

Context and Driver Dependent Hybrid Electrical Vehicle Operation [★]

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Abstract: This paper studies the driver and context changes during the operation of a hybrid electric vehicle (HEV) and their influence on fuel consumption. Firstly, a context estimation model to recognize driving styles is developed based on machine learning techniques, for which a realistic scenario with simulation of urban mobility (SUMO) and car modeling platform (IPG Carmaker) integration is designed. Secondly, a novel context-aware control strategy based on model predictive control with extended prediction self-adaptive control (MPC-EPSAC) strategy is proposed. The control objective is to achieve optimal torque-split distribution, while optimizing fuel consumption in the parallel HEV. The simulation results suggest that an improvement in fuel economy can be achieved when the driving style in the control loop is adequately considered.

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1. INTRODUCTION

Context-aware vehicular systems have gained intensive attention from the automotive industry and academia, because this concept is essential for advanced driver assistance, safety, fuel efficiency and transportation networks. The context information applied on vehicles topic relates to any information that describes the driving situation such environment information, system-and-application, and context awareness (Vahdat-Nejad et al. (2016)). Based on the driving context information, CASs adapt to the changing driving events.

Context awareness is integrated in Advanced Driver Assistant Systems (ADAS), providing improvement of knowledge about the states of the car, the external conditions

and the driver's psychological state (e.g., attention, fatigue levels). Based on context-aware driving style detection, applications for ADAS, safety and fuel efficiency are further discussed.

A brief literature survey reveals that classification of driver behaviours typically depends on the objective of the application. The driving style has an essential impact on fuel consumption and safety, as well as the technological characteristics of the car and the road conditions as it was reported in Vaiana et al. (2014), Xiong et al. (2020). Therefore, the awareness of the driver's state, along with recognition of driving style and intention inference plays the most important role in CASs. The data about driving pattern (e.g., acceleration, speed), traffic conditions (e.g., location of the personal cars and other in the traffic) and environmental information (e.g., slippery road, bumps) can be acquired through the available sensors integrated in the cars or through other technologies (e.g., Global Positioning System (GPS)).

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A complete example of intelligent management system is the HEV (hybrid electrical vehicle). The operation of an HEV takes place in a fast changing environment and human behaviour has critical consequences upon the performance of the system as a whole. Changing settings as ECO, SPORT, SAFE modes require a self-optimization of the delivered torque as a function of context. Some studies have been developed to reduce the fuel consumption of a series/parallel hybrid electric bus based on roadway types and traffic conditions (Zhang and Xiong (2015), Li et al. (2016), Lin and Li (2019)).

Currently, the human related information integrated into the system is not exploited at its full potential. For instance, if multi-loop and multi-level information flow are used for self-detection of events (driver sleepy) then performance or road safety can be optimized. Similarly, as mentioned above, the driving style has an essential impact on fuel consumption. This paper proposes to incorporate driving styles (aggressive and calm driver) into an adaptive energy management system to optimize the torque split between the internal combustion engine (ICE) and the electric motor (EM) to improve fuel economy.

This paper is organized as follows. Section 2 describes the context estimation block for driving style based on machine learning techniques. A brief description of the parallel HEV model is given in section 3. The adaptive energy management system based on the model predictive control with extended prediction self-adaptive (MPC-EPSAC) strategy is proposed in section 4. The simulation results and discussion are presented in section 5. Finally, the conclusions are summarized in section 6.

2. CONTEXT ESTIMATION

This section discusses the design of the context estimation block, providing the driving style classification. Two types of driving styles (aggressive and calm driver) are considered in this paper. In recent years, this topic has received a great deal of attention from the scientific community, especially in the automotive area, to incorporate in the design of intelligent vehicles the capability to detect driver states and driving style. It can be used to warn the driver of possible problems and (over)take control in emergency situations (e.g. driver asleep). Some applications related to early warning systems for safe driving have been developed through the use of smartphones (Arroyo et al. (2016), Li et al. (2019)). The context estimation block consists of the following four main stages:

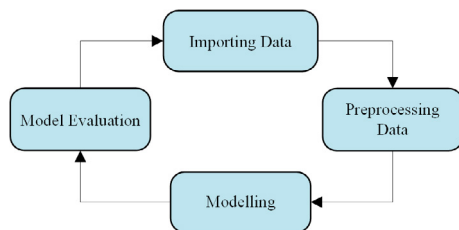


Fig. 1. Design and validation stages for the context estimation block

2.1 Driving Database

The first step in designing the context estimation block is to have information based on a driving database. This dataset has been generated using SUMO and IPG Carmaker integration (Codeca and Härrri (2017)). SUMO allows modelling of intermodal traffic systems including road vehicles, public transport and no vehicle dynamics (Lopez et al. (2018)). IPG Carmaker is a simulator for Model-Based Design, development and vehicle dynamics tests such as cars, motorcycles and trucks. The objective of this integration is to obtain detailed and more realistic vehicle data (i.e. pedal positions, gear shifts, steering wheel angles, etc.) from SUMO vehicle simulation data. Therefore, SUMO provides to IPG Carmaker the information of vehicle position (x,y,z), velocity profile (based on distance & time based) and driving style. A labeled dataset is generated from IPG CarMaker, which contains vehicle information.

2.2 Preprocessing Data

The dataset is prepared for classification, considering three steps:

- (1) *Split data*: The dataset is divided in two parts: training (70 %) and evaluation (30 %) data.
- (2) *Remove correlated variables*: The first step in selecting relevant features is to filter out highly correlated variables based on a manually specified threshold. A threshold=0.95 is selected for our application. The correlation matrix is depicted in Fig. 2. However, in this case, the correlation coefficients remain relatively low (< 0.9).

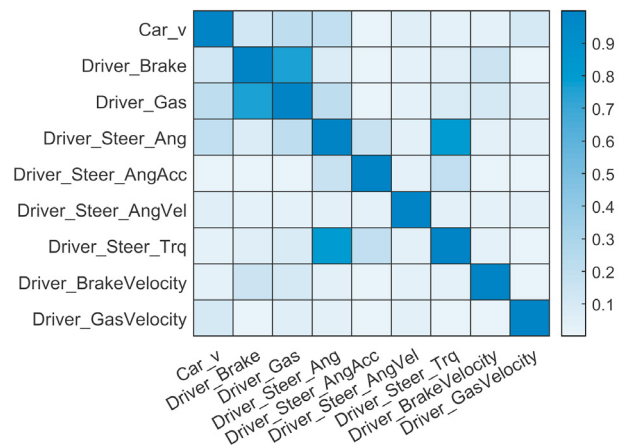


Fig. 2. Correlation matrix

- (3) *Feature Selection*: After filtering out highly correlated variables, the next step is to select the most contributing features correlated with the driving style labels. In order to minimize the effect of fluctuation in feature values and characterize the feature distribution effectively, we adopted the statistical feature values such as mean, minimum, maximum, and standard deviation. In addition, a recursive feature elimination based on wrapper forward method (Panthong and Srivihok (2015)) is applied to remove dependencies

that may exist in the model. A list of the final selected features from the dataset is summarized in table 1.

Table 1. Selected features

Dataset	# features	Description
IPG Carmaker	8	Gas pedal max
		Steering torque max
		Gas pedal mean
		Braking std. deviation
		Speed max
		Braking speed min
		Gas pedal std. deviation
		Gas pedal speed std. deviation

2.3 Modelling

Machine learning methods have been studied in previous works to explore driver behaviour and driving style detection. The results show a good performance of these algorithms e.g. decision tree, random forest, k-nearest neighbors (K-NN) algorithm, multilayer perceptron (MLP), etc. (Li et al. (2019), Pedregosa et al. (2011) Ferreira et al. 2017). Among these methods, the Random Forest (RF) algorithm demonstrates a better accuracy, precision, and recall under different scenarios. Besides, RF has the lowest calculation time compared to the other algorithms. Here, the RF algorithm will be used to design the driving style classifier.

The RF algorithm has different parameters that can be selected to improve the estimation accuracy. These parameters are chosen based on hyperparameters selection method (Wu et al. (2019)) such as moving window. For each of these windows, a number of statistics (e.g. mean, variance, minimum and maximum) are calculated. Fig. 3 shows the results of this selection, where the most optimal window size is obtained with 20s.

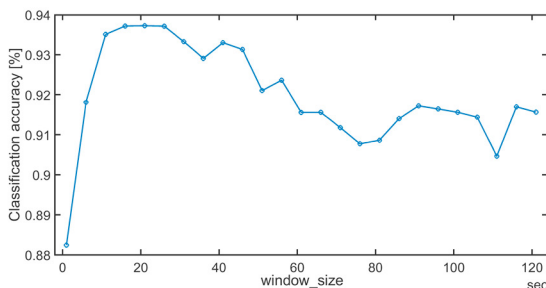


Fig. 3. Influence of rolling window

2.4 Model Evaluation and Post-processing Data

There are several methods to evaluate the classification model trained based on the evaluation dataset described in section 2.2. Classification accuracy and confusion matrix are chosen for this purpose.

The classification accuracy represents the number of correctly predicted labels with respect to the total number of predictions. Alternatively, the confusion matrix gives an overview of the different normalized classification accuracies (true/false positive/negative rates). The results with both evaluation methods are presented in Fig. 4 and Fig. 5.

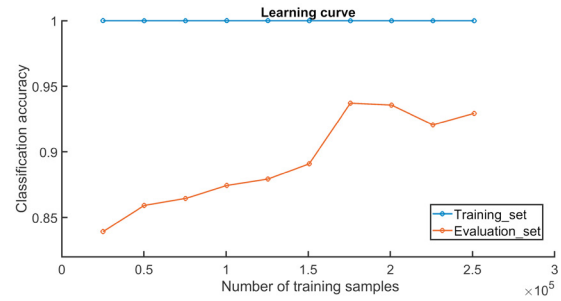


Fig. 4. Accuracy versus number of training samples for the driving style model

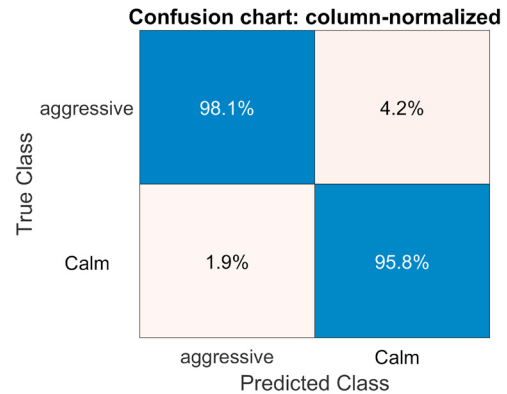


Fig. 5. Confusion matrix example

Fig. 4 shows that by using training samples $> 1.5 \times 10^5$, a classification accuracy $> 94\%$ in the evaluation process is obtained, thus avoiding overfitting.

On the other hand, the confusion matrix in Fig. 5 reveals that the algorithm used achieves a true positive classification of 98.1% with the aggressive class and 95.8% with the Calm class. Besides, the classification algorithm gets a false positive of 1.9% with the aggressive class and 4.2% with the Calm class. These results indicate that the classifier has an average accuracy of 96.9% for the driving style recognition.

3. HEV MODEL DESCRIPTION

For this study, a parallel HEV configuration is considered as the benchmark testing platform. It consists of two power sources (i.e., electric motor (EM)/battery and a gasoline Internal Combustion Engine (ICE)) mechanically coupled to the transmission. The parallel HEV powertrain structure is shown in Fig. 6.

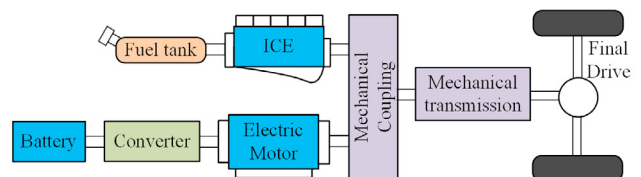


Fig. 6. Parallel HEV powertrain structure

In this paper, we use simplified models of each HEV subsystem, as the detailed dynamics have little effect on the entire system performance. The parameters of the HEV and vehicle are given in Table 2.

3.1 Internal Combustion Engine model

Our study focuses on the characteristics of fuel consumption. Hence, the dynamic response of ICE torque is simplified as a second-order process (See Zheng (2011), Alt et al. (2013)):

$$T_{ICE} = \frac{8.33}{0.25s^2 + 0.7s + 1} U_{ICE} \quad (1)$$

where, U_{ICE} is the engine control signal. The fuel flow rate can be estimated as:

$$\dot{m}_{fuel} = \alpha \cdot \omega_{ICE}^2 + \beta \cdot T_{EM} \cdot \omega_{ICE} \quad (2)$$

where, α and β are constants (See Kohut et al. (2009)).

3.2 Electric Motor Model

Similarly to the ICE, the dynamics of the EM also can be simplified as a second-order process (See Zheng (2011), Alt et al. (2013)):

$$T_{EM} = \frac{13.63}{0.25s^2 + s + 1} U_{EM} \quad (3)$$

where, U_{EM} is the motor control signal. The relation between the power into the EM and battery state of charge (SOC) is represented in Fig. 7.

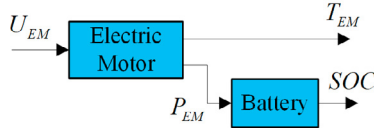


Fig. 7. EM and battery model structure

3.3 Battery Model

The battery can be modeled as a resistive Thevenin equivalent circuit model (Yan et al., 2012). Therefore, the actual SOC of the battery can be calculated as:

$$SOC = SOC_{init} - \frac{3.9216e^{-07}}{s(0.5s + 1)} P_{EM} \quad (4)$$

where SOC_{init} is the initial battery SOC. P_{EM} is the power into the EM and it can be calculated as:

$$P_{EM} = \frac{\omega_{EM} \cdot T_{EM}}{\eta(\omega_{EM} \cdot T_{EM})} \quad (5)$$

where, $\eta(\omega_{EM} \cdot T_{EM})$ is the EM power efficiency.

Table 2. Basic parameters of the Parallel HEV

Component	Value
Gasoline ICE	Nominal power 90 kW Peak torque 750 Nm
Electric motor	Nominal power 110 kW Peak torque 1500 Nm
Battery	Capacitance 4.4 kWh
Vehicle curb weight	1380 kg
Wheel radius	0.3 m
Frontal area	2.5 m ²
Drag coefficient	0.2
Air density	1.2 kg/m ³
Rolling friction coefficient	0.02

3.4 Vehicle Model

The longitudinal vehicle dynamics is described as:

$$m \cdot \frac{dv}{dt} = \frac{T_{driver}}{r_w} - \frac{1}{2} \rho A_f C_d v^2 - m \cdot g \cdot c_r \quad (6)$$

where, m is the vehicle mass, v is the vehicle speed, C_d is the drag coefficient, A_f is frontal area of the vehicle, ρ is the air density, r_w is the wheel radius, c_r is the rolling friction coefficient and T_{driver} is the driver request torque. The driveability constraint requires that:

$$T_{driver} = T_{ICE} + T_{EM} \quad (7)$$

4. ADAPTIVE CONTROL STRATEGY

The proposed HEV control strategy consists of a speed tracking controller and a MPC-EPSAC (Extended Prediction Self-Adaptive Control) algorithm as depicted in Fig. 8. This section does not describe in detail the EPSAC formulation as it has been previously extensively described in several works (Fernandez et al. (2019), Ionescu and Copot (2019)).

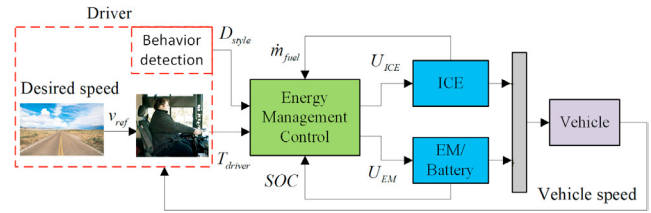


Fig. 8. Driver-in-the-loop control strategy

The speed tracking controller simulates the drivers decision on requested torque based on the desired and actual vehicle speeds. Here, a typical proportional integral (PI) controller is used for this purpose. Meanwhile, MPC-EPSAC controller optimizes the torque split between the internal combustion engine (ICE) and the electric motor (EM) in order to minimize fuel consumption. A cost function that minimizes the fuel consumption and tracks a predefined level of battery SOC while following a driving cycle is proposed as follows:

$$J = \sum_{k=N_1}^{N_2} w_1 [SOC_{ref}(t+k|t) - SOC(t+k|t)]^2 + w_2 [\dot{m}_{fuel}(t+k|t)]^2 \quad (8)$$

subject to

$$\begin{aligned} T_{EM_{min}} &\leq T_{EM} \leq T_{EM_{max}} \\ T_{ICE_{min}} &\leq T_{ICE} \leq T_{ICE_{max}} \\ T_{driver} &= T_{ICE} + T_{EM} \\ SOC_{min} &\leq SOC \leq SOC_{max} \end{aligned} \quad (9)$$

where, \dot{m}_{fuel} is the fuel flow rate, N_1 is the minimum prediction horizon; N_2 is the maximum prediction horizon and SOC_{ref} is the reference SOC.

Note that J is a composite objective function based on the weighted-sum method (Marler and Arora (2010)) and their inputs are normalized ($SOC, \dot{m}_{fuel} \in (0, 1)$). Hence, the weighting parameters are chosen such that $w_i > 0$ and $w_1 + w_2 = 1$.

The adaptive control strategy is based on the driving cycle with driving style to select the corresponding close-to-optimal control parameters. In this way, the adaptive effect of the execution for each detected driving style is obtained. The current driving style is provided by the context estimation block and represented by the Boolean variable (D_{style}).

On the other hand, the control parameters are the weighting factors w_1 and w_2 of the objective function defined in eq. (8). This set of parameters (w_1, w_2) are obtained according to the current context (aggressive/calm) with rule-based approach to adapt the weighting factor of the MPC-EPSAC. This gradient search for the close-to-optimal parameter set is performed offline using the driving cycle and context change. In addition, it is important to indicate that the proposed approach is a long-term control for fuel economy (i.e. it has the greatest impact on long-distance trajectories).

5. SIMULATION RESULTS AND DISCUSSION

The simulation is conducted for a parallel HEV model using MATLAB. The requested torque is generated by the PI controller based on the driving cycle shown in Fig. 9, with different parameter settings (speed, acceleration, deceleration, etc) for each type of driver (aggressive and calm).

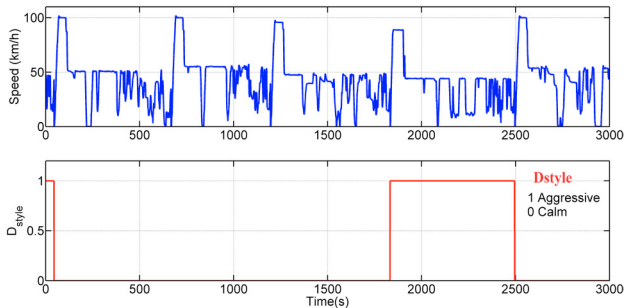


Fig. 9. Driving cycle and context information

The PI controller parameters are defined by $k_p = 0.2$ and $k_i = 0.15$ as its proportional and integral terms, respectively. This torque request (T_{driver}) is one of the inputs to the energy management control (MPC-EPSAC) as well as battery SOC, fuel flow rate (\dot{m}_{fuel}) and current driving style (D_{style}). The adaptive controller proposed in this paper is compared with the normal control without driving style information.

The close-to-optimal parameters for this controller are calculated exploring the influence of the weighting-parameters on the objective function described in eq. (8). An initial SOC of 0.5 is chosen with lower and upper bounds of $SOC_{min} = 0.2$, $SOC_{max} = 0.8$, with a reference SOC of 0.3. MPC-EPSAC parameters are set to $N_1 = 1$, $N_2 = 15$, sampling period $T_s = 0.2s$, and control horizon ($N_u = 1$). The results with different weighting-parameters are depicted in Fig. 10.

The close-to-optimal weighting parameters obtained for the normal controller are $w_1 = 0.7$ and $w_2 = 0.3$. The parameters for the adaptive controller are obtained based on the ruled-based approach in each driving style. These

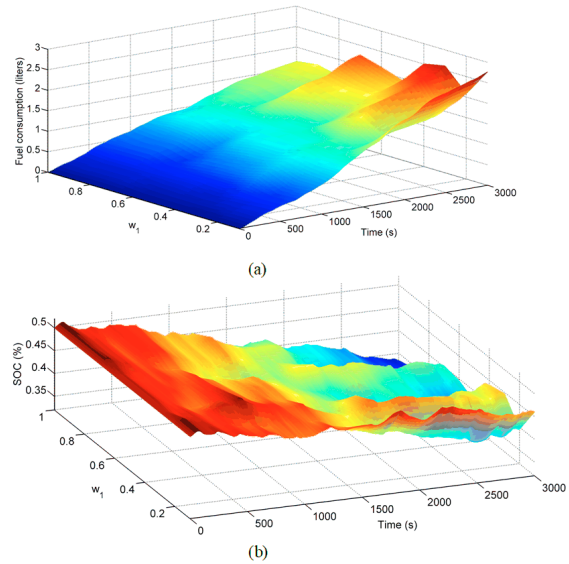


Fig. 10. Influence of weighting parameters on (a) fuel consumption, (b) battery SOC

parameters are defined for aggressive driver case ($w_1 = 0.7$, $w_2 = 0.3$) and calm driver case ($w_1 = 0.9$, $w_2 = 0.1$). The comparison results for both controllers is shown in Fig. 11 and Fig. 12.

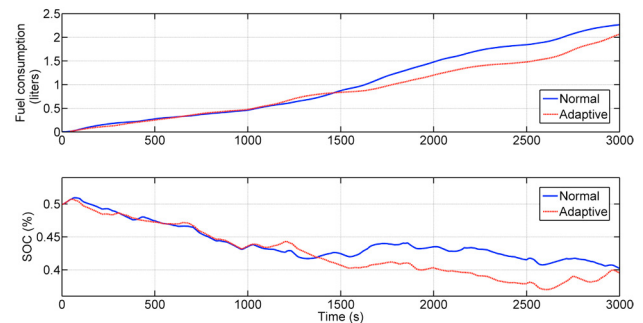


Fig. 11. Comparison of fuel consumption results with normal control and context-aware control

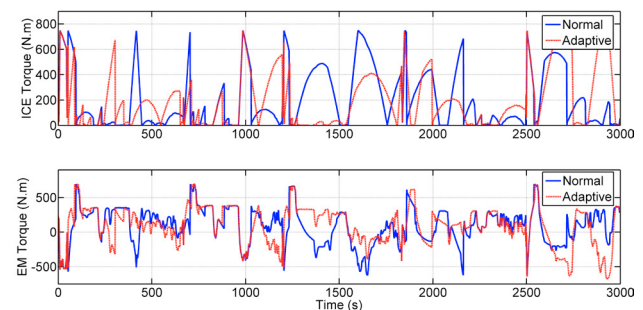


Fig. 12. Comparison of torque-split results with normal control and context-aware control

According to Fig. 11, the battery has an initial SOC of 50% at the beginning of the driving cycle and the vehicle works more in the electric mode. Hence, on certain occasions the ICE is off to minimize the fuel consumption (see Fig. 12), while the battery is discharged towards the predefined reference SOC. Finally, the fuel economy performance of

the adaptive control is improved by 8.83% compared to the normal control. This is equivalent to a fuel economy of 0.2 liters for a trip of around 50 min.

6. CONCLUSIONS

This paper illustrated the dependency of fuel consumption on driver context changes for an HEV. According to the results, a fuel economy improvement of 8.83% is achieved with the context-aware control proposed by including only the driving style information. The next step in this research is to analyze fuel economy, when additional information about road type combined with driving style is incorporated. Additionally, control strategies based on driving cycle information, road type, driving style operation can be used for applications of autonomous fleets/connected car ecosystem, in which the trajectories are previously established based on demand/utility/priority/traffic density/regulatory issues (e.g. Pendelbus, Post, AEDs).

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