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Influence of driving style, infrastructure, weather and traffic on electric vehicle performance

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ABSTRACT

Internal and external circumstances affect a vehicles' fuel consumption. Various studies reviewed internal combustion engine vehicles (ICEVs) energy consumption. While Battery Electric Vehicles (BEVs) are expected to replace ICEVs, more research is necessary to understand their energy performance. To fill this research gap, a microscopic traffic model and an energy prediction model were combined to estimate the effects of driving styles, weather, traffic and infrastructure on the energy consumption of BEVs. By using a VISSIM model, various scenarios were tested. This resulted in a qualitative insight into the energy consumption and travel time, which was validated by performing 30 driving tests and by using dynamometer data. The results indicate that built environment variables have a large effect on the energy consumption of BEVs. An increasing traffic intensity has been found to not always increase the energy consumption. Moreover, the energy consumption can be decreased by choosing a more energy-efficient route.

1. Introduction

The transportation sector holds a share of 27% of GHG (greenhouse gas) emissions in the EU (EEA, 2019). Internal combustion engine vehicles (ICEVs) produce a large portion of the total GHG emissions (IPCC, 2014; EPA, 2019; Clarke, 2017), noise and fine particles (Jochem et al., 2016). The European Union has set up strategies for the transportation sector to reduce the negative externalities of mobility and achieve the goals of the climate agreement (European Commission, 2016). This EU strategy focuses on 1) increasing the transport system efficiency; 2) speeding up the deployment of low-emission fuels, and 3) speeding up the deployment of zero-emission vehicles.

Battery electric vehicles (BEVs) are expected to reduce the negative externalities of mobility and enhance economies, by releasing the demand for fossil fuels and reducing energy intensity (OECD/IEA, 2018). However, to reach the climate agreement, it is necessary to not only shift to vehicles with more efficient fuel types but also to increase the energy efficiency of these vehicles. Boriboonsomsin et al. (Boriboonsomsin et al., 2012) found that 46% of the trips in Sweden could save energy by choosing a different route and Brundell-Freij et al. (Brundell-Freij and Ericsson, 2005) found that driving style had a significant influence on the energy consumption of ICEVs. Logically, different energy efficiency strategies will be targeted at different target groups, based on for example trip length (45% of the emissions are being produced by 9% of the trips) and travel motive (53% of the emissions are being produced by non-work-related travel) (Van Essen et al., 2017). The Dutch road authority mentions that, to reach lower emissions through behavioral change, more insights in microscopic driving behavior are necessary, to create good strategies for different target groups (Van Essen et al.,

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2017).

Research has focused on increasing penetration rates by addressing the barriers to BEV uptake such as range anxiety (Deloitte, 2018), battery capacity (Tate et al., 2008; Brady, 2010; Sonnenschein, 2010), long charging time (Wynn and Lafleur, 2009) and improving the charging infrastructure (Deloitte, 2018; Nilsson, 2011). Breakthroughs in batteries are not expected to solve range anxiety in the short term (Yong et al., 2015; Cluzel and Douglas, 2012) and batteries are expected to be constrained by weight and cost issues (Wang et al., 2017). Simultaneously, issues with charging infrastructure exist, including the practical feasibility (Cuijpers et al., 2010), legislation (ACEA, 2018) and grid peaks due to preferences for private charging at peak hours (Cuijpers et al., 2010; Mathieu, 2018; Morrissey et al., 2016). Recently, some researchers have investigated the impacts of internal (such as driving behavior) and external (such as infrastructural design, traffic intensity, weather, etc.) circumstances on the energy consumption of BEVs (Wang et al., 2017; Wu et al., 2015; Fukushima et al., 2018). They developed models for BEVs based on the Comprehensive Modal Emission Model (CMEM) (Barth et al., 2010). Wu et al. (Wu et al., 2015) and Fukushima et al. (Fukushima et al., 2018) used historical speed measurements but were not able to accurately predict energy consumption upfront due to a lack of weather, infrastructure and traffic intensity information. Wang et al. (Wang et al., 2017) included the impacts of weather and route information on BEVs energy consumption.

Research into the energy-efficiency of ICEVs has been carried out for decades (Boriboonsomsin et al., 2012; Brundell-Freij and Ericsson, 2005; Barth et al., 2010; Ericsson, 2001; Barth and Boriboonsomsin, 2009). Both macroscopic models and microscopic models have been established for ICEVs. Macroscopic models, such as MVEI and MOBILE, have been established to predict the aggregated energy consumption of a road network but lack microscopic driving behavior (Barth et al., 2010). A second-to-second vehicle emissions model using fuel-rate data from the CAN bus to predict real-time energy consumption has been built, the CMEM model (Barth et al., 2010), which formed the basis of many research projects (Boriboonsomsin et al., 2012; Brundell-Freij and Ericsson, 2005; Ericsson, 2001; Barth and Boriboonsomsin, 2009). Due to this second-to-second approach, the CMEM model was able to evaluate microscopic driving behavior. It has been used for BEVs as mentioned before. However, CMEM doesn't incorporate weather conditions (Chamberlin et al., 2011) and uses parameters based on vehicle categories instead of individual vehicle parameters (Barth et al., 2005).

To accurately model microscopic driving behavior, complex driver and car characteristics, microscopic traffic simulation has been used (Hamdar, 2012; Immers and Logghe, 2012; Fellendorf and Vortisch, 2010). Many theoretical models have been created to model realistic driving behavior. Three widely applied models are the car-following model, the lane-changing model, and the route choice model. Car-following models determine the driving speed based on the leading vehicle's speed (Saifuzzaman and Zheng, 2014). In congested situations, the distance between vehicles will be reduced after which the behavior of the following vehicle will be mainly determined by the leading vehicle (Barth and Boriboonsomsin, 2009). Many variables have been added to the basic model (Gazis-Herman-Rothery) such as desired acceleration and deceleration, (Gipps, 1981), randomness factors (Nagel and Schreckenberg, 1992), maximum deceleration rates (Krauss et al., 1997), velocity, driving behavior, and maximum space headway (Treiber et al., 2006). Immers and Logghe (Immers and Logghe, 2012) found that the closer two cars are to each other, the larger the accelerations of these vehicles. This effect is researched by Sugiyama et al. (Sugiyama et al., 2008) as the shockwave effect. Vehicle automation could lead to lower time headways in the future (Schoenmakers, 2018) which could reduce velocity oscillations (Hoogendoorn et al., 2013) and therefore increase the energy efficiency of BEVs (Barth and Boriboonsomsin, 2009). Lane-changing models have been first created by Gipps (Gipps, 1986) to model lane changing behavior and are often based on the infrastructural situation, speed, other vehicles, driving behavior (Gipps, 1986), incentives to change lanes (Yang et al., 1999), politeness (Kesting et al., 2007) and lateral and longitudinal acceleration (Mahapatra and Maurya, 2013). Route choice models are typically probability models based on the utility of optional routes (Fellendorf and Vortisch, 2010). Models have been created which distribute vehicles based on the utility of a route based on travel time (Burghout, 2004), travel distance (Ben-Akiva et al., 2004), generalized cost (Fellendorf and Vortisch, 2010) and extra link-level costs (Bert et al., 2005). Shortest path algorithms, such as the Dijkstra (Dijkstra, 1959) or Bellman-Ford (Bellman, 1958; Ford, 1956) have been used in many shortest path problems (Singal and Chhillar, 2014), while later models have been created using the k-shortest path algorithm (Yen, 1971) and C-logit model (Kesting et al., 2007) as they created more realistic traffic distributions. Based on these microscopic models, complex vehicle operations could be modeled giving speed profiles as an output. These speed profiles form the input for energy consumption models. Therefore, combining microscopic traffic simulations and energy prediction models could be used to accurately predict energy consumption based on complex microscopic vehicle operations for BEVs.

Many microscopic influences have been individually identified for ICEVs and BEVs, such as rolling resistance (Michelin, 2003; Goubert and Sandberg, 2016; Ejsmont et al., 2016), hilly driving (Liu et al., 2017), traffic calming elements (Johnson and Nedzesky, 2014; Gupta, 2014; Ahn and Rakha, 2009), traffic intensity (Sugiyama et al., 2008), vehicle automation (Hoogendoorn et al., 2013; Schoenmakers, 2018; Heijne, 2014), driving style (Boriboonsomsin et al., 2012; Gundana et al., 2018; Kedar-Dongarkar and Das, 2012; Fonseca et al., 2010; Zhu et al., 2018) and weather influences (Wang et al., 2017; Evtimov et al., 2017; Kavalchuk et al., 2015; Geringer and Tober, 2012). In the built environment, these individual elements come together. Current energy consumption models in vehicles base the prediction on historical energy consumption and lack detailed route, weather and traffic information (Wang et al., 2017). Zhang et al. (Zhang et al., 2020) created an energy consumption model for hybrid electric vehicles (HEV) using a cellular automaton simulation. They combined different slopes, winds and traffic conditions, however, many other infrastructural and driving style characteristics were out of their scope. Waloyo et al. (Waloyo et al., 2019) and Kusuma et al. (Kusuma et al., 2019) further investigated respectively HEVs and extended-range EVs energy consumption, mainly based on vehicle specifications. Gao et al. (Gao et al., 2019) extensively researched the influence of internal vehicle components on the energy consumption of EVs. Wu et al. (Wu et al., 2019) showed promising results predicting driving cycles and energy consumption using deep learning reducing the computation time of energy calculations. Chen et al. (Lv et al., 2018) show how insights in driving styles and other parameters can lead to automated EV driving cycles using a cyber-physical systems approach. Real driving measurements conducted by Huang et al. (Huang et al., 2019) found significant influences of route choice on the energy consumption of HEVs.

It is clear that there is a lack of thorough understanding of BEVs' energy consumption performance at the microscopic level which takes both driving styles and external impacts into consideration. Therefore, this research focuses on the influence of driving styles, weather variables, infrastructural design and traffic intensity on the energy consumption of BEVs at the microscopic level. The research is organized as follows. First, the research methodology is discussed in Section 2, describing the setup of the energy prediction model, the modeling of individual elements, a case study and the VISSIM modeling process. Section 3 shows the results of the calculations for both individual elements as for the case study. Finally, the paper ends with a discussion and conclusion.

2. Methodology

To get more insight into the energy consumption of BEVs, a combination of microscopic traffic simulations and energy prediction modeling was used. Section 2.1 describes the basic energy consumption model based on a BMW i3. Section 2.2 explains in detail how each element was modeled, in order to take the influence of driving style, weather, infrastructure and traffic intensity into account. Section 2.3 shortly describes the case study in Nieuwegein (Utrecht, the Netherlands), which has been chosen as a real-life scenario for model demonstration, and explains the setup of the microsimulation model in VISSIM.

2.1. Energy consumption model for BEVs

Based on the literature, an energy consumption model was set up. Basic physics theory (Wang et al., 2017) shows that the tractive forces (F_{tr}) of a vehicle are determined by the rolling resistance, aerodynamic drag force, gravitational forces, and acceleration forces, leading to the following equation:

$$F_{tr} = f_r mgcos(\theta) + \frac{1}{2}\rho AC_d(v - w)^2 + mgsin(\theta) + 1.05*ma \tag{1}$$

Where f_r is the rolling resistance coefficient, m [kg] is the mass of the vehicle and driver, g [m/s^2] is the gravitational constant, θ [rad] represents the road slope, ρ [kg/m^3] represents the air density, A [m^2] being the frontal area of the vehicle. C_d is the aerodynamic drag coefficient of the car, v and w [m/s] are the driving speed and wind speed (tailwind) and a [m/s2] represents the acceleration.

The auxiliary energy consumption includes climate control, window heating devices, fans, lights, audio systems, wipers and the navigation system (Evtimov et al., 2017; Kavalchuk et al., 2015). Kavalchuk et al. (Kavalchuk et al., 2015) estimated the power required to heat up a vehicle with a temperature difference of $\Delta T = 20\ ^\circ C$ to be 2 kW, while Reichmuth (Reichmuth, 2016) estimated the energy required to cool the vehicle is about half of the energy to heat it. Evtimov et al. (Evtimov et al., 2017) estimated that lighting systems require power (P_{lights}) of 76 W (for LED 16 W) during daytime and 95 W (for LED 64 W) during nighttime driving. Kavalchuk (Kavalchuk et al., 2015) and Geringer et al. (Geringer and Tober, 2012) estimated that wipers use 60 W (P_{wipers}) during rainfall. Based on (Kavalchuk et al., 2015; Geringer and Tober, 2012), an extra 30 W of constant power is added to cover radio and navigation systems ($P_{radio\&nav}$). As it is hard to estimate power requirements of other small electrical features, such as side windows, various sensors and small systems, an assumption was made based on (Kavalchuk et al., 2015), that they need 30 W of constant power in all conditions. The auxiliary power is then calculated as:

$$P_{aux} = P_{lights} + P_{climatecontrol} + P_{wipers} + P_{radio\&nav} + 30W \tag{2}$$

To cover the internal losses of the vehicle (also referred to as powertrain losses), the powertrain efficiency ($\eta_{powertrain}$) has been set to 85% based on (Wang et al., 2017; Lohse-Busch et al., 2013). Therefore, the tank-to-wheel energy consumption of a BEV would be calculated as in (Clarke, 2017). Where v is velocity, P_{aux} is the auxiliary power, t is the travel time, and $\eta_{powertrain}$ is the powertrain efficiency.

$$E_{Tank-to-wheel} = \frac{(F_{tr}*v + Paux)*t}{\eta_{powertrain}} = \frac{((f_r mgcos(\theta) + \frac{1}{2}\rho AC_d(v - w)^2 + mgsin(\theta) + 1,05*ma)*v + Paux)*t}{\eta_{powertrain}} \tag{3}$$

Regenerative braking is the process of kinetic energy being regenerated to electrical energy during braking (Clarke, 2017; Xu et al., 2016). The equation is shown in (Jochem et al., 2016). Where m [kg] is the mass of the vehicle and driver and v [m/s] is the driving speed. The efficiency depends on the use of the regenerative brakes and the use of the mechanical brakes (Cocron et al., 2013). Based on Walsh et al. (Walsh et al., 2010) and Gao (Gao, 2008), the use of regenerative brakes has been set to 15% for aggressive drivers, 40% for normal drivers and 90% for trained eco-drivers.

$$E_k = \frac{1}{2}mv^2 \tag{4}$$

The model parameters were calibrated using BMW i3 dynamometer data from Argonne National Laboratory (Argonne National Laboratory). The dataset contains tests on different driving cycles representing different scenarios (Urban Dynamometer Driving Schedule (UDDS, 12 km), Highway (Hwy, 16.5 km) and Supplemental Federal Test Procedures (US06, 12.8 km)) under different temperatures between 0 and 25 °C, relative humidity, solar radiation, climate control settings and window positions. Next to this, the model parameters were calibrated using real driving tests from Wang et al. (Wang et al., 2017). The measured energy consumption during the dynamometer tests and the on-road driving tests were compared to the predicted energy consumption of our model to calibrate the parameters.

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

The following subsections discuss how driving style, weather variables and infrastructural design were implemented in the model, and how they were quantified.

2.2.1. Driving style

Three driving styles were modeled: eco-driving, normal driving and aggressive driving. Driving style has been characterized by the driving speed (Barth and Boriboonsomsin, 2009; Zhu et al., 2018), acceleration and deceleration (Wang et al., 2017; Kedar-Dongarkar and Das, 2012; Fonseca et al., 2010), lateral acceleration (Wang et al., 2017; Reymond et al., 2001) and regenerative braking efficiency (Gao, 2008; Reymond et al., 2001). The acceleration percentage rate and speed oscillations also characterize the driving style (Barth and Boriboonsomsin, 2009). Data to quantify these last two variables are lacking, however, these are closely related to the other variables, so they will automatically be higher for aggressive drivers (Boriboonsomsin et al., 2012; Barth and Boriboonsomsin, 2009). Based on Barth and Boriboonsomsin (Barth and Boriboonsomsin, 2009) and Zhu et al. (Zhu et al., 2018), eco-drivers are modeled with 95% of the driving speed of the normal driving style, while aggressive drivers are modeled to drive at 105% of the normal driving speed. The desired acceleration and deceleration of the eco-driver are 1.5–2 m/s^2, 2–3 m/s^2 for normal drivers and the aggressive driver prefers 3–4 m/s^2 (Wang et al., 2017). The lateral acceleration at low speeds is 4.5 for eco-drivers, 6.5 for normal drivers and 8.5 for aggressive drivers (Wang et al., 2017).

2.2.2. Weather variables

The weather variables which influence energy consumption are the ambient temperature, air pressure, relative humidity, air density, wind speed and direction, and the minimal sight distance (Evtimov et al., 2017; Hollweck et al., 2018). Two temperature scenarios have been selected to represent a winter scenario (0 °C) and an average Dutch scenario (12 °C), while the air pressure and relative humidity have been set to 1011.3 hPa and 79% (KNMI, 2018). The effect of tail- and headwind will be calculated in the individual calculations. Current models to accurately model wind speeds and directions for real situations, such as computational fluid dynamics, are currently not considered to be realistic for second-to-second models. As wind in urban situations is coming from all directions due to the presence of buildings, the wind speed in the Nieuwegein case-study is set to be 0 m/s to simplify the situation. Further research is needed to completely cover the effect of wind in real situations.

2.2.3. Infrastructural elements

The infrastructural design of a road and its posted speed limits influence the speed profile of a vehicle and thus its energy consumption. Infrastructure also influences various tractive forces. To measure these influences, various infrastructural elements have been selected based on a literature study. Rolling resistance is influenced by the road type (Goubert and Sandberg, 2016) and was modeled using the following equation, based on literature (Wang et al., 2017; Goubert and Sandberg, 2016; Ejsmont et al., 2016; Sandberg et al., 2013; Bendtsen, 2015):

$$f_{r,pervious\ \ concrete} = 0.0118 - 0.00013*T \tag{5}$$

With T being the ambient temperature [°C]. Based on Wang et al. (Wang et al., 2017) and Den Hollander (den Hollander, 2018), a multiplication factor has been set to cover an average rolling resistance for all Dutch road types. The multiplication factor is 1.00 for motorways and trunk roads (100–130 km/h), 1.05 for distributor roads (80 km/h), 1.15 for access roads (60–70 km/h), 1.20 for city access roads (50 km/h), 1.25 for neighborhood access roads (30 km/h) and 1.4 for home-zones (15 km/h).

The speed reduction in curved road sections is determined by the lateral acceleration (a_y) (Wang et al., 2017) and is calculated as (Deloitte, 2018). With v being the maximum driving speed [m/s] and R being the radius of the curve [m].

$$a_y = \frac{v^2}{R} \tag{6}$$

Five different traffic calming measures were modeled based on their different lengths and speed reductions (Johnson and Nedzesky, 2014; Gupta, 2014; Ahn and Rakha, 2009) to cover the Dutch infrastructure (Struyk Verwo Infra, n.d.). The speed bump, with a length of 30 cm, has the largest speed reduction of 80%, followed by the speed cushion (3 m, 60%). Lower reductions are caused by the Watts speed bump (3.7 m, 50%) and the Seminole speed bump (6.7 m, 40%) followed by the speed slot (6.7 m, 20%). The speed reductions were modeled as desired speed profiles using a normal distribution to create some variation in behavior.

2.3. Nieuwegein case study

To find the influence of traffic intensity and the interconnection between elements mentioned in 2.2, the southern part of Nieuwegein was modeled by using VISSIM. Three comparative routes with the same OD (Origin-Destination) and similar travel times have been chosen, including different road types, speed limits, traffic calming measures, slopes, signalized and unsignalized intersections and various public transport lines. The first route is the shortest (3.1 km), takes 5–8 min depending on the traffic and is a typical *residential route* with a speed limit of 30–50 km/h and many traffic calming measures. The second route (3.7 km) goes through the *city* *center*, takes 5–12 min, has multiple lanes with a speed limit of 50 km/h and is largely influenced by multiple signalized junctions. The last route is the longest (4.5 km) but also takes 5–9 min since it uses the *motorway*.

Four scenarios have been separately tested to measure vehicles' speed profiles of the three driving styles by using VISSIM. The profiles, with a granularity of 0,1 s, were used as input for the energy consumption model. To test the influence of infrastructural elements on energy consumption, the first scenario measures vehicles in an empty network. This scenario will function as a baseline scenario. To test the influence of traffic intensity, the second scenario is measured with morning peak traffic (based on measurements done by VRU (Huisman, 2018)). To find the influence of weather, the third scenario uses the speed profiles of scenario two, but with winter settings in the energy consumption model. Finally, to test what would happen if our eco-driving strategy would be implemented, the fourth scenario sets all non-measured vehicles in the network to the eco-driving style. The other three scenarios are mixed traffic scenarios containing drivers with different driving styles. By using driving style indicators in VISSIM, we could collect the data for each separate driving style. Each scenario uses previously defined measurement vehicles representing the three driving styles.

2.3.1. VISSIM modeling

Speed profiles, which form the input for the energy consumption model, were gathered through the output of VISSIM simulations. Driving speed was modeled as desired speed profiles around which the real driving speed is oscillating. A desired speed profile was created for each speed limit and each driving style. The profiles were created using a normal distribution. The values of the eco-driver's desired speed are 5% lower than the normal driver, the values of the aggressive driver's desired speed are 5% higher. The average of all profiles is 5% above the posted speed limit which corresponds to the legal driving speed in The Netherlands.

Acceleration and deceleration were modeled through a maximum, minimum and average preferred profile. The preferred acceleration and deceleration of each vehicle oscillate around the average preferred profile but always stay within the boundaries of the maximum and minimum profiles. The shapes of the profiles are based on Wang et al. (Wang et al., 2017).

Traffic calming measures were created by using reduced speed areas. These are areas in which the desired speed alternates from the speed limit. By using these areas, vehicles will temporarily slowdown, which represents traffic calming measures. For each different type of traffic calming measure and for each driving style, different desired speed profiles were created and used in the reduced speed areas. The same was done for (sharp) curved road sections to reduce speed.

Signalized junctions are controlled by using a standard control file setup by using VISVAP 2.16. Three detection loops were used to control the green times based on queue lengths, sometimes giving priority to busses and trams.

The VISSIM model has been calibrated using real-world data to make the results more realistic. This has been done by using datasets of traffic counts and public transport information, expert insights and observing the area and its infrastructural elements during test drives.

2.3.2. Validation

To validate the results of the Nieuwegein case study, 30 on-road driving tests were conducted by the author on the three routes in Nieuwegein using a BMW i3. Speed profiles were collected using a Transystem GL-770 GPS logger and were used as input for the prediction model. The predicted values were compared to the real energy consumption, which is measured by the vehicle and could be accessed through the dashboard and the BMW remote app. The tests included driving with and without the climate system running and were conducted in different time slots (including morning peak traffic and off-peak traffic) to cover possible situational differences. The average temperature within the measurement period (in May 2019) ranges between 10.8 and 19.2 °C and covers typical Dutch weather conditions (KNMI, 2018).

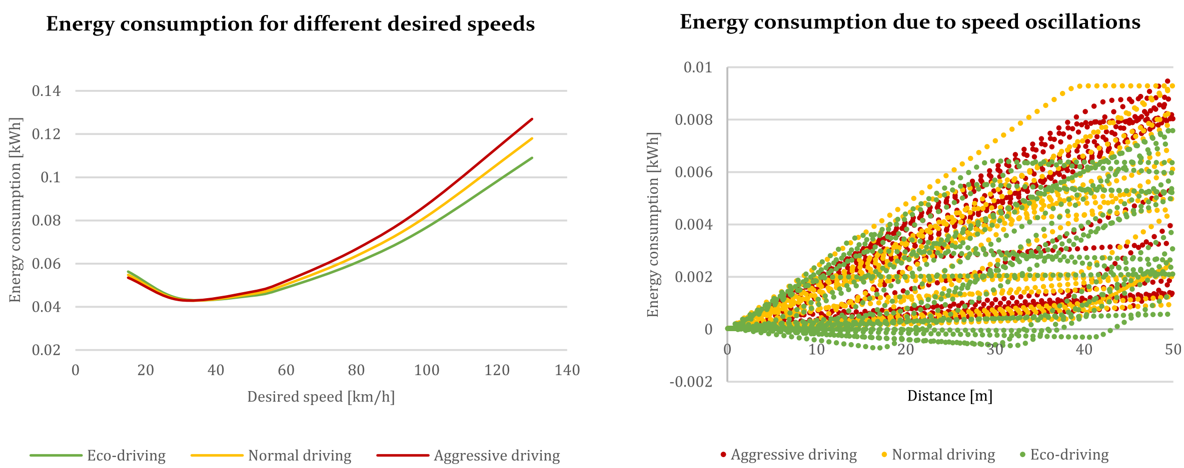

Fig. 1. Influence of driving styles on the energy consumption of BEVs.

3. Results

3.1. Results of the calculations of individual elements

This section describes the results of the calculations of individual elements. These elements have been grouped into three categories: driving style, weather variables, and infrastructural elements. By using the energy consumption model and a VISSIM model of a straight road section, the influence of the different elements has been evaluated.

3.1.1. Influence of driving style

Fig. 1 shows the influence of different desired speeds on energy consumption. As expected, the results show that the aggressive driver uses more energy than the eco-driver while driving at high speeds. The relative difference increases to 17% as the speed increases (130 km/h), due to the high influence of aerodynamic drag. At very low speeds, the eco-driver uses 5% more energy due to the longer travel times. This is due to the higher energy consumption of the climate system.

Combining the higher acceleration of the aggressive driver with the slightly higher desired speed resulted in an increase of 25–30% in energy consumption during the acceleration, regardless of the initial speed and desired speed. Energy consumption (or regeneration) during deceleration is highly dependent on the use of the regenerative braking system.

Driving speed oscillations negatively influence energy consumption of BEVs. The larger the oscillations, the higher the energy consumption. While small oscillations of 0.1 m/s^2 don't significantly influence energy consumption, larger oscillations of 0.3 m/s^2 do (with a gain of 14% for eco-drivers, 37% for normal drivers and 53% for aggressive drivers). After performing 60 measurements in VISSIM, aggressive drivers used 22% more energy with an oscillation of about 0.2 m/s^2, while the energy consumption of eco-drivers only raised with 1%. The results show the efficiency of cruise control, especially for non-eco-drivers.

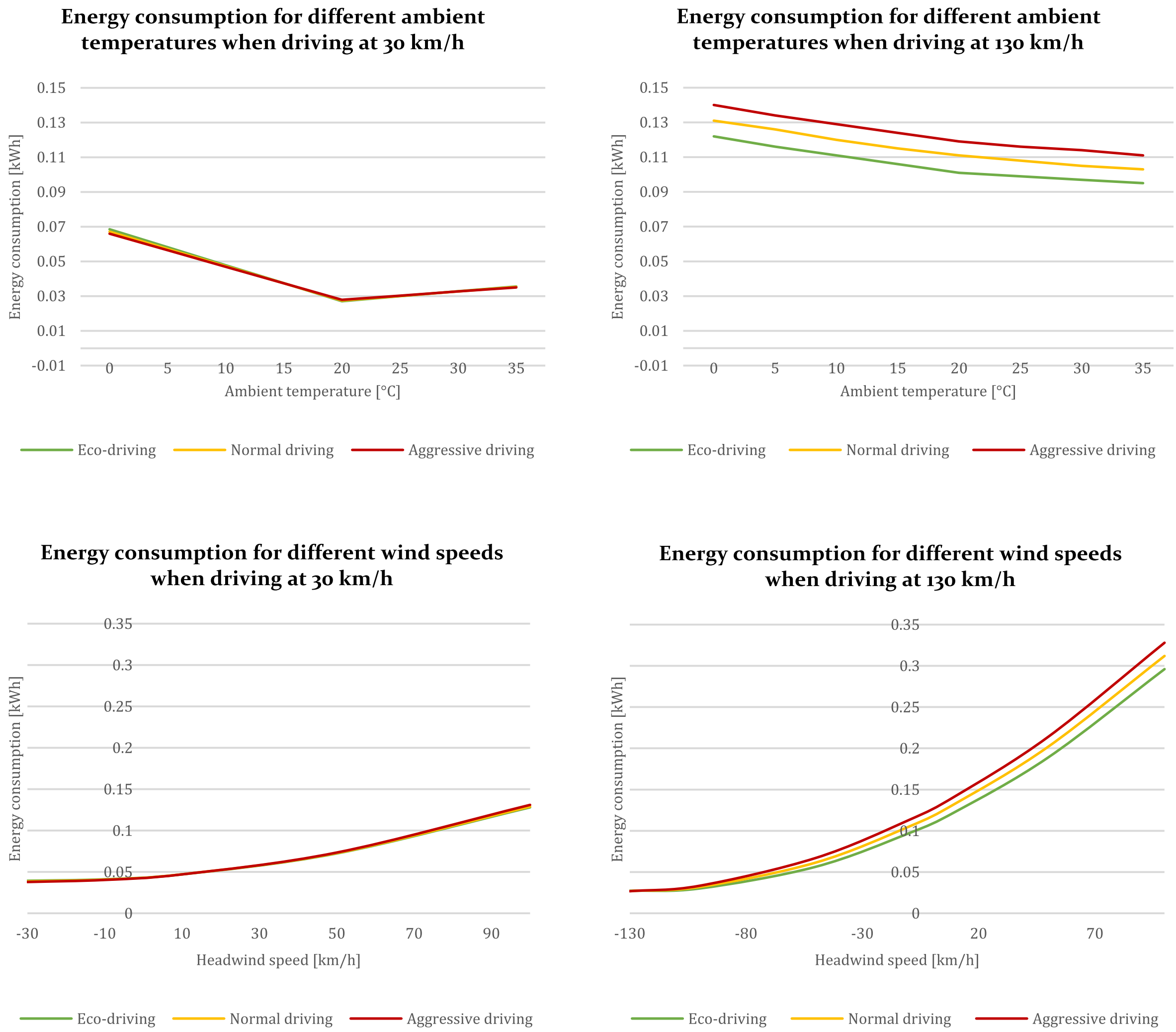

Fig. 2. Influence of weather variables on the energy consumption of BEVs.

3.1.2. *Influence of weather variables*

Energy consumption is largely influenced by weather factors. Fig. 2 shows the influence of ambient temperature and wind speed on energy consumption. Results show that at low driving speeds (30 km/h), the relative influence of the ambient temperature is extremely high. Next to the climate system, energy consumption is also influenced by higher rolling resistance forces and aerodynamic drag during cold weather. The lowest energy consumption is gained at a temperature of 20 °C. For higher driving speeds (130 km/h), the relative influence of the temperature is significantly lower. Simultaneously, the lower aerodynamic drag at high temperatures results in the fact that for very high speeds, the highest efficiency is gained at high temperatures.

Wind also affects energy consumption differently for different driving speeds. At lower driving speeds, the influence of wind is independent of the driving style, while at higher speeds, the aggressive driver uses significantly more energy than the eco-driver (11%) when driving through strong headwinds of 100 km/h. At these wind speeds, the drivers use about three times as much energy compared to a windless scenario.

The difference between LED and conventional lighting has been calculated. Results show that LED is more efficient, however, compared to the rest of the influences, the influence of lighting is relatively small.

3.1.3. *Influence of infrastructural elements*

Infrastructural elements influence energy consumption through multiple resistance forces (Fig. 3). First, the results show that the road type influences the rolling resistance, resulting in a 20% higher energy consumption on home-zone roads compared to motorway roads. Road slopes influence energy consumption through the gravitational forces. A slope of 1° would almost double the energy consumption of BEVs driving at 30 km/h, while it adds about 30–35% to the energy consumption during motorway driving (130 km/h). Higher slopes result in such a high gravitational force that the differences between the driving styles disappeared. Curved road sections, traffic calming measures and signalized intersections influence energy consumption through the acceleration forces. Due to the more aggressive acceleration of aggressive drivers, results show that these situations mainly affect the more aggressive driving styles. Elements causing a higher speed reduction have the most influence on the energy consumption, such as sharp curves at 50 km/h

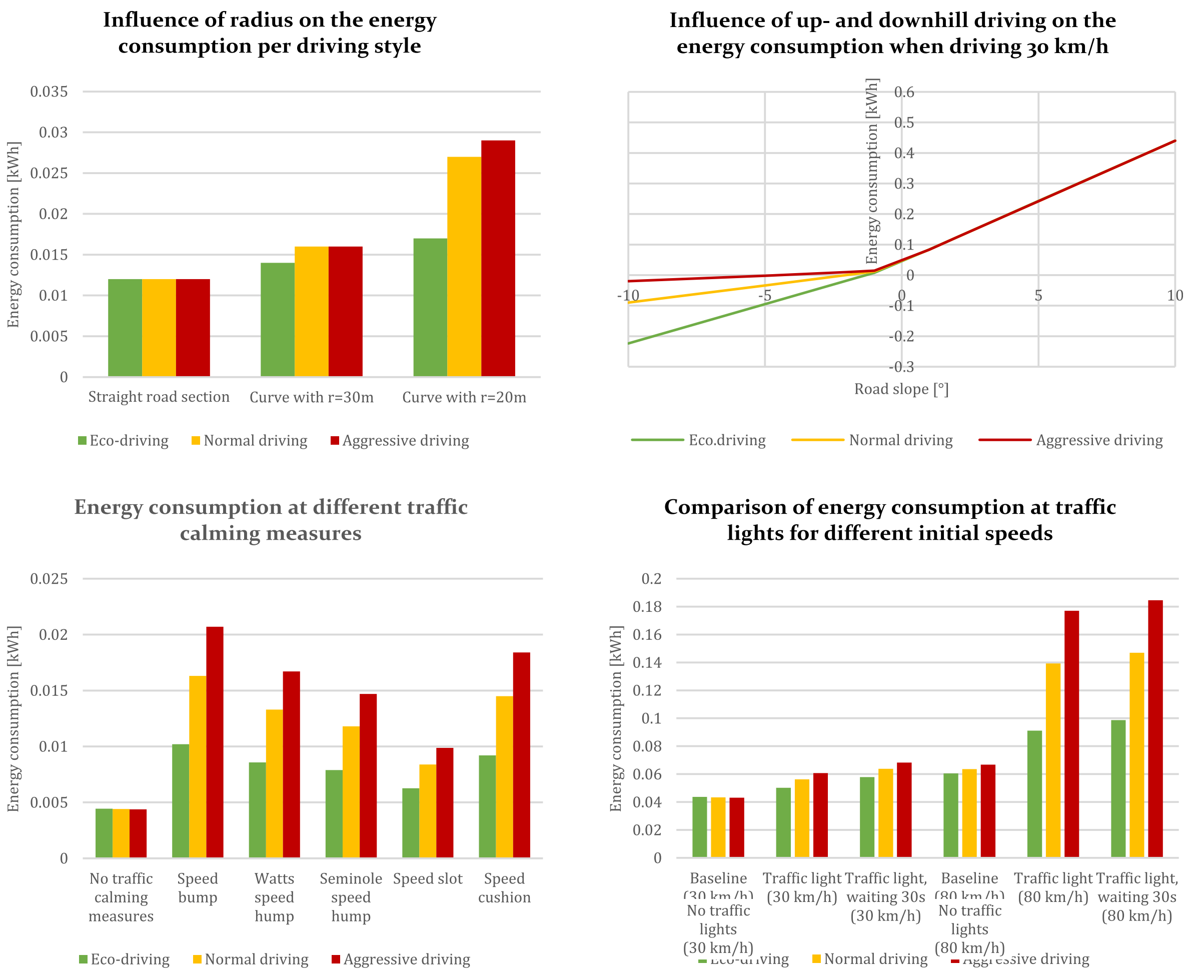

Fig. 3. Influence of infrastructural elements on the energy consumption of BEVs.

(+142% compared to a straight road section for aggressive drivers, +42 for eco-drivers), speed bumps at 30 km/h with 80% speed reduction (+371% for aggressive drivers, +132% for eco-drivers) and stops at traffic lights while driving 30 km/h (+163% for aggressive drivers, +62% for eco-drivers). A waiting time of 30 s at traffic lights adds another 70% to the energy consumption at ambient temperatures of 12 °C (regardless of the driving style) and 105% with ambient temperatures of 0 °C. Accelerating to only 75% of the desired speed in between two speed bumps resulted in a reduction of 10% in energy consumption, while the travel time only rises 2%.

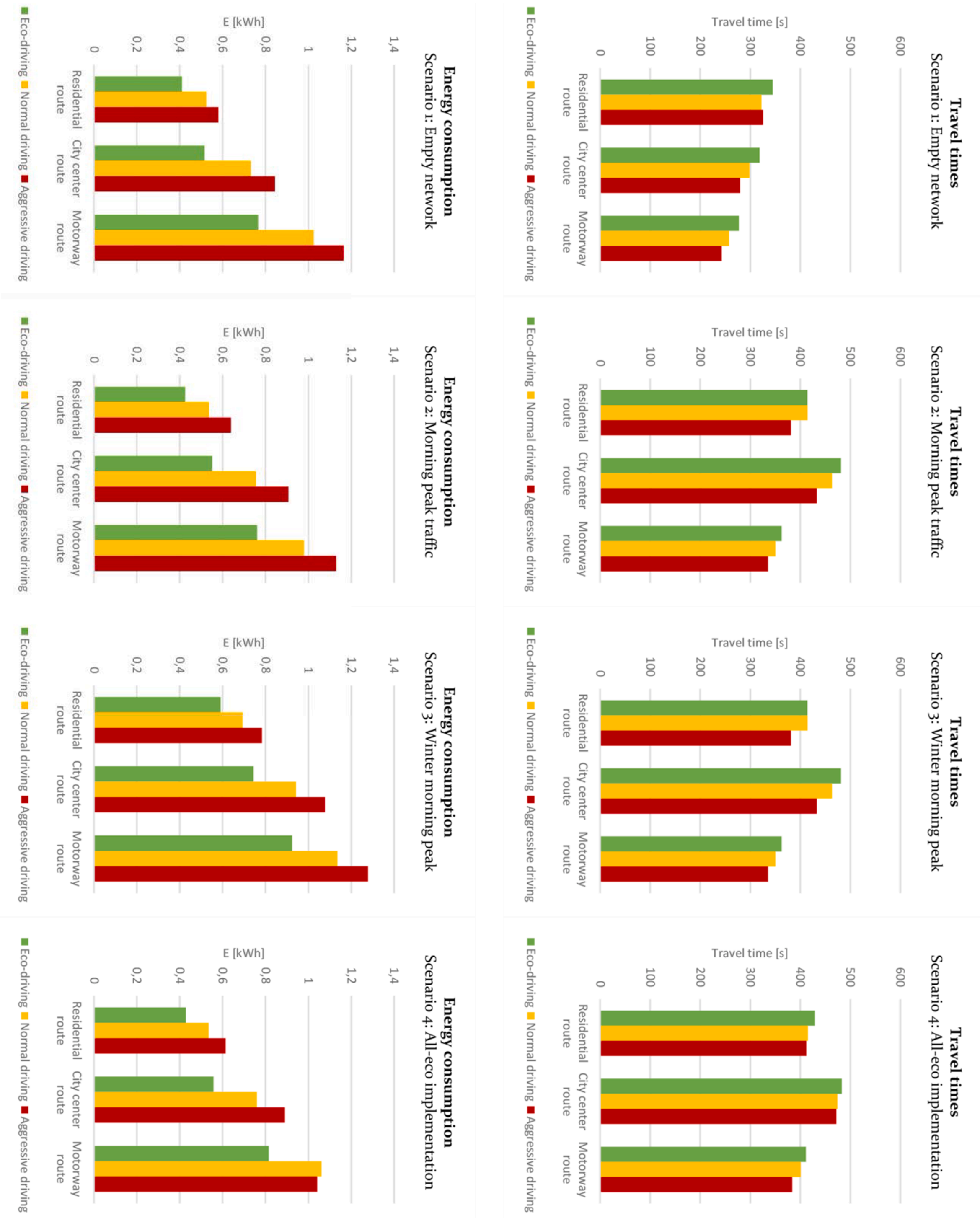

Fig. 4. Comparison of energy consumption and travel times for different routes and driving styles.

3.2. Results of the Nieuwegein case study

In this section, the results of the Nieuwegein case study are presented. Four scenarios are presented, which include 990 calculated energy profiles of vehicles in total.

3.2.1. Travel time and energy consumption

Fig. 4 shows the comparison of the average travel times and energy consumption on different routes with different driving styles. As expected, the travel times rise significantly when the traffic intensity rises. This effect is the strongest on the city center route, due to a large number of signalized junctions. While the energy consumption at the residential and city center route slightly rises due to the traffic intensity, the energy consumption at the motorway drops. This is caused by the lower aerodynamic drag due to the lower average speed during higher traffic intensities.

During winter, the energy consumption rises significantly. This is caused by the high energy consumption of the climate system (especially on the residential and city center route), the higher rolling resistance (18%) and the higher aerodynamic drag forces (4%,

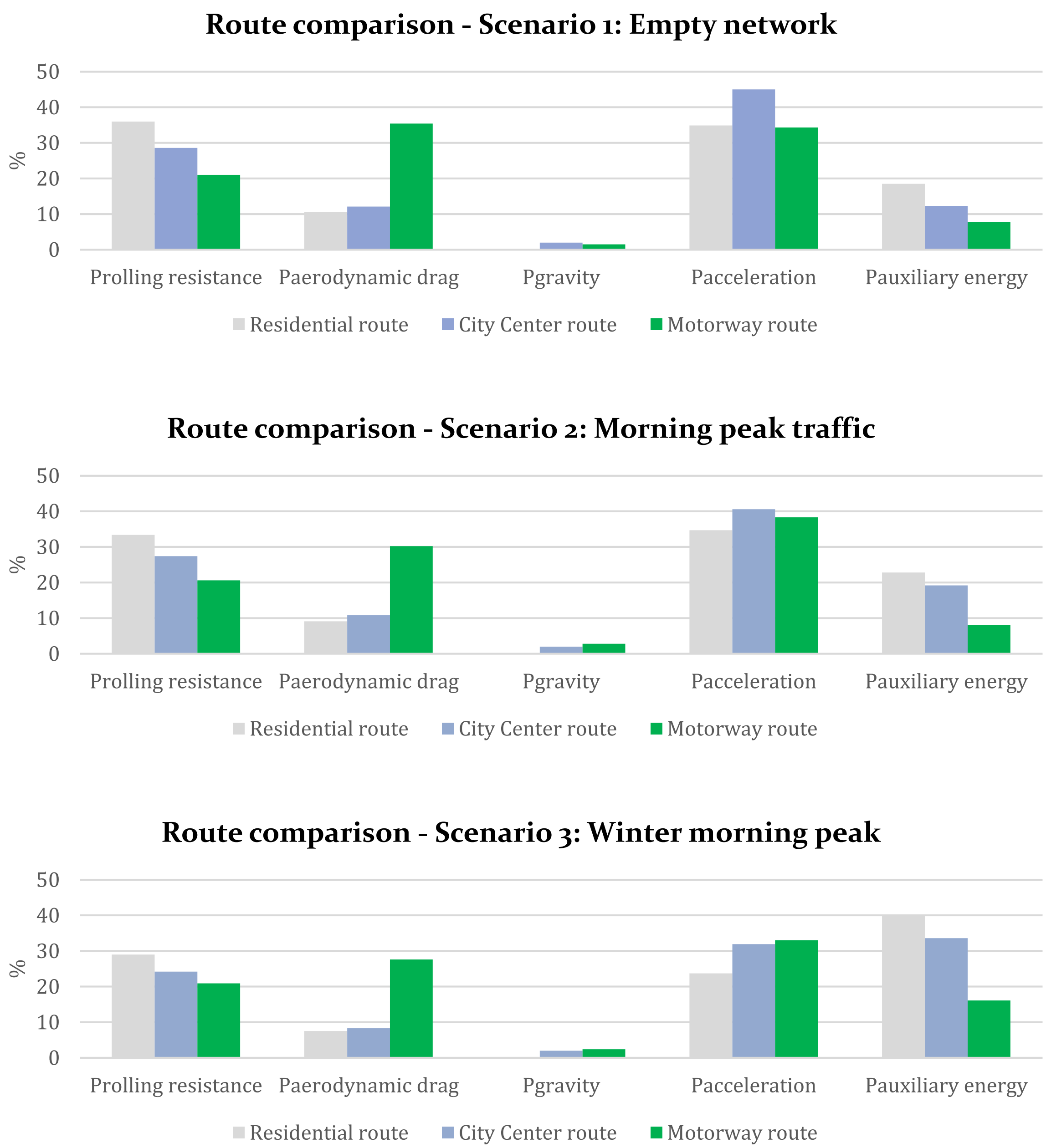

Fig. 5. Comparison of different powers during a trip for different routes and scenarios.

especially on the motorway route). In the hypothetical situation that all vehicles in the network would drive with an eco-driving style (except for the measured ones), the travel times rises significantly. Congestions have been found in the simulations due to the low speed and calm acceleration of the eco-drivers. In the residential route, which is a single-lane route, the aggressive driver adapts the speed to the slowest leading vehicle and therefore drives as slow as the eco-drivers. However, the aggressive driver still uses more energy than the eco-drivers, due to the higher speed oscillations. Therefore, in an all-eco scenario, eco-driving turns out to be the most efficient when considering both travel time and energy consumption. However, the maximum capacity of the roads will be reached earlier due to slow driving speed, so the capacity of the infrastructure has to be closely monitored.

3.2.2. Dominant influences

Due to the differences in driving style, infrastructural design, weather conditions and traffic intensity, different influences are found to be dominant for different routes and scenarios. Fig. 5 shows the results. The results indicate that rolling resistance and acceleration forces are dominant in the city center and residential routes, while aerodynamic drag is dominant on the motorway. Due to the longer travel times, higher traffic intensity increases the share of auxiliary power. As stated earlier, the traffic intensity also decreases the aerodynamic drag on the motorway. In a winter scenario, the share of auxiliary energy rises to 40% at the residential route, while also the absolute values of the rolling resistance and aerodynamic drag increase. The all-eco scenario is not presented. Due to the congestions in the network, the power breakdown did not reflect a realistic scenario.

3.2.3. Validation

The results have been validated by performing 30 on-road driving tests in Nieuwegein. The Mean Absolute Percentage Error (MAPE) has been used to calculate the prediction error (Wang et al., 2017):

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{E_{measured} - E_{predicted}}{E_{predicted}}\right| \quad (7)$$

Fig. 6 shows the MAPE for different time slots and routes. The MAPE has been calculated per individual trip (to represent the accuracy of short-distance trips) and for the total time slot (aggregating all individual trips in that time slot, representing long-distance trips). As shown in Fig. 6, the last two time slots are outliers. This could be explained by the fast driving speed on these routes. Shitzer (Shitzer, 2006) found that at higher speeds, the heat transfer coefficient rises almost linearly with the driving speed. Since a higher heat transfer coefficient requires more thermal power to heat up an object, the climate system would need more power at higher driving speeds. This effect isn't taken into account in the energy model. Further research should determine how to model the power consumption of the climate systems at high driving speeds since the energy consumption rises significantly. Excluding the outliers, the MAPE for short trips (<5km) is 7.8%, while longer trips (5–20 km) resulted in a MAPE of 3.4%.

Finally, the model was compared to the BMW i3 specifications (BMW, 2018). Results show that the given average efficiency from BMW (13.1 kWh/100 km) is very optimistic and could only be reached in windless scenarios, at the optimal driving temperature, without running the climate system while driving with an eco-driving style on non-hilly routes. Results of all the Nieuwegein cases showed efficiencies between 13.1 and 28.8 kWh/100 km.

4. Discussion

To reach the goals in the EU energy directive and increase the energy efficiency of using BEVs, this study researched the influences

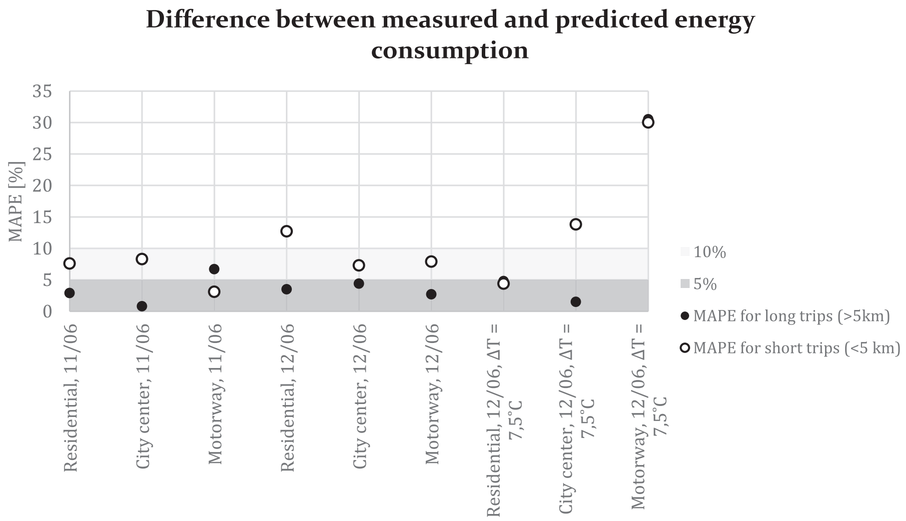

Fig. 6. Difference between measured and predicted energy consumption.

of driving styles, weather variables, infrastructural design and traffic intensity on the energy consumption of BEVs. To do so, a combination of energy prediction modeling and microscopic traffic modeling was used. This combination of methods could predict energy consumption accurately. It shows the potential to reuse for other cases in other locations since seasonal differences could be easily adapted in the energy consumption model, and microscopic traffic models allow for a wide range of traffic simulations.

Driving style has a significant influence on the energy consumption of BEVs. Combining a higher speed, more aggressive accelerations and decelerations and higher speed oscillations results in a significant increase in energy consumption, which supports findings by Wang et al. (Wang et al., 2017) and Ericsson (Ericsson, 2001). This research extends Wang et al. (Wang et al., 2017) by finding that the combination of individual driving style elements significantly increased the differences between driving styles. It extends Ericsson's (Ericsson, 2001) findings by providing evidence that high speed oscillations have a higher impact on aggressive driving styles compared to eco-driving styles.

This paper shows how different weather variables influence energy consumption. Cold temperatures have a significant influence on the energy consumption due to the use of the climate system, potentially increasing energy consumption by 50% in Dutch scenarios. This confirms findings by Hollweck et al. (Hollweck et al., 2018) and Evtimov et al. (Evtimov et al., 2017). This thesis gives new insights by taking an increased aerodynamic drag (5%) and an increased rolling resistance (18%) during winter driving into account.

The research extensively investigated the influence of infrastructural design on the energy consumption of BEVs. It extends research projects using only vehicle trajectories such as Wang et al. (Ericsson, 2001), since using microscopic traffic simulations enabled us to research infrastructural elements individually, while also allowing us to research combinations of individual elements. By combining infrastructure with driving style and weather information, the model could research very specific situations, such as the dependency of the weather on the energy consumption at signalized intersections and differences in energy consumption while driving in between two traffic calming measures. On top of that, we implemented different lateral accelerations for different driving styles, affecting the energy consumption on curved road sections.

Finally, the microscopic traffic model allows researching the influence of traffic intensity. Different traffic intensities and vehicle and driving style mixes were modeled. Using these variations makes the methodology suitable for modeling the effects of many transport policies. The combination of multiple variables and different scenarios gives insights into which potential energy efficiency strategies would be most effective for different situations. Therefore, both the results as the methodology contribute to the EU climate agreement.

A few limitations need to be addressed for future research. First, the regenerative braking system did not consider advanced car mechanics. For future research, a more extensive regenerative braking model could improve energy prediction. Second, a lack of data about wind speed limits the accuracy of energy consumption prediction. Thirdly, microscopic modeling requires much computational power and time. This, therefore, opens opportunities for further research into mesoscopic modeling to predict energy consumption. Additionally, driving tests for the validation are done with only one driver. Testing with multiple drivers would not only give a more reliable validation but would also generate new insights into different driving styles. Finally, to create a more practical application, it would be necessary to research how to scale the energy predictions and how to link all the data to create better traffic management systems.

5. Conclusions

To better understand the influence of driving styles, infrastructure, weather and traffic intensity on the energy consumption of BEVs, a microscopic traffic model and an energy prediction model have been combined. First, individual situations have been modeled, after which the model was used in a case study in Nieuwegein. The results have been validated by performing 30 driving tests and by dynamometer data from Argonne National Laboratory.

The results show an increase in efficiency for eco-drivers compared to other driving styles, due to the lower acceleration forces and aerodynamic drag. Weather influenced the energy consumption through higher auxiliary energy consumption, higher aerodynamic drag and higher rolling resistance. A decrease of 12 °C in ambient temperature led to an increase in energy consumption of 11% for motorway driving (130 km/h) up to 55% for residential driving cycles (30 km/h). The wind is also found to have a large influence; however, more research is needed to create realistic and practically applicable wind models for transport models. The infrastructural design influenced energy consumption through all tractive forces. The road type affects rolling resistance forces, while hilly driving largely increases gravitational forces. Other elements, such as traffic calming measures, signalized intersections and sharp curves largely increased acceleration forces. This mainly influenced the aggressive driving style.

The study indicates that built environment variables have a large effect on the energy consumption of BEVs. In some cases, drivers could reach an energy reduction of 35% only by shifting driving styles, while shifting routes could lead to 35–50% energy reduction for all tested scenarios. This shows the potential energy reduction of electric passenger mobility. In the longer run, the results of this research could be an input for autonomous vehicle settings, optimizing energy consumption. This research, therefore, aims to contribute to the climate goals in both the short and long term.

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