Het gebruik van stedelijke data om de actieradius en routekeuze van elektrische voertuigen te optimaliseren

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Samenvatting

Hoe kun je elektrische auto's verder laten rijden zonder grotere batterij? 'Range anxiety' – de angst om met een lege batterij stil te komen staan op de weg – is één van de voornaamste reden voor het niet kopen van elektrische auto's (EVs). Door betere inzichten in het energieverbruik van deze voertuigen kunnen we bestuurders beter informeren om op korte termijn een versnelling van de adaptatie van EVs te realiseren. Op lange termijn kunnen deze inzichten leiden tot nieuwe businessmodellen en duurzaamheidsoplossingen.

Dit onderzoek legt een verband tussen rijstijlen, weersomstandigheden, infrastructurele ontwerpelementen en verkeersdruk en het energieverbruik van elektrische voertuigen. Het beantwoordt hoe we data kunnen inzetten om deze effecten te kunnen voorspellen, om het energieverbruik te kunnen verminderen. Hierbij is gebruik gemaakt van een energievoorspellingsmodel en een VISSIM-model van Nieuwegein (Utrecht, Nederland). Middels meer dan 1000 simulaties zijn verschillen in rijstijl, weersomstandigheden, infrastructuur (wegtypes, bochten, hellingen, drempels, verkeerslichten) en verkeersintensiteiten berekend. De experimenten geven inzicht in de invloed van verschillende scenario's op het energieverbruik en de reistijd. Het model is gevalideerd met 30 rijtesten en laboratoriumonderzoek (met een BMW i3) en blijkt de realiteit met een nauwkeurigheid van 97% te kunnen voorspellen.

In het onderzoek is gezocht naar de invloedsfactoren en omstandigheden die bepalend zijn voor de optimale route en rijstijl voor een elektrische auto. Daarbij is gekeken naar de invloed op het energieverbruik van persoonlijke voorkeuren in rijstijl en de buitentemperatuur.

Het onderzoek heeft geleid tot inzicht in de rol van data in het bepalen van de beste route. Vervolgens is de uitdaging om de bestuurder te informeren en om energieverbruik mee te nemen in dynamisch verkeersmanagement. Met dit onderzoek wordt de zoektocht geopend naar een systeem waarbij data een prominentere rol krijgt in dynamisch verkeersmanagement en wordt nagedacht over hoe we met een dergelijk systeem de bestuurder kunnen informeren.

1. Introduction

Internal combustion engine (ICE) - vehicles largely influence the quality of life in cities due to their production of greenhouse gases (GHG) emissions *(44, 45, 3)*, noise and fine particles *(4)*. Electrification of our transport is a necessary step towards cleaner mobility and provides many economic opportunities *(5)*. Range anxiety is one of the biggest consumer concerns *(6)* caused by low battery capacities *(7, 8, 9)*, long charging times *(10)* and a lack of charging infrastructure *(6, 11)*. Reducing range anxiety would give a boost to the adoption of EVs. Since breakthroughs in battery capacity *(12, 13, 14)* and charging infrastructure *(15, 16, 17, 18)* are not expected, other ways have to be found. By using less energy – the most fundamental Trias Energetica rule – an EV could drive further with the same battery capacity. Currently, 46% of all trips could save energy by choosing a different route *(19)*. To do so, we need more insights in the energy consumption of electric vehicles.

Researchers have created many models to predict the energy consumption (*2*). In general, these models have three characteristics:

1. They aggregate vehicles into groups and use macroscopic variables
2. They use historical vehicle data
3. They do not take the full influence of the built environment into account

To reduce range anxiety, models are needed which can predict the energy consumption for *individual vehicles* using *real-time data* taking the *full influence of the built environment* into account. More recent energy prediction models, such as CMEM, use second-to-second data as an input, enabling researchers to evaluate the effect of microscopic driving behavior on the energy consumption.

With the introduction of microscopic traffic simulation, we are able to simulate complex individual driving behavior and vehicle characteristics *(20, 21, 22)*. The output of these microscopic models, speed profiles of individual vehicles, could be used as the second-to-second input for energy prediction models and therefore, microscopic traffic simulations could be perfectly used to research the influence of traffic situations on the energy consumption.

Some microscopic influences on the energy consumption have been researched, such as rolling resistance (*23, 24, 25*), hilly driving (*26*), traffic calming elements (*27, 28, 29*) traffic intensity (*30*), vehicle automation (*31, 32, 33*), driving style (*19, 34, 35, 36, 37*) and weather influences (*14*, *38, 39, 40*). However, a complete overview is lacking, and therefore a research gap exists in the influence of the built environment on the energy consumption of electric vehicles. By knowing these effects, data can be used to better predict the energy consumption of EVs. This also leads to a second gap in research, namely how to provide this data to the driver, in order to actually increase the range of EVs. To create more knowledge and fill these gaps, this research focusses on two research questions. Firstly, *how could we use data (concerning driving style, weather, infrastructure and traffic intensity) to better predict the energy consumption of electric vehicles?* and secondly, *how could we provide this information to the driver in order to improve the range of EVs?*

First, the methodology will be discussed in section 2. Section 3 will discuss the results of the first research question, after which section 4 will discuss implications on dynamic traffic management which answers the second research question. Finally, section 5 provides the conclusions.

2. Methodology

This research aims to answer two research questions. This section discusses how we aimed to answer these questions. First, section 2.1 discusses the energy consumption model which has been used to predict the energy consumption of EVs. Secondly, section 2.2 shows how different individual elements are modeled into VISSIM and how speed profiles are being extracted from these VISSIM models. Section 2.3 explains how a case study in Nieuwegein has been performed and section 2.4 discusses how different implications on dynamic traffic management have been found.

2.1 Energy consumption model for BEVs

An energy consumption model, used in (14) has been used to predict the energy consumption of EVs. The equations of tractive energy used in the wheels reads:

$$F_{tr} = f_r mg cos(\theta) + \frac{1}{2}\rho A C_d(v - w)^2 + mg sin(\theta) + 1.05 * ma \qquad (i)$$

With f_r being the rolling resistance coefficient, m [kg] being the mass of the vehicle including the driver, g [m/s2] is the gravitational constant, θ [rad] describes the road slope, ρ [kg/m^3] represents the air density and A [m^2] is the frontal area of the vehicle. The aerodynamic drag coefficient of the car is described with C_d, the driving speed and wind are respectively described with v and w [m/s] and the acceleration is mentioned as a [m/s^2]. Besides tractive energy, vehicles also consume auxiliary energy. These account for lights, climate control, wipers, radio, navigation system and other small electrical features. The total consumption depends on the use of these systems and on the scenario (temperature, day/night) and is described in (*2*).
Finally, internal losses have to be covered. Since this research uses a BMW i3, the powertrain efficiency has been set to 85% based on calculations by (*2*):

$$E_{Tank-to-wheel} = \frac{(F_{tr}*v + Paux)*t}{\eta_{powertrain}} = \frac{((f_r mg cos(\theta) + \frac{1}{2}\rho A C_d(v-w)^2 + mg sin(\theta) + 1,05*ma)*v + Paux)*t}{\eta_{powertrain}} \qquad (ii)$$

The final equation indicates that the energy consumption is almost fully related to the speed profile of the vehicle. EVs use a regenerative braking system in which kinetic energy is being regenerated to electrical energy when braking (*3, 46*). The efficiency of this process depends on the driving style and has been set to 15% for aggressive drivers, 40% for normal drivers and 90% for eco-drivers by (*2*).

2.2 Modeling driving style, weather variables, infrastructural elements and intensity

Different individual influences have been modeled, either in VISSIM or externally (by using Excel). The following subsections describe how.

Driving style

The model compares three driving styles: eco-driving, normal driving and aggressive driving. Based on literature research, variables describing these three driving styles have been selected and used in VISSIM. Eco-drivers drive with 95% of the speed of normal drivers, while aggressive drivers drive 5% faster than normal drivers. Differences are also found in acceleration and deceleration (14, 57, 58), lateral acceleration (14, 70) and the efficiency of regenerative braking (69, 70), quantitatively described in (*2*).

Weather variables
Weather variables have been modeled by adapting variables in the energy consumption model. Via the ambient temperature, air pressure, relative humidity, air density and wind speed the outcome of the tank-to-wheel energy consumption could be altered. Different Dutch weather scenarios have been described in (*2*) and are used in the scenarios. In VISSIM, it is also possible to edit the minimal sight distance. The effect of this phenomena on the energy consumption has not been researched but could easily be done in future research.

Infrastructural elements
Based on expert judgement and by comparing other research, infrastructural elements influencing the energy consumption have been selected. Infrastructural elements either influence the energy consumption by changing the speed profile (through acceleration and deceleration or by limitations of lateral acceleration) and by the different rolling resistances. (*1*) describes the setup of different infrastructural elements.

2.3 Nieuwegein case study
After finding individual influences of different variables on the energy consumption, a case study has been performed in Nieuwegein (Utrecht, The Netherlands) to test the interconnection of these elements. Three routes have been chosen with the same origin-destination and comparable travel times. These routes have been selected based on their rich amount of individual elements and therefore contain different road types, speed limits, infrastructural elements such as speed bumps, slopes, (signalized) junctions, bus stops and tram crossings. The first route, named as 'residential route', is a typical residential street with a speed limit of 30 km/h and a number of speed bumps. The second route, named as 'city center route', is a 50 km/h road with signalized junctions, bus and tram crossings and high traffic intensity. The third and last route is the 'motorway route', which is longer in distance but due to the higher speed competitive in travel time. These routes have been modeled in VISSIM to test multiple scenarios. First, the network has been tested without any traffic. In the second scenario, morning peak traffic has been added and in the third, these vehicles are all set to eco-drivers to test the influence of a large scale eco-driving strategy. Finally, a winter scenario has been tested.

2.4 Implications on dynamic traffic management
After finding the influence of different variables on the energy consumption of EVs, route optimization based on real-time information with respect to these variables comes into consideration. The effect of this route optimization has been proven in (*2*). To provide drivers with this information, changes in the structure of dynamic traffic management could be made. A review of the current information structure with respect to traffic management has been made, after which we apply new insights on a possible future structure which includes real time information based on public data.

3. Results

Section 3 will show the results of the first part of the research. The graphs show VISSIM outputs which went through the energy consumption model, and therefore represent the energy consumption for different trips with different characteristics. First, individual phenomena will be discussed, after which the case study performed in Nieuwegein will be shortly emphasized.

3.1 Results of the calculations of individual elements

Influence of driving style
Driving style influences the energy consumption due to the different speed profiles related to different driving styles. Various elements of the driving style have been researched. First, a difference in energy consumption has been found for different driving speeds (figure 1 *(1))* with bigger differences between the driving styles at higher speeds (17% at 130 km/h). At very low speeds, the energy consumption rises due to the longer running time of the climate system of the vehicle. Therefore, the optimal speed depends on the use of the climate system, but will be about 30 km/h for average Dutch circumstances. The second graph in figure 1 shows the influence of speed oscillations on the energy consumption. The difference is significant (53% increase in energy consumption for aggressive drivers with large oscillations) and is larger for aggressive drivers than for eco-drivers. This result proves the efficiency of cruise control.
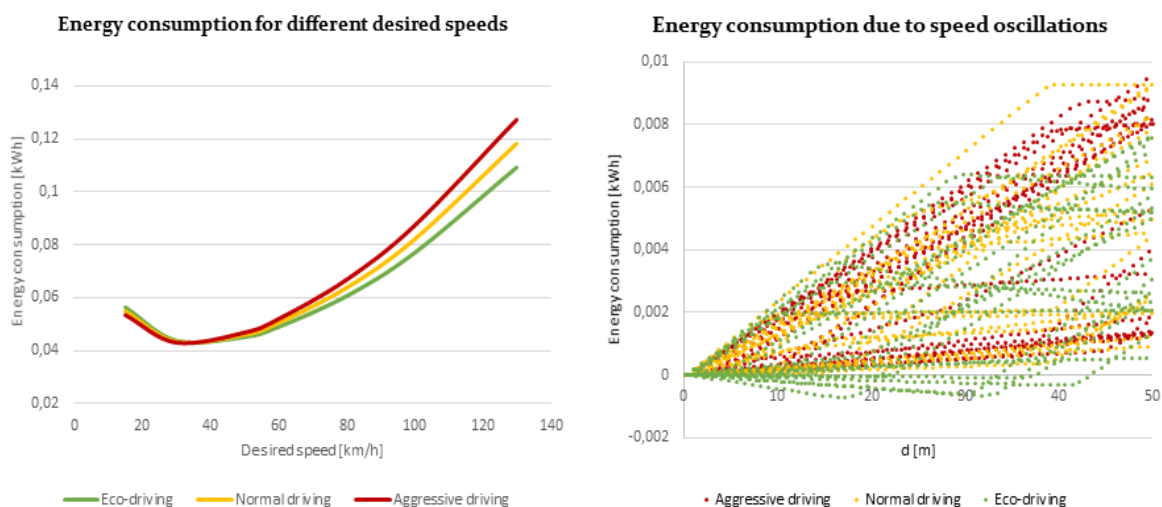

FIGURE 1. Influence of driving styles on the energy consumption of EVs

Influence of weather variables
Energy consumption of electric vehicles is also largely influenced by weather factors (figure 2, *(1)*).Especially at low driving speeds, the influence of the weather is extremely high due to the use of the climate system. The energy consumption with an ambient temperature of 0°C is about twice as high as the energy consumption at 20°C. The influence is lower for higher driving speeds.

  Wind also highly influences the energy consumption. Independent of the driving speed, the energy consumption could triple at very high headwind speeds (100 km/h) compared to windless scenarios.
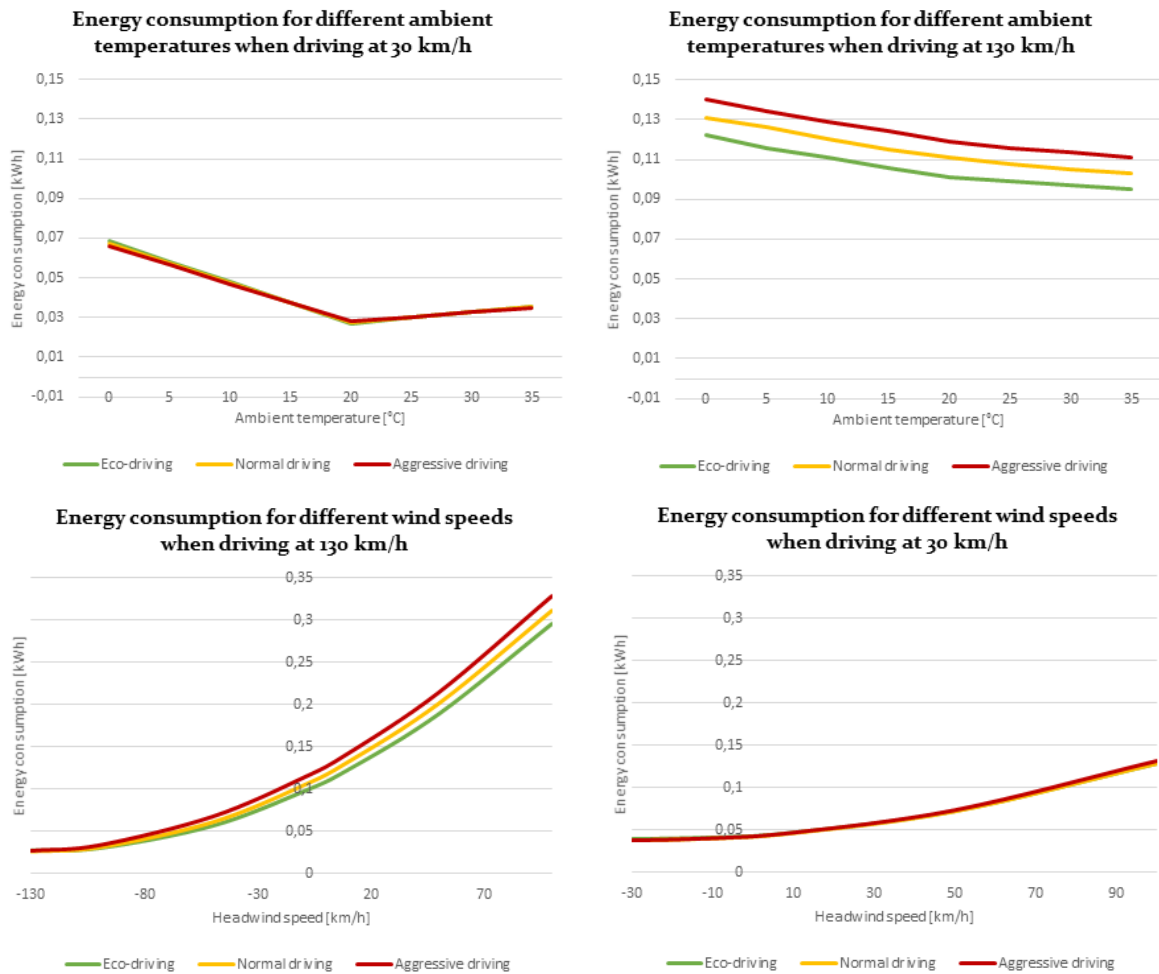
FIGURE 2. Influence of weather variables on the energy consumption

Influence of infrastructural elements

The energy consumption of EVs is influenced by infrastructural elements due to the rolling resistance, gravitational forces and the deceleration and acceleration at typical stop-and-go situations. Different infrastructural elements have been researched to quantify their influence on the energy consumption in (figure 3, (*1*)). For rolling resistance, an increase of 20% in energy consumption has been found for urban roads compared to motorway road surfaces, while a slope of 1° would increase the energy consumption with about 30% for faster drivers (130 km/h) and almost double the energy consumption when driving 30 km/h. Interesting is the high influence of speed bumps due to the deceleration before the speed bump and the acceleration after the speed bump. This influences aggressive drivers more than eco-drivers, due to the more aggressive acceleration. For the worst speed bumps, this could lead to two times the energy consumption for eco-drivers and four times the energy consumption for aggressive drivers. This effect is similar at signalized junctions, however, the waiting time also influences the energy consumption (due to the climate system which keeps running). Therefore, waiting time influences the energy consumption more when driving through cold weather.
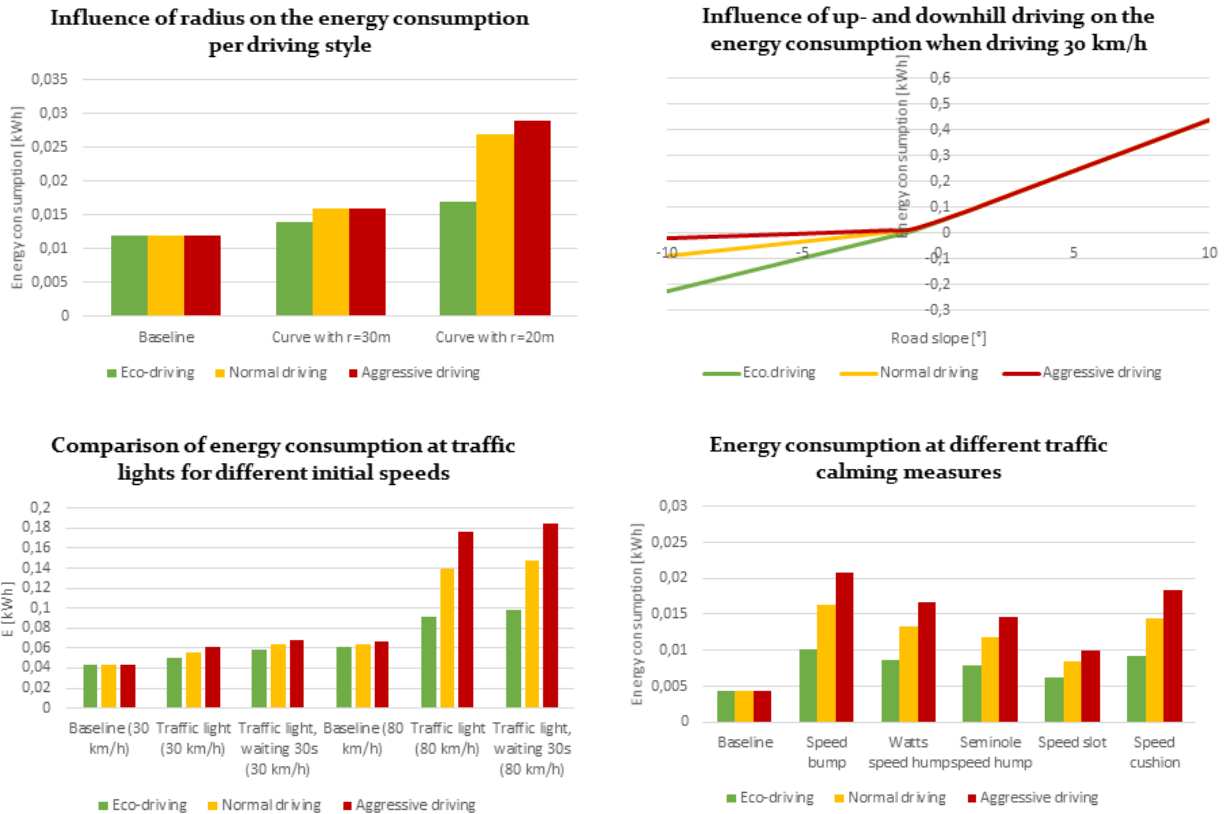
Influence of radius on the energy consumption per driving style

Influence of up- and downhill driving on the energy consumption when driving 30 km/h

Comparison of energy consumption at traffic lights for different initial speeds

Energy consumption at different traffic calming measures

FIGURE 3. Influence of infrastructural elements on the energy consumption

3.2 Results of the Nieuwegein case study
A VISSIM network has been created, containing the three routes mentioned in section 2. By generating 990 individual energy profiles of vehicles during different driving circumstances, four scenarios have been designed.

Travel time and energy consumption
Figure 4 (*1*) shows the average travel times and energy consumption for different scenarios. The first scenario shows runs in the empty network and shows logical results in terms of travel time and energy consumption. The second scenario shows a typical morning peak scenario. As expected, the travel times rise significantly. However, the energy consumption during peak hour traffic did not rise too much, and even reduced for some aggressive driving scenarios. This is mainly due to the lower driving speeds during the peak hour, reducing the aerodynamic drag forces significantly. Scenario 3 shows the influence of a massive all-eco strategy. The results showed that the energy consumption of the eco-drivers is lower, however, the travel times increased massively. During the end of the morning peak runs, congestions occurred at almost every intersection, due to the low acceleration of the eco-drivers. Therefore, the advice is to closely monitor the macroscopic effects when applying large scale eco-driving strategies. During winter, the energy consumption rose significantly, and had relatively high impact on slower drivers and routes with low speed limits. At the residential route, 40% of all energy consumed by eco-drivers during winter has been used by the climate system.
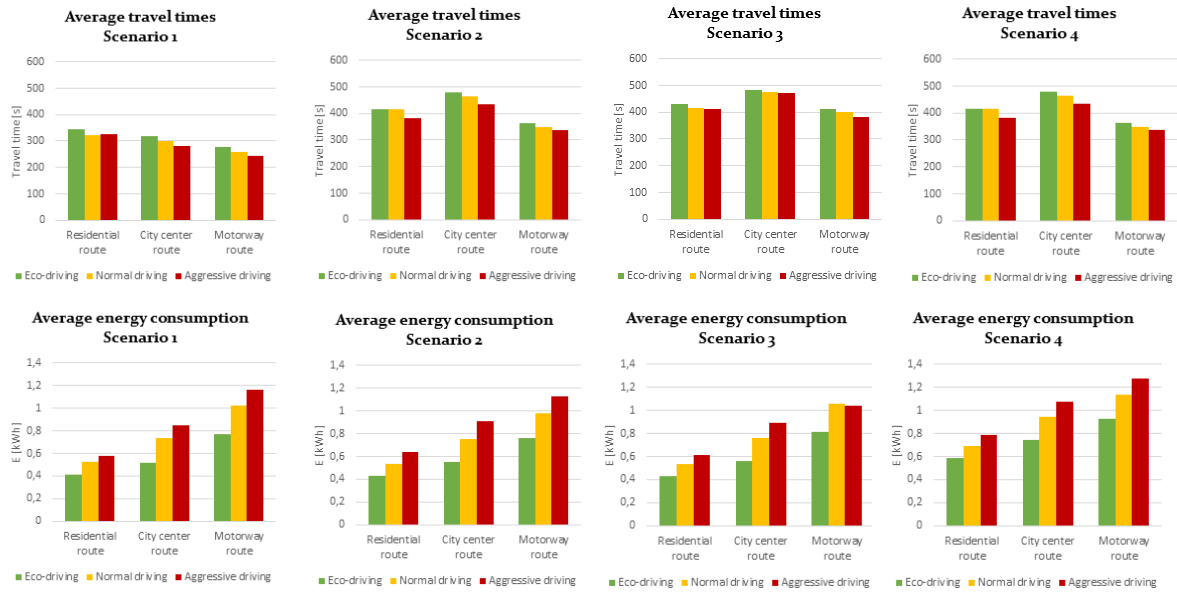
FIGURE 4. Comparison of energy consumption and travel times for different routes and driving styles

Validation

The results have been validated by performing 30 driving tests in Nieuwegein (figure 5, (*1*)), by using dynamometer data from Argonne National Laboratory (41) and by comparing the results to the technological specifications of BMW itself (42). The energy consumption model could predict the Argonne National Laboratory results with an accuracy of 98,5% (for all temperatures between between 0 and 25 °C). The driving tests performed in Nieuwegein showed that the model could predict the energy consumption with a Mean Average Prediction Error of 7,8% for short trips (below 5 km) and 3,4% for longer trips. This is extremely accurate, compared to other models used in different research projects (14). Comparing the results to the BMW specifications shows that BMW is very optimistic about the range of the i3. BMW promotes the efficiency of the i3 to be 13,1 kWh/100km, while this research found efficiencies between 13,1 and 28,8 kWh/100km. Since BMW uses a standard calculation method, we as society should question whether we should change this system and be more transparent about the actual range of EVs.
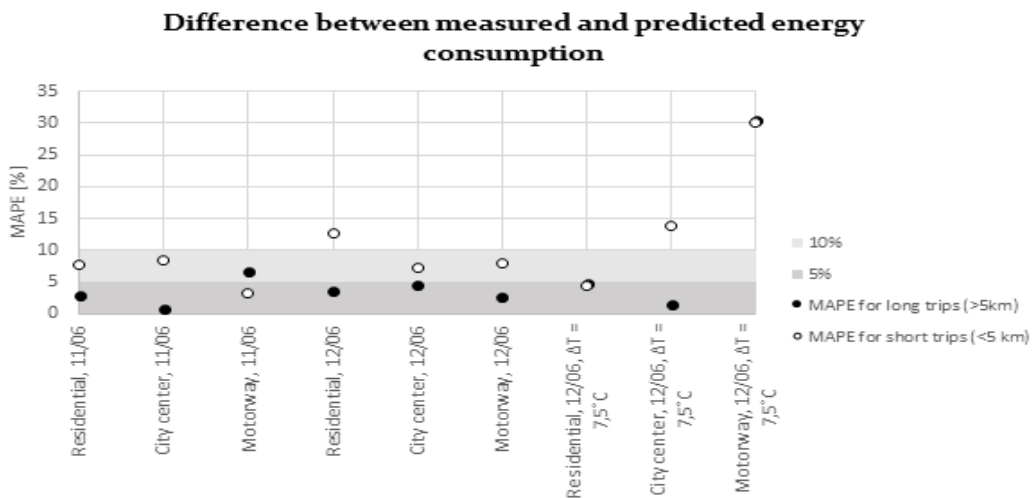

FIGURE 5. Difference between measured and predicted energy consumption

4. Implications on dynamic traffic management

After proving that using real-time data can provide us with more accurate information about the optimal route and driving style in (*2*), one could think of actually using this data to make traffic more efficient by optimizing routes and driving styles. Section 4 explores how future information system architecture should look like to enable these developments.

4.1 Current information structure

Current and former traffic management systems often make use of (mainly) historical data and knowledge, which form the input for the system, together with some algorithms (figure 6). These algorithms enable the system to make calculations for many applications, such as the green times at signalized intersections, dynamic traffic management scenarios and shortest path algorithms in navigation systems (43). However, on a system architecture level, many systems lack feedback loops, resulting in a one-way information provision. Therefore, many parts of traffic management systems cannot – or not fully – adapt their information to the current scenario.
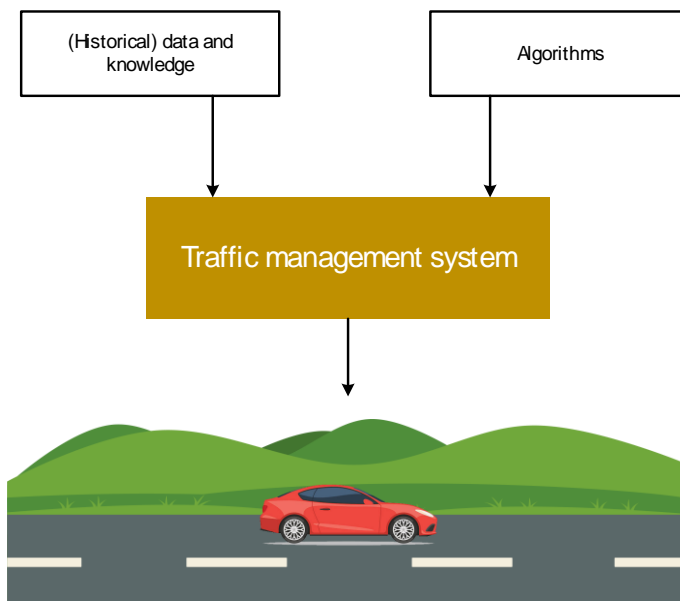

FIGURE 6. Current information structure of traffic management systems

4.2 Future information structure

To enable traffic management systems to become more dynamic, a shift in the information architecture should be made. This shift should account for technological, mental and infrastructural elements as these all are required as input. Figure 7 shows how a feedback loop has been implemented (in purple). It includes real-time data measured by sensors (weather stations, infrastructural sensors such as loops and in-car sensors) but also provided by predictions made in digital twins, information generated from wearables, smartphones and other GPS devices and personal information about the drivers' preferences. This real-time data describes the current state of the traffic, the weather and infrastructural elements, but might also include personal preferences and the driving style of the driver. The latter two could be used to give a more personalized feedback to the driver, similar to other digital services, such as Netflix, Spotify or Google Maps. Such a personalized approach would both make the traffic management system

more comfortable for the end-user and also makes it easier for this user to adapt to the system. The information could be provided to the end-user through multiple channels, including smartphones, navigation systems, other in-car systems, signalized intersections, smart road signs and could also be used in future V2V (vehicle to vehicle), V2I (vehicle to infrastructure) and V2X (vehicle to everything) applications.
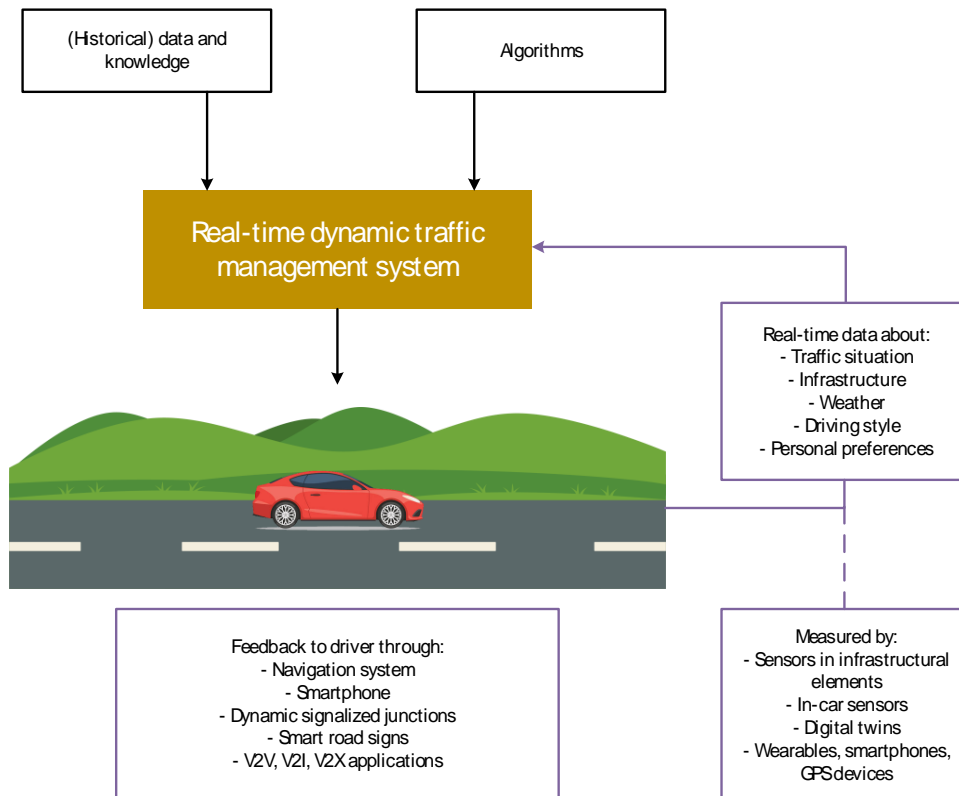

FIGURE 7. Future information structure of traffic management systems

4.3 Implications

The systematic change enables many new features in dynamic traffic management systems. The following subsections describe a selection of these.

Implications for navigation companies

By using real-time data, navigation systems could better predict the optimal route. In (*2*), we proved that not only the fastest route, but also the most energy efficient route are dependent on many variables. By implementing these real-time data feedback loops in the system architecture of traffic management systems, navigation systems could provide drivers with more accurate information.

Implications for dynamic road signs and signalized intersections

Current dynamic road signs, such as the green-wave or alternative route scenarios, mainly focus on the traffic throughput. However, in a society which demands more and more for sustainable transportation, one could think of dynamic road signs which not only focus on travel time, but also on the energy consumption. 'Simple' data, such as the ambient temperature, could be easily used to calculate the most optimal route and driving style (*1*) and therefore dynamic road signs could be used to inform the driver about these.

Signalized intersections could also use real-time information to provide better green times and reduce the traffic delays. A start has been made with iVRI systems (*47*), which proved to decrease the traffic delays significantly. By adding more data, these systems could develop even more in the future.

Implications for in-car communication systems
Similar to the dynamic road signs, in-car communication systems could be used to inform the driver. A nice addition to the in-car communication systems is that they can be used personally, with a decentral information supply. Therefore, they could adapt their information based on the personal preferences of a driver. A typical eco-driver would be informed about the CO_2 reduction of a certain driving style, while a driver which highly valuates travel costs would see the reduction of these due to a lower energy consumption on a certain route.

(Future) implications for the driver
The driver itself remains a huge research gap: how is he/she going to adapt his/her driving style based on the current information? Could we reduce human errors and create a more rational driving style and route choice? And what if a driver simply does not want to adapt? More research is necessary to find the most efficient nudging techniques. Simultaneously, the interesting development of autonomous vehicles enables car manufacturers to impose optimal route choice and driving style to the driver, simply because the vehicle itself decides 'how to drive'. It is good to know that the use of real-time data makes it easier to launch the autonomous vehicles on our road networks, but it is also good to keep actively discussing the more ethical questions related to autonomous driving. How much freedom do we want the driver to have? And what do we as a society find more valuable: sustainability, safety, travel time or money?

Who owns the data?
The last ethical question we would like to raise, is about the data generated within the city. Not only should we stick to legal regulations, traffic engineers could (and should) also think of the possession of this real-time data. A perfect system would only exist in a world of open data, but businesses struggle with sharing a lot of data due to commercial reasons. Could we find business models where sharing data could actually be valuable to both the owner of the data, and to society?

5. Conclusion

To conclude, this research focused on two research questions. Firstly, how could we use data (concerning driving style, weather, infrastructure and traffic intensity) to better predict the energy consumption of electric vehicles? We found that many variables influence the energy consumption of (electric) vehicles and that we can use real-time data to make very accurate predictions of the energy consumption. We also found that different optimal routes exist for different scenarios and for different personal preferences/driving styles. Therefore, the second research question aimed to find a systematic way of providing information, extracted from real-time data, to the driver, in order to improve the range of their EVs. A new approach in the information structure of dynamic traffic management systems has been provided which uses a feedback loop to create a circular information stream which continuously adapts itself to the current situation. This approach could be used in many cases, of which some have been provided in this research.

This research should be seen as an exploring study towards the possibilities of using real-time data in dynamic traffic management systems. Many questions still exist, and additional research should be done before we can make the step towards valuable business models.

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