Integration of Traffic Simulation and Propulsion Modeling to Estimate Energy Consumption for Battery Electric Vehicles

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Abstract. The introduction of battery electric vehicles (BEV) creates many new challenges. Among them is driving a vehicle with limited driving range, long charging time and sparse deployment of charging stations. This combination may cause range anxiety for prospective owners as well as serious practical problems with using the products. Tools are needed to help BEV owners plan routes that avoid both range anxiety and practical problems involved with being stranded by a discharged battery. Most of these tools are enabled by algorithms that provide accurate energy consumption estimates under real-world driving conditions. The tools, and therefore the algorithms must be available at vehicle launch even though there is insufficient time and vehicles to collect good statistics. This paper describes an approach to derive such models based on the integration of traffic simulation and vehicle propulsion modeling.

1 Introduction

Increasing motorization of the developing world has led to political and economic problems such as increased cost of automotive fuels and balance of trade difficulties between nations. Presently automotive fuels are almost exclusively petroleum based, and in recent years petroleum production has not kept up with increased demand. Battery electric vehicles (BEV) promise to enable diversification of the transportation energy feedstock thereby reducing the dependence on petroleum for transport. In addition to reducing gasoline dependence it can also help to reduce greenhouse gas and other emissions, reduce global warming and provide more sustainable individual transportation.

The governments of the US, European Union, China, Japan, Korea and others have aggressively promoted vehicle electrification objectives and the major automobile companies of the world are being challenged for the first time by consumers and governments to produce battery electric vehicles. Several companies have accepted the challenge, even though there is relatively little technical acumen on deployment of these vehicles.

Deployments of BEVs present a host of new challenges including those resulting from a current lack of supporting infrastructure. Charging stations are relatively rare,

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charging takes considerable time and currently range is more limited than with conventional vehicles. It results in range anxiety and hampers customer acceptance of the product.

To alleviate range anxiety, new vehicle electronics features are needed to help vehicle operators make driving choices that avoid discharged battery situations, extend vehicle range, and combine charging with other good uses of time. Development of these features requires practical meta-models that can accurately predict energy consumption on the public roads.

Building meta-models from field-test vehicle data requires statistical regression of public-road vehicle data (PRVD) over very large geographic areas. At present; there are not enough production test vehicles available to collect a sufficient amount of data, noise factors are not well controlled, and data collection is too time consuming to support product launch. As a result modeling and simulation are essential tools in analysis of BEV performance.

In this work we propose implementation of traffic simulation combined with propulsion modeling for determining electric vehicle energy consumption. We use traffic micro-simulation to create surrogate PRVD data that has many of the properties of actual PRVD data, specifically capturing the stochastic nature of vehicles moving through roads with traffic. The surrogate data is analyzed using propulsion simulation to estimate the amount of energy the vehicles will consume in a specific driving maneuver to derive statistical information.

2 Simulating Energy Consumption

The simulation approach used here begins with geographical information about roads and basic parameters about the vehicle of interest. The road data is coded into a microscopic traffic simulation program in which model vehicles are input into the simulation and surrogate drive data is produced. This is input into a propulsion modeling system that outputs the energy consumption of individual vehicles in the model. This data is collected and analyzed through statistical regression. The resulting energy consumption data is used to calibrate an energy consumption meta-model that can be used to estimate the energy consumption of a vehicle using surrogate data from the traffic simulation.

Scenarios of different road networks under different external conditions are simulated. For example, a road network could consist of a highway interchange or a stretch of a specific kind of road. External conditions would be such things as topography, weather, and traffic load. The traffic simulation contains BEV vehicle and other vehicles that create the traffic conditions for the sample vehicles. Regression analysis is used to create an energy consumption meta-model that predicts average energy consumption as well as the stochastic distribution. By comparing scenarios it is possible to determine main effects to build a meta-model of energy consumption from geographical data and data available in traveller information systems.

Advantages of the method include developing energy consumption models during the design process before physical testing is possible. These models can be used to improve the design and support the deployment of BEV vehicles into the consumer market. In addition, statistical information is produced that can be used to bound the results and produce better low-energy routing algorithms.

In the simulation planning phase representative scenarios are defined that can be used to develop extensible meta-models (see Fig. 1). The scenarios must be defined using the kinds of data that are typically found in vehicle route guidance systems so they will be useful in the car.

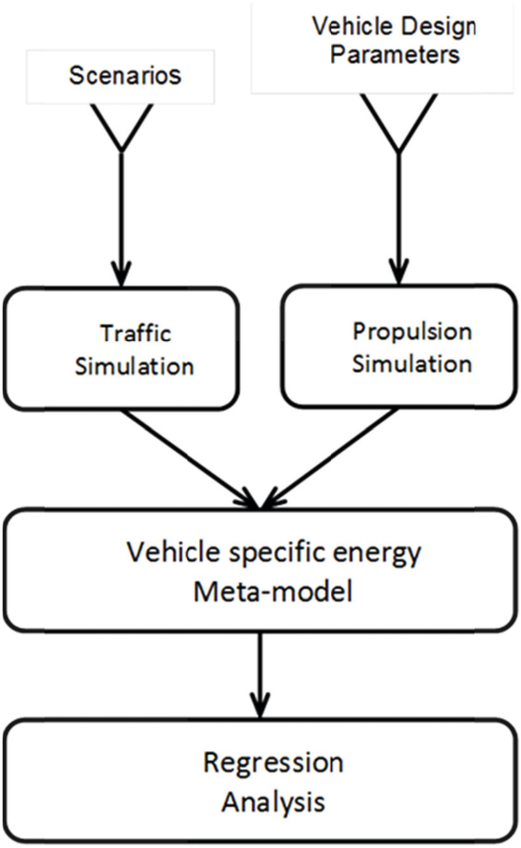

Fig. 1. Process flow for estimation of energy consumption based on integration of traffic and propulsion simulation

The scenarios are then coded into a traffic simulation code and tested under a variety of conditions that include road type, weather, traffic, gradient and vehicle parameters. The output of the traffic simulation is a set of drive cycles which are a time series of distance travelled, velocity, acceleration, lane changes.

Drive cycles are then converted into estimated energy consumption for each sample vehicle driving through a scenario. This can be done using a meta-model for energy consumption for the vehicle. In our project this meta-model was a set of energy maps, each map for a different cargo load on the vehicle. The maps were developed using regression analysis of surrogate data from propulsion modeling and related acceleration and speed to energy consumption per distance travelled. Non-propulsion losses (accessory loads) were handled separately based on travel time.

The total energy consumption for each vehicle in a scenario under a given set of conditions is then analyzed using statistical regression to provide a predictive model for the scenario under the given conditions.

2.1 Propulsion Simulation

Propulsion system simulation is a desktop computer method for directly simulating vehicle drive cycles using a complete model of a vehicle propulsion system that represents key interactions between driver, environment, vehicle hardware and vehicle controls. There are a number of examples of tools, methods and applications of propulsion system simulation programs in the literature that use dynamic systems modeling to estimate energy consumption given a drive cycle. The primary purpose of these applications is to identify key design elements that influence performance, test control algorithm alternatives and determine the effect specific propulsion system features have on drivability. One significant example is the PSAT (Powertrain System Analysis Toolkit) (Argonne National Laboratory) tool developed in 1999 as part of a collaborative effort with U.S. OEM's (Ford, GM, and Chrysler).

Many automotive OEMs and Tier 1 suppliers have proprietary propulsion system modeling and simulation tools with a team of developers and simulators capable of computing energy consumption from drive cycles. Typically the drive cycles are from laboratory tests specified by the government regulations, obtained from driving studies or created by simulation. Generally these tools are supported by databases of proprietary hardware component information and controls strategies and calibration data specifically representative of the manufacturer's products. They are configured to support investigation of systems that design changes can be modeled through simulation. One such modeling application is Ford Motor Company's Corporate Vehicle Simulation Program (CVSP) that was used in the modeling effort described in this paper [3].

CVSP is a critical tool used mainly for projection of fuel economy capability of vehicles with internal combustion engines. These projections are used to make critical hardware and technology decisions that determine vehicle program content and ultimately impact vehicle program cost. Results from the CVSP simulations are also used to cascade targets to key subsystems and components (e.g. battery, power electronics and electric machines for HEV's).

Within Ford, a significant amount of time and effort has been invested in verifying the accuracy of CVSP simulations. This is critical for development of high confidence fuel economy roadmaps and subsystem/component targets for vehicle programs. With good system model accuracy, targets can be specified with much higher precision, thus avoiding over-design of components to deliver aggressive fuel economy targets. In the later stages of a program, an accurate system model can support vehicle testing for fuel economy attribute development. The model can be used to assess selected propulsion system control strategy and calibration changes which can help refine vehicle test plans and improve efficiency of vehicle test efforts.

The vehicle system model integral to CVSP is implemented in the Matlab/Simulink® environment using the Vehicle Model Architecture (VMA) standard [2]. Models of each VMA subsystem are stored in libraries and inserted into the architecture for simulation using automated model configuration tools. The system model incorporates submodels for physical and control elements of the vehicle system. As an example, for power split hybrid electric vehicle system simulation, the set of submodels includes a power split transaxle subsystem model, a high voltage (HV) electrical subsystem model including high voltage battery and a model of the power split vehicle system controller. The system model represents the longitudinal dynamics of the chassis and one-dimensional rotational dynamics of the powertrain system. All mechanical and electrical component losses that have impact on energy usage and fuel consumption are included and distributed across the relevant subsystems. These losses are typically represented by component maps derived from bench/lab tests or high fidelity physical models. Further discussion of the CVSP simulation environment and how it is applied to electric vehicle system assessment can be found in [4] and [3].

2.2 Traffic Simulation

Traffic micro-simulations are proposed as a way to produce realistic drive cycles. These simulations have been developed for testing the performance of roadway designs and signal light timing schedules, and generally for improving the performance of transportation infrastructure. Typically they are used in the domain of the traffic engineer and not traditionally used for vehicle simulation.

Traffic micro-simulations are time-event driven simulations that implement a driver model for individual vehicles that are placed on a model roadway. They implement psychophysical driver models that employ vehicle physics and a physiological model of driver following behavior. A detailed discussion of driver models for micro-simulation modeling is found in [6].

Roadways are modeled as directed graphs in micro-simulation and individual vehicles placed on the model roadways have proven to be a reasonable way to model traffic flows that consider jams, congestion and different driver behaviors. Other factors can also be considered such as weather and topography.

A primary advantage of micro-simulation over other methods of producing drive cycles is that there is a straightforward analytical model that links physical features of the road, traffic and human perception to the creation of synthetic drive cycles. Models are calibrated using in-vitro data such as that collected in driving simulators, established psychological theory and observation traffic behavior from aircraft. Frequently micro-simulation software is calibrated for good results for bulk traffic flows consistent with those observed by traffic monitors or detection equipment placed in the roadway.

There are a number of traffic micro-simulation packages readily available from open-source, commercial and academic sources. In our study we used VISSIM [5]; a mature, full featured traffic simulation package. VISSIM is a time driven microscopic simulation package from PTV that can analyze private and public transport operations under constraints such as lane configuration, traffic composition, traffic signals, public transportation stops, etc., thus making it a useful tool for the evaluation of various alternatives based on transportation engineering and planning measures of effectiveness. VISSIM can be applied as a useful tool in a variety of transportation problem settings. Simulated Vehicles are allowed to run through a road model, each vehicle having a driver model and a vehicle dynamics model. The driver model consists primarily of four parts; a psycho-physical following model [7]; [8], a lane changing model, a launch model and a speed holding model. The output of the driver model is the driver's desired speed, acceleration and lane angle. These are later modified to conform to the vehicle's performance limits.

In addition, VISSIM has two features that may be important in future work; the ability to introduce a user driver model with lane-changing and following behavior, and an interface for the dynamic routing function that allows exploration of routing algorithms using a programming interface.

2.3 The Scenarios

Three representative road types were used to build traffic scenarios. The road types were chosen to be exemplary of the types of roads that might populate a full scale analysis project; the residential street, urban highway and limited access highway. Road models were based on actual roads near Dearborn, MI, USA where the work was done and coded into the traffic simulation program. This allowed easy access to collect data and calibrate the models (see Fig. 2). Fig. 2 presents a 3-mile stretch along US I-96 (between exit 179 and 183) that was coded into the simulator as a representative section of freeway. The base model is a 3 lane road with no ramps entering or leaving the freeway. The traffic composition included 4% heavy goods vehicles and 2% battery electric vehicles. The remaining 94% were internal combustion vehicle of varying lengths consistent with personal transportation. To differentiate between a BEV and an internal combustion vehicle drivetrain, different desired acceleration profiles (speed vs. maximum acceleration desired by the driver) have been used. The vehicle input was set at 5000 vehicles per hour over 3 lanes. Stochastic distributions of driver desired speeds are defined for each vehicle type within each traffic composition. The desired speed of both the conventional cars and the BEV was a roughly normal distribution with a mean of 62 MPH (100 km/h) distributed between 83 MPH (130 km/h) and 50 MPH (80 km/h). At this speed aerodynamic drag exceeds all other vehicle specific load components except possibly accessory loads. If not hindered by other vehicles, a driver will travel at his desired speed with variations determined by the driver following model.

The urban highway model is based on a 6 mile stretch along US-24 (Fig. 3) with multiple traffic signals at intersections 1 mile apart. The vehicles enter at one end of the road and exit only at the other end. There were a total of nine synchronized traffic signals along the road, with multiple signals at some intersections. Although the actual road had 4 lanes along part of the stretch, the base model had 3 lanes throughout to simplify interpretation of the results. The traffic was composed of 98% conventional cars and 2% battery electric vehicles. The desired speed varied between 42 and 48 MPH (68 km/h – 77 km/h).

Traffic light timing was on roughly 60 second cycles such that during a typical evening rush hour packs of about 90 cars build up at a red light. The light would change to green and the vehicles would launch from a standstill. Except for the lead vehicles, each vehicle's launch rate was limited by the vehicle ahead. The pack of vehicles would reach the next light and stop for a few moments, and then continue to the next light.

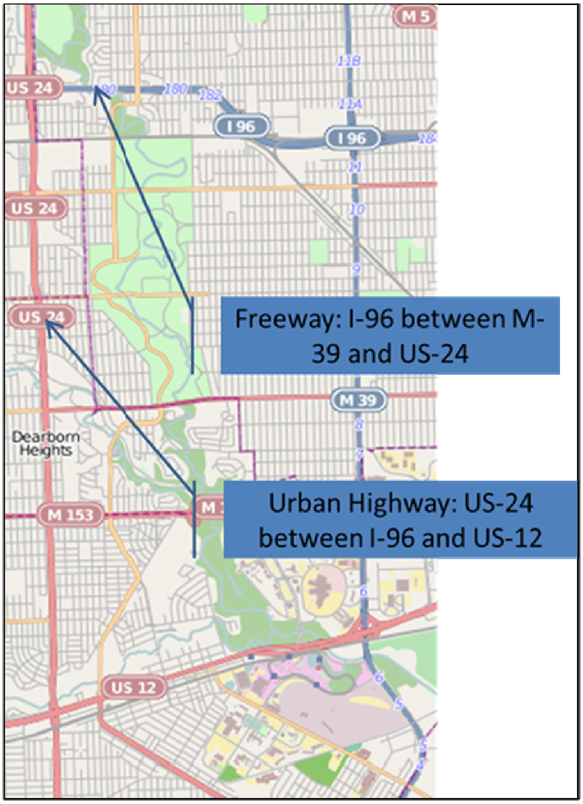

Fig. 2. The urban highway is a six mile stretch of Telegraph road and the freeway is a three mile stretch of I=96. For reference, the GPS coordinates of the intersection of M-39 and I-96 is 42.378780 and -83.216972.

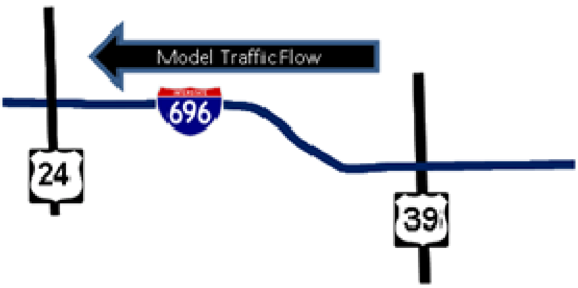

Fig. 3. This is a schematic view of the three miles stretch along I-696 between state routes 39 and 24 that was used as the "freeway model"

The residential road scenario was one mile long with multiple stop signs. The base model had 5 stop signs in each direction with a flow of 80 vehicles per hour in each direction. Similar to most residential roads, there was a single lane in each direction. The desired speed of the vehicles had a distribution that varied between 22 and 28 MPH (36 and 46 km/h), based on the assumption that the median desired speed would be the speed limit, 25 MPH (41 km/h).

Deceleration into and launch from each stop sign was largely under the control of the driver model, not constrained by the vehicle ahead. There was a dwell time at each sign in which vehicle speed dropped to zero followed by a launch. The length of the dwell was based on cross traffic and the driver characteristics of each individual car.

The scenarios were created using a road model with varying external conditions. They were selected to explore the scenario space to determine which conditions were significant factors for energy consumption. The factors used were as follows:

- Road characteristics
  - Road Gradient
  - Number of lanes
  - Traffic characteristics
  - Vehicle flow rate
  - Vehicle mix (Number of trucks, buses, cars and battery electric vehicles)
- Driver characteristics
  - Desired speed
  - Use of cruise control
- Accessory load per unit time

Two types of energy consumption were considered in this analysis; propulsive energy consumption and accessory energy consumption. Propulsive loads were computed using maps of energy per distance travelled. Accessory energy consumption was in units of energy per unit time and kept constant through any given scenario.

The independent variables for the energy maps were vehicle speed and acceleration. Four maps were made for the BEV vehicle for different payloads weights; 1-4 occupants. The acceleration used in the energy calculation was the sum of road gradient acceleration and vehicle acceleration.

We determined both experimentally and using the Student-T analysis that 125 BEV test vehicles were necessary to get sufficient statistical power. So each scenario was run until 125 BEV had passed through the scenario. For each BEV the energy consumption was computed for each time step, multiplied by the distance of each time step and accumulated for the entire drive cycle. This was added to the energy consumption attributable to the accessory loads and saved. The average and standard deviation of all the drive cycles were then computed for each scenario, and the scenarios were plotted and compared to determine the main effects.

3 Results of the Energy Consumption Modeling

The results are presented in the following manner. First the results of energy consumption under different scenarios for each of the road types are presented followed by a comparison of these results across road types. The tables give the mean energy consumed by a battery electric vehicle for that particular scenario. The units are Watt-hours unless mentioned otherwise. The original analysis was done with data for a specific vehicle, but because of the proprietary nature of this data it has been normalized and the results are more qualitative.

3.1 Freeway

Fig. 4 shows the average energy required by 125 battery electric vehicles to travel the 3 mile stretch of freeway at various gradients and traffic flows. The bold lines in Fig. 4 represent the mean energy consumed and the dotted lines represent the 95% confidence interval. It can be seen that gradient has a prominent effect on the energy consumption of a battery electric vehicle. There is a rapid increase in the energy values as we move from a gradient of -4% to 4%. This is because, the vehicle needs more energy to climb uphill (positive gradient) and it can gain energy through regenerative braking while going downhill (negative gradient). Congestion has a much smaller effect than gradient on energy consumption. There is a slight reduction in energy as the flow conditions approach a congested scenario. This effect is directly related to the decrease in the speeds for congested flows.

Table 1 shows the impact of desired speed and the number of lanes on the energy consumption under different flow regimes. Fig. 5 presents the data in such a way as to show that vehicle speed is much more significant than the number of lanes. A vehicle travelling at around 60 mph will consume about 30% more energy than a vehicle travelling at around 50 mph. Also, the number of lanes on the freeway doesn't seem to have an effect on the overall energy consumption.

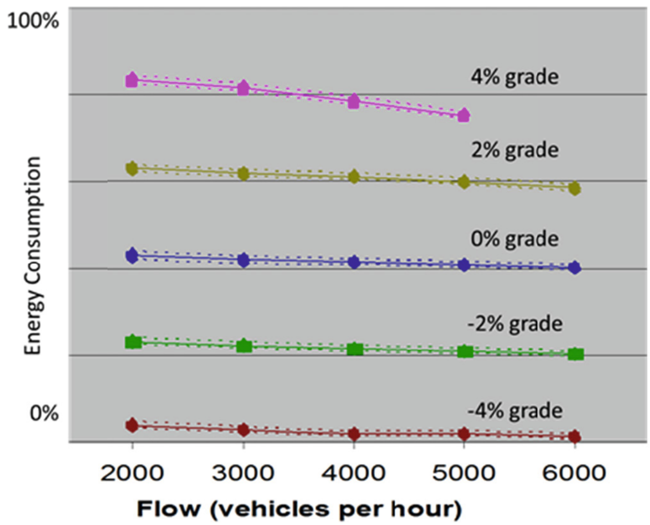

Fig. 4. Energy consumption for vehicle travelling on the freeway at different grades

Table 1. The effect of desired speed and number of lanes at different flow rates

	60 mph		50 mph	
Flow (VPH)	**3 lanes**	**4 lanes**	**3 lanes**	**4 lanes**
2000	1.16	1.18	0.88	0.88
3000	1.14	1.15	0.86	0.87
4000	1.12	1.14	0.85	0.86
5000	1.11	1.15	0.85	0.86
6000	1.09	1.14	0.84	0.86

Table 2 shows a comparison of the energy usage of vehicles travelling in cruise control with that of vehicles not travelling in cruise control for two different speeds. It is assumed that in the cruise control scenario only the battery electric vehicles are in cruise control mode. All other vehicles are travelling without cruise control.

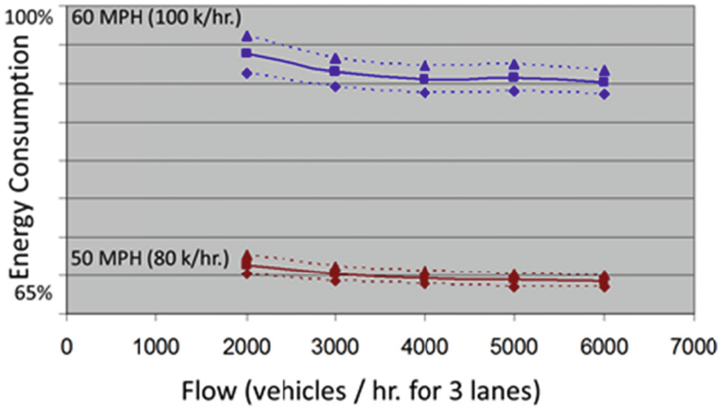

Fig. 5. The figure shows energy consumption for two vehicle parameter sets, one with drivers whose average desired speed is 60 MPH and the other averaging 50 MPH

Table 2. Effect of gradient on energy consumption at different vehicle flow rates for a 3 lane road

	Grade				
Flow (vehicles per hour)	**-4%**	**-2%**	**0%**	**2%**	**4%**
2000	0.09	0.58	1.08	1.59	2.11
3000	0.07	0.56	1.06	1.56	2.06
4000	0.05	0.55	1.04	1.55	1.98
5000	0.05	0.53	1.03	1.51	1.90
6000	0.03	0.51	1.01	1.48	

Table 3. The effects of traffic load, desired speed and cruise control on energy consumption

	60mph (100 k/hr.)		50mph (80 k/hr.)
Flow (VPH)	**No cruise**	**Cruise**	**No cruise**
2000	1.20	1.11	0.91
3000	1.18	1.11	0.89
4000	1.16	1.11	0.89
5000	1.15	1.09	0.88
6000	1.13	1.09	0.87

From Table 3 and Fig. 6, it can be seen that the vehicles travelling in cruise control use significantly lower energy than the vehicles travelling without cruise. The fluctuations in acceleration/deceleration and hence the speed results in higher energy consumption for vehicles which are not using cruise control. The drop in energy consumption with increase in flow values is directly related to the drop in speeds as the flow conditions become congested. It should also be noted that the energy consumption and its variation remains fixed across different flow values when the cruise control is set to 50mph. But, in the case of cruise control at 60mph, there is a larger statistical variance in energy usage (dotted lines diverge) as the flow values increase. This is because at high flows, the vehicles are unable to maintain a cruise speed of 60mph due to the increase in flow density. But, the vehicles seem to maintain a cruise speed of 50mph even when the traffic flow increases.

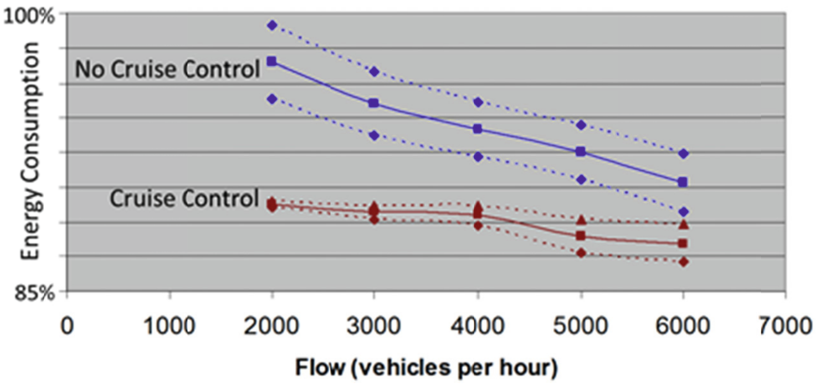

Fig. 6. The effect of traffic load on energy consumption both with and without cruise control driver models is demonstrated for 125 vehicles

3.2 Urban Highway

The results show the mean energy required by a battery electric vehicle to travel the 6 mile stretch. The main difference between an urban road and a freeway would be the stop-go behaviour of the vehicles at traffic signals. As a result, because of the regenerative capability of a battery electric vehicle, the energy consumed per mile will be lower on an urban road. Also, the lower speeds on urban roads will result in lower energy consumption. But the trade-off between an urban road and a freeway will be in the travel times. A comparison is presented in the later sections of this chapter.

Table 4 shows the mean energy consumed on the urban highway by a BEV under different traffic flow and gradient conditions. Similar to the freeway, the gradient has a very significant effect on the energy consumption on the urban highway as well. It is significantly greater than the effect of traffic loads.

Table 4. The effect of grade and traffic load (VPH) on energy consumption for the urban highway

	Grade		
Flow (VPH)	**-2%**	**0%**	**2%**
1000	16%	57%	100%
2000	15%	56%	99%
3000	14%	56%	98%
4000	14%	55%	0%

Also, simulations have been performed to understand the effect of the number of lanes on the overall energy consumption. It has been observed that the number of lanes has a very small effect on consumption in these traffic flow scenarios.

3.3 Residential Street

The results for residential roads show the mean energy required by a battery electric vehicle to travel the 1 mile stretch of residential street with multiple stop signs. The stop signs and the lower speeds on residential roads will significantly reduce the energy consumption of a BEV due to aerodynamic drag, but will increase the significance of other factors such as road grade or stop starts. Due to regenerative braking the effects of stop start are expected to be smaller on BEV than would be normally expected from conventional vehicles (see Table 5).

Fig. 7 shows the effect of gradient on energy consumption. It is expected that the energy usage will be negative for a gradient of -4%. This shows that the battery of the vehicle is gaining energy because of the regenerative braking.

Up to this point the effect of various traffic/road/driver characteristics on the energy usage for each of the individual road types has been discussed. In the next section, a detailed comparison of the energy usage across the three different road-types is presented to better understand how some of the scenarios impact the lowest energy routes and distance-to-empty.

Table 5. The effect of stop-signs per mile on the energy consumption

Number of stop-signs per mile	**Energy (W-hours)**
5	149.5
10	148.4
15	148.0

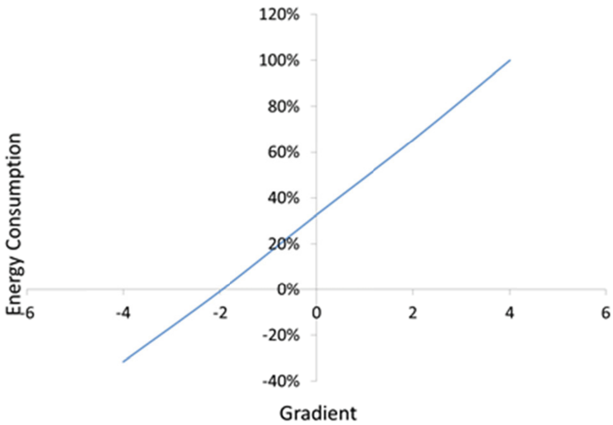

Fig. 7. The effect of gradient on average energy consumption for 125 vehicles for the residential street

3.4 Comparison across Road Types

Figure 8 shows the impact of accessory loads on the energy consumption across the three road types. The bars represent the energy usage in W-hours per mile and the three bold dots represent the average travel time in seconds to travel a distance of one mile on each of those roads. It can be seen that for a given accessory load the energy usage is the lowest for a residential road and highest for a freeway, mainly because of low speeds and stop-go nature of traffic on a residential road. In fact, the energy usage per mile with 400W accessory load is more than halved from a freeway to a residential road. But, the travel time on a residential road is almost four times that on a freeway. This shows a trade-off between travel times and energy usage. Increase in the accessory loads has very little impact on the energy usage on a freeway where high speed is the primary driver of energy consumed. On the other hand, the accessory loads drastically affect the energy usage on a residential road to such an extent that, the energy used per mile with 2000W accessory load is almost the same as that on an urban road.

Fig. 8 shows that gradient has a very dominating effect on the energy consumption of a battery electric vehicle. For a particular road type, the increase in energy consumption with every 2% increase in gradient is about 150W-hrs per mile. High gradients like 4% or -4% are not very common for a freeway.

The three road types each have different speed limits, and for each simulation the drivers' 'desired speed' is input as a statistical distribution around the speed limit for the road. Some drivers will drive above the limit and others below, but most will be close to the speed limit. Fig. 8 shows the energy consumption for vehicles with the following desired speeds: Freeway – 65 MPH, Urban road –45 MPH, Residential road – 25 MPH. These values are almost identical to the speed limits on the corresponding road types. The graph shows that the speed of the vehicles has a strong influence on the energy usage. Also, the stop-go behavior of vehicles on urban and residential roads has a significant effect on energy consumption because of regenerative braking.

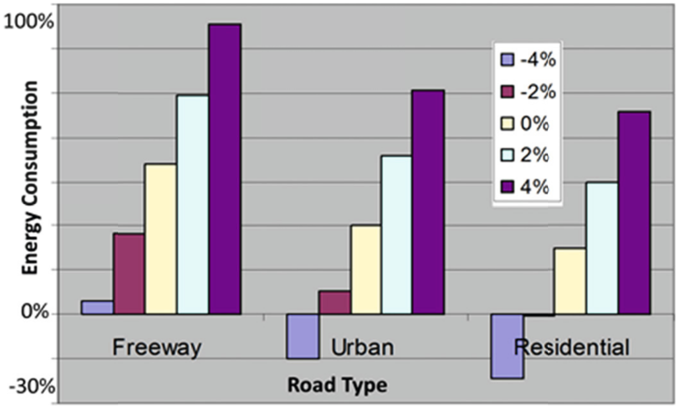

Fig. 8. Comparison of the effect of road gradient on the three types of roads: freeway, urban highway and residential road

4 Energy Consumption Calculation

Using the results presented in Fig. 8 and Fig. 9 It is possible to develop a meta-model to estimate energy consumption over a section of road if the distance d is known and the travel time t can be estimated.

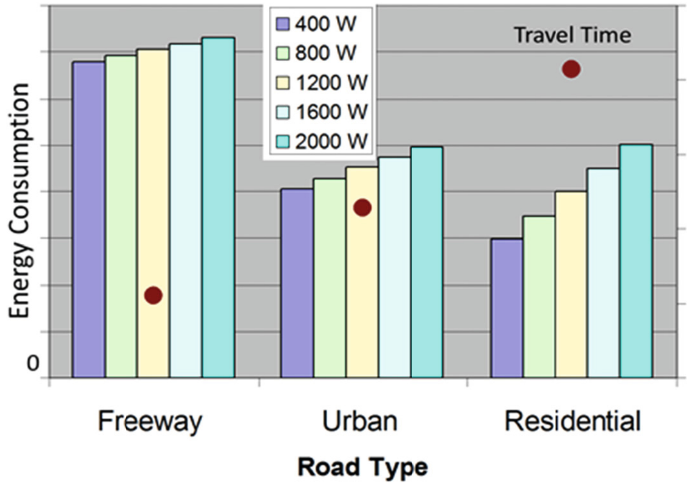

Fig. 9. The effect of accessory loads on the energy consumption on flat ground on the three road types

The energy consumed on a segment is given by an equation of the form:

$$E = Pt + Wd \tag{1}$$

Where:

E = The energy consumed
P = The power consumed by accessory loads
W = The work done on the vehicle based on distance traveled
t = time
d = distance traveled

Power is the sum of the time dependent terms consisting primarily of accessory loads. A model is needed to predict those loads based on factors such as climate control requirements, lighting requirements, windshield wipers, etc. Lacking that model we use different levels of accessory loads to create scenarios.

The prior results demonstrate that speed and gradient are major factors in work, and to a lesser extent the road type. We take work to be the sum of gradient factors B and speed factors A. An equation for B is developed for each road type in Fig. 8 where s is the slope of the road in degrees.

The speed (V) component (C) of work is given by:

$$C = A_{aero}V^2 + B_{aero}V + C_{aero} \tag{2}$$

Substituting (B+C) for W and A for P, energy consumption can be computed as:

$$E = At + (B+C)d \tag{3}$$

The factors $A_{freeway}$, $C_{freeway}$, $A_{highway}$, $C_{highway}$, A_{street}, C_{street}, D are fit functions primarily related to the road, and the factors A_{aero}, B_{aero}, C_{aero} are fit factors related to the aerodynamics of the vehicle.

This equation was plotted for a set of 150 routes generated at a mapping website assuming no gradient. The results are plotted in Fig. 10 where it is seen that under high accessory loads there is a minimum energy speed at about 20 MPH. In the case where there is low accessory load the energy consumption appears to asymptotically approach zero energy consumption. In fact, in the low accessory load cases there is also an optimal energy consumption speed, but at a much lower speed than vehicles are ordinarily driven.

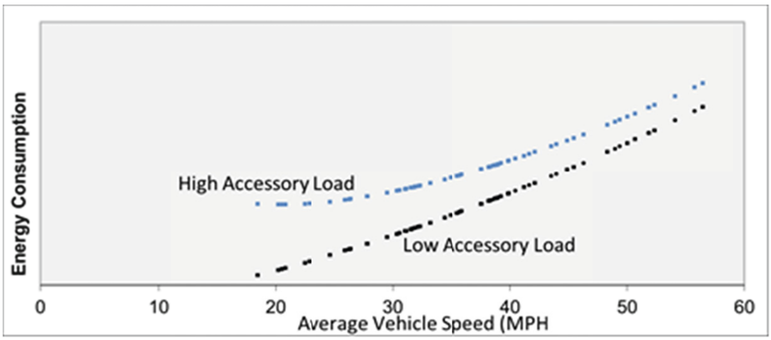

Fig. 10. The meta-model results applied to routes through 20 different cities in the US

5 Conclusions

A methodology for creating meta-models for energy consumption from surrogate data from simulation has been demonstrated. The method was used to determine the main effects and a simple meta-model that can be run in embedded processors in the vehicle or on off-board computing platforms has been developed. The energy consumption meta-model enables vehicle functions such as; distance to empty, remaining charge needed and low-energy routing. These in turn enable vehicle features that give the driver greater confidence in the product and therefore improves acceptance and deployment of electric vehicles.

The traffic simulation code VISSIM and the propulsion modelling code sCVSP were combined via a surrogate meta-model to provide energy consumption data for developing a comprehensive energy consumption meta-model.

By developing different scenarios it was possible to determine main effects such as road gradient and vehicle speed. It is widely believed that the driver has a large impact on energy consumption. From our results we see this is likely mostly a factor of the driver's desired speed, how it is moderated by traffic. Probably route choice is a significant factor that would differentiate drivers.

Road gradient is another important factor, but is mostly a factor of the potential energy build-up or loss going up or down a hill. BEV are different from hybrid electric and conventional vehicles in that much of the energy lost going uphill is regained coming down. Unlike hybrid vehicles, the BEV battery is large enough to recover this energy on many hills.

A third main effect is accessory loads. These come from many sources in a BEV, but the largest factor is generally warming or cooling the vehicle. This can easily account for 50% of the energy consumed by the vehicle and is the only factor that favours faster travel time.

Each of these three areas; vehicle speed, road gradient and climate control require further study. Vehicle speed on an un-crowded road is largely a factor of how fast the driver wishes to drive. This may vary depending on the speed limit and on safety considerations. On a crowded road vehicle speed also can be determined by how effective a driver wishing to travel quickly is at maintaining this desired speed while interacting with slower moving vehicles. The biggest factor in velocity drag is aerodynamic drag which is assumed in our models to increase with the square of the velocity. However, the situation on the public roads is quite a bit more complicated where there is wind, ground turbulence, air density, disturbance by nearby traffic and other factors to consider.

Road gradient is expected to always be a major contributor to energy consumption, but other road factors that are not included in our model are soft road surfaces, partially inflated tires and many other factors. For the energy consumption meta-model to be accurate it is necessary to break a road into segments that either rise or fall. If a segment goes up then down a hill, the energy consumption will not be accurate. How real road surfaces will be broken into segments that provide good results must be considered.

Finally, the predicting of accessory loads is quite complex and is the topic of another paper. Loss by the climate control system is controlled by several factors. External factors include ambient temperature, humidity and sun load. The vehicle configuration is a major factor as are several controls that are under the manual control of the driver. However, this is changing and in the near future most climate control features operated by the driver will migrate to a control system for driver convenience and to meet new Corporate Average Fuel Economy (CAFÉ) standards.

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