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Estimating Energy Consumption of a PHEV using Vehicle and On-board Navigation Data*

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Abstract— **This paper presents a novel approach for predicting the energy consumption of a plug-in hybrid electric vehicle (PHEV). We propose to estimate energy consumption strategy from data via regression applied to trip recordings. Descriptors of the trip elements are obtained from both recordings and statistics provided by a GPS navigation system. Trips are then split into elementary units corresponding to an homogeneous driving context. For each trip element, the optimal energy consumption strategy is computed via (expensive) dynamic programming simulations. Here, data analysis is used so as to identify descriptors of this trip element that are relevant to predict the energy consumption. Then, a polynomial model is fit to the data so as to estimate, for each new trip element, the optimal energy consumption strategy from the expected driving condition, rather than using dynamic programming. Our approach distinguishes itself by the fact that road context, driver style, road slope and auxiliary electrical power are taken into account to estimate the energy consumption of a PHEV. The accuracy of the prediction process is evaluated over test data, and demonstrates the interest of our approach in predicting energy consumption.**

Keywords: PHEV, energy consumption, learning, route preview, prediction, dynamic programming.

I. INTRODUCTION

Improving vehicle efficiency is one of the main challenges of modern vehicle industry. For this purpose, many techniques can be used to reduce the fuel consumption of a conventional vehicle, such as engine downsizing, size, weight and drag reduction, or driving behavior management. The problems of identifying the driving features related to fuel consumption of internal combustion engine vehicles, and their use to improve driving efficiency, have been addressed in [1], [2].

Alternative powertrains are also a solution for improving efficiency. Plug-in hybrid electric vehicles (PHEV) represent a promising alternative for reducing the pollutant impact of vehicular traffic in terms of fuel consumption and gas emissions [3]. A classical hybrid electric vehicle is powered by an internal combustion engine and one to two electric motors depending on its architecture. PHEVs have a longer all-electric range (between 15 and 50km) and can restore electric energy from the electric grid at a cheaper cost. A PHEV requires an energy management system to coordinate operations of the different powertrain organs to meet the driver's torque request and maintain the traction battery at an adequate state of charge. While an appropriate management of both fuel and electrical energy is necessary to achieve fuel savings [7], PHEV energy management systems generally use a crude strategy consisting in depleting the battery before using the combustion engine when the state of charge reaches a low value [5].

When the future driving conditions (speed profile and road grade) are perfectly known in advance, an optimal control strategy may be planned by using Dynamic Programming (DP) [6]. Despite the fact that DP is often used as benchmark for other energy management systems, it is not suited for an onboard implementation because of its computational cost and the requirement that the driving conditions be known in advance. The first problem can be tackled by the use of a remote clusta besoiner of servers to process the data [8], or reducing computation cost of DP [18]. Other instantaneous energy management approaches consist in regulating the battery state of charge around a predefined constant target [9], [10], [11], [12], [13]. Alternately a supervised learning approach based on DP results for determining the instantaneous power split of a hybrid electric truck has been studied in [14]. We stress here that the exact future driving conditions, required to compute the optimal control strategy over the entire trip, is in practice impossible to get: the trip may indeed be subject to unexpected perturbations (such as traffic jams, accidents, etc) and the behavior of the driver may change as well (e.g., from cautious to aggressive). Recent onboard navigation systems can provide the energy management system with a road description and statistics on driving conditions through dedicated protocols [15]. Thus, predictive strategies using available traffic and road grade information have been developed based on fuzzy logic controllers [16], two-scale DP [8] and equivalent consumption minimization strategy [17]. Each of these existing prediction approaches is strongly linked to the choice of the real time EMS algorithm.

In this work, we present the first element of a global optimization strategy of the battery discharge of a PHEV. More precisely, we propose to estimate the optimal energy consumption model for a trip element based on descriptive features of the expected driving conditions (such as vehicle speed, and acceleration, road grade, etc). We consider several trip recordings for which driving conditions have been observed. Each of these trips is first cut into elements corresponding to homogeneous driving conditions, such as road type, speed, grade, etc. The corresponding optimal energy consumption curve is then computed offline via DP simulations. Using data mining techniques, we identify the

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relevant driving features for the purpose of estimating these optimal energy consumption curves. Furthermore, we show that a polynomial model may be fit so as to estimate the optimal energy consumption curve of any new trip element from its descriptive features. Therefore, the optimal energy consumption strategy may be obtained, for a new trip, by cutting the trip into trip elements, retrieving its descriptive features, and predicting the corresponding optimal discharge curve. These curves can then be used as inputs for the global optimization strategy performed via algorithms such as A* or quadratic programming [19]. Note that due to lack of space, the global optimization strategy cannot be presented here, and is left for further presentation.

This paper is organized as follow. Section II presents how DP can be used to generate optimal consumption curves associated to a trip element. Section III describes the data and presents how a trip may be cut into elements on which the relevant descriptors for predicting the optimal energy consumption strategy are identified. The impact of road grade and auxiliaries power on energy consumption is also discussed. In Section IV, we present experimental results showing that our approach makes it possible to accurately predict energy consumption in real-life conditions. Concluding remarks and perspectives of future work are made in Section V.

II. PHEV OPTIMAL ENERGY CONSUMPTION MODEL

In this section, we detail how the optimal energy consumption curve for a trip element may be computed via dynamic programming (DP). Such a curve consists in linking the electric consumption, represented by the state of energy (SoE) variation (thereafter written ΔSoE), to the fuel consumption under specific driving conditions[1]. More particularly, each point on this curve gives the lowest fuel consumption that needs to be paid in order to achieve a particular SoE variation at the end of the trip element. Thus, for any trip element meeting the same driving conditions, the optimal compromise between fuel and electric energy consumption may be reached using this curve. . Our study is based on a 1650kg PHEV with a parallel architecture, a 6.6kWh battery and a three-gear clutchless gearbox.

DP is based on Bellman's optimality principle and is used to find optimal control sequences for constrained nonlinear programming problems [20]. In [6], it was shown that DP can be used to compute the optimal discharge strategy of the vehicle using a quasi-static vehicle model with engine and motor maps. Computations are carried out backwards in time from the last instant of the trip element recording, for which a desired target SoE is fixed (in our experiments, this value was set to 50% to capture as large SoE variations as possible). At each instant t, the algorithm determines the cost that must be paid (in terms of fuel consumption) in order to reach at $t+1$ each admissible SoE value, given the most favorable admissible combination of the control

[1]Following the work in [25], SoE is chosen as the battery state measure rather than SoC.

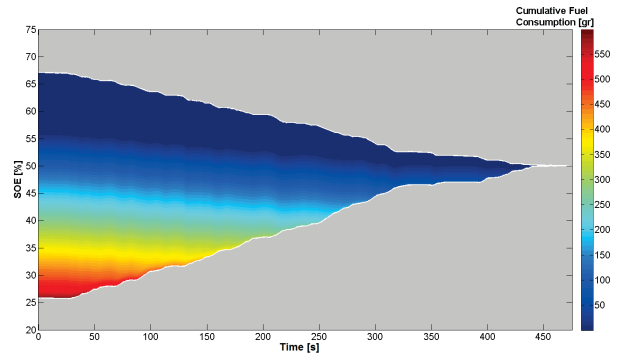

Fig. 1. Example of the cost-to-go matrix computed by DP on an urban cycle with boundaries precalculation (white lines)

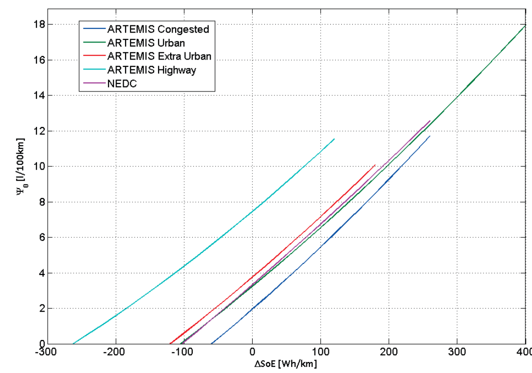

Fig. 2. Fuel Consumption Curves examples for five test cycles

variables (gear ratio and torque split). These values define a bidimensional cost-to-go function: this function displays, for each instant of the trip element, the optimal cumulated fuel consumption that must be paid to reach the desired target SoE given a current SoE value (see Fig.1 for an illustration). Thus, the values corresponding to the instant $t = 0$ of the trip element correspond to the optimal cumulated fuel consumption necessary to attain the desired target SoE for each initial SoE value. Then, the optimal cumulated fuel consumption for the trip element can be expressed as a function of the normalized variation of SoE

$$\Delta SoE = \frac{SoE_{\text{tgt}} - SoE_{\text{ini}}}{\ell}, \qquad (1)$$

where SoE_{ini} and SoE_{tgt} respectively correspond to the initial and desired target SoE values for the trip element, and where ℓ stands for the length of the trip element. Distance normalization makes it possible to compare optimal cumulated fuel consumptions for elementary trips of different lengths. In the following, we will refer to the curve giving the optimal cumulated fuel consumption as a function of ΔSoE as *fuel consumption curve (FCC)*. In [23], an approach was proposed to identify categories of driving situations, based on features extracted from the driving recording. These driving classes were used to generate normative ARTEMIS driving cycles. Fig.2 displays the curves corresponding to the four ARTEMIS classes (urban, rural, highway and traffic jam) as well as the one corresponding to the New European

Driving Cycle (NEDC). Let us note that all FCCs present a convex shape with (approximately) the same inclination and curvature, but different y-axis offset and boundaries. We thus propose to model each FCC by a second-order polynomial. Note that similar approaches were applied to PHEV [25] and ICEV alternators [19]. Furthermore, we associate each polynomial with a validity range, in which the quadratic assumption holds. Outside this range, excessive battery discharge (with no fuel consumption) or charge (in which case the combustion engine is operated at maximum power) are known to reduce the efficiency of the energy management strategy. Thus, these two modes will not be considered. With the three coefficient provided by the polynomial regression Ψ_i (for $i = 1, 2, 3$) and the lower and upper bounds on ΔSoE, each FCC is thus described by a five element vector $\overline{fcc}$:

$$\overline{fcc} = [\Psi_2, \Psi_1, \Psi_0, \Delta SoE_{min}, \Delta SoE_{max}]^t, \qquad (2)$$

where Ψ_0, Ψ_1 and Ψ_2 respectively correspond to the y-intercept, first and second-order coefficients of the polynomial, respectively; and where ΔSoE_{min} and ΔSoE_{max} determine the validity range for the FCC.

III. Inference of FCC from trip observations

Computing the optimal cumulated fuel consumption using DP, as presented in Section II, is computationally expensive. Hence, we advocate an approach where the FCC is estimated via DP for a set of trip elements. Then, polynomial regression can be used to link attributes of the trip elements to the FCC. Thus, the FCC associated to any new trip element can be estimated using this model, rather than computed via DP.

A. Descriptors

The dataset used in our study consists in real-world driving recordings of three different drivers. One of the drivers (driver 1) is a professional who had predefined trips with different precise driver style instructions (eco, normal, aggressive driving); the remaining two (drivers 2 and 3) are non-professionals who had the car to use for their daily work activities without any driving instruction given. More details on the recordings are given in Tab.I. During each trip, time, speed, longitude and latitude were recorded at a frequency of 1Hz. These data were then enriched with road description and traffic statistics. The recordings were first matched using the HERE API platform[21] to georeferenced trip elements. Then, the corresponding descriptors were added:

- the classification of the road according to its importance of the national network, or functional class (NAV_FC);
- the speed limit in km/h (NAV_SL);
- the global average speed recorded over a year (NAV_GAS) and the average traffic speed according to the day of week and time of day (NAV_ATS) in km/h;
- the road grade inclination in percentage (NAV_RG).

Adjacent trip elements with similar road and traffic context descriptors were then merged. Thus, each trip element corresponds to specific road and driving conditions (see e.g. Fig.3). Note that such scale of study based on micro-trips has

TABLE I
RECORDING DATABASE DETAILS

driver	nb. trips	nb. trip elements	distance traveled [km]
1	27	665	1867
2	260	4005	8481
3	294	4434	8172
Total	581	9104	18 522

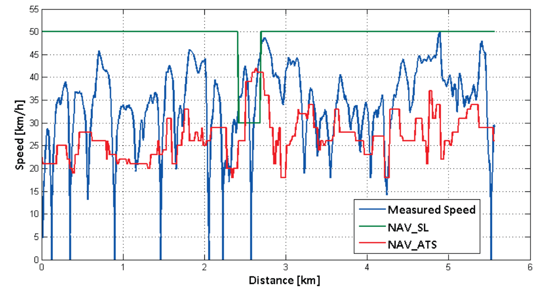

Fig. 3. Trip element example obtained after map matching for an urban road element

been proposed in [22] as a trade-off between instantaneous speed and global trip analysis, it has been developed in [23] using trip elements of constant length regardless of the road description. Finally, for each trip element, our database was further enriched with 28 features inspired by previous studies on ICEV fuel consumption [24], [1] focused on the speed profile.

B. FCC estimation

In [25], the type of a road element was predicted according its descriptive features via logistic regression. The study suggested that for any new trip element, once the corresponding category had been determined via classification, the corresponding FCC could be used to determine the optimal energy consumption strategy.

However, we may point out several limitations. Fig.4 displays a set of curves, computed over the trip elements of driver 1 of our database using offline DP corresponding to urban driving sequences with a speed limit of 50 km/h. It is obvious that even for the same road description, a strong dispersion of the FCC is observed, which suggests that a road type has to be linked to a group of FCC rather than to a single one. Moreover, the analysis of these families of curves for the various ARTEMIS categories (shown on Fig.2) shows that a given FCC may correspond to several road classes: for instance, the families of FCC corresponding to the "rural" and "highway" classes overlap. This justifies an approach where the FCC is determined from the descriptive features of the trip elements via regression rather than classification.

Following previous works [2], [26], we chose to focus our analysis on the impact of the driving behavior (more particularly, on the speed profile) on the FCC. For this reason, road grade and electrical auxiliaries, which have a significant influence on energy consumption, are treated separately and prior to our data analysis.

In order to explicit the influence of road grade on the FCC,

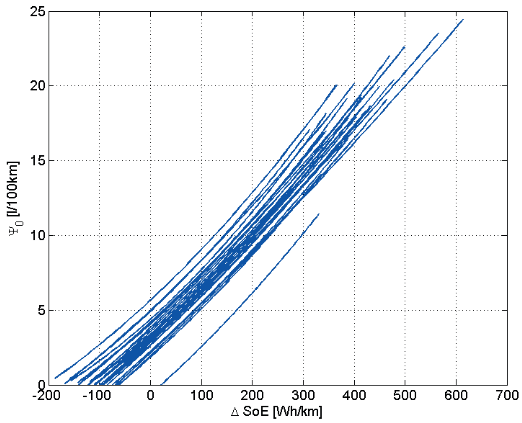

Fig. 4. Fuel Consumption Curves examples obtained using DP for a set of driving recording made on roads with a speed limit of 50 km/h

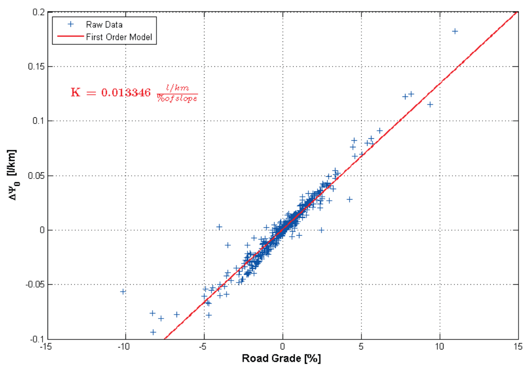

Fig. 5. Impact of road grade on Ψ_0

we conducted the following experiment. Each trip element was processed offline twice via DP: first by considering a constant zero road grade, and then by using its measured value (obtained from the navigation system). We remarked that integrating road grade when estimating the optimal fuel consumption strategy results in a vertical shift of the FCC. Thus, the difference between the corresponding y-intercepts Ψ_0^G and Ψ_0 (with and without taking road grade into account, respectively) corresponds to the additional cost (in terms of fuel consumption) that must be paid for this particular road grade. Fig.5 displays the difference $\Psi_0^G - \Psi_0$ as a function of road grade G. The results suggest that road grade can be taken into account by applying a linear correction to the y-intercept Ψ_0 estimated: $\Psi_0^G = \Psi_0 + K \cdot G$, where K is determined via linear regression from the data at hand.

In the same way, we propose to take the average auxiliary power into account by applying a correction term to the estimated FCC. Since the use of auxiliaries with power $\overline{P}_{aux}$ induces on average a constant electrical energy loss by distance $E_{aux} = \frac{\overline{P}_{aux}}{\overline{v}_i}$ on each road segment with average speed $\overline{v}_i$, we propose to apply a translation over the x-axis corresponding to the ΔSoE variation. The remaining of this study is focused on driving behavior impact with zero road grade and zero $\overline{P}_{aux}$ simulations.

Finally, we processed the FCC parameters obtained on the

TABLE II

CORRELATION ANALYSIS RESULTS

Characteristics	Ψ_0	$\Delta\Psi_0$	ΔSOE_{max}
DRV_VR_AVG	0,9		-0,71
DRV_V_MAX	0,89		-0,79
DRV_V_AVG	0,89		-0,71
NAV_ATS	0,83		-0,64
NAV_GAS	0,8		-0,64
NAV_SL	0,75		-0,55
DRV_PKE		0,83	
DRV_RPA		0,83	

trip elements of the database (and corresponding to zero road grade) using Principal Component Analysis (PCA). The results suggest that most of the variance in the data is explained by Ψ_0 and ΔSoE_{max}. The parameters Ψ_1 and Ψ_2 appear to be almost constant, and can therefore be replaced, in this context of energy consumption estimation, by their average values computed over the database. The value ΔSoE_{min} is highly correlated to Ψ_0 (which seems reasonable since it corresponds to the intersection abscissa of the FCC with the x-axis), and can thus be computed using estimates of Ψ_0, Ψ_1 and Ψ_2. These results thus suggest that the FCC can reasonably be estimated via the y-intercept Ψ_0, since it is the most characteristic feature of a FCC. The value of ΔSoE_{max} can be set to the limit battery recharge by the engine, for instance using the driveability constrains. Section III-C addresses how relevant features for predicting Ψ_0 may be identified using the data at hand.

C. Identification of relevant predictors

We present here how the FCC y-intercept Ψ_0 may be estimated from the descriptive characteristics of the corresponding trip element. First, we detail how the relevant predictors were identified via correlation analysis and PCA of the data at hand, focused on driving behavior so as to get rid of the influence of road grade, without neglecting its effect in the study (see Section III-B). Then, we show that a polynomial regression model may be fit to the resulting selected features in order to predict the value of Ψ_0.

The relevant features were identified as the ones with the strongest correlation to Ψ_0 and ΔSoE_{max}. The features with the highest correlation (absolute value greater than 0.7) are given in Tab.II. It may be seen that the average running speed (DRV_VR_AVG), average speed (DRV_V_AVG) and maximum speed (DRV_V_MAX) are strongly linked to selected FCC parameters, as well as the average traffic speed (NAV_ATS) are key variables to explain the y-intercept Ψ_0.

Note that Ψ_0 exhibits a large variance for trip elements with average speed under 80km/h (see Fig.6). This suggests that the average speed is not enough to precisely predict the value of Ψ_0. To refine the prediction of Ψ_0, we grouped the trip elements into classes according to their average speed (DRV_VR_AVG). Then, we introduced the difference $\Delta\Psi_0$ between the y-intercept Ψ_0 of the FCC and the average y-intercept of all FCC in the same road category. Correlation analysis shows that $\Delta\Psi_0$ is strongly correlated to speed

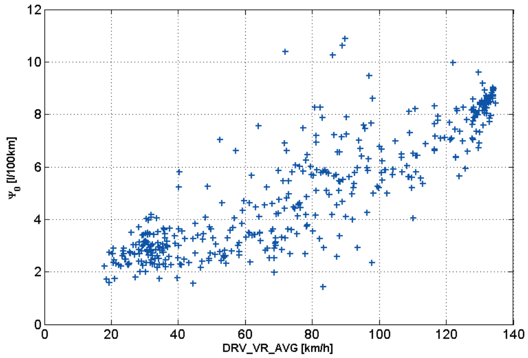

Fig. 6. FCC Ψ_0 versus segment average speed

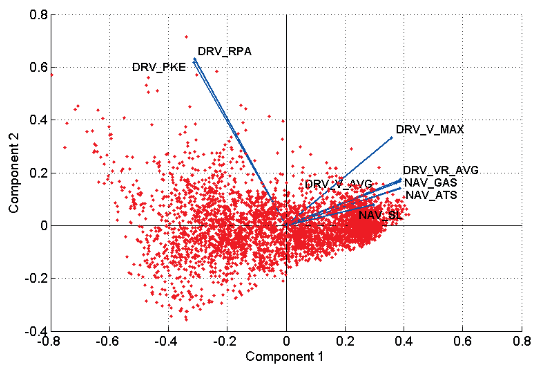

Fig. 7. PCA axes on predictors

oscillation characteristics such as relative positive acceleration (DRV_RPA) and positive kinetic energy (DRV_PKE) (see Tab.II). Furthermore, none of the available statistical road features obtained via map matching account for $\Delta\Psi_0$, which suggests that such "driving style" information must be measured on-board during driving and propagated in time. Remark that further study of road characteristics might allow to identify meaningful variables (such as the presence of intersections, traffic lights, or stop signs); however, predicting accurately the variation $\Delta\Psi_0$ according to these variables, many of which are qualitative, seems a challenge.

The relevant characteristics identified via correlation analysis were further processed using PCA (see Fig.7). The first two components explain 88.6% of the total variance. The first one corresponds to speed, and the second one to acceleration-related variables. Note that for each trip element, some of the variables (e.g., nominal speed or acceleration) are observed during a trip, and thus depend on driving conditions that may be difficult to predict (such as traffic or weather). From a formal point of view, they correspond to random variables, the realizations of which have to be predicted according to driving conditions. However, statistical descriptors (such as average speed) are computed over large sets of data, and may thus be interpreted as estimates of the expectations of the former variables. This suggests that the correlations between actual and expected (statistical) driving conditions might be exploited in an energy consumption optimization system. When predicting nominal values is likely to fail due to uncertain driving conditions, their statistical counterparts may instead be used to estimate the FCC parameters. Note that other driving characteristics, such as relative positive acceleration can also be propagated during the trip.

IV. Prediction performances

We report here a simple experiment to validate our fuel consumption estimation strategy. We considered the recordings of driver 2 (the process is similar for the others). First, we selected four trip recordings that will be used for testing the accuracy of our estimation process; those trips totalized 288 km of driving under various conditions. Using the remaining data, we estimated the y-intercept Ψ_0 as described in Section III-B, via polynomial regression. We used Matlab procedure for computing the best fitting polynomial, for different orders. In the best model, in term of trade-off between coefficient order and precision, DRV_VR_AVG and DRV_RPA are respectively second and fourth-order variables; the coefficient of determination is $R^2 = 0.82$ and the accuracy compared with training data in term of root mean square error ($RMSE$) equals to 0.61 l/100km. Fig. 8 displays a detailed representation of the generated model.

As mentioned in Section III-C, future vehicle speed and relative positive acceleration cannot be known in advance when a driver initiates a new trip. Then, DRV_VR_AVG can be approximated by NAV_ATS — note that we apply a correction according to the measured difference between NAV_ATS and the average driving speed measured over the past 300s. These latter speed values are also used to estimate DRV_RPA, which is then propagated to future road segments according to vehicle capabilities. When these estimates are used in place of the nominal speed and RPA values, the accuracy of the estimation process decreases to a RMSE=0.64 l/100km.

V. Conclusions and perspectives

In this paper, we presented an approach for estimating the optimal energy consumption of a PHEV based on a dataset of driving recordings. First, we showed that the optimal consumption strategy obtained via Dynamic Programming, represented by a fuel consumption curve, can be modeled by a second-order polynomial. Furthermore, we identified the descriptive features of the driving conditions that can be used to predict the coefficients of this polynomial. Our approach consists in learning the coefficients using a database of trip recordings.

Then, for any new set of values describing the driving conditions on a trip element, the optimal consumption strategy is determined by retrieving the corresponding coefficients. Note that future driving conditions can be estimated by using describing statistics of the corresponding road element, or by propagating the observed driving characteristics of the driver. The results obtained on real data show that our approach makes it possible to accurately estimate the optimal fuel consumption using observed or estimated driving features.

The approach presented in this paper is part of a trip-scaled global battery discharge optimization system based

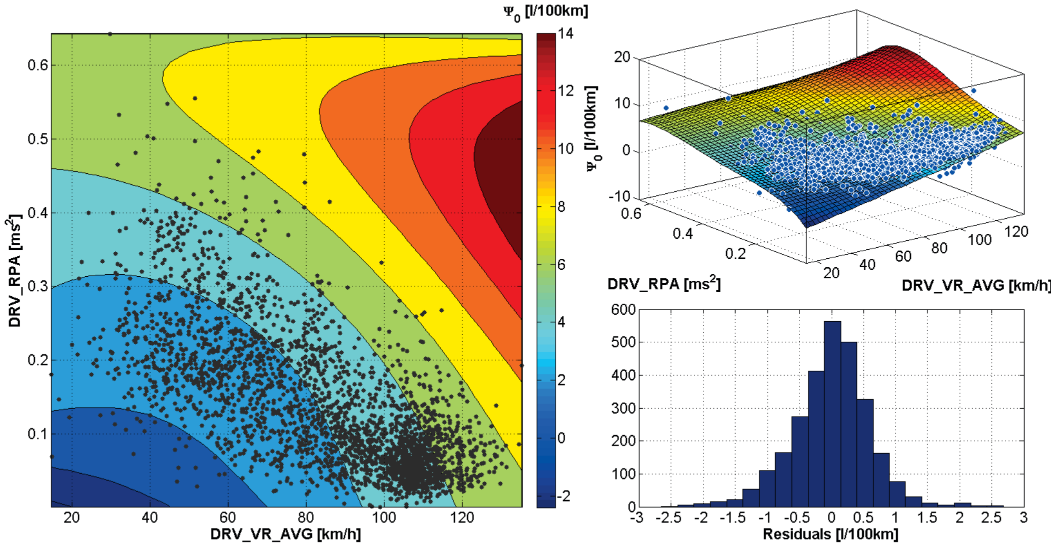

Fig. 8. FCC Ψ_0 regression model

on route preview information. In future work, the optimal consumption strategies specific to trip elements will be used in a global energy management system. Such a system consists in computing the globally optimal battery discharge trajectory with a local real time energy management system to evaluate potential savings in term of fuel consumption.

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