Proceedings of the 8th IEEE Mediterranean Conference
on Control and Automation (MED 2000)
Rio, Patras, GREECE 17-19 July, 2000

PREDICTIVE TRANSIENT CONTROL OF EGR/VTG FOR INTERNAL COMBUSTION ENGINES

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Abstract: Modern engine control systems basically use stationary curves and 3D maps in order to control internal combustion (IC) engines. Future legislative emission restrictions, however, will require an additional optimization of the transients between different static operating points. This contribution presents a model based predictive optimization of transient EGR (exhaust gas recirculation) and VTG (Turbocharger with variable turbine geometry) control settings between two operating points. Basic transient functions, which are piecewise linear, are introduced. The parameters of these transient functions are then optimized concerning the emissions-consumption trade-off. The model base is realized by fast neural networks. A DSP-based process computer system allows a fast application of the optimization tool at the engine test stand.

Key Words: Dynamic modeling, predictive control, optimization, automotive, neural networks

1. INTRODUCTION

Modern engine control systems are controlled mainly based on stationary curves and 3D maps. These maps are usually optimized for a good stationary performance of the engine concerning emissions, consumption, drivability, noise etc., where the optimum would be a minimum consumption with fulfilling the constraints of emissions, drivability, noise etc. In recent years, new technologies have been introduced in order to enlarge the engine power (turbochargers with variable turbine geometry: VTG) and to lower critical emissions (Exhaust gas recirculation: EGR). Both methods dynamically influence the free oxygen mass which is available for the combustion and interact one with another.

So far, the EGR was mainly controlled stationarily in an open loop and the charge pressure in a closed-loop by means of the turbocharger. Both control strategies normally based on stationary 3D maps. The amount of recirculated exhaust depends on the pressure difference between intake air and exhaust gas, which in turn depends on the VTG-settings of the turbocharger. Vice versa, the performance of the turbocharger is influenced by the recirculated gas which lowers the exhaust pressure responsible for powering the turbocharger's turbine.

Due to this mutual interdependence, sub-optimal dynamic settings for EGR and VTG could worsen the emission behavior of transients dramatically. Future legislative emission restrictions, however, will require an additional optimization of the transients between different static operating points of the engine.

This paper proposes special transient strategies for EGR- and VTG-settings in order to improve the dynamic emission behavior of IC engines. The parameters of the transient functions are automatically determined by a model based predictive optimization routine which minimizes a cost function considering the emissions, the specific fuel consumption and the offset of the desired engine torque. The optimization bases on dynamic engine/exhaust models which were realized by dynamic neural networks. The proposed optimization environment was implemented in MATLAB/Simulink and can be evaluated online at an dynamic engine test stand on a special DSP-based computer system.

2. TURBOCHARGED ENGINE WITH EXHAUST GAS RECIRCULATION

The schematic diagram of a turbocharger combustion engine with EGR is shown in Fig 1. The actuators are powered pneumatically by a vacuum line and the EGR flow $\dot{m}_{EGR}$ is open loop controlled by the EDC via the EGR valve.

The turbocharger controls the desired boost pressure p_2 by varied guide blade positions. The charge-air intercooler lowers the intake air temperature thus further increasing the maximum possible air-mass in the cylinder.

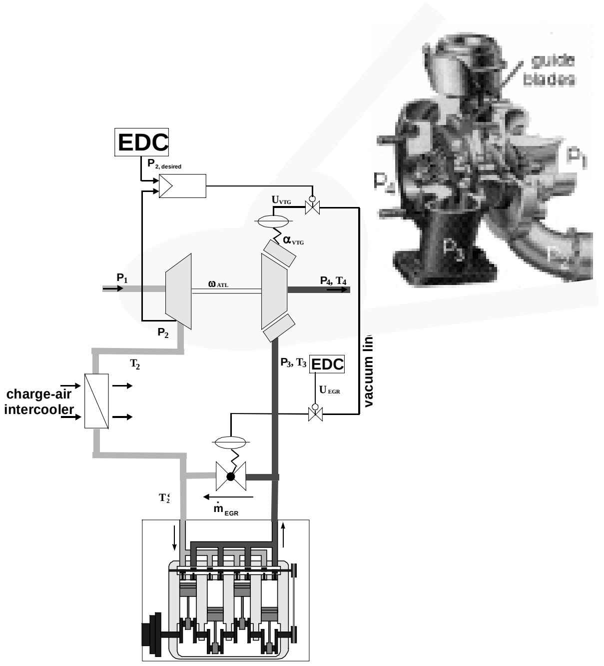

Fig 1: Turbocharged Diesel engine with VTG and EGR

Turbochargers enlarge the power of an engine with a given cylinder volume by using the exhaust's energy to compress the intake air and thereby enlarge the air mass in the cylinder. The additional air allows a higher amount of fuel to be burnt and increases the engine's power.

Exhaust gas recirculation (EGR) diverts exhaust gas back to the intake manifold in order to lower the flame temperature and to reduce the emissions of harmful nitrogen oxides, [1]. EGR and VTG interact one with another: On the one hand, recirculating exhaust gas means taking away a fraction of exhaust that is no longer available for driving the turbine of the turbocharger, on the other hand, the blade position of the turbocharger influences the pressure difference between intake air and exhaust gas and consequently the EGR rate. Due to this mutual interdependence, sub-optimal settings for EGR and VTG could worsen the emission behavior of dynamic transients dramatically. Uncontrolled air flow dynamics could lead to low air-to-fuel ratios and unacceptable smoke formation.

3. DYNAMIC ENGINE MODELS

The proposed optimization environment bases on dynamic emission- and engine models. An experimental model deduction by means of neural networks is suggested, as a theoretical modeling of combustion engine exhaust is very complex and far from real-time applicability. The special fast neural network (FNN) LOLIMOT was used in this contribution. In addition to approximating static relations of nonlinear processes, special neural networks like the FNN LOLIMOT are capable of simulating the dynamic behavior of processes. The LOLIMOT algorithm is based on the idea of dividing the input space of a nonlinear process into M regions, where local linear models (LLM) are estimated and the model output is

$$y = \sum_{i=1}^{M} \left(w_{0i} + w_{1i} * x_1 + \ldots + w_{ni} * x_n \right) * \Phi_i\left(\underline{x}, \underline{c}_i, \underline{\sigma}_i\right) \tag{1}$$

with w_{oi} ... w_{ni}: parameters of the local models, x_1 ... x_n: process inputs, Φ_i: normalized Gaussian validity functions, $\underline{\sigma}_i$: standard deviations and $\underline{c}_i$: center coordinates of the local submodels. The Gaussian validity functions determine the regions of the input space where the specific local linear models are active. The structure of the net is automatically adapted to the nonlinearity of the process by a binary tree construction algorithm.

In order to model dynamic processes, a time-delay approach can be taken [2]. The current process output is represented by a function of the current process inputs and, additionally, by time-delayed process in/outputs:

$$y(k) = f\,(x(k),...,x(k-m),y(k-1),...,y(k-m)) \tag{2}$$

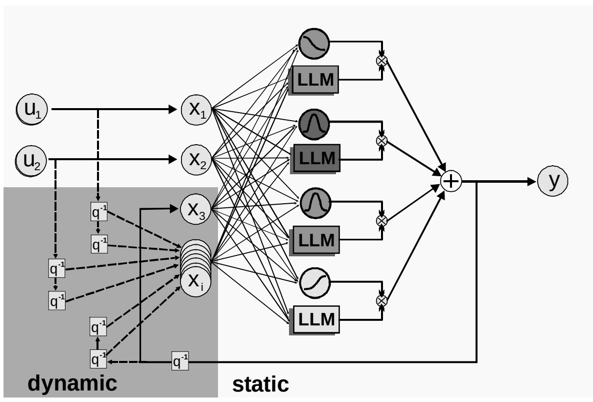

Fig 2: Structure of the dynamic neural network

The representation of LOLIMOT with different local linear models (LLM), their respective validity functions and its external extension towards a dynamic neural network is illustrated in Fig 2. The time-delays are realized by time-shift operators q^{-1}. For further details concerning the LOLIMOT algorithm refer to [3,4].

The described FNN LOLIMOT is now being used for a dynamic modeling of emissions, specific fuel consumption (sfc) and engine torque. The prediction of the impacts of EGR/VTG on the engine behavior is used for the model based optimization which is described later in this paper.

Fig 3 shows the generalization behavior of two dynamic neural models for the NO_X emissions and the exhaust temperature after the turbocharger T_4. The model outputs are compared to measured data, that was not used for the training of the net. The simulated curves follow the measured data very accurately with mean errors of less than 5%. The models, which use the five most relevant influences on the output as inputs, respectively, consist of 15 neurons and 1st order dynamics, leading to a differential equation e.g. for NO_X of the following type:

$$NO_X(k) = f\,(NOx(k-1), EGR(k-1), Torque(k-1), n_{eng}(k-1), \theta_{inj}(k-1), VTG(k-1)) \tag{3}$$

The NO_X model will be directly integrated into the optimization environment which will be described in the next sections. The T_4 model can be used in order to estimate oxidation processes in the exhaust gas which depend on the temperature.

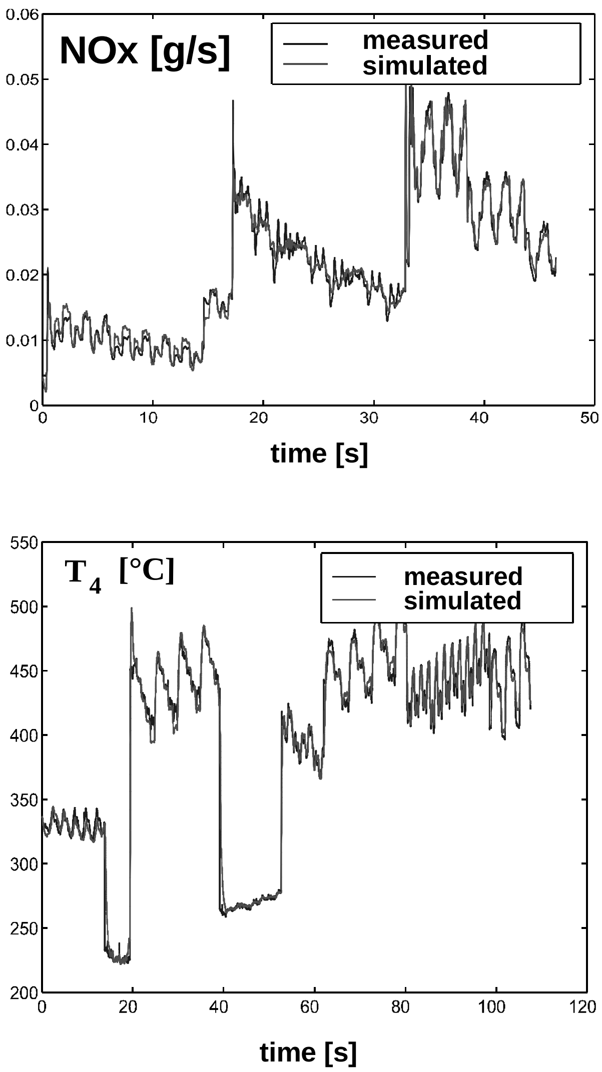

Fig 3: Dynamic neural emission and exhaust temperature model

The training data which is required to build the presented models has to be thoroughly chosen. For accurate dynamic models it is significant to excite the process in all important amplitudes and frequencies of interest. In order to create dynamic models which are valid in all considered engine operating regimes, the process was excited at different amplitudes and frequencies at the operating points shown in Fig 4.

The next step in building the optimization environment is to find adequate dynamic transient functions for the inputs in equation 3, especially for EGR/VTG.

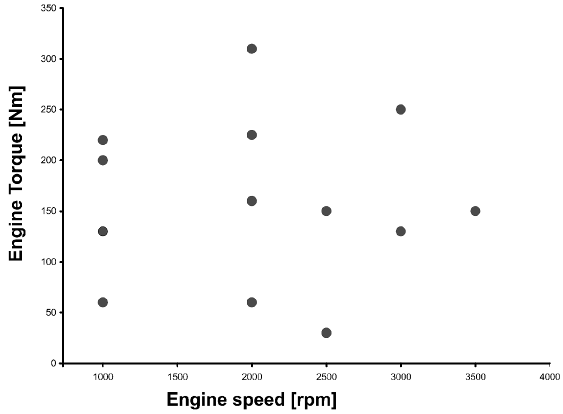

Fig 4: Operating points for training of the neural networks

4. TRANSIENT SETTING FUNCTIONS FOR EGR/VTG

In state-of-the-art open loop controls, changing engine operating points triggered by changed acceleration pedal positions lead to an immediate output of the new actuator settings of the new operating point. Dynamic influences due to the interactions of EGR/VTG are not being considered. Therefore, the following adjusted transient functions are suggested for dynamic control of the engine settings, see Fig 5.

The initial and final values s1 and s2 of the transients are the stationary settings taken from the production car ECU. Two different strategies are supposed for the transients:

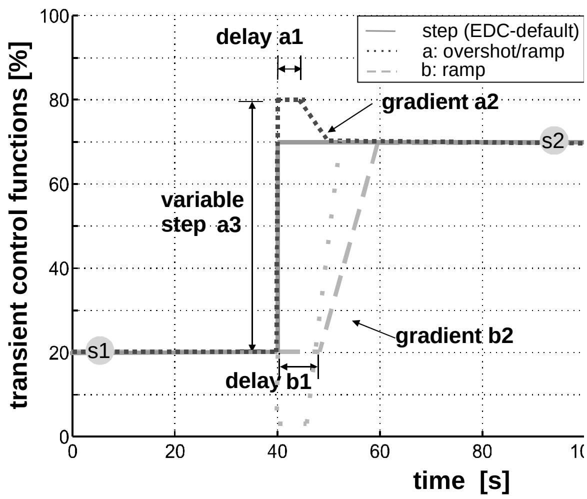

Fig 5: Transient control functions

a) an overshot to a variable value a3 between 0 and 100% followed by a variable delay time a1 and finally a ramp with the gradient a2 to the final value
b) a ramp with the gradient b2 after a variable delay time b1

Strategy a) gives more flexibility to influence the exhaust formation and was therefore used as the transient control function for EGR and VTG. In order not to have too many parameters to be estimated, the delay time a1 was set to constant values between 0 and 1 seconds and the gradient a2 was chosen proportional to the difference between step-height a3 and s2. By varying a3 it was then possible to vary the recirculated exhaust gas and the intake air compression from zero to maximum before reaching its final values s2, respectively. Suspending e.g. the next stationary EGR setting value for a while could help avoiding high soot emissions due to a delayed air supply caused by time delays from the turbocharger. Strategy b) was used to allow an adjusted fuel injection in order to avoid too low air-to-fuel ratios.

5. TRANSIENT OPTIMIZATION ENVIRONMENT

Fig 6 gives an overview on the transient optimization environment which can be divided into three main sections. The optimization is triggered by a new acceleration pedal position signaling the driver's demand for a different engine operating point. The control settings for the desired operating point (s2) are extracted from a static engine map and mark the final values of the transient functions which start at the current settings (s1). Now, with a first guess for the optimization parameters a3 for the EGR and VTG transients (compare to Fig 5), the loss function J is evaluated as a weighted sum of the emissions, the consumption and the torque deviation over the transient.

$$J = w_1 \sum_{transient} NO_X + w_2 \sum_{transient} Opacity + w_3 \sum_{transient} sfc + w_4 \sum_{transient} \Delta Torque \quad (4)$$

The weighting factors w_i allow a flexible trade-off between different terms within the loss function, [5]. The core of the loss function is represented by the dynamic neural models for the respective emissions, specific fuel consumption (sfc) and the engine torque, which were partly presented above and can slightly be seen in Fig 6.

The loss function J evaluates the impacts of specific EGR-/VTG settings on exhaust formation, consumption and torque derivation. J is then minimized by iterative nonlinear optimization routines, [6], leading to optimal parameters a3-EGR and a3-VTG for the respective transients which cause minimum emissions/consumption, dynamically.

Fig 7 and 8 illustrate the results of optimized transient control settings for EGR and VTG for a load-increase triggered by a changing acceleration pedal position from 40% to 90% at an engine speed of 2500 rpm. The driver's demand for an increase in engine torque from 50 Nm to 205 Nm was extracted with help of the above pedal input from a static engine map. The weights in

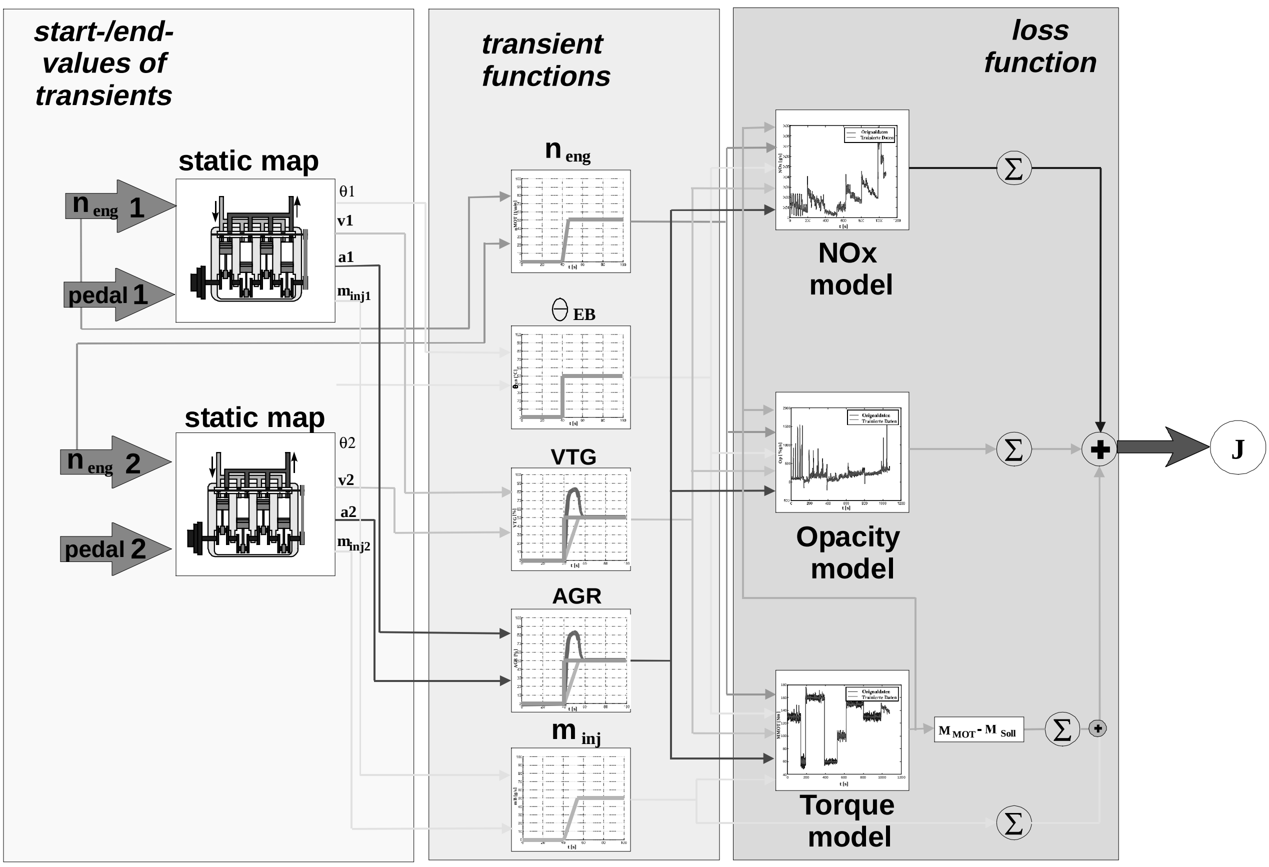

Fig 6: Transient optimization environment

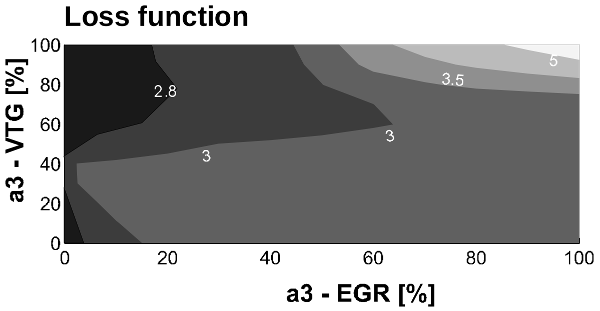

Fig 7: Contour of loss function for EGR- and VTG a3-settings varied from 0-100%

equation 4 were all set to 1, so all components of the loss function were treated equally.

The loss function in Fig 7, where the EGR/VTG a3-parameter were varied from 0 to 100%, respectively, clearly demonstrates, that high EGR-overshots combined with high VTG steps would lead to a worse performance than low dynamic EGR settings with high dynamic VTG. It is now the task of a nonlinear optimization algorithm to minimize the loss function in Fig 7.

The optimized transients are plotted in Fig 8. These settings – in comparison to an immediate step to the final values of the new operating point – minimizes the soot peak due to the lack of oxygen at the cost of slightly higher NO_X emissions. The overall performance, however, could be improved by 12%, compared to standard-steps which are plotted as dotted lines in Fig 8.

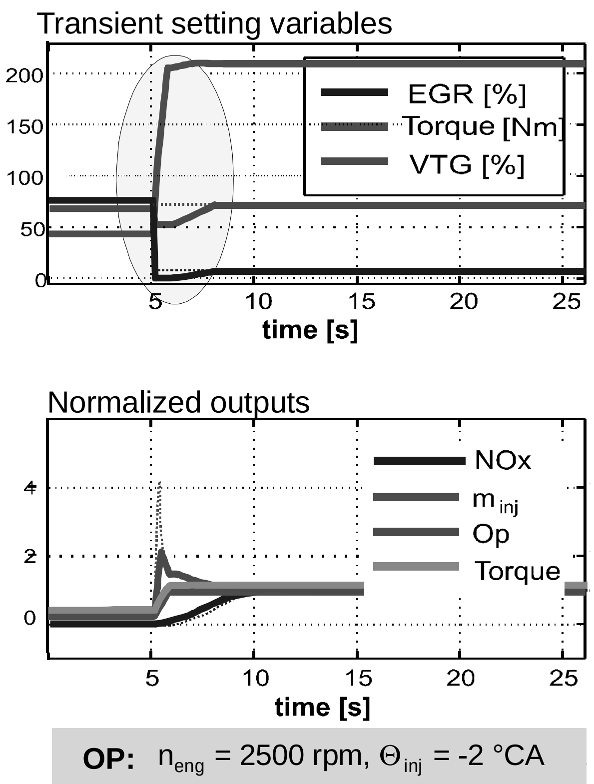

Fig 8: Optimization results for transient EGR/VTG control settings

6. RAPID CONTROL PROTOTYPING SYSTEM

A DSP-based Rapid Control Prototyping system (RPC) has been used for an implementation of the presented application at a real engine.
The goal of RPC systems is to enable a very fast and easy implementation and testing of new control concepts on real-time hardware coupled to the real process. The user is enabled to code newly developed algorithms from block diagrams (e.g. MATLAB/Simulink) on a host PC and download the code by means of an automatic code generation software to the real-time hardware with a mouse click.

Fig 9 illustrates this process and gives a hardware example of a RPC-system, which is combined with an indication system. The control- and optimization algorithms are being evaluated on a 300 MHz alpha-processor.

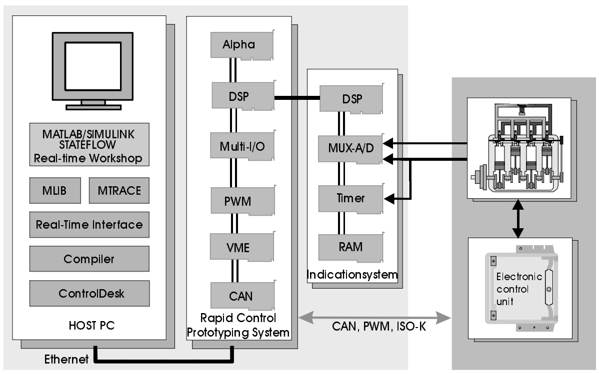

Fig 9: Rapid Control Prototyping system

CONCLUSIONS

An optimization of the transient control of EGR and VTG has been presented motivated from the fact, that stationary open loop control of EGR and VTG usually is not optimal because dynamic interactions are not being considered. The optimization itself is based on dynamic neural network models for emissions, fuel consumption and engine torque. It adjusts specific parameters of special piecewise linear transient function which allow flexible strategies for an improved transient control of EGR and VTG. The proposed optimization environment was implemented in MATLAB/Simulink and can be evaluated online at an dynamic engine test stand on a special DSP-based computer system.

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