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Data-based speed-limit-respecting eco-driving system

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ABSTRACT

The paper describes application of data-based Bayesian approach to model identification and control problems in the field of fuel consumption optimization for conventional vehicles. The main contributions of the presented approach are: (i) analysis of data measured on a driven vehicle; (ii) data-based model construction, its real-time estimation and adaptation; (iii) control criterion using simultaneously setpoints for fuel consumption and speed; and (iv) universal recursive Bayesian algorithms of estimation and control implemented as semi-automatic eco-driving system. Experiments with real data report reduction in fuel consumption.

1. Introduction

Reducing fuel consumption and CO_2 emissions is the important problem that concerns both the automotive industry and drivers. Eco-driving is a variety of solutions and techniques designed to solve this problem.

Conceptual eco-driving solutions such as hybrid and electric vehicles are intensively developed by the automotive industry, see e.g., Pistoia (2010), Wirasingha and Emadi (2011) and Moura et al. (2011). They are environmentally friendly and promise significant fuel savings. However, their purchase price is still rather high (although in recent years it is reduced) due to the increased complexity of the powertrain, which compensates fuel savings. This supports a demand for conventional vehicles with combustion motors in the market.

Solutions proposed in this field for conventional vehicles can have a form of in-vehicle assistance or automatic eco-driving systems. The first of them inform the driver about fuel consumption, advise when and which gear shift is appropriate, etc. They are based on changes in driving style so that fuel consumption is reduced. Influence of driving style on fuel consumption is considered in many studies reporting fuel savings due to the use of eco-driving systems (Sivak and Schoettle, 2012; Strömberg and Karlsson, 2013; Vagg et al., 2013; Nozaki et al., 2013; Larsson and Ericsson, 2009).

In this paper we focus on automatic eco-driving systems which actively intervene in the process of a vehicle control. Algorithms for them are intensively studied. Approaches based on reducing dynamics in speed in traffic flow are presented in Saboohi and Farzaneh (2009), Barth and Boriboonsomsin (2009) and Raubitschek et al. (2011). Estimation of fuel consumption model is proposed in Ben Dhaou (2011). Advanced control approaches considering influence of external road characteristics on fuel consumption are addressed in Hellstrom (2005), Park et al. (2012) and Kamal et al. (2011). Model predictive control algorithms oriented at eco-driving are reported in Kamal et al. (2013).

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Most of the found methods are based on the use of a physical model of fuel consumption. In contrast, this paper focuses on statistical analysis of data continuously measured during driving and presents a purely data-based Bayesian approach Kárný et al. (2005) to estimation and control in the fuel consumption optimization field. A driven vehicle is considered as a system, observable and to be controlled. The main idea is to formulate the eco-driving task as a servo problem, where the control criterion includes setpoints both for fuel consumption and vehicle speed. These setpoints are desired values of instantaneous fuel consumption and recommended route-dependent speed respectively. The aim is to design an optimal control, balancing between these two demands and respecting speed limits. As the main optimized control variable is pressing the gas pedal, the developed algorithms are intended for implementation as semi-automatic eco-driving (intervening) system, leaving a possibility of its fast turn-off and turn-on by the driver during driving.

Specific aims the present paper deals with are as follows:

- select the most informative variables from preliminarily available measurements;
- construct a *data-based* model of the observed driver-vehicle system including the model structure estimation;
- estimate model parameters in real time using actual data;
- design the control, in real time minimizing fuel consumption and simultaneously penalizing deviations of speed from the recommended speed for the given route;
- validate the control using software vehicle simulator and real vehicle on the considered route.

Possibility of real-time recursive estimation and adaptation of the observed and controlled system is one of the key features of the presented systematic approach. This opens the way to its further extension not limited by the application domain, however rather by availability and informativeness of data.

The pre-given limit-respecting recommended speed, extracted from optimal eco-driving measurements on the known route, is one of the current limitations of the approach. Modeling and estimation of optimal recommended speed for unknown route (not computed from the current speed of traffic flow) will be addressed elsewhere.

The layout of the paper is organized as follows. Section 2 provides theoretical background of used algorithms. Section 3 describes their application to modeling a driver-vehicle system, its estimation and control with the aim of reducing fuel consumption. Section 4 is devoted to validation of the proposed control and presents results reporting efficiency of the described approach. Conclusion and plans of future work can be found in Section 5.

2. Theoretical background

This section introduces necessary theoretical and algorithmic bases that applied further for the problem solution.

2.1. Model

We consider a system which produces a vector of observable outputs $y_t = [y_{1;t}, \ldots, y_{n_y;t}]'$ influenced by the control input vector $u_t = [u_{1;t}, \ldots, u_{n_u;t}]'$ and by a vector of external disturbances $v_t = [v_{1;t}, \ldots, v_{n_v;t}]'$ at discrete time instants $t \in \{1, \ldots\} \equiv t^*$, where n_y, n_u and n_v are dimensions of column vectors y_t, u_t and v_t respectively. Let us denote the data $d_t \equiv \{y_t, u_t, v_t\}$ and $d(t) = \{d_0, d_1, \ldots, d_t\}$, where d_0 denotes a prior information.

The system is described by the conditional probability density function (pdf)

$$f(y_t|\psi_t, \Theta), \tag{1}$$

where

- $\psi'_t = [u'_t, v'_t, y'_{t-1}, u'_{t-1}, v'_{t-1}, \ldots, y'_{t-n}, u'_{t-n}, v'_{t-n}, 1]$ is a regression vector,
- n is the model order
- and Θ are model parameters to be estimated.

In the paper, pdf (1) is taken as the multivariate normal regression model

$$y_t = \psi'_t\theta + e_t = b_0u_t + c_0v_t + \sum_{i=1}^{n}(a_iy_{t-i} + b_iu_{t-i} + c_iv_{t-i}) + k + e_t, \tag{2}$$

where

- $[b_0, c_0, a_1, b_1, c_1 \ldots, a_n, b_n, c_n, k] = \theta'$ are regression coefficients,
- e_t is the normally-distributed noise with zero mean and a fixed covariance matrix r
- and $\Theta \equiv \{\theta, r\}$.

2.2. Model structure estimation

The model order n can be determined using the so-called structure estimation. For this purpose, data d_τ preliminarily measured for discrete time instants τ with $\tau^* \notin t^*$ are normalized so that they have zero mean values and unit variances. It means that for each data item $d_{j;\tau}$ with $j \in \{1, \ldots, (n_y + n_u + n_v)\}$ it is performed

$$d_{j;\tau} = \frac{d_{j;\tau} - \hat{d}_{j;\tau}}{\sigma_{j;\tau}}, \tag{3}$$

where $\hat{d}_{j;\tau}$ denotes the mean value of the corresponding variable and $\sigma_{j;\tau}$ – its standard deviation. The normalized data are then prepared to be used for the least squares method estimation. The data are substituted to equations of model (2) in a row, one under another, for each time instant $\tau = \{1, \ldots, N_\tau\} \equiv \tau^*$ until they take the following matrix form

$$\underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \ldots \\ y_{N_\tau} \end{bmatrix}}_{Y} = \underbrace{\begin{bmatrix} \psi'_1 \\ \psi'_2 \\ \ldots \\ \psi'_{N_\tau} \end{bmatrix}}_{\Phi'} \underbrace{\begin{bmatrix} b_0 \\ c_0 \\ a_1 \\ b_1 \\ c_1 \\ \ldots \\ a_n \\ b_n \\ c_n \\ k \end{bmatrix}}_{\theta} + \begin{bmatrix} e_1 \\ e_2 \\ \ldots \\ e_{N_\tau} \end{bmatrix}, \tag{4}$$

where the matrix Φ' contains rows of regression vectors $\psi'_\tau = [u'_\tau, v'_\tau, y'_{\tau-1}, u'_{\tau-1}, v'_{\tau-1}, \ldots, y'_{\tau-n}, u'_{\tau-n}, v'_{\tau-n}, 1], \forall \tau \in \tau^*$, of some pre-chosen maximal order n. According to the well-known least square method, the vector of parameter point estimates is obtained

$$\hat{\theta} = (\Phi\Phi')^{-1}\Phi'Y. \tag{5}$$

The obtained entries of this vector are compared with some pre-determined level (for example, 10%) from the biggest of them. Those which do not exceed this level are rejected from the model along with delayed variables corresponding to these parameters. Delayed variables $d_{\tau-n}$ with the order n corresponding to parameters a_n, b_n, c_n exceeding this level are selected for the model. Nice illustration of this approach to the model order selection is given in Fig. 1, where it can be seen which delayed variables have the biggest influence on modeled ones.

If composition of the data vector is not assumed to change qualitatively (in a sense of addition of new variables), the model structure estimation can be performed preliminarily once off-line.

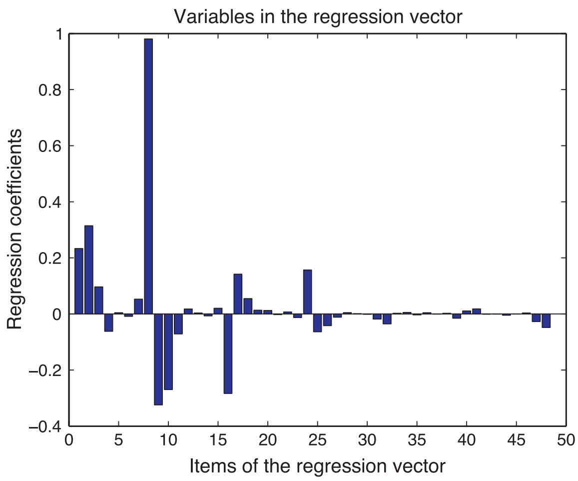


Fig. 1. Regression coefficients of delayed variables in regression vector. Variables with very small coefficients have negligible influence to modeled variables.

2.3. Parameter estimation

Using data $d(t)$ including actual measured d_t, parameters $\Theta \equiv \{\theta, r\}$ have to be estimated recursively. Under Bayesian methodology Kárný et al. (2005), the pdf of unknown parameter Θ is evolved in time in the following way:

$$f(\Theta|d(t)) \propto f(y_t|\psi_t, \Theta) f(\Theta|d(t-1)), \tag{6}$$

where $\propto$ means proportionality (quality up to the normalization constant) and $f(\Theta|d(t-1))$ denotes a prior pdf at the time instant $t-1$. In case of the normal regression model (1) the parameter estimation (6) reduces to a straightforward recursive computation of statistics with a conjugated prior Gauss-inverse-Wishart (GiW) pdf. This recursion can be found in many sources, e.g. Peterka (1981) and Kárný et al. (2005). Here, we will describe it briefly. The multivariate model (1) is written in the form

$$f(y_t|\psi_t, \Theta) = (2\pi)^{-n_y/2}|r|^{-1/2} \exp\left\{-\frac{1}{2}[y_t - \theta'\psi_t]' r^{-1} [y_t - \theta'\psi_t]\right\} = (2\pi)^{-n_y/2}|r|^{-1/2} \exp\left\{-\frac{1}{2} tr\left(r^{-1}\begin{bmatrix}-I\\ \theta\end{bmatrix}' D_t \begin{bmatrix}-I\\ \theta\end{bmatrix}\right)\right\}, \tag{7}$$

where tr denotes a trace of a matrix, I is the unit matrix of the appropriate dimension and

$$D_t = \begin{bmatrix} y_t \\ \psi_t \end{bmatrix} [y\prime_t, \psi\prime_t] \tag{8}$$

is the data matrix at time t. The conjugated prior GiW pdf has the following form

$$f(\Theta|d(t-1)) \propto r^{-0.5k_{t-1}} \exp\left\{-\frac{1}{2} tr\left(r^{-1}\begin{bmatrix}-I\\ \theta\end{bmatrix}' V_{t-1} \begin{bmatrix}-I\\ \theta\end{bmatrix}\right)\right\} \equiv GiW_\Theta(V_{t-1}, k_{t-1}), \tag{9}$$

which is reproduced during estimation for the posterior pdf $f(\Theta|d(t))$ in (6). The statistics of (9) are the information matrix V_{t-1} and the counter k_{t-1}. With the help of substituting (7) and (9) in (6), the statistics are recursively computed with chosen initial statistics as follows:

$$V_t = V_{t-1} + D_t = V_{t-1} + \begin{bmatrix} y_t \\ \psi_t \end{bmatrix} [y'_t, \psi'_t] = V_{t-1} + \begin{bmatrix} \underbrace{y_t y'_t}_{V_{y_t}} & \underbrace{y_t \psi'_t}_{V'_{y\psi_t}} \\ \underbrace{\psi_t y'_t}_{V_{y\psi_t}} & \underbrace{\psi_t \psi'_t}_{V_{\psi_t}} \end{bmatrix} \tag{10}$$

$$k_t = k_{t-1} + 1. \tag{11}$$

The updated information matrix V_t is partitioned according to (10), i.e.,

$$V_t = \sum_{t=1}^{N} \begin{bmatrix} V_{y_t} & V'_{y\psi_t} \\ V_{y\psi_t} & V_{\psi_t} \end{bmatrix}, \tag{12}$$

and the point estimates of parameters θ and r at time instant t are computed as

$$\hat{\theta}_t = V_{\psi_t}^{-1} V_{y\psi_t} \text{ and } \hat{r}_t = \frac{V_{y_t} - V'_{y\psi_t} V_{\psi_t}^{-1} V_{y\psi_t}}{k_t}, \tag{13}$$

respectively.

The described procedure can be used both for pre-estimation from prior data and for real-time estimation from actual measured data.

2.4. Control

Our main aim is to control the considered system. However, according to Feldbaum (1961), the dual control is not feasible. Thus we should use a suboptimal solution to adaptive control, i.e., substitute point estimates obtained separately in the time cycle as fixed parameters during the control design. In other words, control with known parameters is considered.

The optimal control is achieved by minimization of expectation of the following quadratic criterion

$$Q = \min_{u(T)} E\left[\sum_{t=1}^{T} Q_t | d_0\right], \tag{14}$$

where

- $E[\cdot]$ denotes the expectation to be minimized,

- T is the control horizon,
- $u(T) \equiv \{u_1, u_2, \ldots, u_T\}$ are the control input values for time $t = 1, 2, \ldots, T$,
- Q_t is the loss function at each time instant t such that

$$Q_t = (y_t - s_t)' \omega (y_t - s_t) + (u_t - u_{t-1})' \lambda (u_t - u_{t-1}), \tag{15}$$

where the expectation of y_t (i.e., its prediction) using model (2) with the substituted point parameter estimates from (13) should be used (notice E in (14)),

- and ω and λ are weight vectors of dimensions n_y and n_u respectively.

Such formulation of the control criterion (14) and the loss function (15) expresses that the demand is to have outputs in the vector y_t as close as possible to their desired values given in the vector s_t, and, at the same time, control values should not change too sharp and rapidly. In other words, it is necessary to penalize (i) deviations of entries of the vector y_t from entries of the vector of setpoints s_t and (ii) the input increments in order to avoid sharp control jumps and offsets.

The chosen way of minimization of criterion (14) is the dynamic programming. Generally it can be shown, see e.g. Bellman (2003), that optimal control values can be computed recursively backward, starting at the end of the control horizon T. The computations are summarized as the following algorithm.

Algorithm 1.

1: Set the finite control horizon T.
2: Denote the minimized expectation of the criterion $E[Q_t | s(T), u_t, d(t-1)]$ at time t by φ_t^*, where $s(T)$ are setpoints on the whole control interval,
3: Set $\varphi_{T+1}^* = 0$.
4: **for** $t = T, T-1, \ldots, 1$ **do**

expectation

$$\varphi_t = E\left[Q_t + \varphi_{t+1}^* | s(T), u_t, d(t-1)\right],$$

minimization

$$\varphi_t^* = \min_{u_t} \varphi_t,$$

end

where the result of the minimization is the optimal control $u_t^*(d(t-1), s(T))$ dependent on data and the point estimates from (13) are substituted instead of parameters.

In the case when availability of future setpoint values is assumed, the dynamic programming can be used non-standardly with setpoint pre-programming. We propose to use it as follows.

Dealing with regression model (2) of the second and higher order, it is advantageous to transform this model into the state-space form. Due to this, the obtained state-space model is always of the first order which facilitates computations in the considered case. A simple construction of the state-space form from the regression model (here shown for the second order model only to save space) can take the following form:

$$\underbrace{\begin{bmatrix} y_t \\ u_t \\ v_t \\ y_{t-1} \\ u_{t-1} \\ v_{t-1} \\ 1 \end{bmatrix}}_{x_t} = \underbrace{\begin{bmatrix} a_1 & b_1 & c_1 & a_2 & b_2 & c_2 & k \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 & 0 & 0 \\ I & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{M} \underbrace{\begin{bmatrix} y_{t-1} \\ u_{t-1} \\ v_{t-1} \\ y_{t-2} \\ u_{t-2} \\ v_{t-2} \\ 1 \end{bmatrix}}_{x_{t-1}} + \underbrace{\begin{bmatrix} b_0 \\ I \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}_{N} u_t + \begin{bmatrix} e_t \\ 0 \\ \epsilon_t \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$y_t = [I, 0, 0, 0, 0, 0, 0] x_t, \tag{16}$$

where x_t is the system state vector of dimension $n_x = n(n_y + n_u + n_v) + 1$; I are unit matrices of appropriate dimensions; the external disturbance is modeled as the random walk $v_t = v_{t-1} + \epsilon_t$; and matrices M and N contains the point parameter estimates obtained in the vector $\hat{\theta}_t$ in (13).

The loss function (15) should be rearranged in order to correspond to the state equation in (16) and takes the form

$$Q_t^x = (x_t - s_t)' \Omega (x_t - s_t) + (u_t - u_{t-1})' \Lambda (u_t - u_{t-1}), \tag{17}$$

where the vectors s_t and u_t are completed by zeros up to the dimension of the vector x_t (i.e., $s_t \to [s_t, 0, 0, 0, 0, 0, 0]'$, etc.), and Ω and Λ are diagonal matrices with ω and λ at the beginning of the diagonal and with zeros instead of the rest of diagonal entries. After substitution of the state equation from (16) into (17) and algebraic rearrangements Algorithm 1 takes the following form:

Algorithm 2.

1: Initialize zero matrices $\mathcal{A}$ of dimension $(n_x \times n_x)$, B of dimension $(n_u \times n_u)$, C of dimension $(n_x \times n_u)$, D of dimension $(n_x \times 1)$, $\mathcal{E}$ of dimension $(n_u \times 1)$ and $F = 0$.
2: Set ω, λ depending on control demands (the bigger penalization, the stronger demand of setpoint tracking).
3: **for** $t = T, T-1, \ldots, 1$ **do**

$$\begin{aligned}
R &= M'(\mathcal{A} + \omega)M,\\
S &= M'[(\mathcal{A} + \omega)N + C],\\
W &= \left(N'\mathcal{A}N + 2N'C + B + \lambda\right)^{-1},\\
U &= N'D + \mathcal{E} - N'\omega s_t,\\
V &= M'(D - \omega s_t),\\
\mathcal{A} &= R - SWS',\\
B &= \lambda - \lambda' W \lambda,\\
C &= SW\lambda,\\
D &= V - SWU,\\
\mathcal{E} &= \lambda' WU,\\
F &= G - U'WU,
\end{aligned}$$

and finally $u_t = -W\left(S'x_{t-1} - \lambda u_{t-1} + U\right)$,

end

which is computed at each time instant taking into account future values of setpoints.

Hereby this section completes description of theoretical background applied for construction of the eco-driving intervening system.

3. Application to eco-driving system

Let us now demonstrate how the described algorithms can be applied to specific tasks introduced in Section 1.

3.1. Available data

We consider a driven vehicle and a driver as the observed system which has to be controlled with the aim of reducing fuel consumption.

Data are measured with a time period 0.2 s on a vehicle with the direct-shift (DSG) automatic gearbox, driven on a selected route. The route of a length about 38 km out of Prague is composed of parts of highway, out-of-town roads and roads passing through small towns with corresponding speed limits. The data are provided by Škoda auto (see www.skoda-auto.com). Supposing that these data will be further measurable continuously, we should select informative variables influencing fuel consumption to construct a model of the system.

Originally, the measurements contained a significant number of variables. The most important among them were the following: (1) instantaneous fuel consumption [μl]; (2) average rear wheels speed (identified with speed of vehicle) [km/h]; (3) angle of rotating steering wheel [degrees]; (4) pressing the gas pedal [%]; (5) pressing the brake pedal [bar]; (6) gear of transmission; (7) engine torque [Nm]; (8) engine speed [rpm]; (9) lateral acceleration in multiples of gravimetric acceleration; (10) yaw rate [degrees]; (11) distance traveled from the last measurement [m]; (12) time travelled [s]; (13–14) the Universal Transverse Mercator (UTM) X and Y coordinates of vehicle position [m]; (15) road altitude (height above sea level) [m]; (16) road gradient [%]; (17) vehicle course [degrees]; (18) radius of the curve road (m); (19) average fuel consumption (L/100 km). The data were measured for different driving styles, i.e., some of drivers tried to save fuel and some of them not, in order to ensure dynamics necessary for proper estimation.

Typical measurements of instantaneous fuel consumption, speed and pressing the gas pedal are shown in Fig. 2, where it can be seen (for instance, around 800 or 2000 time periods) how fuel consumption and speed are changing when the gas pedal is not pressed.

3.2. Driver-vehicle model

According to Section 2.1, for construction of the system model (1), we divide the data among three following groups: (i) the vector y_t of controlled outputs related to a vehicle itself; (ii) the vector u_t of inputs that control the outputs and (iii) the vector v_t of external disturbances expressing influence of the outer world.

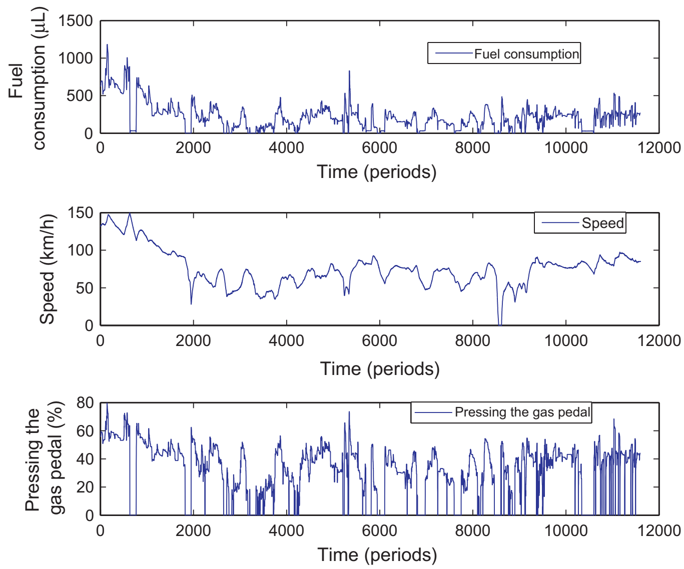


Fig. 2. Fuel consumption (top), speed (middle) and pressing the gas pedal (bottom) measured on the whole route with the sampling period 0.2 s.

According to the structure estimation from Section 2.2, we use model (2) of the second order, where

- y_t includes: (i) instantaneous fuel consumption; (ii) speed; (iii) engine torque; (iv) engine speed; (v) distance traveled per period;
- u_t includes: (i) pressing the gas pedal, (ii) pressing the brake pedal, (iii) selected gear;
- and v_t is: (i) road gradient, (ii) coordinates of vehicle position.

3.3. Real-time model estimation

Parameters of model (2) are estimated in real time according to Section 2.3, taking into account newly measured data. Due to this adaptability, the model is able to respond to changing data. Proper choice of the initial statistics V_0 in (10) (for instance, the information matrix obtained during some successful estimation from prior data) accelerates the model learning.

3.4. Control for eco-driving system

3.4.1. Optimal automatic control of pressing the gas pedal

To apply the algorithm from Section 2.4 to control the driver-vehicle system and reduce fuel consumption, we need to specify outputs y_t which enter the loss function (15), their setpoints s_t and penalizing weight vectors ω and λ. The finite control horizon $T = 5$ is proved to be the most successful during experiments.

3.4.1.1. Loss function. Choosing outputs y_t for the loss function (15), or more precisely (17), we should keep in mind that we have two control aims at each time instant t : (*i*) minimize fuel consumption and (*ii*) keep the recommended speed. If we use only fuel consumption to enter the loss function, the control leads to reducing speed until full stop of a vehicle (the parked vehicle has zero fuel consumption). Hence, at each time instant t instantaneous fuel consumption and speed in the vector y_t must be as close as possible to their desired values specified in the vector s_t. They enter the loss function. We do not have demands to the rest of outputs from the vector y_t (see Section 3.2), so they do not enter the loss function.

3.4.1.2. Setpoints. The vector $s_t = [s_{1;t}, s_{2;t}]'$ entering (15) is chosen in the following way.

The entry $s_{1;t}$ is the setpoint at time t for instantaneous fuel consumption. Any realistic desired value (for instance, 4 L/100 km converted to μL per distance travelled per time period) can be used as $s_{1;t}$ constantly at each time instant. Another possibility we prefer is to use prior available data for a choice of setpoints. In this case instantaneous fuel consumption from prior measurements of the most economic driving reduced to its, for instance, 85%, can be taken at each time instant.

The entry $s_{2;t}$ is the setpoint at time t for speed. Currently it is prepared as follows. We have values of the recommended speed for the considered route (provided by experts from economic driving measurements) collected in the form of a vector. Dimension of this vector is equal to the length of the route divided by intervals of 5 m. It means that for each location on the route with the interval 5 m a value of the recommended speed is available. The location of the vehicle is determined by UTM or GPS coordinates at each time instant. The value from the vector of the recommended speed vector corresponding to this location is substituted as $s_{2;t}$ at each time t.

This is surely a limitation of the described approach, however, it is planned to be extended by modeling the recommended speed in real time. Average speed of surrounding vehicles can be also used instead, however, there is no guarantee that they drive with an optimal and not exceeding limits speed. Estimation of the recommended speed in real time in dependence on actual values of driving variables will enable to use the approach for unknown route.

3.4.1.3. Weight vectors. In this way, as regards the part of the loss function (15) related to outputs, the optimal control should balance between penalizations of deviations of instantaneous fuel consumption and speed from their setpoints, which is defined by the vector $\omega = [\omega_1, \omega_2]'$ respectively. This balance is greatly influenced by the choice of ω. In the control theory the traditional choice of the weight vector entries penalizing outputs is 1. However, in the considered case, the weight entries should express our preferences to track one of the setpoints better than another. The compromise between them is hard to find. A series of experiments was conducted with different settings (manual and automatic, see Suzdaleva et al. (2012)) of weight vectors.

Currently the most successful choice of ω is $[0.01, 5]'$ set by experts manually. It can be modified in the initialization part of the control algorithm from Section 2.4. The reader can use this setting of ω as the initial point for own experiments.

3.4.1.4. Optimal control variable. The optimal control variable obtained according to Section 2.4 is automatic pressing the gas pedal to be implemented in the intervening eco-driving system. In the loss function (15), or more precisely (17), its increments are penalized by the weight λ to suppress its sharp changes and provide smoother pressing. We use $\lambda = 8$. It can be seen again that this manual expert-based choice differs from traditional 0.1 for input increments.

Using pre-programming setpoints according to Algorithm 2 from Section 2.4, the optimal pressing the gas pedal is computed in dependence of future values of the recommended speed. It gives a possibility not to press the gas pedal excessively and take advantages of inertia which reduces fuel consumption.

In this way, the algorithm provides the control where braking is realized only by engine. Besides efforts to save fuel, the reasons for that are as follows.

- Attempts to involve the brake pedal as the optimal control variable were not successful due to bad excitation of model estimation: in prior available data the brake pedal was not practically used because drivers tried to brake by engine. And if it was used, it was caused by some deterministic event as a speed limit or a pedestrian and when braking by engine is not sufficient.
- Another reason is that we consider the model of the driver-vehicle system, where a vehicle is equipped by the DSG automatic gearbox. Thus, in the experts opinion, a single way of reducing fuel consumption in this case is to use neutral gear automatically while driving on flat road or slightly downhill (with a recommended speed).

For these reasons we propose to add the auxiliary deterministic control block, which provides values of pressing the brake pedal and neutral gear.

3.5. Auxiliary deterministic control

The auxiliary deterministic control block represents a group of logical conditions "*if* ..., *then* ...". At each time instant it needs coordinates of the vehicle position (generally available UTM or GPS) and values of the recommended speed, limits and road gradient for each location of the route.

The auxiliary control block intervenes

- by the brake pedal *only* in case of exceeding speed limits. Generally, braking by engine from the optimal control and following the recommended speed should be enough not to exceed limits. In un-modeled traffic situations requiring braking, pressing the brake pedal is left to the driver, which turns off the eco-driving system and takes over the vehicle control immediately. The block also prohibits simultaneous pressing the gas and the brake pedals.
- by selection of neutral gear in case of driving on flat road or slightly downhill under condition that the vehicle is driven with a recommended speed.

Just in this sense the described control is semi-automatic, because (i) in case of need a driver can immediately take over the vehicle control and (ii) the control algorithm corrects the automatic gearbox.

4. Results

The presented approach is implemented in Matlab. Below we report results of validation with the help of the software vehicle simulator. During validation, the simulator works as a vehicle driven on the considered route, which in real time obtains values of pressing the gas and the brake pedals and gear as inputs from the algorithm and in real time reacts to them by producing outputs, where the most interesting for us are fuel consumption and speed.

We compare the obtained results with real drivers. Fig. 3 demonstrates pressing the gas (left) and the brake (right) pedals for the whole considered route. In this figure the optimal controller uses braking by engine to prevent exceeding speed limits, but sometimes the brake pedal is used by the deterministic controller. Pressing the brake pedal is restricted to be between 0.8 and 25 bar according to the minimal and the maximal pressure in the brake system of the vehicle. Noisy real measurements around 0.8 bar in Fig. 3 (right) corresponds to minor fluctuations of the minimal pressure caused by electronics of the brake system, but not by the driver. The eco-driving system is implemented to start pressing the brake pedal from 0.8 bar.

Fig. 4 (left) presents the automatic use of neutral gear in comparison with a real driver manually selecting neutral gear on the DSG automatic gearbox. Neutral gear was selected more often in parts of the route with often meeting speed limits 90, 50 and 30 km/h. During driving on highway the neutral gear was not used that in Fig. 4 (left) corresponds to the part of the route from its beginning to 2000–2500 time periods. Instantaneous fuel consumption with the eco-driving system is plotted in Fig. 4 (right).

Fig. 5 (left) compares the obtained speed with the recommended speed, speed of the real driver and speed limits for the whole route. In this figure, the beginning of the route is a highway with limit 130 km/h. The exit from the highway with limit 90 km/h can be seen around 2000 time periods. Further the out-of-town road with limit 90 km/h alternates with entrance to small villages with limits 50 and 30 km/h. In Fig. 5 (left) we compare results with a speed of the most disciplined driver from

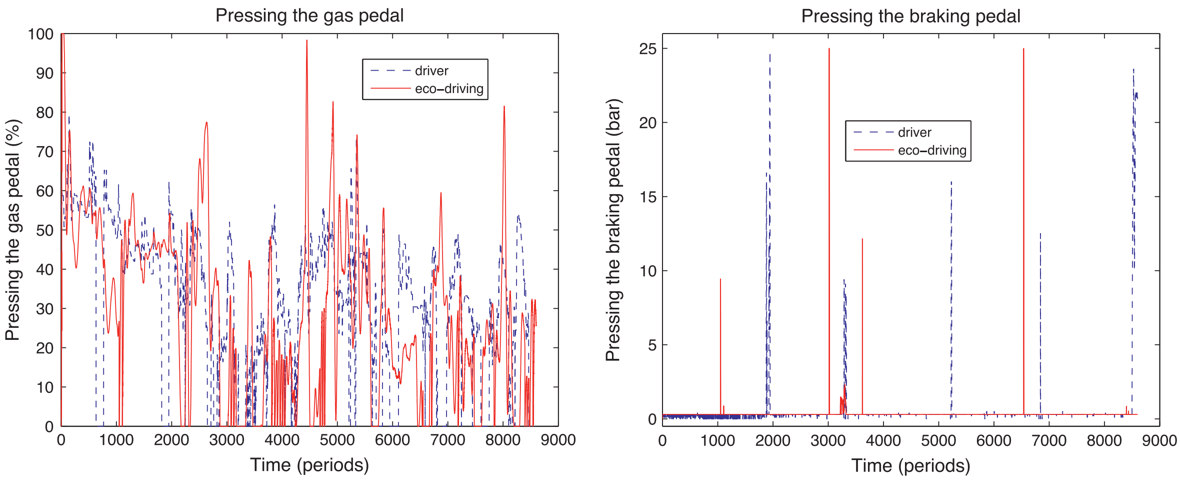


Fig. 3. Pressing the gas (left) and the brake (right) pedals compared with a real driver.

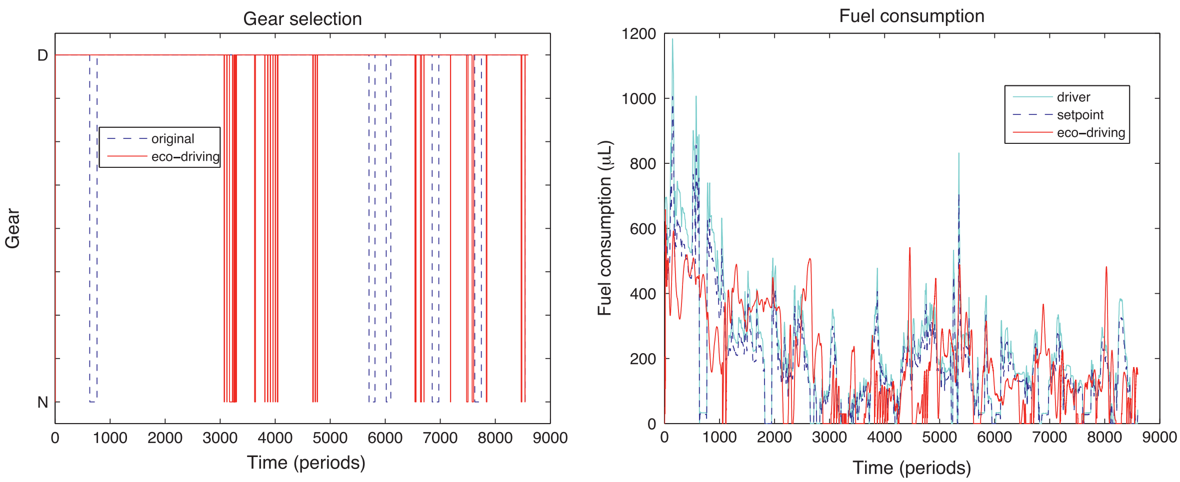


Fig. 4. Neutral gear selection (left) and instantaneous fuel consumption (right) compared with a real driver using the DSG automatic gearbox, where N denotes "neutral" and D – "driving".

available data who tried to drive economically. For comparison, Fig. 5 (right) provides speeds of several other real drivers which are much more dynamic even in comparison with the real driver in Fig. 5 (left) and repeatedly exceed limits.

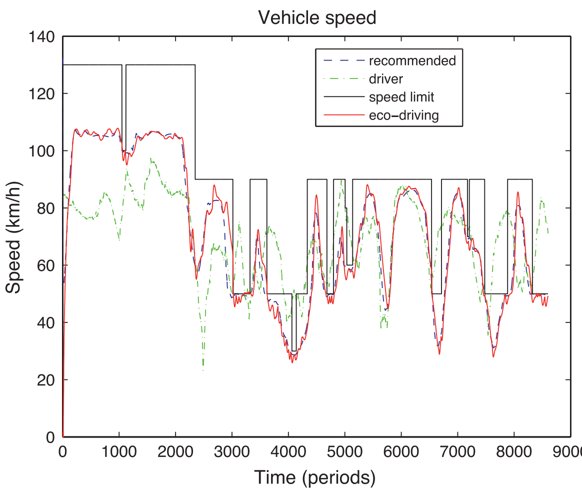
However, in Fig. 5 (left) we can see that the driver exceeds limits, while the eco-driving system not (for instance, around 3000, 4000 or 4800 times periods). The speed of the eco-driving system follows the smooth recommended speed and is not slow as it was reported in previous results (for instance, Suzdaleva et al. (2012)). It presents just a smooth and calm driving. Fuel savings reached during such a driving are presented in Table 1, where average speed is also compared with real drivers. The driving time is not presented here due to the fact that the precise length of the whole travelled distance differs a bit from driver to driver. Thus average speed is a more informative result.

Validation of the eco-driving system on a real testing vehicle is currently running in its initial phase. It is realized with the help of control units connected to the notebook with the running algorithm and operating rods connected to the gas and brake pedals and the gear lever. During validation the vehicle is driven on the considered route. For possibility of immediate system shutdown in the case of any un-modeled maneuver (overtaking, excessive braking, pedestrian, etc.) or system failure the driver has a red button on the instrument panel and takes control of the vehicle. After finishing the maneuver, the driver starts the eco-driving system again.

Unlike the station wagon (European combi) body-style of the vehicle used for prior measurements, the eco-driving system is tested on a sport utility vehicle (SUV). It has different characteristics and wittingly higher fuel consumption. Thus the model adaptation should prove itself. Table 2 reports average fuel consumption and average speed from testing the eco-driving system on a real vehicle in comparison with a real driver.

4.1. Discussion

It is obvious that validation on a real vehicle is much more complicated than on the simulator. It requires at least several steps for final setting the eco-driving system – primarily, penalizations in the optimal control and conditions in the auxiliary



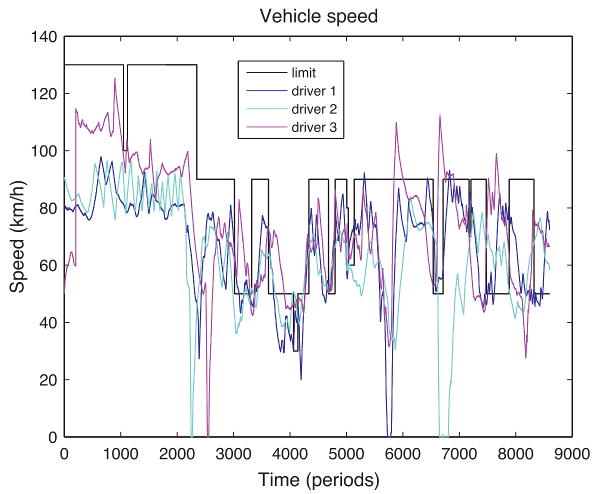


Fig. 5. The eco-driving speed (left) and speed of real drivers (right).

Table 1
Comparison of the eco-driving system on the simulator and real drivers.

	Average fuel consumption (L/100 km)	Average speed (km/h)
The eco-driving system on the simulator	4.88	70.89
Real drivers	5.44	70.72

Table 2
Comparison of the eco-driving system on a real vehicle and a real driver.

	Average fuel consumption (L/100 km)	Average speed (km/h)
The eco-driving system in the real vehicle	5.48	72.68
Real driver	5.93	69.72

deterministic control. Nevertheless, the results look promising. The eco-driving system reduces fuel consumption both on the software simulator and on a real vehicle, see Tables 1 and 2.

Minor problems detected by experts during the validation are primarily concerned with oscillating speed, sharper pressing the gas pedal after start of the system and demand of more often selecting neutral gear. These problems will be fixed soon.

Among the remained open problems and limitations of the approach we can highlight the following:

- The use of only the optimal controller brings more fuel savings. However, the road gradient of the given route does not enable to satisfy speed limits only by engine braking. Thus, optimization of braking is still planned to be solved. The same can be said about using the gearbox. Selection of neutral gear on relevant parts of the route significantly contributes to saving fuel. However, its optimization is much more complicated task requiring a separate research.
- The recommended speed is one of the limitations of the approach. Surely measuring speed of surrounding vehicles combined with available information about limits can be used instead. However, it does not guarantee that speed of other drivers is optimal from economy viewpoint and that they do not exceed speed limits. We plan to construct a data-based model of recommended speed to estimate it in real time. This means that when estimation of the optimal recommended speed will be solved as a separate task, the presented algorithm will be able to apply on-line for unknown route.
- Data from surrounding vehicles (distance to the preceding vehicle, its speed, etc.) were not among available measurements, which means that currently the approach is limited to the free driving conditions. Involving these data into the model is worth exploring.

5. Conclusion

The paper presents results of the project directed at development of algorithms for reducing fuel consumption in conventional vehicles. The algorithms are supposed to be implemented in the form of the eco-driving intervening system, i.e, enabling semi-automatic control. The task of the presented eco-driving system is not only to reduce fuel consumption, but also to intervene in case of exceeding speed limits. The experiments with the software vehicle simulator demonstrate reducing fuel consumption while driving with the recommended speed. Tests in a real driven vehicle are in its initial phase and also report fuel savings.

In this paper the described general data-dependent Bayesian approach focuses on solution to eco-driving considered in the conventional vehicles' context. However, the approach is universal and possesses a high potential for extension up to the hybrid and electric vehicle context, related to available measured data. Construction of optimal eco-driving strategy as an open problem joins conventional and hybrid and electric vehicles since (i) conventional vehicles need to reduce fuel consumption and emissions; (ii) hybrid vehicles should be driven optimally not to lose a benefit of the use of hybrid powertrain; (iii) electric vehicles need to model a travel range before recharging, etc. Thus, such extensions will be desired.

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