

Validation Experiments for Fuel Consumption Optimization Algorithm

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Abstract

The paper presents actual results of the project oriented at development of algorithms for the advising system for eco-driving. The paper discusses the experiments for validation of the control algorithm used for the fuel consumption optimization problem within the project. Using adaptive optimal control algorithms under Bayesian methodology, the experiments show that a compromise between fuel consumption minimization and preserving the recommended speed can be reached. Research is performed in collaboration with Škoda Auto (www.skoda-auto.com).

Keywords: eco-driving, fuel consumption optimization, vehicle, feedback control

1 Introduction

Most drivers naturally wish to drive more economically. Reducing the fuel consumption and CO_2 emission concerns also the automotive industry, especially in view of recent requirements about it in the governmental level. Most manufacturers invest a lot in development and support of various conceptual solutions for eco-driving which can be mainly found in the form of hybrid and electric vehicles [2, 3, 4]. They are environmentally friendly and promise significant fuel savings. However, both only in exploitation. The purchase price of hybrid or electric vehicles is still rather high (although in recent times it is decreased) which compensates fuel savings.

For modern conventional vehicles, some automobile manufacturers propose the eco-driving solutions (but not limited to) via built-in advising systems that prompt drivers how to make a driving style more economic and ecologic. In our project we focus on development of adaptive algorithms for advising system for optimization of fuel consumption within the research project performed in collaboration with Škoda Auto (www.skoda-auto.com).

Many studies can be found in this field, for example, [5, 6, 9, 1] that investigate influence of driving style on fuel consumption and emissions. This confirms relevance of the eco-driving topic. However, algorithms founded in the discussed field are mostly based on physical model of fuel consumption, taking into account surrounding traffic conditions, e.g., [7, 8, 10, 11]. Within our project, we use a data-dependent approach based on Bayesian methodology [12]. Here we describe the experimental part of the work directed at a validation of the used control algorithm.

2 Theoretical Background

As the main emphasis of this paper is to present validation experiments of the control algorithm used for the advising system for eco-driving, we should indicate very briefly the used theoretical background. In details it can be found in [15, 16, 17].

The problem of fuel consumption optimization is formulated as follows: (i) construct a model of a “driver-vehicle” system; (ii) estimate model parameters using measurements; (iii) design a real-time (on-line) control which has to push both the fuel consumption and the speed to their desired values as close as possible simultaneously.

The “driver-vehicle” system is described by the following probability density function (pdf):

$$f(y_t|\psi_t, \Theta), \quad (1)$$

where $\psi'_t = [u'_t, v'_t, y'_{t-1}, u'_{t-1}, v'_{t-1}, \dots, y'_{t-n}, u'_{t-n}, v'_{t-n}, 1]$ is a regression vector and Θ denotes model parameters. A well-known Bayesian recursive parameter estimation, e.g., [13], is used.

The fuel consumption optimization task is solved as the feedback control algorithm which combines dynamic programming with setpoint pre-programming described in [17]. According to the project aim, the algorithm is conceived for subsequent implementation in advising system in a vehicle. It means that the control values produced by the algorithm will then be used as real-time advices for a driver how to save fuel. However, in order to validate them, we should test the algorithm as the automatic control of the vehicle (i.e., as if a driver would follow the advices automatically). This is the main emphasis of this paper.

Selection of data to be used for the model and experiments of testing the algorithm are demonstrated in subsequent sections.

3 Data Selection

The data used for the considered task were provided by Škoda auto (see www.skoda-auto.com). They were measured on a specially equipped vehicle Škoda Octavia 2.0 TDI with a DSG automatic gearbox, driven on a selected route. The route of a length about 38 kilometers out of Prague is composed of parts of highway, out-of-town roads and roads passing through small towns with corresponding speed limits. To ensure necessary dynamic, the data were measured for different driving styles, i.e., some of the drivers tried to save the fuel and some of them not. Totally 8 data samples with a sampling period 0.2 seconds are available.

Originally, the available data samples contained a significant number of variables influencing driving. The most informative data to be involved in the model are selected as follows.

The controlled output vector includes:

- fuel consumption,
- speed,

where they both are to be pushed to their desired values (setpoints) as close as possible,

- engine torque,
- engine speed,
- distance traveled from the last measurement,

while these three outputs have to be only properly constrained, but without setpoints to be pushed to. The control input vector includes:

- pressing the gas pedal,
- pressing the brake pedal,
- gear.

It should be noted that according to advices from the eco-driving experts, braking should be realized mostly by engine in order to reduce the fuel consumption. The brake pedal should be used for complete braking and stopping or in situations where braking by engine is not sufficient. Thus, braking is a not a result of optimization, but a deterministic control action.

The external variable vector:

- road altitude,
- UTM-X and UTM-Y coordinates of vehicle position,
- radius of the curve road.

4 Using Data as Setpoints

The data selected for the model are used not only for the estimation, but also for a choice of setpoints, i.e., desired values of the optimized variables.

According to advices of experts, the setpoint for the (actual) fuel consumption is chosen as follows. As it was already mentioned, the available data samples provide measurements corresponding to different driving styles, i.e, faster and more dynamic, but with higher fuel consumption, and otherwise, slower and more economic. We take a data sample whose average fuel consumption is the lowest among others. Then we multiply the actual fuel consumption from this data sample by 0.85 so that we have 85% of it. This value at time t is denoted by $s_{1;t}$ and it is the setpoint for the actual fuel consumption.

The speed setpoint is the recommended speed provided by experts for the considered route. This is the speed again from the data sample whose average fuel consumption was the lowest one. Driving with this speed is acceptable from the viewpoint of fuel saving. However, it must also satisfy traffic restrictions. Thus, this speed is preprocessed with the help of application of speed limits existing on the route according to position coordinates or discretized points of a length 20 meters. The obtained value at time t is the setpoint for the speed denoted by $s_{2;t}$. In order to use the recommended speed as the setpoint during the time cycle effectively, it is necessary to get the current UTM-X and UTM-Y coordinates of the vehicle position at each time instant, determine the vehicle location on the route and then take the value of the speed recommended just for this location.

5 Testing Experiments

The testing experiments are performed in Matlab connected via serial ports with a vehicle simulator provided by Škoda auto to test algorithms during the project. The simulator represents a separate software based on a physical model of a vehicle. To validate the control, the simulator works as a vehicle which obtains values of pressing the gas and the brake pedals and gear as the inputs from the algorithm and in real time reacts to them by producing the outputs, where the most interesting for us are the optimized variables – fuel consumption and speed. In real time the simulator also obtains values of external variables on the route. A map with the marked considered route and a transparent view of the driven vehicle is shown in Figure 1. A beginning of the route is denoted by “start”. The current position of the simulated vehicle is marked by red circle.



Figure 1: The map with the marked route and a transparent view of a vehicle. The red circle shows the current position of the vehicle on the route.

About 10000 data items with a sampling period 0.2 seconds is necessary in order to have the vehicle passed through the whole route with a speed close to the recommended one. Figure 2 (left) demonstrates the UTM position coordinates reported by the simulator during passing the route. The route is not characterized by significant clearly expressed hills, see the road gradient in Figure 2 (right).

As a driver, we can choose between two variants of eco-driving according to our preferences. It means that we can preset whether we wish a more dynamic and faster driving, but with a higher fuel consumption, or otherwise, smoother and a bit slower, but more economically. This is reached by values of individual penalizations, see [16, 17]. It should be noted that the first variant – a more dynamic driving - covers the fuel consumption optimization as well. It only represents driving a bit closer to the recommended speed than in the second case.

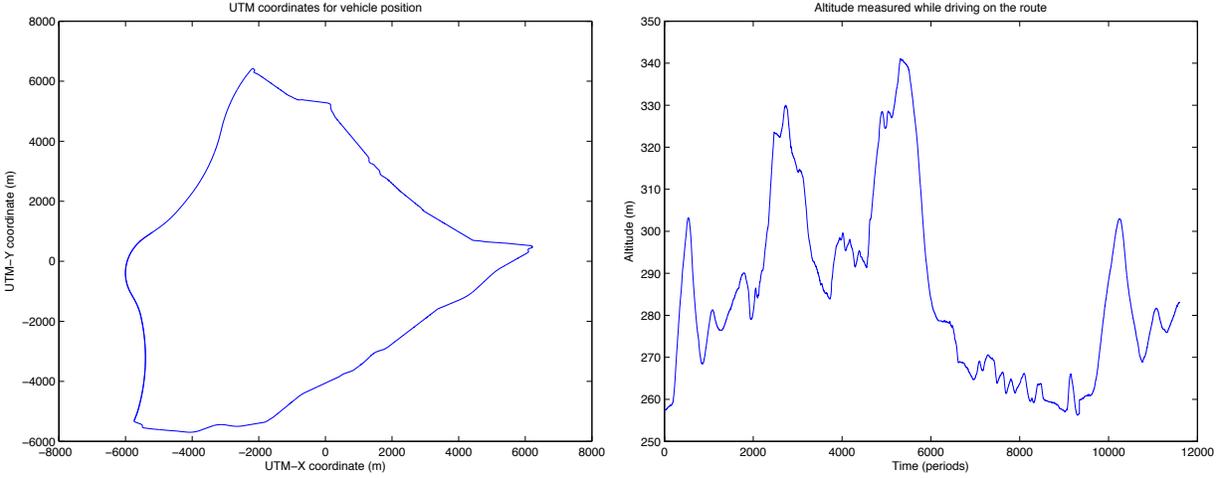


Figure 2: The left plot shows UTM coordinates for vehicle position after passing the whole route by the simulated vehicle. Notice its correspondence to the map in Figure 1. The right plot provides the altitude measured while driving on the route.

We tested the algorithm for both the cases and compared the obtained results with real data.

5.1 Results for a Smoother Driving Preference

Figure 3 (left) demonstrates the speed obtained during driving the whole route in comparison with the recommended speed. The obtained speed is a bit lower than the recommended one, but it is in reasonable ranges. Figure 3 (right) shows the fuel consumption during this driving. Places with the road uphill are the most interesting from the fuel economy viewpoint. They can be found in Figure 2 (right) from 2000 to 3000 time periods and from 4000 to 5000 time periods. It can be seen that the fuel consumption in Figure 3 (right) in these locations has also a more economic course. It should be noted that neither the speed nor the fuel consumption cannot track their setpoints precisely due to the compromise in the penalization settings.

The average fuel consumption is converted from $\mu\text{L}/0.2$ seconds to more presentable $\text{L}/100\text{km}$. For a smoother driving preference, the obtained average fuel consumption is $4.8 \text{ L}/100\text{km}$, which is lower than the real fuel consumption $5.5 \text{ L}/100\text{km}$ computed from the data sample used for validation.

Figure 4 (left) demonstrates pressing the gas pedal during the driving, which has a smoother course in comparison with real data. Figure 4 (right) shows pressing the brake pedal, which is used less often than in real measurements. It allows to reduce the fuel consumption. Prohibition of simultaneous pressing both the pedals can be seen in Figure 4 near 3800 and 7200 time periods: when the brake pedal is pressed, the gas one is not. The lowest level of pressing the brake pedal in Figure 4 (right) is preset as constant 0.85 bar according to minimal pressure in the brake system. The real measurement of the minimal pressure is a bit lower and noisy.

Figure 5 provides selection of gear during the driving.

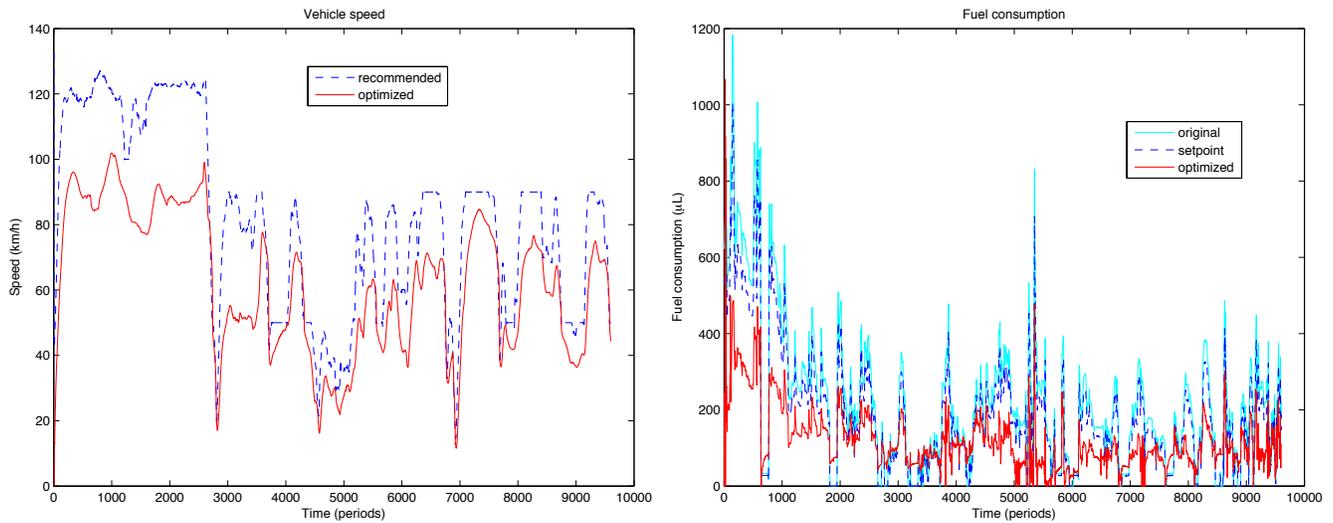


Figure 3: The speed (left) and the fuel consumption (right) for the whole route with a smoother driving preference chosen.

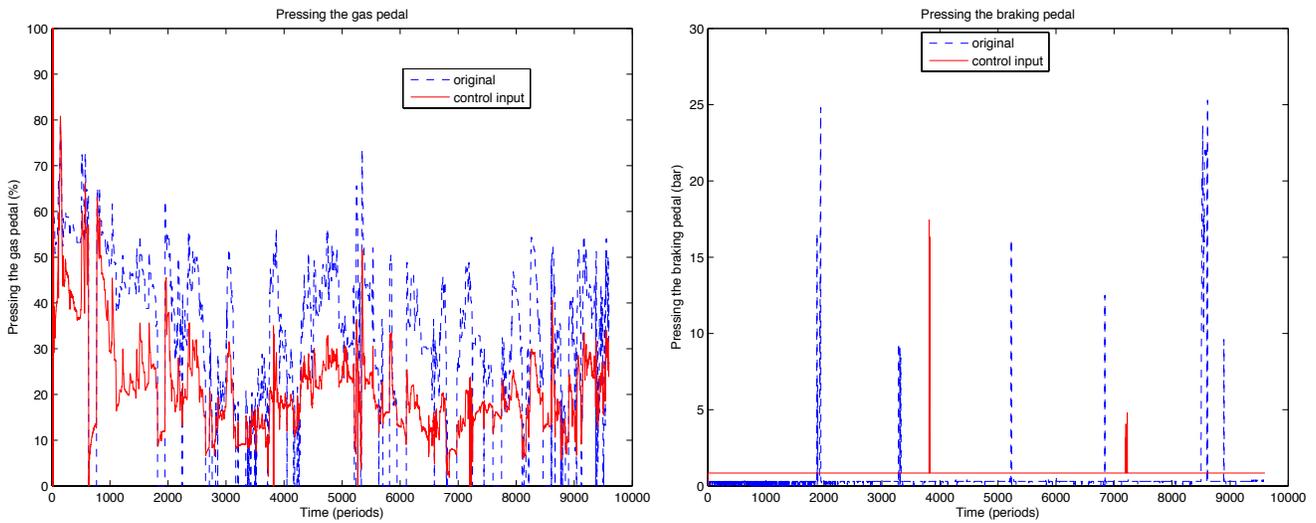


Figure 4: Pressing the gas pedal (left) and pressing the brake pedal (right) for a smoother driving preference. Notice a smoother course of pressing the gas pedal in comparison with real data. Notice also pressing the brake pedal near 3800 and 7200 time periods and the unpressed gas pedal.

5.2 Results for a More Dynamic Driving Preference

More dynamic driving differs from the previous one by more often usage of the brake pedal, see Figure 6 (right), and by sharper changes in pressing the gas pedal, Figure 6 (left). Selection of gear is very similar to that shown in Figure 5.

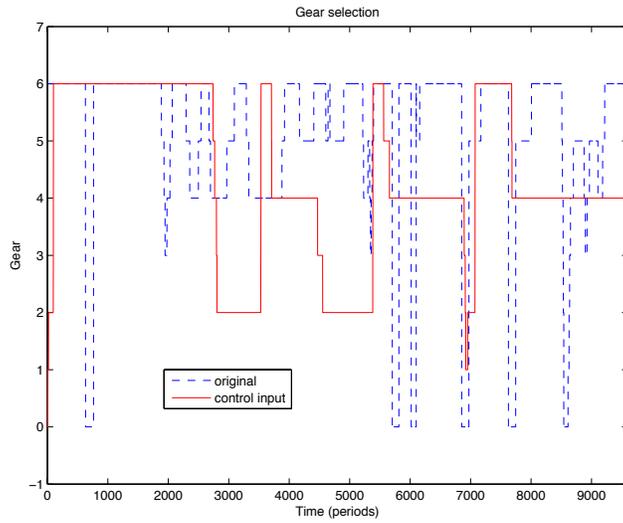


Figure 5: Gear selection advising for a smoother driving preference

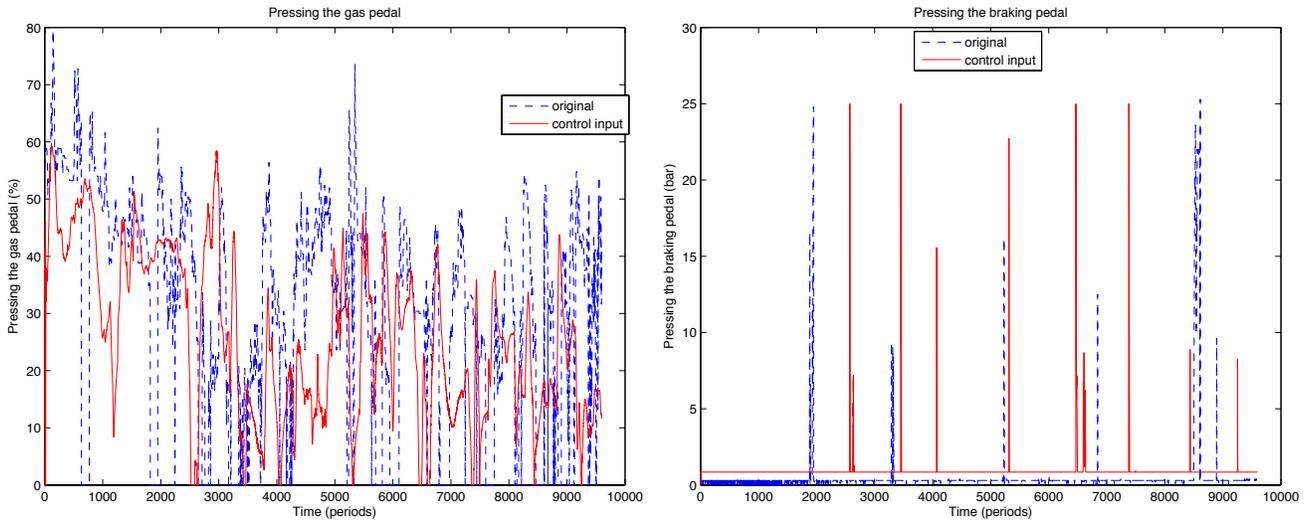


Figure 6: Pressing the gas pedal (left) and pressing the brake pedal (right) for a more dynamic driving preference.

The obtained speed is shown in Figure 7 (left). A necessity to track the setpoint of the fuel consumption does not enable to produce the control so that to keep the recommended speed precisely. However, this speed is closer to the recommended one than in Figure 3 (left). The fuel consumption is shown in Figure 7 (right). Its values are a bit higher than in Figure 3 (right). However, the obtained average fuel consumption is 5.1 L/100km that is lower than the real 5.5 L/100km.

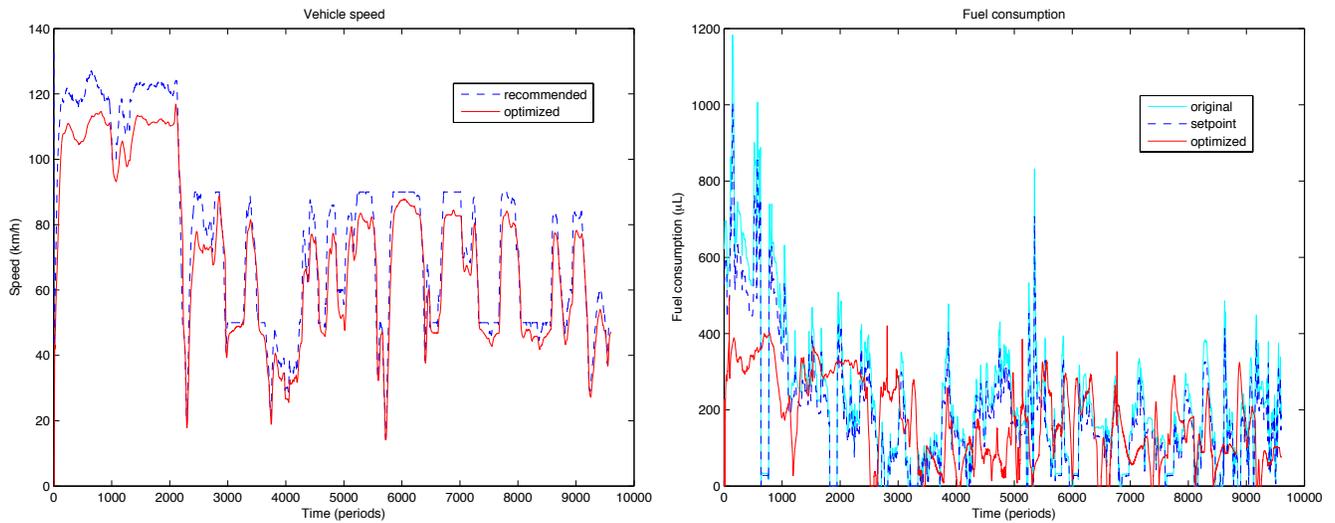


Figure 7: The speed (left) and the fuel consumption (right) for a dynamic driving preference.

5.3 Discussion

To summarize the experimental part of the work, we can say that the presented results look promising. Choosing any of the driving preferences, we can reduce the fuel consumption in comparison with real data. It means that the advising system based on the described approach can be suitable for eco-driving. In the case of a malfunction in the control systems of a vehicle or an accident situation an option to automatic disabling the advising system should be provided.

6 Conclusion

The paper describes experiments of testing the control algorithm performed within the project aimed at fuel consumption optimization. The tests with a hardware vehicle simulator are planned for future work.

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References

- [1] Michael Sivak and Brandon Schoettle. Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy. *Transport Policy*, 22, 2012, pages 96–99.
- [2] G. Pistoia. *Electric and Hybrid Vehicles. Power Sources, Models, Sustainability, Infrastructure and the Market*. Elsevier, 2010, ISBN: 978-0-444-53565-8.

- [3] Wirasingha, S.G. and Emadi, A. Classification and Review of Control Strategies for Plug-In Hybrid Electric Vehicles. *IEEE Transactions on Vehicular Technology*. 60(1), 2011, pages 111–122.
- [4] Moura, S.J. and Fathy, H.K. and Callaway, D.S. and Stein, J.L. A Stochastic Optimal Control Approach for Power Management in Plug-In Hybrid Electric Vehicles. *IEEE Transactions on Control Systems Technology*. 19(3), 2011, pages 545–555.
- [5] E.Ericsson. Independent driving pattern factors and their influence on fuel-use and exhaust emission factors. *Transportation Research Part D: Transport and Environment*. 6(5), 2001, pages 325–345.
- [6] M. van der Voort, M. S. Dougherty, M. van Maarseveen A prototype fuel-efficiency support tool. *Transportation Research Part C* 9(2001), pages 279–296.
- [7] Y. Saboohi, H. Farzaneh. Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption. *Applied Energy*, volume 86, issue 10, October 2009, pages 1925–1932.
- [8] Matthew Barth and Kanok Boriboonsomsin. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment* 14 (6), 2009, pages 400–410.
- [9] Bart Beusen and Steven Broekx and Tobias Denys and Carolien Beckx and Bart Degraeuwe and Maarten Gijbbers and Kristof Scheepers and Leen Govaerts and Rudi Torfs and Luc Int Panis. Using on-board logging devices to study the longer-term impact of an eco-driving course. *Transportation Research Part D: Transport and Environment*. 14(7), 2009, pages 514–520.
- [10] C. Raubitschek, N. Schütze, E. Kozlov, and B. Bäker. Predictive Driving Strategies under Urban Conditions for Reducing Fuel Consumption based on Vehicle Environment Information. *Proceedings of IEEE Forum on Integrated and Sustainable Transportation Systems*, Vienna, Austria, June 29–July 1, 2011, pages 13–19.
- [11] Ben Dhaou, I. Fuel estimation model for ECO-driving and ECO-routing. *Proceedings of IEEE Intelligent Vehicles Symposium (IV)*. Baden-Baden, Germany, 2011, June 5–9, pages 37–42.
- [12] M. Kárný, J. Böhm, T. V. Guy, L. Jirsa, I. Nagy, P. Nedoma, and L. Tesař, *Optimized Bayesian Dynamic Advising: Theory and Algorithms*. London, Springer, 2005.
- [13] V. Peterka, “Bayesian system identification,” in *Trends and Progress in System Identification*, P. Eykhoff, Ed. Oxford: Pergamon Press, 1981, pp. 239–304.
- [14] E. Suzdaleva, I. Nagy and L. Pavelková. Fuel consumption optimization: early experiments. *Preprints of the 16th IFAC Symposium on System Identification Sysid 2012*, Brussels, Belgium, 2012, July 11–13, pages 751–756.
- [15] E. Suzdaleva, I. Nagy, L. Pavelková, T. Mlynářová. Servo Problem within Fuel Consumption Optimization. *Proceedings of IASTED International Conference on Engineering and Applied Science (EAS 2012)*, Colombo, Sri Lanka, December 27– 29, 2012, pages 100–107.
- [16] E. Suzdaleva, I. Nagy, L. Pavelková and T. Mlynářová. Double Optimization of Fuel Consumption and Speed Tracking. *Proceedings of the 11th IFAC International Workshop on Adaptation and Learning in Control and Signal Processing*, Caen, France, July 3–5, 2013.

- [17] I. Nagy, E. Suzdaleva and T. Mlynářová. Optimization of Driving Based on Currently Measured Data. *Proceedings of the 16th International IEEE Annual Conference on Intelligent Transportation Systems*, The Hague, The Netherlands, October 6–9, 2013, accepted.