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Energy consumption effects of speed and acceleration in electric vehicles: Laboratory case studies and implications for drivers and policymakers

Ray Galvin

School of Business and Economics/E.ON Energy Research Center, Institute for Future Consumer Energy Needs and Behavior, RWTH Aachen University, Mathieustr 10, Aachen 52074, Germany

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ABSTRACT

The number of electric vehicles in service throughout the world has increased from a few thousand in 2009 to some 740,000 in December 2014. These vehicles are often seen as a means of reducing climate and health damaging emissions, and their development is directly supported by some countries and endorsed by the EU. Aside from questions of rebound effects, embedded emissions and cleanness of electricity generation, there are unanswered questions about the energy performance of such cars under a range of driving conditions, and the results of existing studies are not easily interpretable by policymakers and drivers. This study uses the results of extensive dynamometer tests on eight commonly sold electric vehicles. It develops a multivariate model, with regression coefficients around 0.97, to map power demand and energy consumption for all likely combinations of speed and acceleration, producing accessible, easily interpretable displays. While electric vehicles are frequently marketed on the basis of their high acceleration, an important finding is that episodes of modest to high acceleration severely compromise their range and energy efficiency, regardless of speed. This also raises questions as to how well such vehicles perform in the erratic driving conditions of urban traffic.

1. Introduction

This paper develops user-friendly algorithms and graphical displays which offer reliable information on how moment-by-moment battery power demand and energy consumption vary as functions of speed and acceleration in eight different plug-in electric vehicles. Displays and results are also offered for total energy consumption over specific types of journeys. This information can be of use to both energy policy makers and the drivers of these vehicles. There are already existing studies intersecting with this area, but not for a representative range of electric vehicles in actual use. Further, the algorithms offered by existing studies are often of a more limited, technical nature suitable for specialists but not practitioners or members of non-automotive disciplines.

The last five years have seen a rapid increase in the numbers of these vehicles (called 'e-vehicles' in this paper), rising from a few thousand in 2009 to some 740,000 by the end of 2014 (CleanTechnica, 2015). The EU Commission has supported the development of e-vehicles since at least 2009 (EU Commission, 2009), and promoted their development and deployment as part of its policy on deployment of alternative fuels in 2014 (EU Commission, 2014). Some countries such as Norway

E-mail address: rgalvin@eonerc.rwth-aachen.de

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subsidise e-vehicles through tax breaks and free or subsidised electrical charging, while others such as Germany encourage their development as a means of reducing climate damaging emissions and NOx and SO_2 emissions which have direct health impacts (Holtsmark and Skonhoft, 2014; Jochem et al., 2015).

There are moves at government level in the US to develop more sustainable transport (DOT, 2010), and electrification of passenger transport is seen as one of a number of ways to do this. It is argued that electric motors are inherently more efficient than ICE motors, there is already an electricity distribution network in place (compared to light biofuel infrastructure), and there are pressures on the electricity generating industry to reduce its own emissions (*op cit.* 6–7).

Recently a discussion has arisen as to whether e-vehicles do, in fact, reduce overall emissions (Arar, 2010; Jochem et al., 2015; Teufel et al., 2015). For countries generating electricity mostly through fossil fuels, much of the gain at the vehicle itself may be lost at the generating plant (Doucette and McCulloch, 2011; Duke et al., 2009). Even for countries which are moving rapidly towards renewable electricity generation, such as Germany, lifecycle analysis shows that emissions and wastes produced in the manufacture of e-vehicles and their batteries can negate most of the gains (Teufel et al., 2015). This raises the question of how and in what situations e-vehicles are more likely to meet emissions policy goals than internal combustion engine (ICE) or hybrid vehicles (Hawkins et al., 2012).

While these issues are central to discussion of the usefulness of e-vehicles in helping achieve emission reduction goals, a narrower but equally important issue is the power demand and energy consumption of e-vehicles on their journeys, particularly in relation to driving style. Given a country's mix of electricity generation types, emissions due to e-vehicle journeys will be proportional to their energy consumption. In a study on ICE and hybrid vehicles, Ahn et al. (2002) point to six types of variables that influence emission rates, which also apply to e-vehicles: travel-related, weather-related, vehicle-related, roadway-related, traffic-related and driver-related. This study focuses mostly on the driver-related factors of speed and acceleration. Distance traveled is a topic worth pursuing separately, from a behavioral point of view, as it may well be that the introduction of e-vehicles results in more journeys, or new types of car journeys that were previously made by public transport or bicycle or on foot, as Holtsmark and Skonhoft (2014) suggest for Norway.

This study also touches on vehicle-related factors, paying attention to the differences in energy consumption, and therefore emissions, between different e-vehicle models.

While studies on ICE vehicles show energy consumption increasing with speed and acceleration (Ahn et al., 2002; Bakhit et al., 2015), there are currently very few studies relating driver-related factors to energy consumption in e-vehicles. Karabasoglu and Michalek (2013) compare journey energy consumption of one e-vehicle with that of an ICE and several hybrid vehicles, on laboratory driving test cycles based on city and highway driving. They find the e-vehicle does better compared to the ICE and hybrids in the lower speed, interrupted conditions of urban driving, but worse on the open highway. Knowles et al. (2012) made similar findings using actual journeys by one e-vehicle driven by different drivers in turn. The vehicle performed more efficiently on interrupted urban routes than on the highway. This is thought to be largely due to the 'regenerative braking system' (RBS) in these vehicles. As e-vehicles reduce speed, their motor acts as a dynamo, generating energy rather than consuming it, thus returning some of the vehicle's rolling energy to the battery (Xu et al., 2011). Nevertheless, Xu and colleagues found that energy consumption increased with the 'aggressiveness' (propensity to speed and rapidly accelerate and decelerate) of driving style, which in part contradicts this assumption. An important factor is how large the magnitude of energy recovery is on deceleration, compared to the magnitude of energy consumption upon acceleration. Since energy recovery is less than energy consumption, there must come a point where slower but erratic driving is less efficient than faster but steady driving. This issue does not seem to have been explored to date, and is included in this study.

A detailed and comprehensive study of energy consumption in an e-vehicle is offered by Wu et al. (2015). This used a conventional ICE utility van, refitted with an electric motor, drive train, etc. and monitoring equipment. The vehicle was driven a total of 169 journeys on 4 different routes from 'home' to 'work' and back. A physics-based algorithm was developed to model battery power demand and energy consumption, using the independent variables speed, acceleration and angle of road grade, together with fixed values of vehicle mass, aerodynamic rolling and grade resistances, and the electrical characteristics of the motor. Algorithms such as this are useful for vehicle design and for estimating energy consumption in commercially produced vehicles for which these factors are known.

However, as yet there is no study that offers algorithms for energy consumption with speed and acceleration in an e-vehicle that are accessible enough to be used by policymakers or drivers to obtain a working familiarity with a vehicle's energy performance, yet accurate enough to be reliable for most purposes. There is also a lack of graphical displays of the sort that can help drivers see, quite directly, how various combinations of speed and acceleration in their particular e-vehicle will influence battery power demand and journeying energy consumption. This study was designed to fill this gap.

The study uses the data outputs of laboratory dynamometer tests on eight commonly sold e-vehicles. These are the Nissan Leaf SV 2013, Kia Soul Electric 2015, Nissan Leaf 2012, BMW i3 BEV 2014, Ford focus Electric 2013, Mitsubishi I MiEV 2012, Chevrolet Spark EV 2015, and Smart EV 2014. These vehicles are not described in detail here as their features can be readily found on their manufacturers' websites, though their mass is given in Table 1. The dynamometer tests were run by the Argonne National Laboratory in the US, which tests vehicles in each of the categories Plug-In Hybrid Electric, Electric, Conventional, Conventional-Start-Stop and Alternative Fuel, and makes the test result data publicly available (Argonne, 2015).

Dynamometer tests simulate specific journeys for vehicles which remain stationary on rollers in a laboratory. Each test run, or 'driving cycle', is a set of starts, stops, accelerations, decelerations and steady speeds, ordered to represent a chosen

Table 1
Parameters values for setting moment by moment resistance of rollers to wheel rotation in dynamometer tests for eight e-vehicles.

	m (lb)	α (lb)	β (lb/mph)	γ (lb/(mph^2))
NissanSV	3302	31.91	0.11159	0.07757
Kia	3668	25.30	0.42884	0.01654
Mitsubishi	2875	21.30	0.59605	0.01287
BMW	3182	23.60	0.66330	0.01170
Ford	3948	36.43	0.51941	0.01514
Chevrolet	3157	23.36	0.39460	0.01245
Smart	2314	24.35	0.49968	0.01544
Nissan2012	3476	41.06	−0.3082	0.02525

type of route and driving style. A driver sits in the test vehicle and attempts to 'drive' the car so as to match the chosen drive cycle as closely as possible. Resistance power against the car is applied to the wheels via the rollers depending on the wheel speed, and is adjusted and set to vary according to an algorithm programmed into the dynamometer for that particular vehicle (see details in Section 2).

The test cycles run on these vehicles include the NEDC (New European Drive Cycle), WLTP (World Light Vehicle Testing Procedure), UDDS (Urban Dynamometer Driving Schedule), Highway (a US cycle that simulates open road driving), US06 (a US Supplemental Federal Test Procedure), WOT ('wide open throttle'), JCO8 (a Japanese test cycle) and SCO3 (a US Supplemental Federal Test Procedure). These and other standard test cycles are described in detail in Barlow et al. (2009) and Dieselnet (2015), to which readers are referred for detailed descriptions. The NEDC and WLTP will be of special interest to European readers. Currently all new ICE vehicles in the EU have to be tested on the NEDC, which is a set of four identical low-speed sub-cycles followed by a higher-speed cycle. Due to widespread dissatisfaction with the NEDC (Mock et al., 2013), which was devised in 1975, a United Nations workgroup initiated international consultation and research which produced the (WLTP),which is due to become the EU standard by 2017 (Mock et al., 2014). It is designed to reflect actual driving practices today, with higher average speed, maximum speed, average positive and negative acceleration and maximum acceleration than the NEDC. It is also longer and utilizes a more complex set of speed changes. However the NissanSV is the only e-vehicle that has been tested on both these cycles by the Argonne Laboratory.

Up to 36 different test cycles (including repeats) were run for each vehicle. In each test cycle the output of a range of parameters is measured and recorded for each 0.1 s of driving time. Hence, for example, the WLTP cycle produces 18,131 outputs for each parameter, representing 1813 s (plus a start measurement), simulating a drive lasting 30 min and 21 s. The output parameters for e-vehicles are speed, tractive effort, temperature, relative humidity, battery current and voltage, battery state of charge (SOC) and accelerator pedal position. The parameters of interest for this study were speed, acceleration, battery power demand and energy consumption on a moment-by-moment basis. Acceleration was calculated for each 0.1 s interval, using the speed data at the start and end of the interval; battery power demand was calculated from current and voltage for each interval. Energy consumption per unit distance was calculated from the battery power demand for each interval and the reciprocal of the speed in each time interval.

The Argonne test input and output parameters are given in British Imperial Units (lbs, mph, etc.), but the outputs and results in this study are given in metric units to suit a wider readership. Speeds are given in m/s when technical issues are being discussed in relation to acceleration, which is given in m/s^2, but speeds are given in km/h when results of direct interest to practitioners, including drivers, are presented and discussed. Instantaneous battery power demand is given in W, and energy consumption per unit distance is given in kW h/km and W s/m, depending on the context.

Section 2 of this paper describes the methodology, including conceptual and mathematical issues. The results are given in Section 3. Discussion and conclusions are offered in Section 4.

2. Method

During a test cycle the rollers on which the vehicle's wheels are turning is offered a level of resistance that is a function of the speed of the wheels. The level of required resistance is computed moment by moment according to the formula:

$$P_{at\ \ wheel} = \left[m \cdot \frac{\partial V}{\partial t} + F_{road\ \ load}\right] \cdot V \tag{1}$$

where P = power, m = mass of the vehicle, V = velocity, and

$$F_{road\ \ load} = \propto + \beta V + \gamma V^2 \tag{2}$$

where α, β, γ are constants for the particular vehicle under test. In the laboratory procedures m is given in lb ('pounds'), α in lb, β in lb/mph and γ in lb/(mph^2). The first term in Eq. (1) represents the inertia of an accelerating body, while the second represents 'road load' force caused by wind resistance and other vehicle losses, which have been derived empirically from track testing.

The values of these parameters for the eight e-vehicles are given in Table 1. These values were used to set the resistance loading for each particular vehicle under test.

The actual moment by moment power demanded from the battery is calculated from the battery voltage and current, measured and recorded as the test cycle is run. In order to be able to predict the moment by power demand and energy consumption in situations outside the laboratory tests, a modelling equation was produced based on a multi-variate regression of power demand against the most likely combination of speed and acceleration results. If it is assumed that battery power demand should closely track the resistance power at the wheel, a model with a form based on Eqs. (1) and (2) would make a good candidate for regression analysis.

Combining Eqs. (1) and (2) gives a modelling equation of the form:

$$P_{at\ wheel} = \alpha V + \beta V^2 + \gamma V^3 + mV\frac{\partial V}{\partial t} \tag{3}$$

If we assume that ∂V/∂t closely approximates the calculated value of acceleration for each 0.1 s measurement period (i.e. $(V_2–V_1)/0.1$), a good candidate modelling equation would be:

$$P_{demand\ at\ battery} = rV + sV^2 + tV^3 + uVA \tag{4}$$

where A = acceleration and r, s, t and u are coefficients to be found empirically.

This modelling equation was used for all vehicles. In all cases but one the multivariate regression analyses produced an adjusted R^2 value greater than 0.96, with a high of 0.9813 for the NissanSV. The exception was the Nissan2012, where it was 0.9252. A number of alternative modelling equations were tried, but for all vehicles the highest adjusted R^2 value was achieved with an equation of the form of (4).

For the first two vehicles to be modeled, the NissanSV and Kia, the regression analysis was applied using a number of different sets of drive cycles which had been run in sequence on the dynamometer. However, it was found that for each vehicle, results were barely indistinguishable between sets. Hence for some vehicles only a limited number of cycles were used. Table 2 gives the cycles used for each vehicle to obtain the final regression equation used for prediction of power demand and energy consumption, together with the total length of the journey and the number of 0.1 s intervals (and hence data points for speed, etc.).

A feature of drive cycles is that each cycle always uses the same speed and acceleration patterns. Drivers will however also be interested to see how energy consumption can vary for journeys of the same distance with different patterns of speed and acceleration. To simulate this, an extension of the modelling was performed, giving four hypothetical (modeled only) drive cycles to represent four journeys of the same distance. This gave comparisons of energy consumption on the same journey for different driving styles.

3. Results

3.1. Regression equations

Following Eq. (4), for each vehicle the power demand was regressed against V (vehicle speed in m/s), V^2, V^3 and the quotient of speed and acceleration AV, with A in m/s^2. The coefficients of each of these terms for each vehicle, together with the adjusted correlation coefficients R^2, are given in Table 3 (to 4 sf.). The adjusted R^2 values range from 0.9252 to 0.9813, with all but one above 0.9600, and are comparable to those obtained by Ahn et al., 2002 for hybrid vehicles, but using a different method of analysis. Note that the p-values were zero for all parameters in all regressions, meaning that these values were too small to be calculated by a 64-bit computer. This indicates that all the variables were highly significant determinants of power demand. As an illustration of the goodness of fit of the model, Appendix A gives a series of displays showing the errors between actual and modeled power demand with time, for the NissanSV over the full combination of 10 successive drive cycles. The first display (Fig. A1.1), which tracks power demand over time for the full 10 cycles, shows that the error is hardly distinguishable. The second display (Fig. A1.2) gives a close-up of 5000 s of the cycle, from measurement 33,000 to 38,000,

Table 2
Drive cycles used with each vehicle, together with total length of combined cycle and number of data points.

	Number of 0.1 s intervals	Total length of combined cycles (km)	Drive cycles used, in sequence
NissanSV	99,813	144.897	UDDS, HWY, UDDS,US06, 55mph depletion, US06, UDDS, HWY, UDDS, 55mph depletion
Kia	118,182	166.000	UDDS, HWY, UDDS,US06, SSS 65mph, US06, UDDS, HWY, UDDS, SSS 65mph to depletion
Mitsubishi	39,803	40.060	WOTs, UDDS, HWY, SCO3
BMW	48,401	53.355	UDDS, UDDS, HWY, UDDS, US06
Ford	18,221	11.563	SCO3
Chevrolet	48,401	53.385	UDDS, UDDS, HWY, UDDS, US06
Smart	48,401	53.388	UDDS, UDDS, HWY, UDDS, US06
Nissan2012	88,663	119.232	UDDS, HWY, UDDS,US06, US06, UDDS, HWY, UDDS, 55mph depletion

Table 3
Results of multivariate regression analyses for each of eight e-vehicles, giving coefficients of variables, for use in modelling to predict power demand for general driving.

Coefficient of:	V	V^2	V^3	AV	Adjusted R^2
NissanSV	479.1	−18.93	0.7876	1507	0.9813
Kia	468.6	−14.63	0.6834	1593	0.9626
Mitsubishi	840.4	−55.312	1.670	1281	0.9703
BMW	618.4	−31.09	0.9916	1490	0.9717
Ford	1110	−96.61	2.745	1439	0.9611
Chevrolet	701.2	−35.55	1.007	1444	0.9666
Smart	890.8	−43.12	1.273	1039	0.9716
Nissan2012	715.2	−38.10	1.271	1527	0.9252

again showing how hard it is to distinguish the errors visually. Fig. A1.3 plots the magnitude of instantaneous error (in W) with level of acceleration, showing that generally, the closer the acceleration is to zero, the larger the error, rising to almost 10,000 W for $A = 0$. However, Fig. A1.4 shows this as a percentage of the average power demand for the combined cycles, indicating that for most of the journey the relative error is close to zero, except for around $A = 0$, where it is sometimes ±5%, and a set of outliers for negative accelerations peaking at around $A = -2$ m/s^2. However, this does not mean that the model is always inaccurate for low values of acceleration (see Figs. A1.1 and A1.2), but merely that this is the region where most inaccuracies occur, when they occur. The model therefore seems to be as accurate as is needed for most practical purposes.

Using the coefficients in Table 3, the moment by moment power demand for the NissanSV, for example, is given by:

$$P = 479.1V - 18.93V^2 + 0.7876V^3 + 1507VA \quad (5)$$

To find Energy consumed per unit distance we note that:

$$\frac{E}{S} = \frac{P \cdot T}{S} = \frac{P}{V} \quad (6)$$

where E = energy, S = distance, T = time. Hence for the NissanSV:

$$\frac{E}{S} = 479.1 - 18.93V + 0.7876V^2 + 1507A \quad (7)$$

Modeling equations of the form of (7) were used throughout to predict energy consumption per km and per m, using the coefficients in Table 3.

3.2. Displays of results

A set of such modelling equations was used to predict battery power demand and energy consumption per unit distance for all eight cars, for all practical values of speed and acceleration. Figs. 1 and 2 and give an example of how power demand

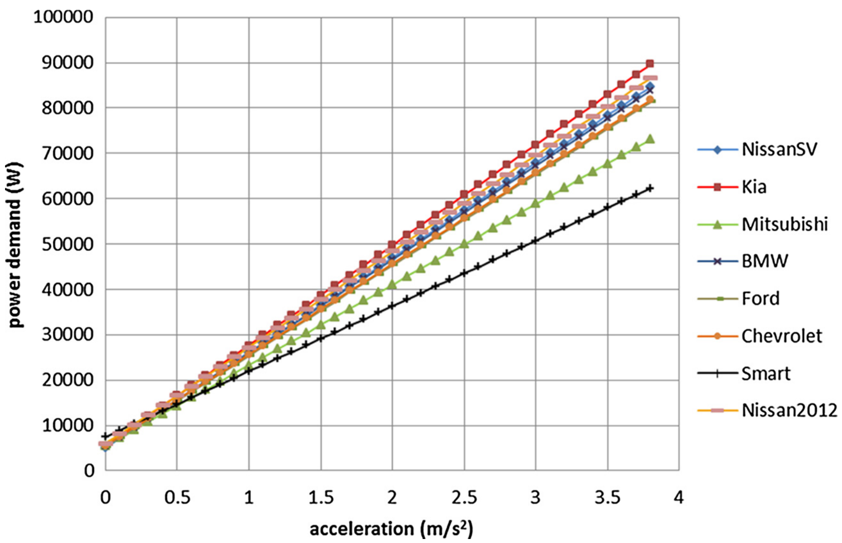

Fig. 1. Power demand with acceleration, for speed of 50 km/h, with eight E-vehicles.

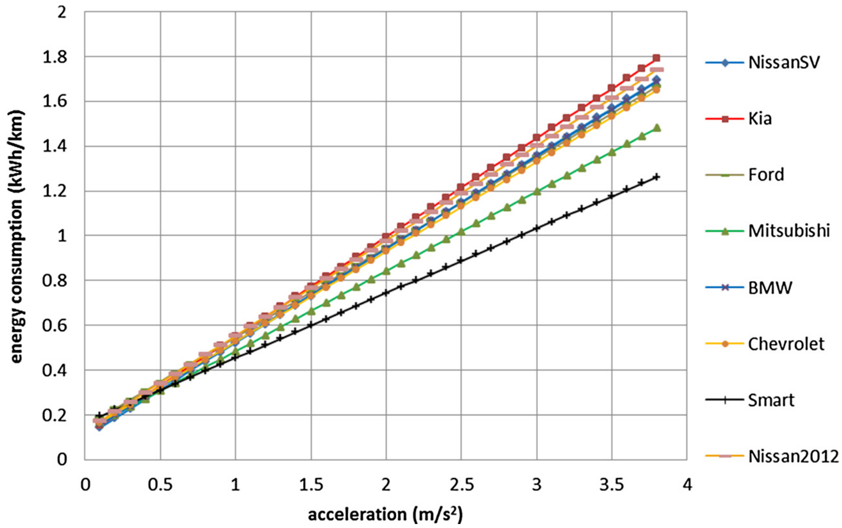

Fig. 2. Energy consumption (kW h/km) with acceleration, for speed 50 km/h, with eight E-vehicles.

(W) and energy consumption (kW h/km) can be expected to vary with acceleration, for a speed of 50 km/h, with each of the eight e-vehicles. Acceleration values are given in meters per second per second (m/s^2). Since many readers do not find it easy to relate feelings of acceleration to figures for acceleration, a practical description is offered in Appendix B.

The shape of the graphs in Figs. 1 and 2 will be intuitively obvious: for a given speed, increasing acceleration causes increasing power demand and energy consumption. Vigorous acceleration of 3.5 m/s^2 demands 495% as much power as sedate acceleration of 0.5 m/s^2, and consumes about 425% as much energy per unit distance traveled.

Other more subtle effects can be seen in Figs. 3 and 4. For these, acceleration is held constant at 2 m/s^2 and the charts show variation in power demand and energy consumption-per-km with speed. The form of Fig. 3 is intuitively obvious. As speed increases, power demand increases at an ever higher rate, as the effect of wind resistance comes to dominate. However, the plots for energy consumption in Fig. 4 show a gradual dip until about 60 km/h, and a gentle but concave increase thereafter. The same shape is evident with all acceleration values, and is most pronounced at $A = 0$. It is not intuitively clear why there should be a dip. Hence this was further investigated.

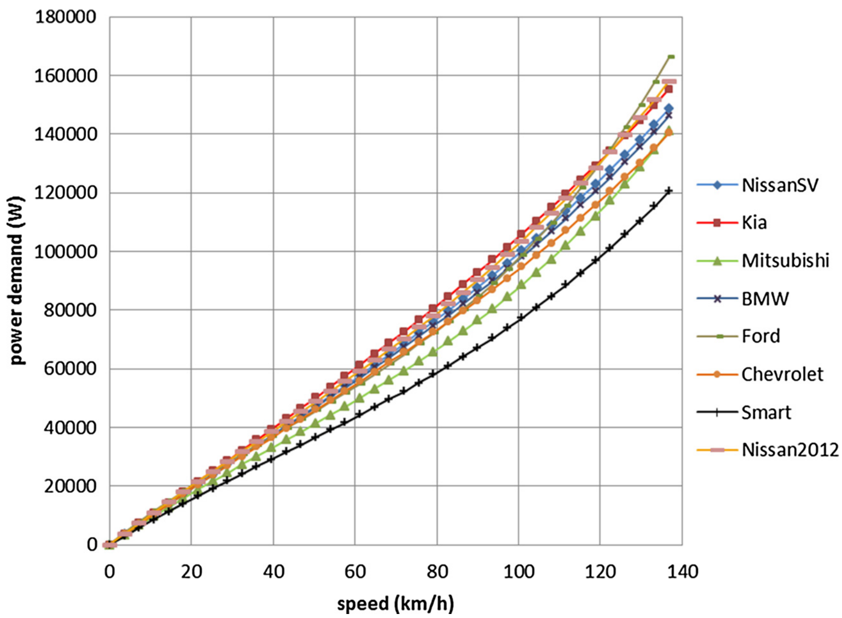

Fig. 3. Power demand with speed, for acceleration of 2 m/s^2, with eight E-vehicles.

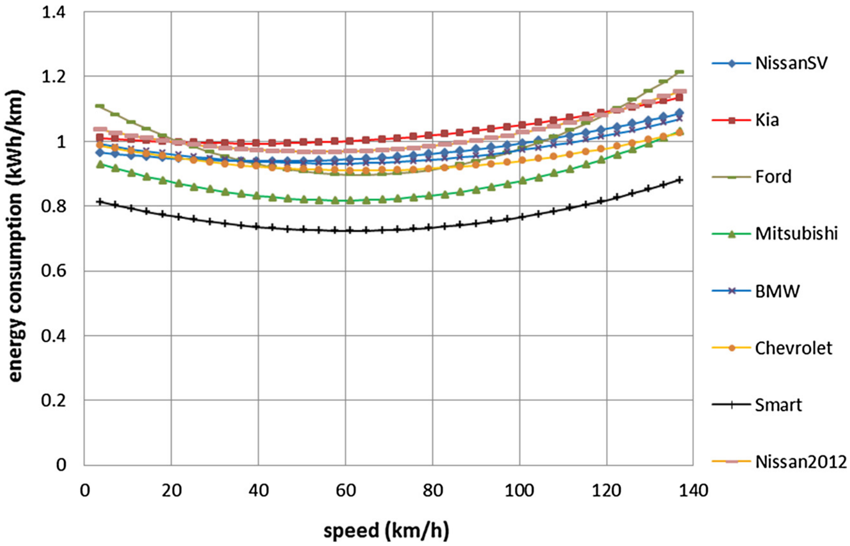

Fig. 4. Energy consumption (kW h/km) with speed, for acceleration of 2 m/s^2, with eight E-vehicles.

3.3. Why the dip in energy consumption

It is important to note the difference between power demand and energy consumption per unit distance. When a car is traveling faster (at a steady speed) it is consuming energy for less time to cover the same distance, which tends partly to cancel out the effect that energy is consumed at a higher rate per unit time. This explains why, for a given level of acceleration, energy consumption per unit distance is not proportionately higher for higher speeds. However, this does not explain the dip in consumption. Part of the reason for the dip may be that the motors are designed to operate at optimum efficiency when the vehicles are traveling at around 60 km/h. However, to investigate whether there may be a fault in the modelling equations, a detailed check was made using the actual, empirically derived data, for three of the vehicles: the Ford, NissanSV and Mitsubishi. For each of these, all the data points were selected where $A = 0$; the measured power was plotted against the speed at each of these points, and the energy consumption per km was calculated for these points using the actual, measured power and speed data. Points where speed was zero were excluded, as these give the result of infinite energy per km (since distance traveled = 0).

Figs. 5 and 6 give the results for the Ford. Fig. 5 gives these results for very low speeds ($0 < V < 0.12$ km/h). Here there is a very sharp dip from 5000 kW h/km down to about 1 kW h/km. The high values are presumably caused by the surge in power demand when the accelerator pedal is pushed while the engine is stationary. The dynamometer does not 'know' that the pedal has been pushed until the wheels start to move; hence the dynamometer roller resistance kicks in late. With data readings every 0.1 s, there are bound to be surges in measured power demand that are not matched by dynamometer loadings. Since the modelling equations are based on the mathematical form of the dynamometer input equations, errors are likely to

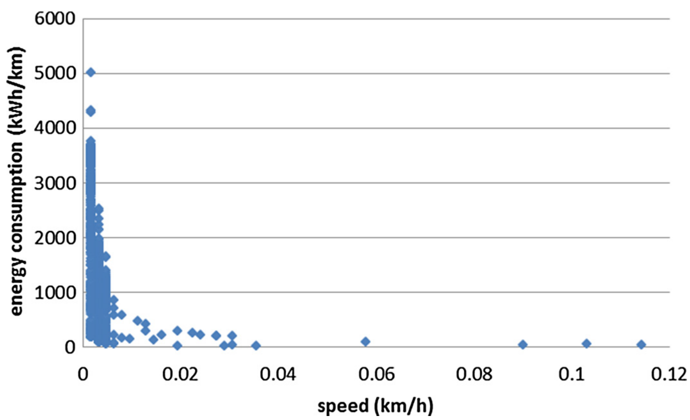

Fig. 5. Energy consumption with speed, for zero acceleration for Ford, including extremely high values of energy consumption for zero or near zero speed.

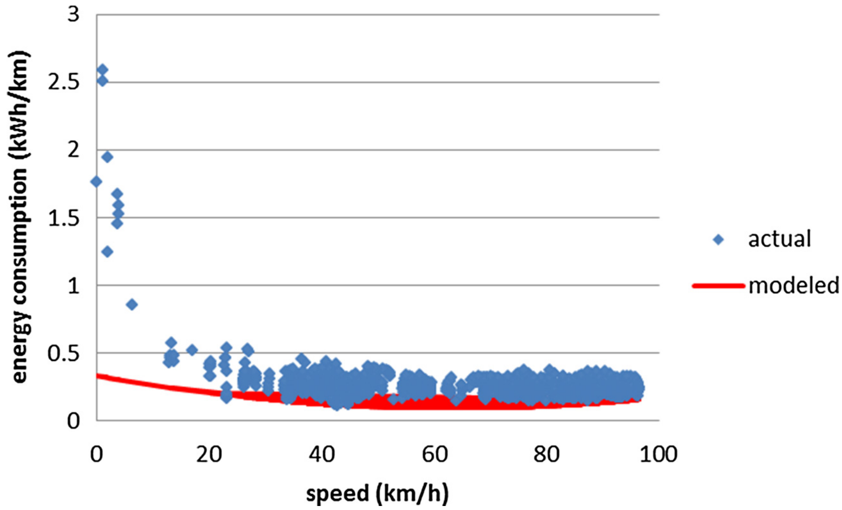

Fig. 6. Energy consumption with speed, for zero acceleration for Ford, after filtering out extremely high values of energy consumption for zero or near zero speed.

occur. This will also be the case when the accelerator pedal is pushed heavily while a vehicle is traveling at steady speed, especially for low speeds where drivers want a quick acceleration.

Fig. 6 gives the results for speeds above 0.12 km/h. Again a pronounced dip is evident, but not as steep as for lower speeds. The points are the actual empirically derived results and the solid line is based on the modelling equation. It can be seen that the modelling equation does not impose a dip that is not there, but does the opposite: it fails to catch the severity of the dip. Presumably the driver was rather heavy-footed when accelerating from zero or very low speed.

The same analysis was performed for the NissanSV, Mitsubishi and Chevrolet. Fig. 7 gives results for the NissanSV, again showing both actual and modeled results, and again filtering out the extremely high values of energy consumption for near zero speed. Here the dip is clearly evident when the remaining data points for the lower speeds are taken into account. Fig. 8 gives results for the Mitsubishi. Here the model seems to exaggerate the level of energy consumption for low speeds, but again the model is very accurate for speeds above about 60 km/h. Fig. 9 gives the display for the Chevrolet, which is similar to that for the Mitsubishi. However, for the Chevrolet empirical data of extremely high instantaneous energy consumption per km for low speeds has been filtered out, as it made the graph axis unreadable. For speeds down to 2 km/h it reached 9kWh/km and for speeds <1 km/h it reached over 700 kW h/km.

A conclusion from these more detailed analyses is that for moderate to high acceleration, the form of modelling equation is adequate for predicting power demand and energy consumption with given levels of acceleration and speed. However, for low acceleration the model is accurate only for speeds above about 60 km/h. This mostly affects graphs of the type of Fig. 4,

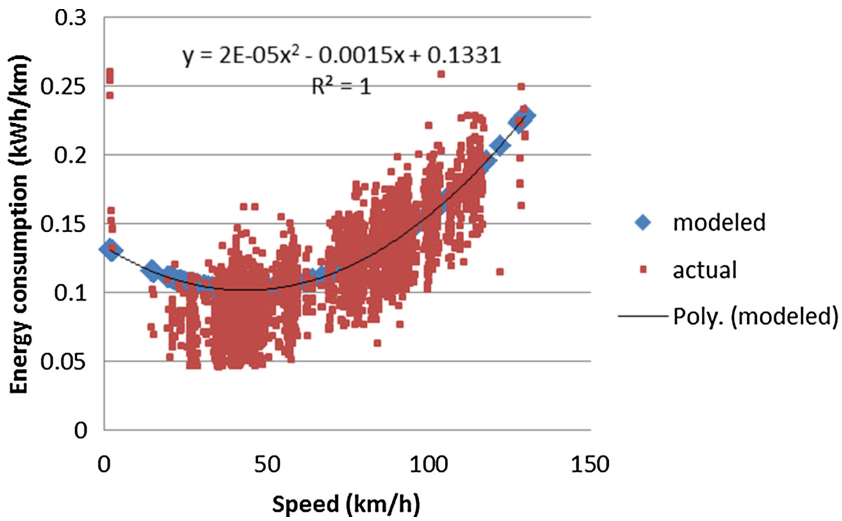

Fig. 7. Measured and modeled energy consumption against speed, for zero acceleration, NissanSV.

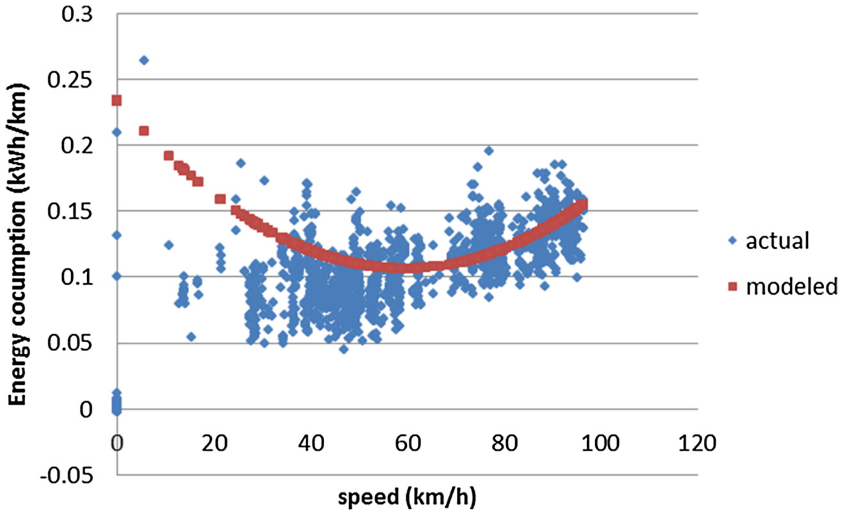

Fig. 8. Measured and modeled energy consumption against speed, for zero acceleration, Mitsubishi.

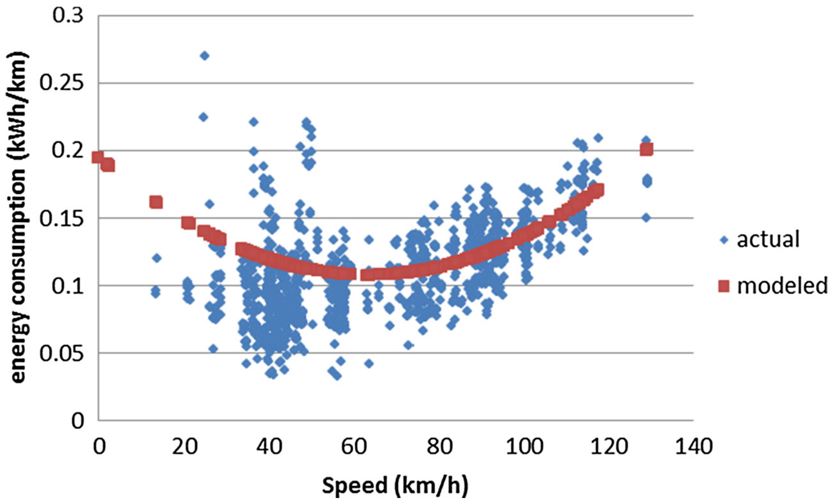

Fig. 9. Measured and modeled energy consumption against speed, for zero acceleration, Chevrolet.

where the focus is on how energy consumption varies with speed for chosen values of acceleration. The errors most likely have to do with different drivers' approaches to the beginning of acceleration sequences. Those who start such a sequence by pressing suddenly and heavily on the accelerator pedal produce a surge of power to the motor, while the dynamometer does not kick back with wheel resistance power until the wheels actually start to accelerate. Hence the battery power demand gets out of synch with the dynamometer resistance. The regression analysis incorporates these surges into its modelling of the coefficients of the variables, thus producing an algorithm that gives high readings of power at the low speed end for lower values of acceleration.

In order to be useful for practical purposes, two interactive spreadsheet pages were produced from the modelling equations. The first gives two graphs corresponding to Figs. 1 and 2, displaying power demand and energy consumption respectively, against speed in km/h, for any chosen level of acceleration in m/s^2. The user changes the acceleration figure in cell B3 of the spreadsheet, and the graphs change accordingly. The second gives displays corresponding to Figs. 3 and 4. The user changes the speed figure, and the graphs give power demand and energy consumption for the full range of positive acceleration, from 0 to 3.8 m/s^2. The spreadsheet is available at http://justsolutions.eu/e-vehicles/InteractiveE-Car-Consumption-Tool.xlsx. Users should note the caveats discussed above, particularly with respect to the graph corresponding to Fig. 4, which should be treated as reliable only for speeds of over 60 km/h.

Table 4
Parameters and results for four modeled drive cycles of the same distance, using different driving styles.

	Acceleration (m/s^2)	Maximum speed (km/h)	Distance (km)	Average speed (km/h)	Energy consumption (Ws)	Duration of journey (s)
Fast & hard	3.5	160	2.400	147.8	2,621,951	66.57
Medium high	2.5	150	2.400	135.5	2,264,345	73.41
Medium low	1.5	130	2.400	114.2	1,735,173	90.59
Sedate	0.5	110	2.400	81.51	1,205,015	137.7

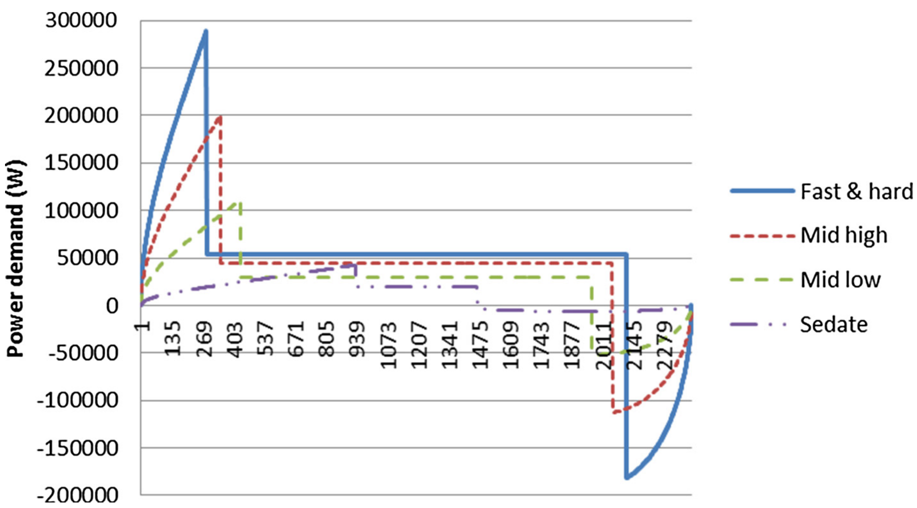

Fig. 10. Instantaneous power demand (W) with distance, for four different simulated drive cycles over same distance of 2.400 km. The horizontal axis is the distance covered, in meters.

3.4. Different driving styles over the same distance

As explained in Section 2, it will be of interest to drivers to see how energy consumption differs for the same journeys with different patterns of speed and acceleration. Four drive cycles were constructed, each of 2.400 km, corresponding to four different driving styles: fast and hard, medium high, medium low, and sedate. The aim was to map the differences in journeying consumption for different driving styles over the same distance.

In all cases the journey was modeled as accelerating steadily at a given rate until it reached a given cruising speed, and remaining at that speed just long enough to be able to decelerate at the same (negative) rate and come to rest at the end of 2.400 km. The NissanSV was used for this exercise. The parameters and results for each cycle are given in Table 4. Note that more than twice the accumulated energy was consumed in the fast and hard cycle as in the Sedate cycle, even though the distances were the same. Fig. 10 gives the moment-by-moment power demand with distance for each journey and Fig. 11 the accumulated energy consumption.

The large peaks at the start of Fig. 10 represent the excess power demand due to acceleration, while the corresponding feature in Fig. 11 is the steep gradient of accumulated energy consumption for this section of the journey. The gradients of accumulated energy consumption in Fig. 11 then differ from each other to a much lesser degree during the cruising phase of the journey, and the negative gradients at the end correspond to the energy recovery taking place as the vehicles decelerate. Fig. 10 indicates that traveling faster does not *in itself* consume much more energy per unit distance traveled, but in order to travel faster a vehicle has to have accelerated harder, and this is where much larger magnitudes of energy are consumed. Also, the faster journeys cover more distance traveling fast because they have shorter deceleration times at the end, and this adds to their increased energy consumption.

In a further test using a journey of the same distance, erratic acceleration and deceleration was used, based on sections of the Argonne test cycles. This resulted in an average speed of 100.6 km/h, which lay between that of the sedate and medium-low cycles, but energy consumption of 2,707,503 W s, almost as high as that of the fast and hard cycle.

A further point is that the energy recovery during deceleration is never as high as the energy consumption during acceleration of the same (inverse) magnitude, as evident in Fig. 11. About 64% of acceleration energy is recovered through deceleration. Although this is better than zero energy recovery as in conventional ICE vehicles, it raises questions as to how economical e-vehicles are for the erratic speed driving typical of urban areas at busy times. Further, deceleration often happens suddenly and rapidly, and there are limits to how fast a battery can receive the sudden charge offered it by deceleration.

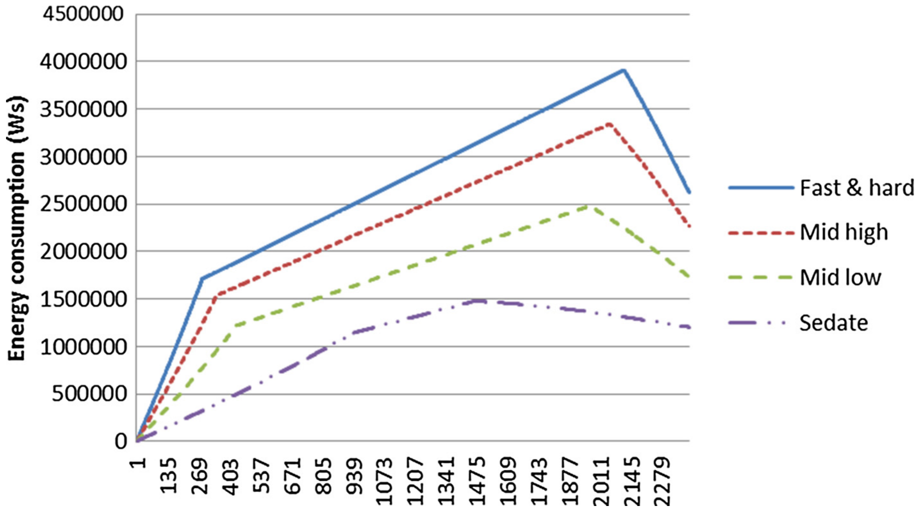

Fig. 11. Accumulated energy consumption (W s) with distance, in four different simulated drive cycles over the sme distance of 2.400 km. The horizontal axis is the distance covered, in meters.

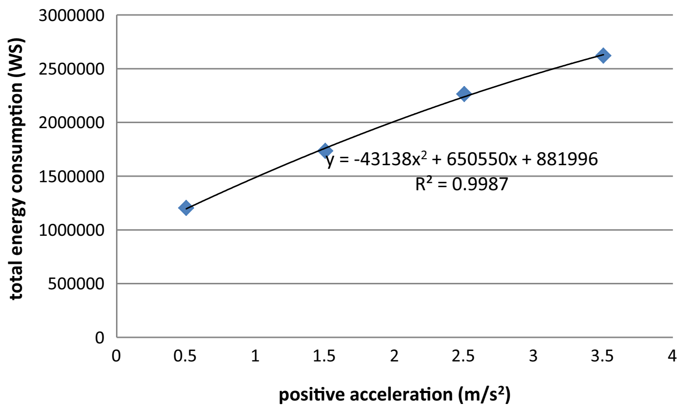

Fig. 12. Relationship between positive acceleration during journey and total energy consumption for journey, for 4 journeys of equal distance but different driving styles, NissanSV.

Fig. 12 shows the relationship between the level of positive acceleration used in these four journeys and the total energy consumption for each.

4. Discussion and conclusions

This study used laboratory dynamometer tests of eight commonly sold electric vehicles, to produce algorithms and displays of power demand and energy consumption against speed and acceleration. It aimed to make these results accessible for policymakers and drivers who are not skilled in the physics of automotive engineering. Unlike the physics-based study of Wu et al. (2015), this study used a pragmatic curve-fitting method to develop its working algorithms, based on the general form of the equation for load resistance of road vehicles. This method has some parallels with that used by Ahn et al. (2002) for mapping fuel consumption and tailpipe emissions based on moment-by-moment speed and acceleration levels in ICE and hybrid vehicles. The main difference in technique is that Ahn and colleagues used a trial and error approach to developing the independent variables for the regression analysis, whereas this study used a standard multivariate analysis based on the finely measured output data of laboratory tests. Further, this study did not use log transformations of the data, as did Ahn and colleagues. This option was explored, producing serviceable results, but there was no significant increase in predictive power. It was therefore abandoned in favour of the simpler method which is more accessible to non-experts in the field. As long as vehicle speed and acceleration are known at any point in time, battery power demand and energy consumption per unit distance can be directly calculated using equations of the form (5) and (7) with the coefficients of V, V^2, V^3 and VA for the particular car, which are listed in Table 3.

The R^2 values here achieved were similar in magnitude to those for fuel consumption developed by Ahn and colleagues for hybrid vehicles. The p-values of the coefficients were extremely low, approaching zero, indicating that the chosen predictors were highly significant in determining power demand. Hence these algorithms, developed through regressing power demand against the independent variables V, V^2, V^3 and VA, are useful and reliable predictors of power demand and energy consumption for these vehicles, at least in conditions covered by the dynamometer tests.

A weakness of the study is its reliance on the results of laboratory dynamometer tests. While these have the advantages of providing large numbers of accurate measurements and thereby facilitating precise comparisons between different vehicles in stringently controlled settings, they cannot simulate real driving conditions which are affected by traffic, weather conditions and variations in road gradient and in weight carried by vehicles. However, they provide an important supplement to field studies such as that by Wu et al. (2015). They offer clear, credible baselines for commonly sold vehicles, against which the more stochastic variations of real world travel can be set.

Within this context, the results of this study offer important information for drivers and would-be drivers of e-vehicles. They show how moment-by-moment speed and acceleration affect power demand and energy consumption, all other things being equal. A significant result is that speed in itself is not always a good predictor of journeying energy consumption, because a faster journey takes less time, therefore the high energy consumption caused by high speed is happening for a shorter duration. What makes speed energy-intensive is largely the acceleration required to reach the speed. Even modest acceleration can increase moment-by-moment power consumption by several hundred percent, and high acceleration is even more costly. Further, traveling at high speed is not often achieved by a single period of acceleration to a steady cruising speed. To maintain high speed a driver often has to overtake other vehicles, and each overtaking maneuver requires acceleration, often at high intensity so as to complete the maneuver safely. Due to the asymmetry of energy recovery systems, not all the excess energy will be recovered on deceleration back to the cruising speed.

A consequent issue for drivers is the degree to which urban travel, with its often erratic speed and acceleration patterns, is economical for e-vehicles. It was commented in Section 3.4 that erratic acceleration patterns increase a given journey's energy consumption significantly. Although popular discourse tends to frame e-vehicles as good for urban journeys, their energy performance may in fact be disappointing if speeds are too erratic.

Using eight different, commonly sold e-vehicles in this study enabled comparisons to be made between vehicles. One important finding is that the Smart EV 2014 outperforms the other seven vehicles in terms of energy efficiency for acceleration above about 0.8 m/s^2, which is not surprising since the Smart has only about 70% of the mass of most of the other vehicles – hence the first term of Eq. (1) has less impact on power demand. However, at steady speed ($A = 0$) its performance is below average at all speeds. This could be because its smaller mass makes it more susceptible to air resistance. The Mitsubishi, which is also a relatively light vehicle, performs almost as well as the Smart and its performance does not fall at steady speed.

Apart from the Ford Focus, the remaining vehicles have very similar energy consumption profiles at high acceleration. The Ford shows a very pronounced concave pattern of energy consumption with speed for low or zero acceleration: it appears to be a very high consumer at low and high steady speeds, but is comparable to the other vehicles in the middle speed range. It is not clear why this should be so, but supplementary tests using data from a range of further drive cycles with this vehicle gave similar results.

Apart from some lingering question marks over the reliability of the graph for energy consumption with speed for given magnitudes of acceleration, the interactive spreadsheet can be used to make comparisons of power and energy consumption between the vehicles, for various speeds and accelerations.

The study raises interesting issues regarding the current policy climate of support for and promotion of e-vehicles. These vehicles are low to moderate consumers of energy when driven at steady speeds, but their energy performance is severely weakened with acceleration. This not only increases the climate- and health damaging emissions from their energy generation sources (if non-renewable), but also drains their batteries and reduces their journeying range. Most current studies maintain that these vehicles are more energy-economical in the stop-start conditions of urban traffic than in the steady, higher speed conditions of highway travel. However, the finer grained analysis of this study suggests this might not be such an advantage if the amount and intensity of acceleration and deceleration reach a certain threshold. It is not uncommon for car manufacturers to promote these vehicles as offering the experience of very rapid acceleration. For example, Telsa's Model X is promoted on the basis that it can accelerate from 0 to 100 km/h in 3.2 s, comparing it to high speed sports cars such as the BMW M5, Corvette Z06, and Porsche Panamera Turbo (Squatrigia and Davies, 2015). If customers buy these vehicles partly because of the acceleration advantages inherent in e-vehicles, they are likely to drive more aggressively and compromise energy economy even further.

The findings suggest that policymakers need to look carefully at the energy consumption characteristics of these cars, when thinking about how and in what journeying situations they can be promoted as energy saving devices. This is in addition, of course, to questions of the emissions produced in the generation of the electricity that powers these vehicles, and the possibility of drivers using them as alternatives to pedal, pedestrian or public transport.

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Appendix A. Visual displays showing errors in between actual and modeled power demand for NissanSV on combination of 10 drive cycles

See Figs. A1.1–A1.4.

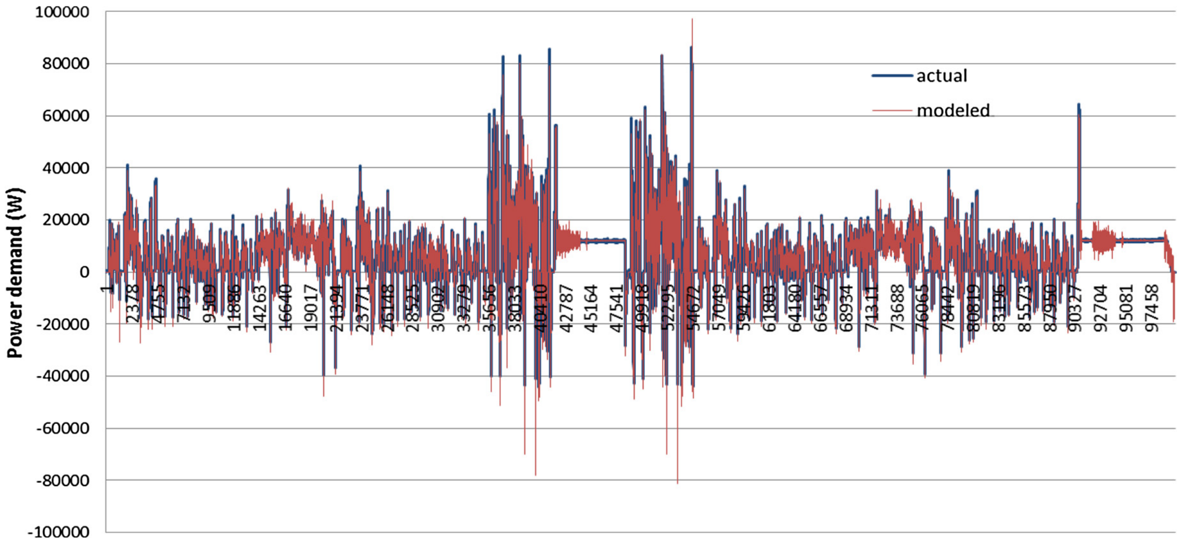

Fig. A1.1. Actual and modeled power demand with time, for NissanSV on combination of 10 successive drive cycles. The horizontal axis is the number of 0.1 s intervals since the start of the combined cycle.

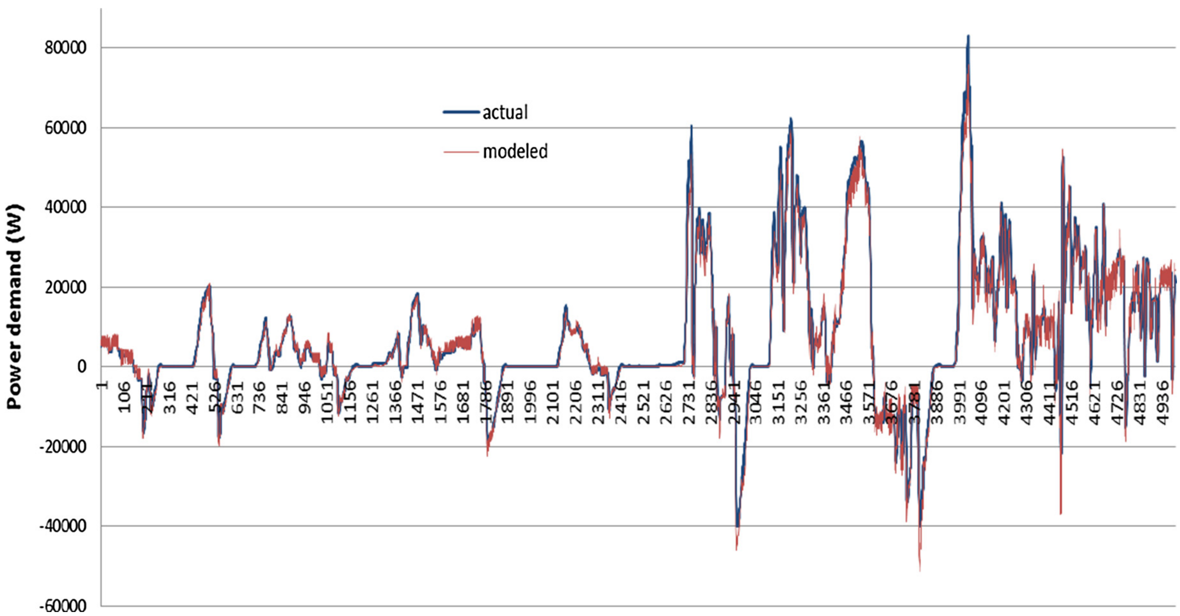

Fig. A1.2. Actual and modeled power demand with time, for NissanSV on combination of 10 successive drive cycles, during the 3300th and 3800th seconds of the test cycle. The horizontal axis is the number of 0.1 s intervals since the3300th.

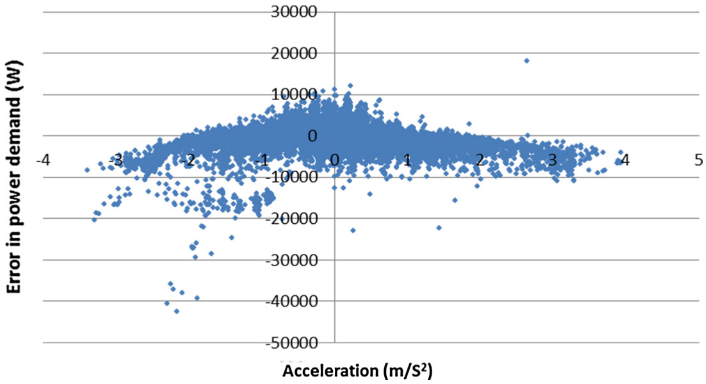

Fig. A1.3. Magnitude of error (W) between actual and modeled power demand for NissanSV, with acceleration.

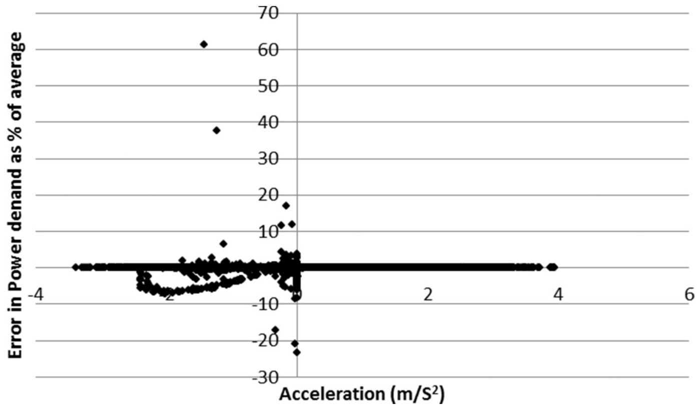

Fig. A1.4. Error between actual and modeled power demand for NissanSV, with acceleration, as percentage of average power demand.

Appendix B. Interpreting acceleration figures

The average positive acceleration achieved by the NissanSV on the WLTP drive cycle was 1.963 m/s^2. It can be difficult to conceptualize what this means. One way of doing so is to note that it will take 14.15 s to go from a standing start to 100 km/h if this is the steady acceleration rate.

On the combined drive cycle used for most of the analysis in this paper for the NissanSV, the maximum acceleration was 3.714 m/s^2. At this rate a standing start to 100 km/h would take 7.47 s.

One of the fastest standard production e-vehicles is the Telsa SUV P-90T which goes from 0-100 km/h in 3.2 s. This represents a steady acceleration of 8.86 m/s^2.

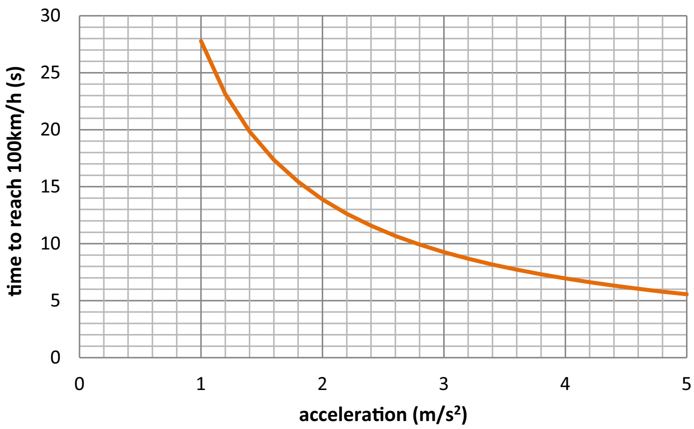

Fig. A2.1. Visualisation aid for understanding acceleration magnitude: time to accelerate from 0 to 100 km/h, for different rates of acceleration in m/s^2.

An e-racing car developed by Swiss students goes from 0-100 km/h in 1.785 s, an acceleration rate of 15.56 m/s^2. It travels only 25 m to reach that speed. By comparison, the accelerative force of gravity is about 10 m/s^2.

A Boeing 747 jumbo jet takes around 50 s to reach its takeoff speed of 260 km/h, or 72 m/s. This represents a sedate average acceleration along the runway of about 1.5 m/s^2.

Fig. A2.1 gives the number of seconds it takes to go from 0-100 km/h at any given rate of acceleration. The range of acceleration on the chart is typical for the e-vehicles studied in this paper. A rough rule of thumb is that with an acceleration of 5 m/s^2 a vehicle will reach 100 km/h in just over 5 s; and for each halving of the acceleration rate the time taken to reach 100 km/h doubles.

References

Ahn, K., Rakha, H., Trani, A., Van Aerde, M., 2002. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. J. Transport. Eng. 128, 182–190.

Arar, J., 2010. New directions: the electric car and carbon emissions in the US. Atmos. Environ. 44, 733–734.

Argonne, 2015. Downloadable Dynamometer Database, Generated at the Argonne National Laboratory, Advanced Powertrain Research Facility (APRF), under the Funding and Guidance of the U.S. Department of Energy (DOE). <http://www.anl.gov/energy-systems/group/downloadable-dynamometer-database/> (Accessed 12 September, 2015).

Bakhit, P., Said, D., Radwan, L., 2015. Impact of acceleration aggressiveness on fuel consumption: using comprehensive power based fuel consumption model. Civil Environ. Res. 7 (3), 148–156.

Barlow, T., Latham, S., McRae, I., Boulter, P., 2009. A Reference Book of Driving Cycles for Use in the Measurement of Road Vehicle Emissions. Department of Transport; Cleaner Fuels and Vehicles 4, Wokingham UK.

CleanTechnica, 2015. Electric Car Demand Growing, Global Market Hits 740,000 Units. <http://cleantechnica.com/2015/03/28/ev-demand-growing-global-market-hits-740000-units/> (Accessed 01 October, 2015).

Dieselnet, 2015. Emission Test Cycles: Worldwide Engine and Vehicle Test Cycles. <http://www.dieselnet.com/standards/cycles/> (Accessed 01 October, 2015).

Doucette, R., McCulloch, M., 2011. Modeling theCO_2 emissions from battery electric vehicles given the power generation mixes of different countries. Energy Policy 39, 803–811.

DOT (Department of Transport), 2010. Transportation's Role in Reducing U.S. Greenhouse Gas Emissions Volume 1: Synthesis Report, Report to Congress, U. S. Department of Transportation.

Duke, M., Andrews, D., Anderson, T., 2009. The feasibility of long range battery electric cars in New Zealand. Energy Policy 37, 3455–3462.

EU Commission, 2009. Clean Transport, Urban Transport: Electric Vehicles. <http://ec.europa.eu/transport/themes/urban/vehicles/road/electric_en.htm> (Accessed 01 October, 2015).

EU Commission, 2014. Directive 2014/94/EU of the European Parliament and of the Council of 22 October 2014 on the Deployment of Alternative Fuels Infrastructure Text with EEA Relevance. <http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32014L0094> (Accessed 01 October, 2015).

Hawkins, T., Singh, B., Majeau-Bettez, G., Hammer Strømman, A., 2012. Comparative environmental life cycle assessment of conventional and electric vehicles. J. Ind. Ecol. 17, 1.

Holtsmark, B., Skonhoft, A., 2014. The Norwegian Support and Subsidy Policy of Electric Cars. Should it be Adopted by Other Countries? Working Paper ISSN 1503-299X, Department of Economics, Norwegian University of Science and Technology.

Jochem, P., Babrowski, S., Fichtner, W., 2015. Assessing CO_2 emissions of electric vehicles in Germany in 2030. Transport. Res. Part A 78, 68–83.

Karabasoglu, O., Michalek, J., 2013. Influence of driving patterns on lifecycle cost and emissions of hybrid and plug-in electric vehicle power trains. Energy Policy 60, 445–461.

Knowles, M., Scott, H., Baglee, D., 2012. The effect of driving style on electric vehicle performance, economy and perception. Int. J. Electric Hybrid Veh. 4 (3), 228–247.

Mock, P., German, J., Bandivadekar, A., Riemersma, I., Ligterink, N., Lambrecht, U., 2013. From Laboratory to Road: A Comparison of Official and 'Real-World' Fuel Consumption and CO2 Values for Cars in Europe and the United States. White Paper, International Council for Clean Transportation (together with TNO, Ifeu and Sidekick).

Mock, P., Kühlwein, J., Tietge, U., Franco, V., Bandivadekar, A., German, J., 2014. The WLTP: How a New Test Procedure for Cars will Affect Fuel Consumption Values in the EU. WORKING PAPER 2014-9. International Council for Clean Transportation.

Squatrigia, C., Davies, A., 2015. Tesla's Model X Is Here, and It's as Awesome as We Hoped. Gear 09.29.2015. <http://www.wired.com/2015/09/tesla-model-x-suv-reveal-specs-price/> (Accessed 08 October, 2015).

Teufel, D., Arnold, S., Bauer, P., Schwarz, T., 2015. Ökologische Folgen von Elektroautos: Ist die staatliche Förderung von Elektro- und Hybridautos sinnvoll? UPI-Bericht Nr. 79. UPI-Institut, Heidelberg.

Wu, X., Freese, D., Cabrera, A., Kitch, W., 2015. Electric vehicles' energy consumption measurement and estimation. Transport. Res. Part D 34, 52–67.

Xu, G., Li, W., Xu, K., Song, Z., 2011. An intelligent regenerative braking strategy for electric vehicles. Energies 4, 1461–1477.