because the author does not know what the values for the outcome might be, he used unsupervised learning algorithm to evaluate the result as in the following rason:

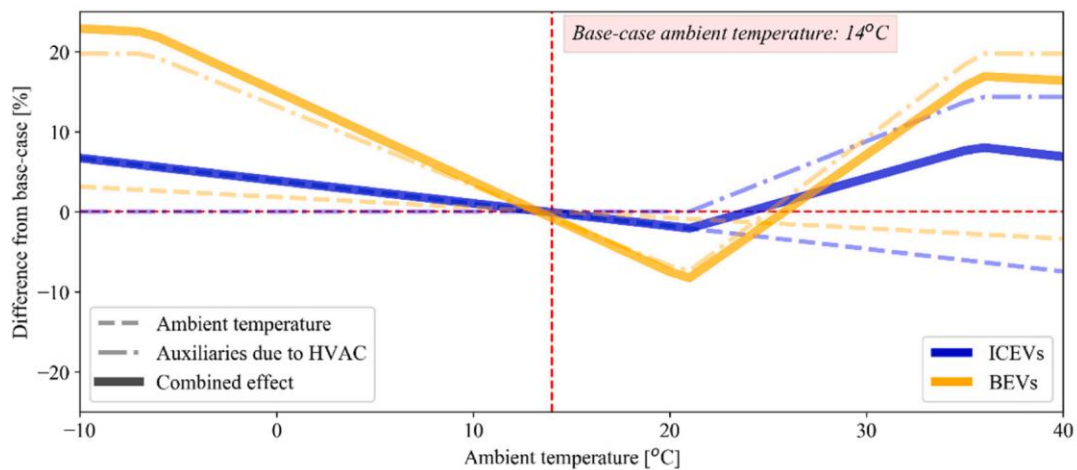
- the data had grouped around with 3 groups number of center point.
- Each individual data observation assigned to a cluster that has closest distance to the center point.
- The represent cluster center point for each cluster

I believe linear regression model is the second model which used from author to identify the final step during the analysis. Below figure shows the range driven with one full battery charge

(left y-axis) for different RW trip distances (x-axis). Each vehicle is represented by multiple dots across a range of trip distances. The trip distances shown do not surpass the manufacturer declared ranges. The dot color indicates the manufacturers' declared the Worldwide Light-vehicles Test Cycle (WLTP) range. The bars show the percentage of vehicles failing to complete the route with 1 full battery (right y-axis).



Below figure shows the individual and the combined effect of the HVAC related auxiliaries, and the vehicle losses, due to the ambient temperature. The gap was higher during cold conditions (ambient temperatures below 14 °C) than warmer conditions (temperatures above 14 °C) for both ICEVs and BEVs, and the best efficiency appeared in an ambient temperature of 21 °C. The impact of the ambient temperature was higher in the case of BEVs because the energy needed for the HVAC was comparable to the energy required for the propulsion, especially for the low-speed trips.



## Conclusion:

I think the result and model implementation during this analysis was clear and understandable, which results show average gap values of 13.5% (best case) and 34.5% (worst case) for conventional vehicles and – 4.5% (best case) and 23.9% (worst case) for battery electric ones.



Warm and cold weather conditions result in 5.5 and 7.5% increases for conventional and hybrids and 7.5 and 15% for electrics, respectively.

Because The transport sector constitutes is one of the main sources of greenhouse gas emissions in the world, I believe the actionable consequence on this case study assessing the correct factors influencing energy consumption in real world driving between certified and realworld consumption on a fleet level and annual temporal resolution.

The analysis tries revealed average values for the warm (spring and summer) and the cold (autumn and winter) months, but also their dispersion. Subsequently, randomly generated temperatures were produced following normal distributions for both periods. According to the randomly generated temperatures, the HVAC consumption was calculated separately for ICEVs and BEVs. Regarding the number of passengers, randomly generated weight for people was produced. The problem identified in future would be related to different variables and climate change items.