10.1515/mecdc-2018-0005

MODEL BASED NONLINEAR PREDICTIVE CONTROL OF IC ENGINE

VÍT DOLEČEK
Czech Technical University in Prague, Department of Automotive, Combustion Engine and Railway Engineering, Technická 4, CZ-16607 Prague 6, Czech Republic, Tel.: +420224352507, Fax: +420224352500, E-mail: v.dolecek@fs.cvut.cz
JAN PELIKÁN, PETR DENK, ZBYNĚK ŠIKA
Czech Technical University in Prague, Department of Mechanics, Biomechanics and Mechatronics, Technická 4, CZ-16607 Prague 6, Czech Republic, Tel.: +420224357452, E-mail: zbynek.sika@fs.cvut.cz

ABSTRACT
In the paper is described development of predictive controller of combustion engine. The basic part of control system is predictive model describing future engine behavior in transient conditions. Accurate identification of controlled system, combustion engine in our case, is very important for high level of control precision. Typical engine operation is defined by driving cycle, which is used for engine operation parameters identification. Developed predictive control system was subsequently tested using software-in-the-loop technique.
KEYWORDS: SIMULATION MODEL, 1-D SIMULATION, CONTROL ALGORITHM, PREDICTIVE CONTROL, PREDICTIVE MODEL, LOLIMOT

SHRNUTÍ
V tomto článku je popsán vývoj prediktivního řídicího systému pro spalovací motor. Základem prediktivního kontrolního systému je prediktivní model popisující chování v krátké budoucnosti přechodového děje. Přesná identifikace řízené soustavy, v našem případě spalovacího motoru, je velmi důležitá z hlediska přesnosti řízení. Typický provoz motoru je definován jízdním cyklem, který byl z tohoto důvodu použit pro identifikaci stavových parametrů motoru. Vyvinutý prediktivní systém řízení byl následně otestován s využitím software-in-the-loop techniky.
KLÍČOVÁ SLOVA: SIMULAČNÍ MODEL, 1-D SIMULACE, ŘÍDICÍ ALGORITMUS, PREDIKTIVNÍ ŘÍZENÍ, PREDIKTIVNÍ MODEL, LOLIMOT

1. INTRODUCTION

Internal combustion engines, as a source of mechanical power, started their development and improvement from the first day of their application. Engine efficiency, together with specific power, was gradually increased to meet demands of vehicles and machines of various kinds. Heavy and complicated steam engines were quickly replaced by ICE, which were simply more economical and also more ecological. Constant development of industry and transportation, mainly in large city agglomerations, was related with negative impact on the environment. This impact in connection with oil crisis was a driving force for implementation of emission limits for combustion engines. Nowadays, the dangerous pollutant emissions are limited together with CO_2, which was identified as a main factor causing global warming. Amount of CO_2 in engine exhaust gases is dependent on carbon fraction in fuel, which oxidizes during combustion process, and a total fuel consumption. Combustion engine total efficiency has to be increased or alternative low carbon fuel can be used to reduce specific CO_2 emissions.

Engine research and development deals with combustion optimization and with exhaust gas aftertreatment optimization intensively to fulfil present and future emission limits. Nevertheless, none of new technologies could be applied to new engines without engine control optimization. Each technology implemented into design of combustion engine, which enables control and setting, brings new parameter for control system. Complexity of engine control systems gradually grows with number of controlled variables. Typical control unit works with look-up tables, which prescribes output for individual inputs. Low computation effort for interpolation in tables is in contrast to high demands for calibration of control unit, which require filling calibration parameters into thousands of tables for each engine type. The engines in automotive industry are produced in large quantities and ECU calibration costs are fractionated among production. More sophisticated control algorithms will probably call for more expensive hardware, which cannot guarantee lower price in mass production. Despite this fact, engine control systems and control algorithms are developed to meet demands of future combustion engines.

One possibility of engine control system with lower calibration effort is implementation of physical relationships among

variables. Results of relatively simple physical models will significantly reduce amount of look-up tables. This approach will potentially lead to complete thermodynamic engine model computed in engine control unit in real time. Results from engine model are applied to the real engine control since engine model behavior is identical to a real one. Furthermore, predicted parameters from engine model will substitute measured signals and possibly reduce number of sensors on real engine. Required number of parameters for engine thermodynamic model setup is dramatically reduced in comparison to simple look-up table based control unit. Most of the parameters are engine physical dimensions together with engine layout, which are all known during engine development. Although this approach is very promising, the cost of powerful electronic control unit hardware prevents utilization of this type of engine control.
Another possibility of engine control system is application of modern control methods, which will treat the considered dynamic system as one complex multi-input-multi-output (MIMO) unit. Model-based predictive control (MPC) [1], [2], [3] is a natural choice here, since discrete predictive models are very well suited to the "clockwork" nature of IC engines. A reliable predictive model of the controlled system is crucial for the proper control function, so one of the important tasks is finding a suitable method of creating such a model, i.e. of the system identification. One of the most promising and universal methods of dynamic systems identification is LOLIMOT [4]. It can produce robust, real time capable predictive models that have the advantage of being piece-wise linear, so that linear predictive control will be based on them. Since LOLIMOT models do not describe physical behavior of controlled system, analogically to other black-box models, the definition of the sets of linear functions is generated during model training. This procedure is important especially in terms of model results accuracy. The model is adapted to the real system outputs according to the system input parameters.

2. MODEL-BASED PREDICTIVE CONTROL SYSTEM

Predictive models have an ability to predict the behavior of a dynamic system in the (near) future, therefore they are used for the calculation of the predictive control law. A predictive model is usually a discrete state model of the system.

2.1 LOLIMOT

LOLIMOT produces a combination of local input-output models that approximate the nonlinear behavior of an identified system by linear functions valid in particular sub-regions of the whole domain of definition. The mathematical models of a system identified with the LOLIMOT are called 'LOLImodels' (LLMs).

The basic principle of LOLIMOT is the approximation of the generally non-linear multivariable input-output function of a system by the scalar product of the vector of linear input--output functions and the vector of validity functions. Each linear function approximates the system output in sub-region determined by a relevant validity function. The output of the model can be written as:

$$
\begin{aligned}
\tilde{y} = \sum_{i=1}^{M} \tilde{y}_i \Phi_i(\mathbf{u}_L) = \sum_{i=1}^{M} \Big(& w_{i,0} + w_{i,1} u_1(k) + w_{i,2} u_1(k-1) + \ldots + \\
& + w_{i,n_1+1} u_1(k-n_1) + w_{i,n_1+2} u_2(k) + w_{i,n_1+3} u_2(k-1) + \ldots + \\
& + w_{i,n_1+n_2+2} u_2(k-n_2) + \ldots + w_{i,n_1+n_2+\ldots+n_{p-1}+p} u_p(k) + \\
& + w_{i,n_1+n_2+\ldots+n_{p-1}+p+1} u_p(k-1) + \ldots + w_{i,n_1+n_2+\ldots+n_p+p} u_p(k-n_p) + \\
& + w_{i,n_1+n_2+\ldots+n_p+p+1} y(k-1) + w_{i,n_1+n_2+\ldots+n_p+p+2} y(k-2) + \ldots + \\
& + w_{i,n_1+n_2+\ldots+n_p+n_y+p} y(k-n_y) \Big) \Phi_i(\mathbf{u}_L)
\end{aligned}
\tag{1}
$$

where M is the number of LLMs, $\tilde{y}_i$ is the output of the i-th LLM,

$$
\begin{aligned}
\mathbf{u}_L = & [u_1(k), u_1(k-1), \ldots, u_1(k-n_1), u_2(k), \\
& \ldots \quad u_p(k-n_p), y(k-1), \ldots, y(k-n_y)]^{\mathrm{T}}
\end{aligned}
$$

is the vector of inputs, $\Phi_i(\mathbf{u}_L)$ is a validity function for the i-th LLM (designed as a normalized orthogonal Gaussian function),

$$
\mathbf{w} = \left\lfloor w_{i,0}, w_{i,1}, \ldots, w_{i,n_1+n_2+\ldots+n_p+n_y+p} \right\rfloor^{\mathrm{T}}
$$

is the vector of the parameters of the i-th LLM.
The process of computing LLMs parameters, i.e. the identification of a given dynamic system, is called 'training of LLMs', and the computation is based on training signals.
LOLIMOT was utilized to produce piecewise-linear predictive model of the engine. LLMs were trained using two independent sources of dynamic response data sets – a simulation model (for a model-in-the-loop simulation) and a real test-bed engine (for a hardware-in-the-loop arrangement).

2.2 PREDICTIVE MODEL BASED ON LOLIMOT

Although calculated LLMs generally constitute a nonlinear predictive system, their big advantage is that they can be directly transformed into a discrete state-space description with *locally* constant state matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{D}$:

$$
\begin{aligned}
\Delta \boldsymbol{x}_{k+1} &= \mathbf{A} \Delta \boldsymbol{x}_k + \mathbf{B} \Delta \boldsymbol{u}_k \\
\Delta \boldsymbol{y}_k &= \mathbf{C} \Delta \boldsymbol{x}_k + \mathbf{D} \Delta \boldsymbol{u}_k
\end{aligned},
\tag{2}
$$

where $\Delta\mathbf{x}$ are system state variables, $\Delta\mathbf{u}$ are system inputs (control variables) and $\Delta\mathbf{y}$ are system outputs (i.e. variables to be controlled).

Three quantities designate the system states – engine speed, turbocharger speed, and boost pressure. LLMs were subsequently calculated of the state variables. Each LLM had five input signals (two actual control inputs and the past values of three state variables themselves). Another LLM was computed for the engine torque, which was (together with the boost pressure) chosen as the controlled quantity.

2.3 MODEL-BASED PREDICTIVE CONTROL

A model-based control scheme utilizes a concurrently running numerical model as a basis for the application of the control law. One of the benefits of this approach is the possibility to replace measurements by computations, which considerably reduces demands on the instrumentation of the whole control system. This have a big impact on both the price and the reliability of the system. Moreover, the simulation model provides some data that are not measurable using standard means (there is a danger of engine damage).

Rewriting the state model (2) for N subsequent steps, while getting rid of the incremental form of the states, inputs and outputs (i.e. writing $\mathbf{x}$, $\mathbf{u}$, and $\mathbf{y}$ instead of $\Delta\mathbf{x}$, $\Delta\mathbf{u}$, and $\Delta\mathbf{y}$), one gets the formula sequence (3). The inclusion of the direct algebraic link between the plant input and output variables (via the matrix $\mathbf{D}$) within the control framework resulted from the practical application requirements.

$$\begin{aligned}
&(\boldsymbol{y}_k = \mathbf{C}\boldsymbol{x}_k + \mathbf{D}\boldsymbol{u}_k)\\
&\boldsymbol{x}_{k+1} = \mathbf{A}\boldsymbol{x}_k + \mathbf{B}\boldsymbol{u}_k\\
&\boldsymbol{y}_{k+1} = \mathbf{C}\boldsymbol{x}_{k+1} + \mathbf{D}\boldsymbol{u}_{k+1} = \mathbf{CA}\boldsymbol{x}_k + \mathbf{CB}\boldsymbol{u}_k + \mathbf{D}\boldsymbol{u}_{k+1}\\
&\boldsymbol{x}_{k+2} = \mathbf{A}\boldsymbol{x}_{k+1} + \mathbf{B}\boldsymbol{u}_{k+1}\\
&\boldsymbol{y}_{k+2} = \mathbf{C}\boldsymbol{x}_{k+2} + \mathbf{D}\boldsymbol{u}_{k+2} = \ldots = \mathbf{CA}^2\boldsymbol{x}_k + \mathbf{CAB}\boldsymbol{u}_k + \mathbf{CB}\boldsymbol{u}_{k+1} + \mathbf{D}\boldsymbol{u}_{k+2}\\
&\ldots\\
&\boldsymbol{y}_{k+N} = \mathbf{C}\boldsymbol{x}_{k+2} + \mathbf{D}\boldsymbol{u}_{k+2} = \ldots = \mathbf{CA}^N\boldsymbol{x}_k + \mathbf{CA}^{N-1}\mathbf{B}\boldsymbol{u}_k + \mathbf{CA}^{N-2}\mathbf{B}\boldsymbol{u}_{k+1} + \ldots\\
&\ldots + \mathbf{CB}\boldsymbol{u}_{k+N-1} + \mathbf{D}\boldsymbol{u}_{k+N}
\end{aligned} \tag{3}$$

Using the sequence (3), the output variables written in a complex matrix form (suitable for the control law derivation) is as follows:

$$\hat{\boldsymbol{y}} = \boldsymbol{f} + \mathbf{G}\boldsymbol{u}, \tag{4}$$

where

$$\boldsymbol{f} = \begin{bmatrix} \mathbf{CA}^1 \\ \mathbf{CA}^2 \\ \ldots \\ \ldots \\ \mathbf{CA}^N \end{bmatrix} \boldsymbol{x}_k ,$$

$$\mathbf{G} = \begin{bmatrix} \mathbf{CB} & \mathbf{D} & \mathbf{0} & \ldots & \ldots & \mathbf{0} \\ \mathbf{CAB} & \mathbf{CB} & \mathbf{D} & \ldots & \ldots & \mathbf{0} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \mathbf{0} \\ \mathbf{CA}^{N-2}\mathbf{B} & \mathbf{CA}^{N-3}\mathbf{B} & \ldots & \ldots & \mathbf{D} & \mathbf{0} \\ \mathbf{CA}^{N-1}\mathbf{B} & \mathbf{CA}^{N-2}\mathbf{B} & \mathbf{CA}^{N-3}\mathbf{B} & \ldots & \mathbf{CB} & \mathbf{D} \end{bmatrix} \begin{bmatrix} \boldsymbol{u}_k \\ \boldsymbol{u}_{k+1} \\ \boldsymbol{u}_{k+2} \\ \ldots \\ \boldsymbol{u}_{k+N} \end{bmatrix} \tag{5}$$

The control is derived from the optimization of a quadratic performance index J_k[2]:

$$\begin{aligned} J_k &= \varepsilon\left\{(\hat{\boldsymbol{y}} - \boldsymbol{w})^T \boldsymbol{Q}(\hat{\boldsymbol{y}} - \boldsymbol{w}) + \boldsymbol{u}^T \boldsymbol{p}\boldsymbol{u}\right\} = \\ &= \varepsilon\left\{(\boldsymbol{G}\boldsymbol{u} + \boldsymbol{f} - \boldsymbol{w})^T \boldsymbol{Q}(\boldsymbol{G}\boldsymbol{u} + \boldsymbol{f} - \boldsymbol{w}) + \boldsymbol{u}^T \boldsymbol{p}\boldsymbol{u}\right\} \end{aligned} \tag{6}$$

The performance index is optimized in the step k using the prediction $\hat{\boldsymbol{y}} = [\boldsymbol{y}_{k+1} \quad \boldsymbol{y}_{k+2} \quad \ldots \quad \boldsymbol{y}_{k+N}]^{\mathrm{T}}$ for the sequence of output vectors. The parameter e is a mean value operator, N is the prediction horizon, $\mathbf{y}$ is the output vector, $\mathbf{w}$ is the desired output vector, $\mathbf{Q}$ is a penalization matrix for the outputs, $\mathbf{p}$ is the penalization of the inputs, and $\boldsymbol{u} = [\boldsymbol{u}_k \quad \boldsymbol{u}_{k+1} \quad \ldots \quad \boldsymbol{u}_{k+N}]^{\mathrm{T}}$ is the sequence of input vectors.

From the requirement of the minimization of the performance index

$$J_{k,\mathrm{opt}} \overset{!}{=} \min_{\boldsymbol{u}}(J_k), \tag{7}$$

the derived control law:

$$\boldsymbol{u} = \left(\mathbf{G}^{\mathrm{T}}\mathbf{Q}\mathbf{G} + \mathbf{p}\right)^{-1}\mathbf{G}^{\mathrm{T}}\mathbf{Q}(\boldsymbol{w} - \boldsymbol{f}). \tag{8}$$

Only the first element of the vector $\mathbf{u}$ is used for the nearest control action.

In terms of the actual work, the following quantities designate the system variables (relevant for the control):

- 2 system inputs $\mathbf{u}$: 1. fuel mass per cycle, 2. rack position of the VGT;
- 3 state variables $\mathbf{x}$: 1. engine speed, 2. turbocharger speed, 3. pressure;
- 2 system outputs $\mathbf{y}$: 1. engine torque, 2. intake manifold (boost) pressure.

The engine is supposed to work in a mode of prescribed engine speed, which is being set externally, while controlled variables are the two above mentioned system outputs. While the choice of the desired engine torque is arbitrary (within certain limits), a function (in form of a 2-D lookup table) is imposed on the online calculation of the boost pressure setpoint, which takes engine speed and torque setpoint into account, and its goal is to provide optimum combustion conditions.

3. ENGINE SIMULATION MODEL

Iveco Tector F4AE0682C six-cylinder diesel engine was used for the purpose of this work. The engine was equipped with common rail fuel injection system. Original turbocharger was replaced by Honeywell turbocharger with variable geometry turbine (VGT) set by electric actuator. Original ECU was replaced by Ricardo rCube2 control system which is fully open and modifiable. The control system developed in MATLAB/Simulink is computed on rCube2 hardware after compilation. Engine maximum power was 194 kW / 2500 min^{-1} and torque of 930 Nm in wide range of engine speed.

Original engine control algorithms are based on a large set of look-up tables where working state is described by engine speed and engine torque. Target value of engine torque is calculated from the accelerator pedal position with respect to engine full load curve. Actual engine torque is not measured as a feedback, therefore only target torque value is used as input for control look-up maps interpolation. Each map output is uniquely defined and used for control with application of correction data. Maximum injected fuel mass is limited by the calculated Air to Fuel (A/F) ratio to suppress excessive smoke production. Feedback control strategy realized by simple PI controller was used only for intake air pressure control. All control maps were calibrated in steady states at the engine test bench. Since original ECU cannot be easily modified, original look-up table based control strategy was programed into rCube2 as a basic control system. MPC controller was later implemented into rCube2 instead of lookup tables.

3.1 CALIBRATION OF 1-D ENGINE SIMULATION MODEL

1-D simulation model was built in GT-Suite software from Gamma Technologies. All geometrical data was measured on real engine. Turbocharger characteristic was delivered by the producer. Combustion model was calibrated using Three Pressure Analysis (TPA) in single cylinder simulation model from high-speed measurement of pressures in cylinder and in intake and exhaust manifolds.

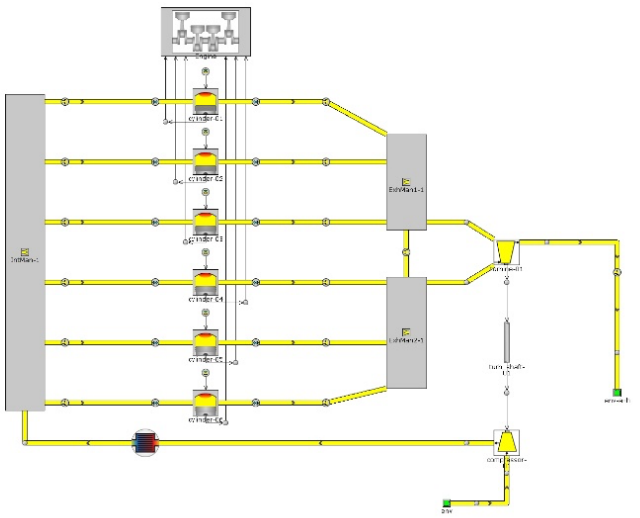

FIGURE 1: Fast Running Model of engine in GT-Power.
OBRÁZEK 1: Rychlý výpočetní model motoru v prostředí GT-Power.

Detailed 1-D model was simplified up to RT model (Figure 1). Number of flow volumes decreased from 360 to approximately 60 for FRM and 30 for RT model. The level of pulsation in turbine inlet is different in FRM and RT models, which affects turbine power especially in transient operation.

Time-averaged data measured at steady states at engine test bench was used to the calibration of engine model. Comparison of measured data with simulation results are displayed in Figure 2. The deviation of calibrated detailed 1-D model is less than 3% in most of measured points. The comparison of maximum cylinder pressure shows good prediction of combustion model. All parameters describing the engine operation are predicted with acceptable level of accuracy.

The agreement of results of detailed 1-D model, FRM and even RT model is very high and transient test proved that unsteady operation predicted by FRM models are as accurate as detailed 1-D models. FRM computation time is 77 times faster than detailed 1-D model and real-time ratio is approximately 3.5. RT model computational time was approximately 0.8 of real time with satisfactory accuracy of engine operation parameters.

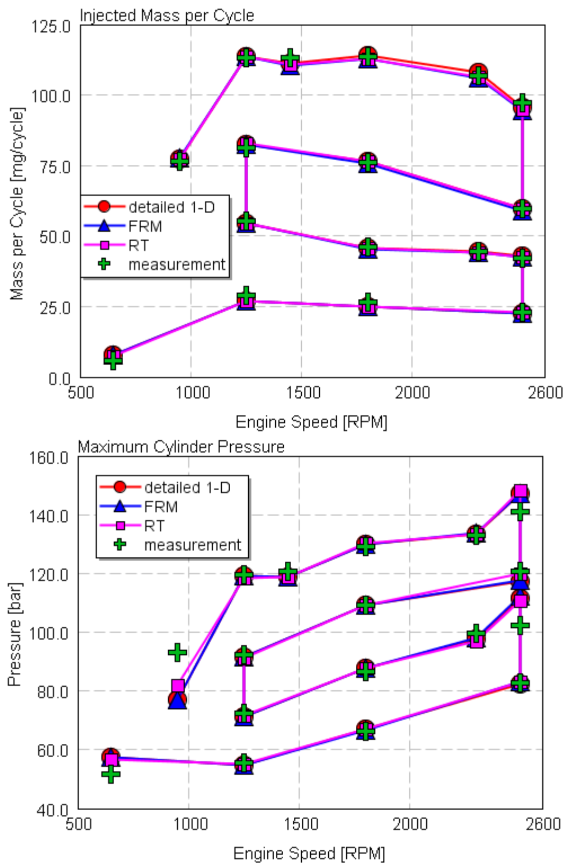

FIGURE 2: Results comparison of detailed 1-D model and FRM model with measured data – injected fuel mass per cycle (upper) and maximum cylinder pressure (lower).
OBRÁZEK 2: Porovnání výsledků podrobného 1-D modelu a rychlého modelu s naměřenými daty – dávka paliva (horné) a maximální spalovací tlaky (dolní).

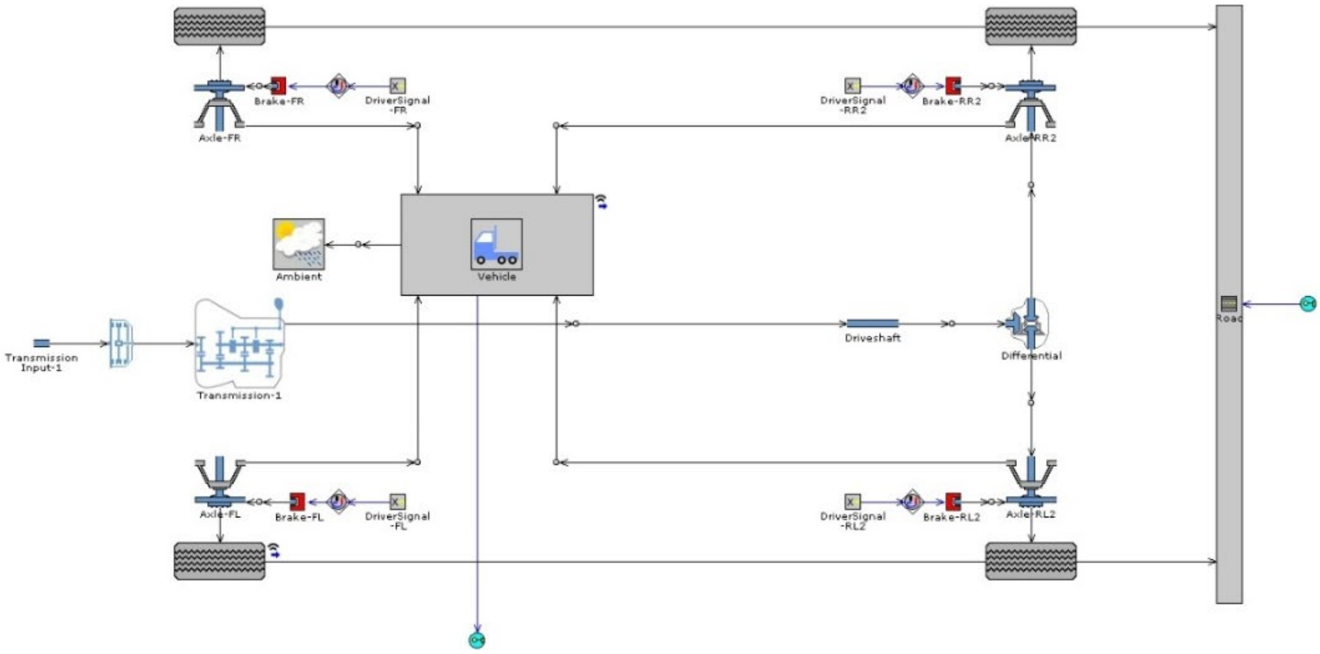

FIGURE 3: Vehicle model built in GT-Suite.
OBRÁZEK 3: Model vozidla v prostředí GT-Suite.

3.2 VEHICLE SIMULATION MODEL

The simulation depth of 1-D models is used in wide range of applications for its high accuracy and low computational demands. Properly calibrated engine model is suitable for predictive model training process for its higher robustness in comparison to the real engine measurement, especially when randomly generated control signal is used (there is no danger of engine damage).

Tested vehicle was represented by IVECO EuroCargo truck with load of 4000 kg. Vehicle model was built in GTSuite – Figure 3. Vehicle driving resistances were assumed with respect to typical values for a vehicle in this category.

The vehicle uses manually shifted six speed transmission. The driver is substituted by several controllers. They are represented by ordinary PID controllers set engine accelerator pedal position, brake position, clutch position and shifted gear. Shifting algorithm evaluates possible engine speed using all gears, available engine torque at all gears and chooses the best available gear from the point of view of low fuel consumption.

The vehicle model is combined with 1-D engine model in single simulation model. Driving resistances calculated by the vehicle model result in engine load, which is controlled by the driver model to follow required vehicle speed. The input signal for the vehicle model is required vehicle speed (driving cycle) with road slope in dependence on route length. The output signals were engine operation parameters.

4. ENGINE PREDICTIVE MODEL TRAINING

The predictive controller utilizes predictive engine model describing ICE dynamic behavior. As a predictive model LOLIMOT model was chosen for its robustness and real-time computational capability. The LOLIMOT model consists of combination of local input-output models that approximate the nonlinear behavior of an identified system by linear functions valid in particular sub-regions of the whole domain of definition. Analogically to other black-box models, the definition of the sets of linear functions is generated during model training. This procedure is important especially in terms of model results accuracy. The model is adapted to the real system outputs according to the system input parameters.

4.1 RANDOMLY GENERATED TRAINING SIGNAL

The question is how the training set of input data should be arranged. All previous work described in [7], [8] and [9] used randomly generated step signal for all system state parameters – Figure 4 and 5. Since the predictive model is applied to the combustion engine, the input parameters are system inputs (fuel mass per cycle, VGT position) and system state variables (engine speed, turbocharger speed, boost pressure etc.).

If the signals for all input parameters are generated independently, it leads to the states which are not common in engine application or even impossible to arrange (e.g. large amount of injected fuel with very low VGT position resulting in high turbocharger speed and boost pressure). Engine

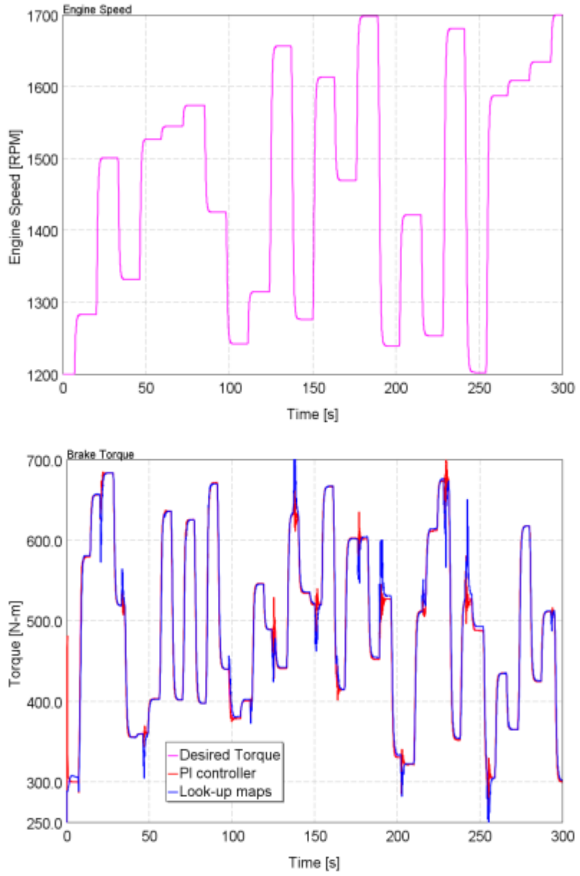

FIGURE 4: Predictive engine model training with random step signal – engine speed (left) and engine torque (right).
OBRÁZEK 4: Trénování prediktivního modelu motoru signálem s náhodně generovanými skokovými změnami – otáčky motoru (vlevo) a moment motoru (vpravo).

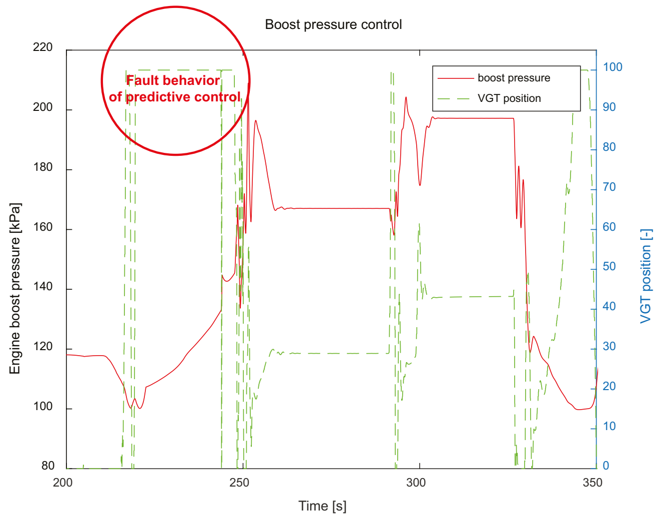

FIGURE 5: Result of predictive engine boost control with fault behavior in acceleration phase.
OBRÁZEK 5: Výsledky prediktivního řízení plnicího tlaku motoru s chybným chováním v průběhu akcelerace.

control unit uses limits and safety circuits to avoid possible dangerous situation and black box model has to learn these limitations during training process.
Quality of predictive control system trained only with randomly generated step signal is strongly dependent on training in the whole multispace of possible situations. Extrapolation of control outside of trained region can result in fault behavior of control system. An example of test cycle is displayed in Figure 5. Acceleration phase starts at 220 s of the test and ends at approximately 245 s. The boost pressure in acceleration phase need to be high to produce maximal engine power, which will be achieved by closing VGT to increase turbine power and turbocharger speed. Figure 5. does not show demanded boost pressure since control algorithm does not work with this variable. Predictive control behavior displayed Figure 5 reacted exactly in opposite way, which resulted in poor dynamic engine behavior. To avoid predictive control extrapolation outside trained region, the trained signal has to be generated in parameters range where engine is typically used, which for vehicle engine is the typical drive cycle.

4.2 TRAINING SIGNAL GENERATED IN DRIVE CYCLE

Accuracy of model prediction depends on quality of all possible system states examination in the multi-space of all input parameters. Randomly generated signal without subsequent evaluation of trained data cannot guarantee high model accuracy in the whole input parameters multi-space.
The highest model accuracy is required in the parameters range where engine is typically used. Which for the vehicle, is typical driving cycle. Therefore, training process will include especially data sampled from driving cycles and not only randomly generated data. This improvement of predictive model training process eliminates extrapolation of model parameters, where engine state prediction accuracy decreases significantly. Nevertheless, some randomly generated signal will be used to learn the limits (low and high engine speed, and low and high load).

4.3 THE VEHICLE VELOCITY PROFILE OPTIMIZATION ON KNOWN ROUTE

The biggest factors directly influencing fuel consumption of vehicle are the set of vehicle and load parameters, trajectory shape and other trajectory properties and especially operating behavior of the vehicle, represented by the current velocity in each point in the prescribed route.
If the driving route is known in advance together with its legal and physical parameters, it is possible to design an optimal control for fuel saving in compliance with the set of external optimization conditions. These conditions are, for example, the arrival times into selected places in the route. Vehicle operating behavior and consequently the real fuel consumption can be

defined on the basis of the vehicle velocity in each points of the route. Resulted profile along optimization on known trajectory is optimal velocity profile.

Route input data splitted in two independent parts:

a. vehicle input parameters
b. input navigation data, based on vehicle route

The vehicle input parameters are given by vehicle construction, vehicle dimensions and complete drivetrain characteristics.

Map navigation input data include waypoints of road shape, road slope profile and the information about legal velocity limit in each navigation points. The navigation data are further extended by the information about vehicle load for all navigation points. Based on this information, for optimization is necessary to determine the real velocity limit for all navigation points. In each point on the prescribed route, the following velocity limits are defined:

a. legal velocity limit
b. physical velocity limit (adhesssion during cornerign)
c. comfort velocity limit (comfort lateral acceleration during cornering)

The resulting maximum velocity profile along the prescribe route is given by the lowest limit of the velocity (Figure 6 – left) and it is the input to the following optimization algorithm.

Vehicle dynamic behavior is affected by route shape, velocity limits and road slope at each point of route. The section of route trajectory is divided into subsections, where the following parameters are constant (Figure 6 – right):

a. slope of the route
b. real velocity limit
c. mass of load

Each section is represented by general velocity profile, which is continuous function, depending on the vehicle position on the prescribed route. Velocity profile consists of four basic driving modes (phases):

a. driving mode with the vehicles acceleration – considered only the constant acceleration of vehicle due to the power drive unit
b. driving mode with constant vehicle velocity – constant vehicle velocity is provided by the power drive unit
c. coasting driving mode – the vehicle is driven by inertia forces and is braked only by driving resistance
d. driving mode with the vehicles deceleration – the vehicle is decelerated by means of the own breaking system or in combination with the resistive torque of the drive unit

The first mode in each section is acceleration mode, followed by constant velocity mode, coasting mode and deceleration mode in this order (Figure 7).

Each velocity profile is parametrized by set of characteristic parameters and the set of external characteristic conditions using the following parameters:

1. v_1 – velocity in the beginning of section and in the beginning of acceleration phase
2. a_a – constant acceleration parameter for acceleration phase

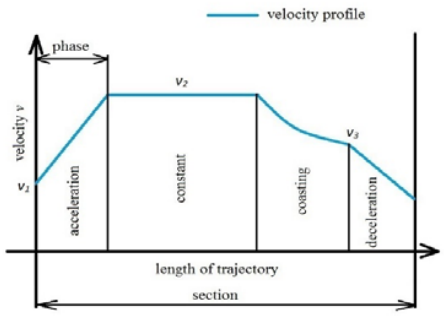

FIGURE 7: Velocity profile and driving phases in each section.
OBRÁZEK 7: Rychlostní profil a rozdělení každé sekce na jednotlivé fáze.

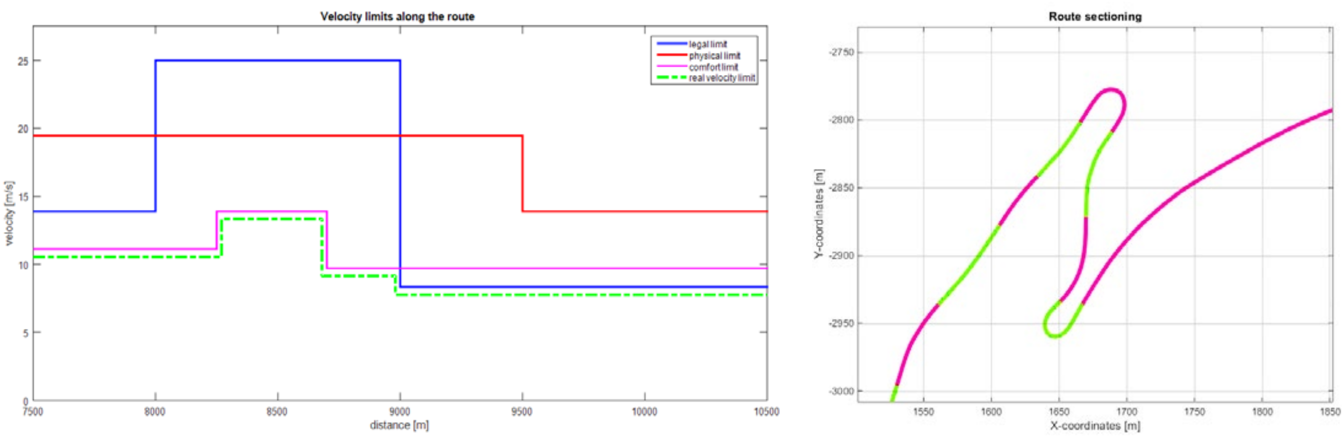

FIGURE 6: Possible velocity limits along the route (left) and route trajectory sectioning by the maneuvers classification (right).
OBRÁZEK 6: Rychlostní omezení na trase (vlevo) a rozdělení trasy na sekce dle klasifikace jízdních manévrů (vpravo).

3. s_a – length of section part with vehicle acceleration
4. s_d – length of section part with vehicle deceleration
5. a_d – constant deceleration parameter for deceleration phase
6. v_4 – velocity on the end of section and on the end of deceleration phase

The total velocity profile along prescribe trajectory is given by the set of individual velocity profiles in all sections. Total velocity profile has to respect continuity condition at the edge of each continuously adjacent section. This condition reduces real set of characteristic parameters into the set of five parameters. The beginning velocity of first section (starting velocity of the whole route) and the ending velocity of the last section (ending velocity of the whole route) are given by chosen constant values. This set of the velocity profiles parameters is set by optimization parameters for subsequent optimization.

The road fuel consumption was integrated using simplified vehicle model, which calculates balance of driving resistance forces and drivetrain driving force. Engine characteristic was based on look-up map model. Suitable transmission gear was determined by the lowest possible gear ratio for desired engine power. The optimum velocity profile has been found by numerical optimization method "Trust-Region Method for nonlinear Minimization". Input data for numeric solution must contain the following data:

a. initial estimate of velocity profile, which is given by maximum real velocity profile
b. local optimization conditions like lower and upper bounds for each optimization parameter
c. global optimization conditions like the total driving time for the whole prescribed route

Optimized vehicle velocity profile ensures minimum energy consumption respecting all optimization conditions.

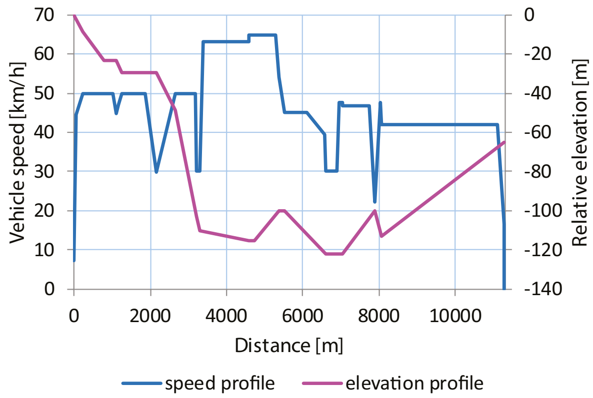

FIGURE 8: Optimized speed and elevation profile on simulated route.
OBRÁZEK 8: Optimalizovaný rychlostní profil a profil sklonu vozovky v průběhu simulované trasy.

4.4 EXAMPLE OF DRIVE CYCLE FOR PREDICTIVE MODEL TRAINING

As an example of predictive model training data, one driving cycle simulation was calculated. Required route, defined by road from VTP in Roztoky u Prahy to Prague Dejvice, used for the simulation purposes was logged by GPS system. The vehicle speed was obtained by route optimization with route constraints (Figure 8). Quite low vehicle speed was caused by low importance of driving time parameter used in optimization setting.

Detailed engine parameters for engine predictive model training was provided by dynamic vehicle model with FRM engine model. The results are displayed in Figure 9. Engine state variables were used as training set for LOLIMOT models together with randomly generated step signal, which will ensure increase of predictive model accuracy mainly in engine speed and load typical for driving.

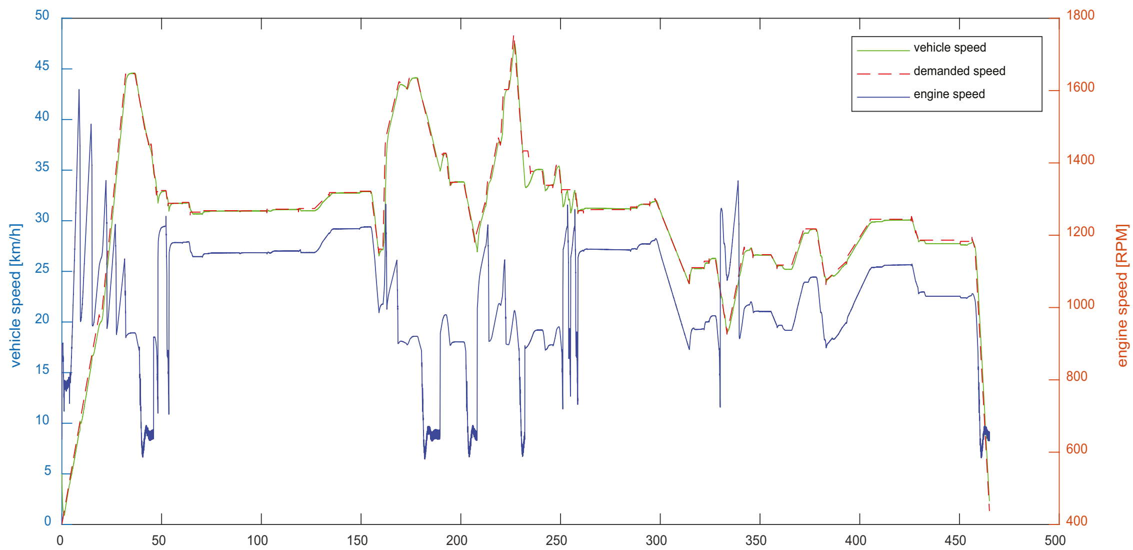

FIGURE 9: Results of drive cycle simulation for engine predictive model training.
OBRÁZEK 9: Výsledky simulace jízdního cyklu použitelné pro trénování prediktivního modelu motoru.

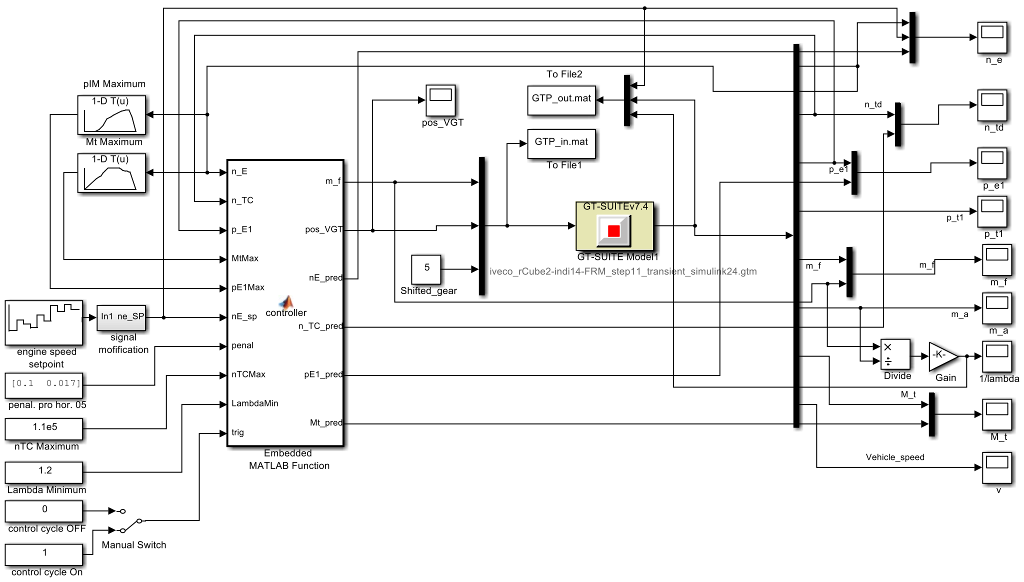

FIGURE 10: Simulink / GT-Suite co-simulation (closed-loop control).
OBRÁZEK 10: Spojená simulace modelů v prostředí Simulink / GT-Suite (řízení se zpětnou vazbou).

5. SIMULATION RESULTS (MIL)

Trained LOLIMOT predictive models were implemented in predictive control system. The developed control method was extensively tested and tuned using a model-in-the-loop (MiL) simulation environment. The MiL system was realized by co-simulation of two models working on different software platforms – an engine simulation model built in GT-Suite and the partial model of a controller programmed in Simulink (co-simulation scheme in Figure 10).

The controller only includes a few chosen input and output signals, which have been specified by training data analysis. The related Simulink model consists mainly of an embedded-MATLAB-function block. The idea behind this implementation was to create a compilable model that will be capable of further reusage in a hardware-in-the-loop system (HiL). However, the solution brought considerable challenges to the task because the embedded-MATLAB code is subject to a number of restrictions.

The main control target was to track a given engine speed setpoint, using the injected fuel mass and the VGT position as the action quantities, and taking into account several constraint conditions. An engine speed and load (given by truck resistance forces) resulting from drive cycle of a WHTC was used for the first test of control system – results in Figure 11. The results of the control process in the MiL environment are very promising, however, it is the first test, and the control system tuning process will continue in the near future.

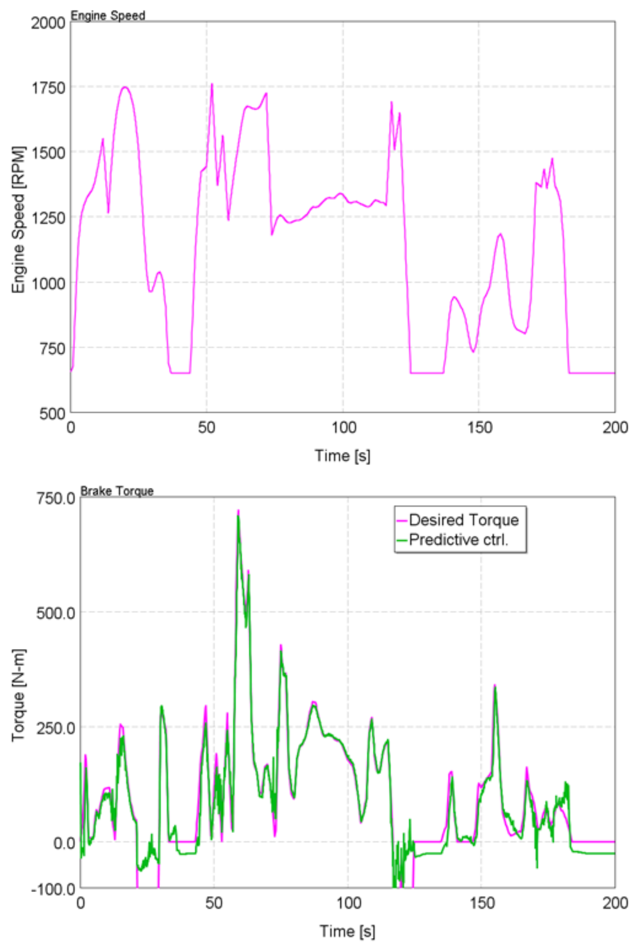

FIGURE 11: Result of simulation of WHTC – engine speed (left) and engine brake torque (right).
OBRÁZEK 11: Výsledky simulací WHTC – otáčky motoru (vlevo) a moment motoru (vpravo).

6. CONCLUSION

Model based predictive control of combustion engines has been investigated. Predictive models are integral parts of predictive control system and their accuracy is the key to successful application to controlled system. Benefit of predictive systems is mainly in accurate control of dynamic system without oscillation and overshooting. Predictive models were generated based on LOLIMOT algorithm, which are capable of predicting future engine states. It is a description of generally nonlinear dynamic system by a combination of linear dynamic systems in subregions of the whole input-output space. Such model can be simply locally linearized and used for efficient optimization of future control inputs. At the same time, the global nonlinear behavior of the engine is taken into account.

Improved methodology of predictive model training is based on extension of training process of engine control system by training in driving cycles, which involve typical engine usage. Increased emphasis on typical engine usage will bring up increase of predictive model accuracy in comparison with training process only with randomly generated step training signal.

The developed model-based predictive control system was successfully tested on the simulation model. The proposed predictive control system controls the engine to keep the predefined controlled vehicle speed profile from off-line optimizer. The control system takes into account several limits for optimal control. Both the prediction ability of the developed predictive model and the quality of the applied predictive control turned out to be very satisfactory, which implies a good potential of developed predictive control. The application of predictive control system will be tested in the near future.

ACKNOWLEDGEMENTS

This research has been realized by the support of:

- Josef Bozek Competence Centre for Automotive Industry, TE01020020
- European social fund within the frame work of realizing the project "Support of inter-sectoral mobility and quality enhancement of research teams at CTU in Prague", CZ.1.07/2.3.00/30.0034
- EU Regional Development Fund in OP R&D for Innovations (OP VaVpI) and The Ministry of Education, Youth and Sports, Czech Republic, project # CZ.1.05/2.1.00/03.0125 Acquisi-tion of Technology for Vehicle Center of Sustainable Mobility
- The Ministry of Education, Youth and Sports program NPU I (LO), project # LO1311 Development of Vehicle Centre of Sustainable Mobility

This support has been gratefully appreciated.

LIST OF NOTATIONS AND ABBREVIATIONS

ECU	Engine Control Unit
FRM	Fast Running Model
ICE	Internal Combustion Engine
LLM	LOLI model
LOLIMOT	Liner Output – Linear Input Models
HiL	Hardware in the Loop
MiL	Model in the Loop
MIMO	Multi-input – multi-output
MPC	Model-based Predictive Control
PID	Proportional Integration Derivation Control
RT	Real Time
VTG	Variable Turbine Geometry
WHTC	World Harmonized Test Cycle

REFERENCES

[1] Camacho E. F., Bordons C., (1999). Model Predictive Control. Springer Verlag, Berlin.

[2] Valasek M., et al., (2005). Model Based Predictive Control of Combustion Engine with Constraints. Review of Automotive Engineering of Japan SAE2005, Vol.26, No.3, pp.349-356.

[3] Sika Z., Valasek M., Florian M., Macek J., Polasek M., (2008). Multilevel Predictive Models of IC Engine for Model Predictive Control Implementation. SAE Technical Paper 2008-01-0209, doi: 10.4271/2008-01-0209.

[4] Nelles O., (1999). Nonlinear system identification with local linear fuzzy-neuro models. Automatisierungs technik, Shaker Verlag, Aachen.

[5] Steinbauer P., Denk P., Macek J., Morkus J., Sika Z., (2015). E-vehicle energy consumption optimization based on fleet and infrastructure information. Book Series: Advances in Intelligent Systems and Computing, Warsaw, Poland, Vol. 393, pp.273-278. doi: 10.1007/978-3-319-23923-1_41.

[6] Steinbauer P., Husák J., Pasteur F., Denk P., Macek J., Sika Z., (2018). Predictive control of commercial e-vehicle using a priori route information. International Journal of Powertrains, vol.7, issue 1-3, pp.53-71. doi: 10.1504/IJPT.2018.090362.

[7] Doleček V., Florián M., Šika Z., (2015). Model Based Nonlinear Predictive Control of IC Engine in Unsteady Operation Mode. XLVI. International Scientific Conference of the Czech and Slovak Universities and Institutions Dealing with Research of Internal Combustion Engines. ISBN 978-80-227-4424-9.

[8] Sika Z., Valasek M., Florian M., Macek J., Polasek M., (2008). Multilevel Predictive Models of IC Engine for Model Predictive Control Implementation. SAE Technical Paper 2008-01-0209.

[9] Macek J., Polasek M., Sika Z., Valasek M., Florian M., Vitek O., (2006). Transient Engine Model as a Tool for Predictive Control. SAE Technical Paper 2006-01-0659.