

SERVO PROBLEM WITHIN FUEL CONSUMPTION OPTIMIZATION

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ABSTRACT

The presented paper deals with a problem of fuel consumption optimization. Today's automotive industry solves this problem mainly via various conceptual approaches (hybrid and electric vehicles). However, it leads to high initial cost of a vehicle. This paper focuses on fuel economy for conventional vehicles. For this aim, recursive algorithms of adaptive optimal quadratic control under Bayesian methodology are used. A stochastic servo problem, including set-point tracking, is a part of the considered adaptive control design. In this paper, fuel consumption and speed of a driven vehicle are the controlled variables, where the first one is to be optimized and the second one is pushed to track its set-point. This set-point is a recommended road-dependent speed. Experiments with real data measured on a driven vehicle are provided.

KEY WORDS

Control systems, adaptive control design, set-point tracking, fuel consumption optimization, vehicles.

1 Introduction

A problem of fuel economy is of importance to today's automotive industry, as well as for usual drivers. A necessity to reduce fuel consumption and emissions forces the automotive industry to call for solutions aimed at optimization of ride. Conceptual approaches such as hybrid and electric vehicles came to the market recently. Their potential and positive effect on environment are surely significant. Many efforts are focused on developing optimal control strategies for them, see, for example, [1, 2].

However, the resulting fuel savings are compensated by high initial cost of vehicles. Moreover, in case of electric vehicles a long out-of-town traveling is still a problem due to the lack of charging stations.

Another way of emission regulation was proposed at a government level in the form of using biofuel and bioadditives. It was expected that it could bring environmental and economical savings. However, in fact, it turned out that biofuel may damage an engine originally not intended for its using. Moreover, consumption of biofuel and fuel with bioadditives is higher than in case of the traditional fuel.

Facts mentioned above suggest that optimization of fuel consumption for conventional vehicles, which is con-

sidered in this paper, still remains desirable from economic and environmental points of view. Many works can be found in this field. For instance, [3] deals with driving strategies based on prediction of urban traffic situations. The main idea is to reduce the dynamics in the velocity profiles of driving situations and, respectively, the fuel consumption in urban traffic. Reducing the velocity dynamics is proposed via a situation-adaptive reaction to every predictively known forthcoming traffic event. The proposed algorithm calculates a fuel consumption optimized driving trajectory at each route section of the vehicle provided that predictive information about the traffic events is available. Used input parameters are temporal and spatial depending constraints of the driving situation as well as other restrictions like a speed-limit. Paper [4] is devoted to modeling an eco-driving strategy of a vehicle based on minimization of fuel consumption in a given route. The vehicle speed and the gear ratio are identified as control variables. The effect of working load is considered according to three engine running processes of idle, part-load and wide open throttle.

The presented paper proposes to solve the task of fuel consumption optimization as a stochastic servo problem within the adaptive control design. The aim of the considered control is to push the controlled variables as close as possible to their specified set-points under constraints on the input ranges. The used approach is based on data continuously measured on a driven vehicle and on external observations. The main controlled variable here are the fuel consumption and the speed of a driven vehicle. Keeping of the recommended road-dependent speed, which can be neither too slow nor too fast, is closely connected with the fuel consumption optimization. Control variables used – pressing the gas and the brake pedals and selected gear of transmission – naturally have restrictions exploited in the control design.

In the presented paper, dynamic driving-related variables are modeled via the fully probabilistic design (FPD) [5] under Bayesian methodology [6]. It allows to use the FPD recursive (on-line) algorithms based on explicit solutions. Thus, numerical computations are avoided as far as possible. For multivariate linear normal autoregression model the FPD coincides with the adaptive quadratic optimal control [7]. Minimization of the fuel consumption under condition of tracking the prescribed speed is performed using adaptive penalizations in criteria of the control algo-

rithm.

Layout of the paper is as follows: Section 2 provides general solution to servo problem within the FPD. Section 3 demonstrates its exploitation with normal autoregression models. Section 4 is devoted to application of the solution to the recommended speed tracking within a task of the fuel consumption optimization. Section 5 demonstrates results of experiments with real data measured on a driven vehicle.

2 Servo Problem Formulation

This section describes general solution of servo problem within the FPD. Advantages of the FPD's use in comparison with other approaches are described in [8], here they are omitted to save space.

Let's consider a stochastic closed loop described by the joint probability density function (pdf) $f(d\{T\}) = \prod_{t \in t^*} f(d_t|d\{t-1\})$, where

- $d\{t\}$ denotes the sequence (d_0, d_1, \dots, d_t) , where $d_0 \equiv d\{0\}$ comprises initial conditions;
- data $d_t \equiv (y_t, u_t)$, where y_t is the observed output vector and u_t is the control input vector;
- t labels discrete time, $t \in t^* \equiv \{1, \dots, T\}$;
- $T < \infty$ is the control horizon;
- and $f(\cdot|\cdot)$ represents a conditional pdf.

This joint pdf, describing the closed loop, is factorized into a product of a system model $f(y_t|u_t, d\{t-1\})$ and a controller $f(u_t|d\{t-1\})$ in the following way

$$f(d\{T\}) = \prod_{t \in t^*} \underbrace{f(y_t|u_t, d\{t-1\})}_{\text{system model}} \underbrace{f(u_t|d\{t-1\})}_{\text{controller}} \quad (1)$$

according to the chain rule [9]. The system model $f(y_t|u_t, d\{t-1\})$ has a form

$$f(y_t|u_t, d\{t-1\}) = f(y_t|\psi_t), \quad \psi_t \equiv [u_t', \phi_{t-1}']', \quad (2)$$

where ψ_t is the regression vector, and ϕ_{t-1} is a finite-dimensional information state.

In the presented paper, all the pdfs (including controllers) are considered in a factorized form, i.e.,

$$f(y_t|\psi_t) = \prod_{i=1}^Y f(y_{i;t}|y_{(i+1);t}, \dots, y_{Y;t}, \psi_t), \quad (3)$$

where a notation of the form $y_{i;t}$ means the i th entry of y_t , Y denotes the length of the vector y_t . Formal decomposition into a product of factors generally helps in designing and applying the resulting algorithms as all the factors are scalar pdfs of respective distributions. It means that all the subsequent discussed formulas are assumed to be in the factorized form, though formally written in the unfactorized one.

The controller using the same information state, i.e., $f(u_t|d\{t-1\}) = f(u_t|\phi_{t-1})$, $t \in t^*$, is the optimized term of the joint pdf (1). It means that the optimizing control design should select the controller, which forces the joint pdf (1) as close as possible to a user given ideal pdf $f^I(d\{T\})$. This ideal pdf describes a desired closed loop. It is decomposed into a product of the ideal system model and the ideal controller similarly as (1), and not forgetting about (3), i.e.,

$$f^I(d\{T\}) = \prod_{t \in t^*} \underbrace{f^I(y_t|\psi_t)}_{\text{ideal system model}} \times \underbrace{f^I(u_t|\phi_{t-1})}_{\text{ideal controller}} \quad (4)$$

The Kullback-Leibler divergence (KLD) [10]

$$D(f||f^I) \equiv \int f(d\{T\}) \ln \left(\frac{f(d\{T\})}{f^I(d\{T\})} \right) \mathbf{d}d\{T\} \quad (5)$$

is a suitable tool to measure proximity between (1) and (4), which is minimized over $\{f(u_t|\phi_{t-1})\}_{t=1}^T$. Reasoning of such a choice can be found in [6].

A considered servo problem can be formulated as follows: *design the control inputs u_t so that to push the controlled outputs y_t as close as possible to their desired (given) set-points y_t^s .*

2.1 Ideal Pdf Construction

The ideal system model entering (4) is constructed using the given set-points y_t^s , i.e., it takes the form

$$f^I(y_t|\psi_t, y_t^s). \quad (6)$$

The ideal controller $f^I(u_t|\phi_{t-1})$ can be modeled as a random walk.

2.2 Optimal Controller Construction

According to [6], the optimal controller minimizing KLD (5) is constructed as follows:

$$f(u_t|\phi_{t-1}) = \frac{f^I(u_t|\phi_{t-1}) \exp[-\omega(\psi_t)]}{\underbrace{\int f^I(u_t|\phi_{t-1}) \exp[-\omega(\psi_t)] \mathbf{d}u_t}_{\gamma(\phi_{t-1})}}, \quad t \in t^*,$$

$$\omega(\psi_t) \equiv \int f(y_t|\psi_t) \ln \left(\frac{f(y_t|\psi_t)}{\gamma(\phi_t) f^I(y_t|\psi_t, y_t^s)} \right) \mathbf{d}y_t. \quad (7)$$

Evaluations run against the time course, i.e., for $t = T, \dots, 1$ and start with $\gamma(\phi_T) = 1$. Proof of this statement is available in [6].

3 Servo Problem for Normal Models

In case of linear normal autoregression models, the FPD coincides with a widely spread quadratically optimal control [6], where penalizations in the squares of variables in the optimality criteria are the main control options. These

penalizations are taken as the inversions of the noise variances of the corresponding factors of the joint (factorized) pdf.

3.1 Normal Autoregression Closed Loop Model

In this case, the system model (2) in the closed loop (1) takes a form of the multivariate normal autoregression model

$$f(y_t|\psi_t) = \mathcal{N}_y(\psi_t'\theta, r), \quad (8)$$

where θ are regression coefficients and r are the noise variances of factors (they are estimated at each step of the time cycle, but for the controls aims they are taken as fixed). The optimized controller (7)

$$f(u_t|\phi_{t-1}) = \mathcal{N}_u(\eta, s) \quad (9)$$

is a part of the closed loop (1) obtained via minimization of KLD, also in the normal form with expectations η and variances s .

3.2 Normal Autoregression Ideal Closed Loop Model

Structurally, the ideal closed loop model stems from the considered closed loop, however, its individual factors should express the control aims.

3.2.1 Ideal System Model

Entries of the output vector $y_t = [y_{1;t}, \dots, y_{Y;t}]'$ must track their set-points collected into a vector $y_t^s = [y_{1;t}^s, \dots, y_{Y;t}^s]'$. Thus, the ideal system model (6) can be chosen, e.g., as the first order autoregression model

$$f^I(y_t|\psi_t, y_t^s) = \mathcal{N}_y^I(y_t^s, R) \quad (10)$$

with some relatively quick dynamics and constant. Using the factorized form, it can be written as

$$y_{i;t} = a_i y_{i;t-1} + k_i + e_{i;t}, \quad (11)$$

where parameter a_i provides the dynamics, and constant k_i is set so that the steady-state value of the output entry $y_{i;t}$ is the corresponding value of the set-point $y_{i;t}^s$. It means that according to the set-point, the constant is obtained as

$$k_i = y_{i;t}^s(1 - a_i). \quad (12)$$

The ideal system model noise $e_{i;t}$ in (11) expresses the expected deviations of the ideal values from those produced by the deterministic model. Inversions of their corresponding variances R form penalizations in the quadratic control criterion.

3.2.2 Ideal Controller

Entries of the input vector $u_t = [u_{1;t}, \dots, u_{U;t}]'$ can be also “dragged” up to their desired given values. It means that set-points can be defined for the input values as well, and they are collected in a vector $u_t^s = [u_{1;t}^s, \dots, u_{U;t}^s]'$. In this case, the ideal controller takes the form

$$f^I(u_t|\phi_{t-1}, u_t^s) = \mathcal{N}_u(u_t^s, S) \quad (13)$$

and can be chosen as a static model for respective factors

$$u_{i;t} = u_{i;t}^s + \varepsilon_{i;t}, \quad (14)$$

or in the form of random walk, operating with the input increments

$$u_{i;t} - u_{i;t-1} = \varepsilon_{i;t} \quad (15)$$

with the set-point $u_{i;t}^s = 0$. The chosen ideal controller ((14) or (15)) generates the input values, where inversions of the noise variances S correspond to the inputs penalizations in the control criterion in the case of (14) or to the input increments penalizations with the use of (15).

3.3 Optimized Controller

Under assumption of normality and using the discussed models (8), (10) and (13), the optimized controller $f(u_t|\phi_{t-1})$ (9) minimizes KLD (5) over all admissible control strategies $\{f(u_t|\phi_{t-1})\}_{t=1}^T$. This formulation leads to the dynamic programming with penalizations of the corresponding factors, resulting in distribution (9), where η are expectations used as the generated inputs.

Up to now, the control based on a model with known parameters was discussed. In reality, the model parameters are not known and have to be estimated. According to [11], the dual problem is not feasible. This suggests some suboptimal solution to the adaptive control to be used.

For the control implementation, a methodology of receding horizon [6] can be used, where the newly computed point estimates of parameters are used as fixed for the control design on a given control interval. After realization of one step of control, new data are measured and used for another estimation. The mentioned estimation is performed on-line for the closed loop model including (8) and (9). The ideal system model (10) and the ideal controller (13) are fixed with the exception of the noise variances which are taken from the mentioned closed loop estimation, i.e., in (10) $R = r$ from (8), and in (13) $S = s$ from (9). Thus, the required penalizations in the control criteria become adaptive. The IST (iterations spread in time) method is recommended, where the repeated solutions to the Riccati equation do not start from initial conditions but from the result achieved in the previous step [7]. Due to this, a very short control interval can be used.

4 Fuel Consumption Optimization

Let us apply the described servo problem solution to a task of fuel consumption optimization with involved tracking of the recommended speed.

Obviously, the main control aim for this task is to design values of the control variables so that to minimize the controlled one – the fuel consumption. However, a simple minimization is not sufficient for solution to the task as it leads to reducing the vehicle speed. This is intuitively understandable: a parked vehicle has a zero fuel consumption. However, a driver wants to get to some destination, and a vehicle should move with some speed not exceeding the existing restrictions. Thus, the vehicle speed should track its recommended values. It means that the recommended speed should be neither too fast (according to traffic rules) nor too slow (for safety, for example, on the highway). Balance of these generally contradictory demands creates the optimum of the considered problem.

4.1 “Driver-Vehicle” Closed Loop

Let us consider a “driver-vehicle” closed loop that is described by model (1). The involved modeled variables $d_t \equiv (y_t, u_t)$ entering the considered closed loop are interpreted as follows:

- the controlled output vector $y_t \equiv [y_{1;t}, y_{2;t}]$, where
 - $y_{1;t}$ denotes the fuel consumption, and
 - $y_{2;t}$ corresponds to the vehicle speed;
- the control input vector $u_t \equiv [u_{1;t}, u_{2;t}, u_{3;t}]$, where
 - $u_{1;t}$ is a pressing the gas pedal,
 - $u_{2;t}$ is a pressing the brake pedal, and
 - $u_{3;t}$ is a selected gear of transmission.

The external variable v_t – a road altitude – must be added to the closed loop description. Thus, model (1) modifies its form to the following one:

$$\prod_{t \in t^*} f(y_t | u_t, v_t, \phi_{t-1}) f(u_t | v_t, \phi_{t-1}) \quad (16)$$

to be used in the factorized form similar to (3).

In general, more modeled variables can be added to the output vector (such as engine speed, engine torque, lateral acceleration, etc.) and to the input vector (rotating steering wheel, etc.) as well as to the vector of external variables (distance travelled, time travelled, information about a vehicle position from the GPS navigation, etc.). But these variables are not to be optimized, and in this section they are omitted for more transparent formulation of the problem. More detailed information about modeling and experiments with the mentioned variables included is available in [12].

4.2 Servo Problem

Adapted to the considered context, the servo problem is now formulated in the following way:

- *design the values $u_{1;t}$ expressing how much the gas pedal should be pressed, the values $u_{2;t}$ related to pressing the brake pedal and the values $u_{3;t}$ defining a gear to be selected so that to*
- *push the fuel consumption $y_{1;t}$ towards its set-point $y_{1;t}^s = 0$ and the vehicle speed $y_{2;t}$ as close as possible to the recommended speed $y_{2;t}^s$;*
- *and, in the same time, the designed values $u_{1;t}$, $u_{2;t}$ and $u_{3;t}$ must be close to their given desired values $u_{1;t}^s$, $u_{2;t}^s$ and $u_{3;t}^s$ respectively.*

4.3 Set-point Choice

It can be seen in the above formulation that the chosen set-point $y_{1;t}^s$ for the controlled fuel consumption is a zero value. As regards the recommended speed $y_{2;t}$, its modeling is a separate subtask. In a case of an unknown road, the recommended speed must be estimated at each time instant with the help of the information obtained from a navigation. For a known road, the prescribed speed can be determined by investigation of a detailed map of the region and assigning the speed values according to experts from the transportation area. At the present time, the research project focuses on the case with a known road and the available prescribed speed. A case with modeling and estimation of the recommended speed for unknown route will be treated soon.

The set-points $u_{1;t}^s$, $u_{2;t}^s$ and $u_{3;t}^s$ are mostly obtained from preliminary measurements or with the help of experts.

4.4 Ideal “Driver-Vehicle” Closed Loop

The ideal closed loop (4) can be constructed as follows. The ideal system model (10) entering the ideal closed loop is defined for the corresponding factors according to Section 3.2.1 via the given set-points: zero for the fuel consumption and the prescribed recommended speed – for the vehicle speed.

The ideal controller (13) is constructed according to Section 3.2.2 mostly using the static model (14) with the given desired values of corresponding entries. Moreover, values of pressing the gas pedal and the brake pedal and of the gear of transmission naturally have upper and lower restrictions which have to be imposed during the implementation.

4.5 KLD Minimization

Minimization of KLD (5) in the adopted context is interpreted as follows. The optimal controller moves the considered “driver-vehicle” closed loop as close as possible to

its ideal counterpart, while deviations from desired values of the optimized variables (fuel consumption and the vehicle speed) are penalized in each control step. Here, penalizations are used for the input deviations as well.

The penalizations obtained as inversions of the estimated variances r from (8) and s from (9) are adaptive and are set automatically. Their choice differs significantly from usually used constant penalizations manually chosen by experts. Results of experiments comparing reducing the fuel consumption with the tracked speed both for the adaptive and constant penalizations are provided below.

5 Experiments

A part of the early experiments aimed at the fuel consumption optimization within the presented research is published in [12]. However, a problem of tracking the speed and “dragging” the values up to the desired ones remained not fully resolved there. Subsequently, a series of experiments based on the described approach with the aim to improve a control quality and resolve the tracking problem have been conducted. Here, one of them with the best results achieved is presented.

The experimental part of the work is carried out in collaboration with Škoda Auto a.s. (see www.skoda-auto.com) which provided real observations. To ensure necessary dynamic, data were measured for driving both with a lower and a usual fuel consumption. Originally, the available measurements contained significant number of variables measured for a selected out-of-town route. A basic data sample including 16 most important variables influencing the driving was selected for modeling the closed loop (i.e., fuel consumption [μl], average rear wheels speed [km/h], pressing the gas pedal [%], pressing the brake pedal [bar], gear of transmission, engine torque [Nm], etc.) Their complete list is available in [12]. For the considered formulation of the servo problem, the best results were achieved with the choice of the variables described in Section 4 extended by the engine torque.

5.1 Experiment Setup

For the presented experiment, the following output vector is taken: $y_t = [y_{1;t}, y_{2;t}, y_{3;t}]'$, where $y_{1;t}$ is the fuel consumption, $y_{2;t}$ – average rear wheels speed (identified with the vehicle’s speed), $y_{3;t}$ – engine torque. The input vector remains the same as in Section 4, i.e., $u_t = [u_{1;t}, u_{2;t}, u_{3;t}]'$, where $u_{1;t}$ – pressing the gas pedal, $u_{2;t}$ – pressing the brake pedal, $u_{3;t}$ – selected gear of transmission. Constraints $0 \div 100\%$ are imposed both on pressing the gas pedal and the brake pedal. Restrictions $0 \div 6$ are chosen for gear, where a zero value is identified with a neutral gear. The external variable v_t is a road altitude.

After the data preprocessing the whole available number of data items was about 20 thousands with a sampling period equal to 1 second. For this experiment, 5000 data

items were used. An additional amount of data items seems not to improve a quality of control and estimation, but it prolongs the computational time.

Usually in practice, the penalizations in the control criterion are used as fixed and chosen manually by experts. Therefore, for comparison, the algorithm was running: (i) with automatic setting of the adaptive penalizations; (ii) with manual setting of the fixed penalizations chosen by experts; and (iii) with manual setting of the fixed penalizations taken from the stabilized values of the adaptive ones. Results of the control with a different choice of penalizations are compared.

5.2 Results

5.2.1 Automatic Setting of the Adaptive Penalizations

Figure 1 demonstrates reducing the fuel consumption obtained using the FPD with the adaptive penalizations. For better illustration a fragment of results for 1000 data items is shown (at the beginning of the time cycle the results of the on-line algorithm were worse). The fuel economy in comparison with the real lower consumption is 14.29%. Such the fuel saving was obtained with the control inputs,

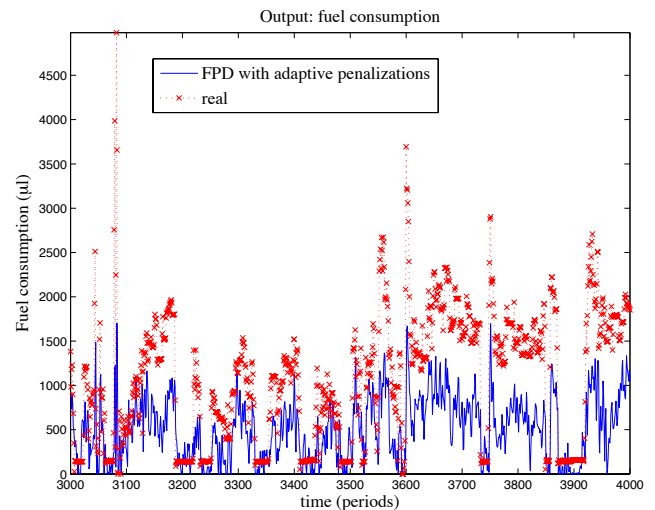


Figure 1. The fuel consumption obtained using the FPD with adaptive penalizations. Notice a difference between the obtained and the real fuel consumptions: the first one has lower values.

i.e., pressing the gas pedal and gear, plotted in Figure 2 (top) and (bottom) respectively. This figure compares them with their real courses. It can be seen in Figure 2 that the computed inputs correspond to the real values with a bit lower pressing the gas pedal and a higher gear that is in accordance with general rules of fuel economy. Pressing the brake pedal is not shown here, as during the available rides a braking was realized mostly by the engine. The obtained engine torque corresponds to the real one (it is not shown

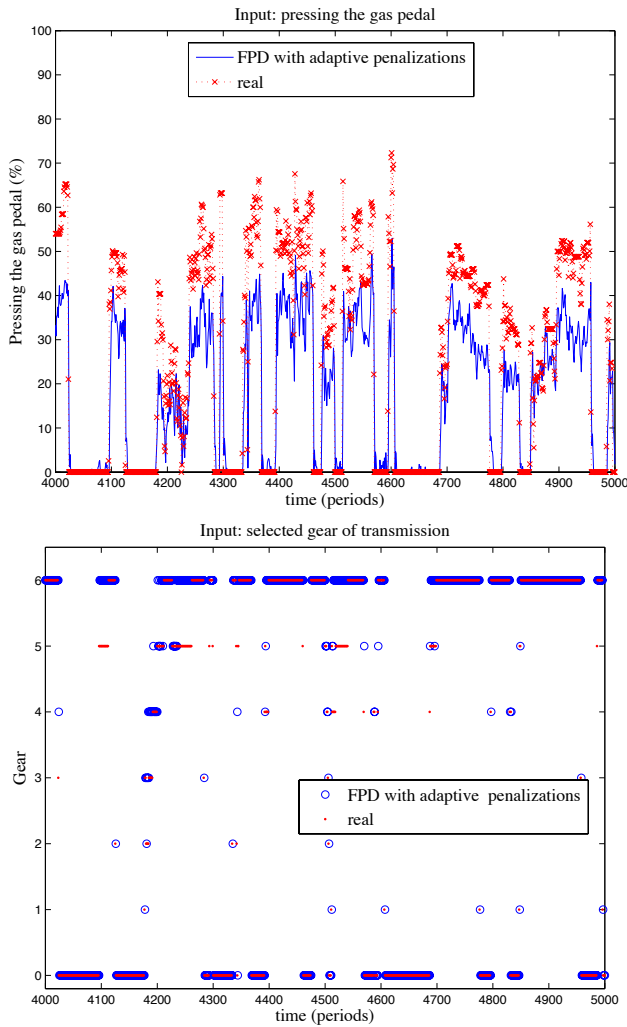


Figure 2. Pressing the gas pedal (top) and the selected gear (bottom), obtained via the FPD with the adaptive penalizations, compared with real courses of these inputs. Notice a smoother pressing the gas pedal in the top plot and a higher selected gear in the bottom plot.

here to save space). This quite suffices for the considered task.

Figure 3 presents the evolutions of the adaptive penalizations of the fuel consumption, the speed, pressing the gas pedal and gear respectively. This figure shows how the penalizations are modifying before they find their correct values. Their stabilized values are as follows: 1.318×10^{-4} for the fuel consumption, 2.852 – for the vehicle speed, 0.029 – for the engine torque, 0.047 – for pressing the gas pedal, 2.196 – for the gear. It can be seen that such a choice is non-trivial, and manually it would be a difficult task even with a help of experts.

The recommended speed tracking is shown in Figure 4, where the controlled speed is lower than the set-point. Table 1 provides comparison of the average controlled speed and the average recommended speed.

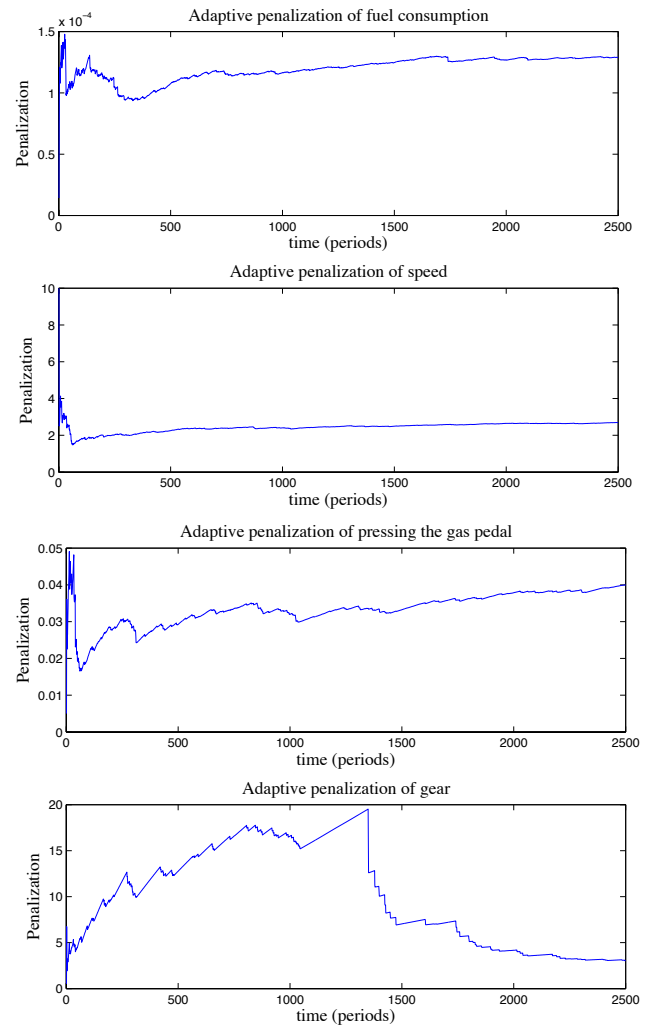


Figure 3. Evolutions of the adaptive penalizations. Notice the changes of the values in the beginning of the time cycle.

5.2.2 Manual Setting of the Expert-Chosen Fixed Penalizations

For comparison, the algorithm was run with the fixed (constant) penalizations, namely, 0.1 for the fuel consumption, 1 – for the vehicle speed, 0.1 – for the engine torque, 0.1 – for pressing the gas pedal, 0.1 – for the gear. This was a modification of a widespread expert-based choice of the constant penalizations (i.e., using inversions of variances 1 for the outputs and variances 10 for the inputs), which was tuned to the considered specific task. However, despite this tuning, the fuel consumption in this case increased by 16% in comparison with real data, see Figure 5.

Figure 6 presents the controlled vehicle speed exceeding the recommended one that could be dangerous. It was caused by a stronger pressing the gas pedal and an unnecessary use of lower gear (not shown here to save space).

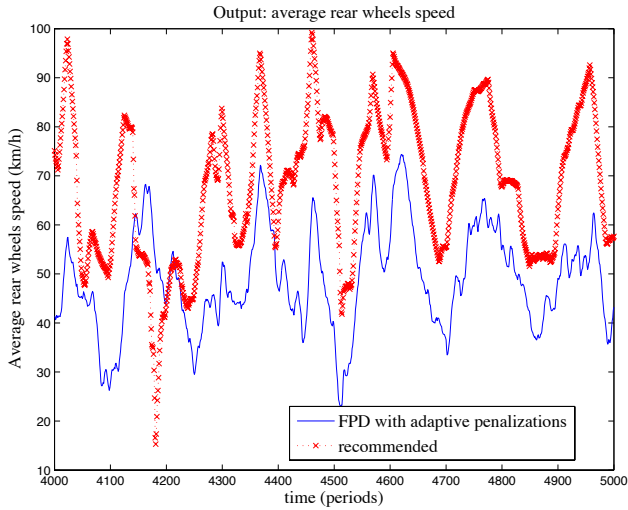


Figure 4. The speed tracking obtained via the FPD with the adaptive penalizations. It can be seen that the controlled speed values are lower than the the recommend ones.

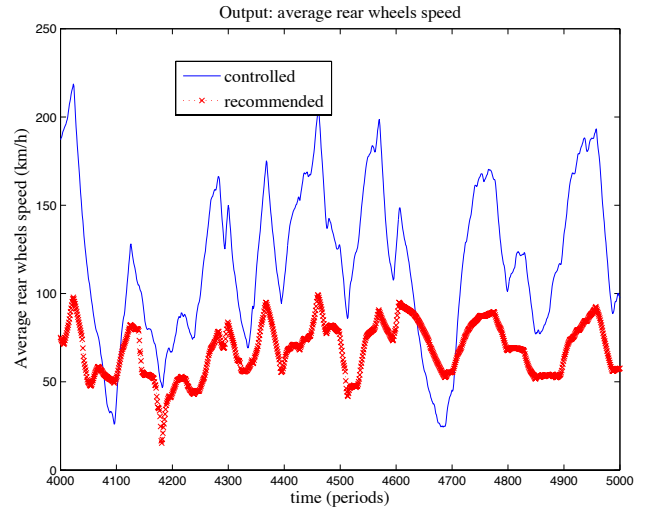


Figure 6. The speed tracking based on the FPD with manually chosen penalizations $[0.1, 1, 0.1, 0.1, 0.1]$. Notice that the controlled values are higher than the recommended ones.

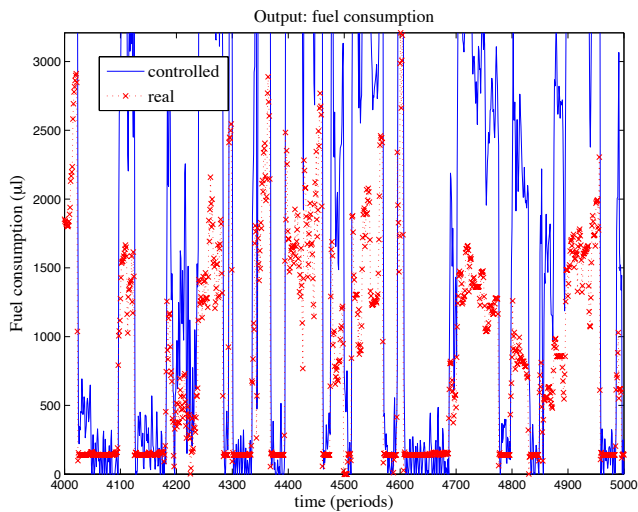


Figure 5. The fuel consumption obtained with the help of the FPD with manually chosen penalizations $[0.1, 1, 0.1, 0.1, 0.1]$. Notice the increased values of the obtained fuel consumption.

5.2.3 Manual Setting of the Stabilized Adaptive Penalizations

Here, the algorithm was run with the stabilized values of the adaptive penalizations obtained in Section 5.2.1, set manually. The best results among the presented ones were achieved. The obtained fuel saving is 4.1%. Despite the fuel saving is less than in the case with the automatic setting, it is compensated by absence of sharp changes in the driving style and keeping a not too slow speed. In the adaptive case described in Section 5.2.1 the controlled speed

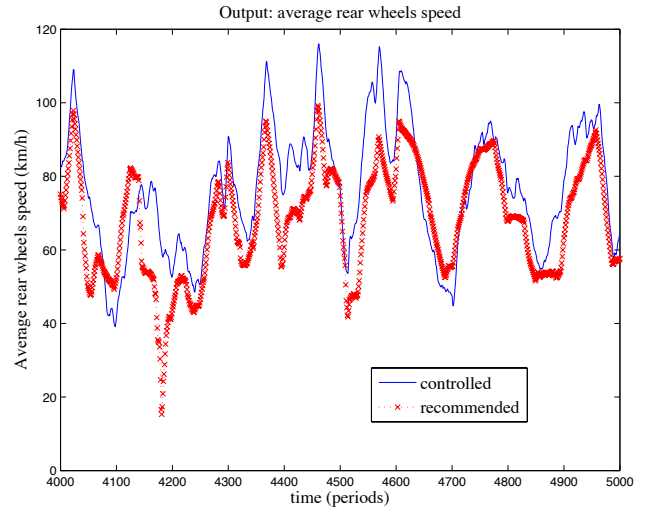


Figure 7. The recommended speed tracking based on the FPD with manual setting of the penalizations taken from the stabilized values of the adaptive ones. Notice that the values of the controlled speed are close to the set-point.

tracking is explained by absence of the initial jumps in the values of the adaptive penalizations. However, notice that this choice would be hardly possible without usage of the approach described in Sections 2 and 3. The obtained pressing the gas pedal is similar to that shown in Figure 2 (top) with a bit smoother course. Table 2 summarizes the resulting fuel savings in comparison with real data.

Table 1. Comparison of the average speeds

	Average speed, <i>km/h</i>
Recommended	71.2
Adaptive case	65.2
Manual expert case	80.5
Manual use of stabilized adaptive case	70.8

Table 2. Fuel saving in comparison with real data

	Fuel saving, %
Adaptive case	14.3
Manual expert case	-16
Manual use of stabilized adaptive case	4.1

5.3 Discussion

To summarize the experimental part of the work, it can be said that the results obtained by using the stabilized values of the adaptive penalizations instead of the constant ones in the manual setting were the best among the presented ones. It means that these stabilized values can serve as a basis for their further modification as needed. Usage of only automatic settings of the penalizations can lead to a loss of the main options to influence reaching the control aim. However, a wrong choice of penalizations can negatively effect the control quality. It indicates that, depending on a specific task, use of the stabilized (or tuned) values of the adaptive penalizations can be the sensible compromise.

The difference among the speed tracking results in Table 1 may seem insignificant. However, it shows that a driving without any sharp changes of the speed, but with a slight modifying in pressing the gas pedal, can bring fuel saving.

6 Conclusions

The paper formulates a task of the fuel consumption optimization for conventional vehicles as the stochastic servo problem, where the optimization is dealt as dragging to the zero set-point, while the recommended speed is used as the set-point for the controlled speed. The main contribution of the paper is to demonstrate that the theoretical servo problem solution can be applied simultaneously to the optimization and the tracking problem. Illustrative experiments with real data are provided.

A work planned in the near future will involve modeling and estimation of the recommended speed for unknown route.

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