Development of a model-based controller for a three-way catalytic converter

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ABSTRACT

The performance of a three-way catalytic converter under transient operation can be improved by controlling the level of oxygen stored on ceria at some optimal level. A model-based controller, with the model estimating the level of ceria coverage by oxygen, can achieve this goal. A simple, dynamic model is based on step responses of the converter and is used to train the controller off-line. The controller is a neuro-fuzzy approximation of a model predictive controller. Thus, it retains a high performance while being less computationally involving. The system performance has been experimentally tested by a specially designed, highly transient test cycle.

INTRODUCTION

The new emission regulations, which are constantly becoming more stringent, push catalytic converter and engine management system manufacturers to improve the system performance. This can be achieved by improving the old and/or developing new exhaust aftertreatment systems. It is known that the performance of the current three-way catalytic converter systems can be improved by accurately controlling the level of oxygen stored on ceria. The applications of oxygen storage controller are, however, scarce mainly due to dynamic complexity of the catalytic converter system. Moreover, the controlled variable, degree of ceria coverage, cannot be measured and a model has to be used as an inferential sensor to estimate this variable on-line. Therefore, a very accurate model is a prerequisite to apply the control. Known control applications are based on simple, integrator-based models, and already show improvement with respect to standard control schemes [1,2].

Various attempts to simply model the dynamic characteristic of three-way catalytic converter have been published in the recent years [3,4,5]. All these models try to capture the oxygen storage/release capabilities of the

converter in a simple manner, such that the models could be used on-line for the control. The model used in this study is basically the one presented in [5] and extended to better describe the process dynamics in a wide operating range. That model already contains an adaptation for changing exhaust mass flows, which has to be linked with the temperature adaptation to make the model applicable for control. The largest model dependence on temperature is present at low temperatures, where the conversion is lower.

The control system is a cascade system of a standard, air/fuel ratio engine controller in the inner loop and catalyst controller in the outer loop. The latter receives the feedback signal from the model. With the explicit presence of the model it is straightforward to use the model in the controller tuning procedure. This leads to application of model predictive control (MPC), which is currently the most applied process control strategy in industry [6]. The controller uses the model to predict the future process behavior and find the optimal control sequence to achieve the control goals and can thus fully exploit the system nonlinearities in order to reduce the emissions as much as possible. The optimization problem has to be solved at each sampling interval what poses a serious computational problem for a fast process. A possible approximate solution is to train a nonlinear function (i.e. neural network) with the off-line calculated outputs of the MPC [7]. This approach is applied here by utilizing the Gaussian radial basis function network to approximate the MPC. This strategy was previously tested in simulation [8]. This paper presents the experimental verification of the controller. The controller has been implemented on a rapid prototyping system on a Volvo 2.0l 5 cylinder engine, and tested on an engine dynamometer. An underfloor Pt/Rh/Ce₂O₃/γ-Al₂O₃ catalytic converter was used in the tests. The performance of the novel controller was compared with the stoichiometric air/fuel ratio engine controller on highly transient test cycles.

MODEL DEVELOPMENT

The model of the catalytic converter is in principle a storage-oriented model, with the main feature being the oxygen storage and release capabilities of ceria. The model is identified on the basis of converter step responses. With such tests the model can be updated as the converter ages.

BASIC MODEL – The goal of the model is to link the unmeasurable degree of ceria coverage and measurable inlet and outlet λ signals. Wide-range λ sensors in front of and behind the converter are needed to use such a model. The main model equations are the following:

$$\frac{d\zeta}{dt} = \frac{1}{k_d(T, m_{ex})} \left(\lambda_{in} f_d(T, \zeta, m_{ex}) + g_d(T, \zeta, m_{ex}) \right) \quad (1)$$

$$\lambda_{out} = \lambda_{in} - k_d(T, m_{ex}) \frac{d\zeta}{dt} \quad (2)$$

Both inlet and outlet lambda values are obtained by subtracting 1 from the measured values. Thus, positive lambda values represent lean mixtures, while negative values represent rich mixtures. The degree of ceria coverage (ζ) assumes the values between 0 and 1, where 1 stands for the completely filled oxygen storage and 0 the completely empty oxygen storage. The relative oxygen level is the mean oxygen level throughout the converter, thus approximating the distributed-parameter system with a concentrated-parameter model. The scaling factor, k_d , reflects the total oxygen storage capacity and applied space velocity (proportional to the OSC and inversely proportional to the exhaust mass flow). This factor does not have to be the same for rich and lean inputs. The nonlinear function, $f_d(T, \zeta, m_{ex})$, describes the reaction rate as function of the temperature, degree of ceria coverage and exhaust mass flow. This function depends on the input direction as there are actually two functions, one for lean inputs $f_L(\zeta)$ and one for rich inputs $f_R(\zeta)$. A static function $g_d(T, \zeta, m_{ex})$ accounts for the desorption of reducing species (CO , H_2) from the catalyst in the beginning of a rich to lean step. This will further be discussed later in the text.

PARAMETER ESTIMATION – The estimation of model parameters in one operating point has been presented in [5] and will only briefly be discussed here. The estimation procedure is based on lambda step responses of the converter. The following algorithm is applied:

$$\begin{aligned} k_d &= \int_0^{T_s} (\lambda_{in} - \lambda_{out}) dt, \\ \frac{d\zeta}{dt} &= \frac{1}{k_d} (\lambda_{in} - \lambda_{out}), \\ f(\zeta) &= 1 - \frac{\lambda_{out}}{\lambda_{in}} \end{aligned} \quad (3)$$

Like in [5] the function $f(\zeta)$ is a piecewise linear function so the estimation is computationally not very demanding. The algorithm (3) can directly be applied if a perfect lambda measurement would be available. It is well known, however, that the lambda sensor behind the catalytic converter does not measure correct lambda value under all conditions [9]. Figure 1 shows a typical step response of the catalytic converter. Note that there is a mismatch in inlet and outlet lambda signals in both rich and lean steady state. Theoretically, when oxygen storage becomes empty or completely filled inlet and outlet lambda signals should match. If the measured signals would directly be applied the model would not converge, so the sensor signals have to be preconditioned before the parameter estimation is applied. This preconditioning involves static scaling of the sensor signal. It is rather straightforward to apply the scaling after the lean step, but the rich step typically exhibits a more dynamical sensor error: overshoot in the signal of the sensor behind the catalyst. This overshoot is probably the result of water gas-shift and steam reforming reactions that have hydrogen as a product. Hydrogen is known to have a large influence on the sensor characteristic, as it diffuses more easily than other species through the sensor catalytic surface [9]. A more elaborate study of this effect is needed to fully understand the processes that lead to these sensor errors. Here it is simply assumed that water gas shift and

Figure 1 Step responses of the catalytic converter. Inlet - thick solid line, outlet - thin solid line, rescaled outlet – dashed line. Reactor temperature 480°C, exhaust mass flow 63 kg/h.

steam reforming reactions start after the oxygen storage has been depleted [10] and, thus, the peak in the sensor response actually depicts the moment when the two lambda sensors should give the same signal. A similar procedure has been applied in [4].

MODEL APPLICATION RANGE - To obtain an accurate model dependence of k_d and f_d on temperature, exhaust mass flow and degree of ceria coverage has to be known (see equations (1) and (2)). The theoretical dependence of $f_L(\zeta)$, $f_R(\zeta)$ and k_d on exhaust mass flow was found in [5]:

$$k_d = \frac{m_{exn}}{m_{ex}} k_{dn}$$

$$f_L \left(1 - \frac{m_{ex}}{m_{exn}} + \zeta \frac{m_{ex}}{m_{exn}} \right) = f_{Ln}(\zeta) \quad (4)$$

$$f_R \left(\zeta \frac{m_{ex}}{m_{exn}} \frac{\lambda_{inn}}{\lambda_{in}} \right) = f_{Rn}(\zeta)$$

where subscript n stands for the nominal case (operating condition in which the model parameters have been estimated). These functions are valid at one temperature, and in most conditions [11]. The nominal function is temperature dependent and should therefore be estimated at several temperatures. It was found in this study that the nominal function undergoes the largest changes at lower temperatures, after the light-off, and then remains almost constant above some higher, 'saturation' temperature. In case of the catalytic converter presented in this paper the full conversion starts around 300°C, while the 'saturation' temperature is around 420°C. The model for temperatures for which the estimation was not performed is obtained by interpolation. Care has to be taken that such obtained model inaccuracies remain sufficiently small. The adaptation (4) for functions f_L and f_R was found to be valid at lower temperatures (apart from that f_R is not dependant on λ_{in}), but only the adaptation for the function f_L was found to be necessary at temperatures above the 'saturation' temperature. The function f_R was constant for various exhaust mass flows. The values of $f_R(\zeta)$ were very close to 1 (100% conversion) for ζ as low as 0.1, which means that the conversion has reached the 'upper saturation' due to a high converter temperature. This very high conversion is reached already at high mass flows and therefore does not change much at lower mass flows.

Another parameter that has to be well estimated is the oxygen storage capacity (OSC) and hence k_{dn} . OSC increases with temperature [12] but is also a function of

Figure 2 Estimated surface oxygen storage capacity as a linear function of flow and temperature.

Figure 3 Rich to lean step responses after a short (above) and long (below) rich period. Inlet –thick line, outlet – thin line, reactor temperature 480°C, exhaust mass flow 63 kg/h.

exhaust mass flow. It was observed that with an increase of the mass flow available oxygen from ceria somewhat decreases. This is in line with theoretical observations in [5]. Figure 2 shows estimated k_{dn} as a function of exhaust mass flow and temperature. A nearly linear dependence on both variables was assumed. The estimation of k_{dn} was performed during lean to rich steps. It was observed that the capacity based on rich to lean steps was always larger. Moreover, it was depending on the length of the previous rich step. This could be due to existence of various layers of ceria, namely layer closer to the surface and layers deeper in the bulk. Figure 3 shows rich to lean steps under same operating conditions after a short and a long period in rich area. It seems that the transfer for the surface to bulk is rather fast, while vice versa is not. Therefore, if the bulk becomes completely depleted after a long rich signal, the observed OSC during a lean transition increases. The surface layer that is involved

during a rich transition is stable and does not depend on the length of previous lean step. Oxygen from the ceria bulk has to be used after the surface oxygen has been depleted but this process proceeds at such a slow rate that it cannot be observed with lambda sensors, and is of no importance for the control. The above hypothesis should yet be checked with more detailed tests. It has been used to add the secondary (bulk) storage to the model, and it has led to satisfactory modeling results for control purposes. The updated model is obtained by combining the following expressions for the scaling factor during lean steps (k_L) with (1) and (2):

$$k_L = k_R + k_\chi \quad (5)$$

where k_R is the scaling factor during rich transients and is proportional to the surface oxygen storage capacity (oxygen stored on bulk ceria is not used fast enough during rich steps), while k_χ is proportional to the amount of empty ceria sites in bulk freed before the current lean transition. The relative change of bulk ceria covered by oxygen (χ) during a lean step (filling) is easily calculated:

$$\frac{d\chi}{dt} = \frac{d\zeta}{dt} \quad (6)$$

The emptying of the bulk ceria starts after the surface storage has been depleted and is modeled as a first order system with a time constant T_b and adaptive gain K_b :

$$T_b \frac{d\chi}{dt} + \chi = K_b(\chi) \quad (7)$$

It was observed that emptying of the bulk ceria is very fast in the beginning and then proceeds at much slower rate as layers closer to the surface have been depleted. Therefore the adaptive gain was used.

A result of the model is a perfect match of inlet and outlet lambda when the oxygen storage is either completely filled or empty. While this is nearly true under lean conditions it was presented in [13] that under rich conditions not only the oxygen storage phenomenon determines the dynamic behavior. The additional dynamics stems most probably from reactions with water (water gas shift and steam reforming). A first order filter with a zero was used in [13] to describe this behavior. It was found here, however, that only a first order filter is adequate to describe rich to lean transitions when surface oxygen storage is nearly or completely empty:

$$T_r \frac{d\lambda_{out}}{dt} + \lambda_{out} = \lambda_{out} \quad (8)$$

where λ_{out} is calculated by (2) and λ_{out} represents the actual outlet lambda signal. The filter time constant, T_r is

zero if oxygen storage is filled above a certain level, but also has to be reduced as bulk ceria storage becomes depleted (see figure 3).

It can be concluded that the behavior of the catalytic converter is much more complex under rich conditions and in order to obtain the accurate model more detailed studies should be conducted. The desired operation of the catalytic converter is, however, where the oxygen storage is half-filled and that is where the model should be the most accurate. Therefore, a rather simplified model under rich operating conditions is allowed.

MODEL TESTING – Model predictions of converter step responses are presented in figures 4 and 5. Figure 4 shows the model prediction at 1200rpm, 40kPa and 80kPa intake manifold pressure, while figure 5 shows the

Figure 4 Model prediction of the converter step responses: above – flow 28 kg/h, temperature 325°C; below flow 63 kg/h, temperature 480°C. Inlet – thick solid line, outlet - thin solid line, prediction - dotted line.

Figure 5 Model prediction of the converter step responses (above, line description as in figure 4) and converter temperature (below). Exhaust flow - 63 kg/h.

model prediction at 1200rpm and 80kPa intake manifold pressure but at lower reactor temperature. Note that the model has been estimated under different operating conditions than those presented in figures 4 and 5, so this is a simple model validation. The model predicts fairly well under different operating conditions, after both shorter and longer rich steps, and therefore is suitable to be used for control in a wide operating range. Most of prediction errors occur during rich to lean steps, as can be seen in the first positive step in figure 5, due to a rather simplified model of the bulk ceria influence. Figure 5 presents also the influence of the reactor temperature on the rich overshoot measured by the downstream sensor, as it becomes remarkable at temperatures above 400°C. That is in line with the activation of water gas shift and steam reforming reaction [10].

CONTROLLER DEVELOPMENT

The cascade control scheme is shown in figure 6. The outer loop is the catalytic converter controller, while the standard model-based engine controller is in the inner loop. This is basically the same scheme as proposed in [5]. The Internal Model Controller (IMC) controls the engine air/fuel ratio. The controller contains the wall wetting compensation [14] and intake air prediction. The latter is predicted on the basis of the throttle signal. The bandwidth of the inner loop is typically larger than of the outer loop and therefore the inner loop dynamics, apart from the transfer delay, can usually be neglected during the tuning of the catalytic converter controller [8]. In this study, however, the oxygen storage capacity of the catalytic converter is rather low so the engine dynamics cannot be neglected. The inner loop (engine+controller) model used for the tuning of the catalytic converter controller is a first order filter with a delay. Its transfer function in Laplace domain is:

$$\frac{\lambda_e(s)}{\lambda_{ref}(s)} = \frac{1}{1 + T_e s} e^{-T_d s} \quad (9)$$

The above equation, together with the converter model (1,2) represents the control-oriented model of the process that is used to tune the catalytic converter controller. The difference between the lambda value (λ_e) predicted by (9) and actual λ value is a disturbance on the control system. This disturbance is not present in the steady state due to the inner control loop. The catalytic converter controller, as shown later in the text, is a Gaussian network type controller tuned off-line by the MPC. The latter can provide the optimal transition control that minimizes emissions yet preserving the speed of transition as much as possible. The reason for this approximation of MPC is that it needs to solve an optimization problem at every sampling interval, which cannot be calculated on-line due to computing limitations in the on-board computer so it has to be estimated by a faster controller with a similar performance.

Figure 6 Basic scheme of the cascade control system. A standard engine air-fuel ratio controller is in the inner loop, while the controller for the catalytic converter is placed in the outer loop.

CONTROLLER TUNING - The controller first has to find the optimal ceria coverage for given operating conditions. This will then become the reference signal for the controller. The optimal point can be defined as the point where the conversion remains the highest if lean or rich perturbations of the inlet lambda occur. In general, the optimal relative oxygen level varies for different exhaust mass flows. Large variations between neighboring steady state points can, however, sometimes lead to higher exhaust emissions than with one sub-optimal, but fixed relative oxygen level. The optimal relative oxygen levels $[\zeta_1, \dots, \zeta_n]$ for n distinct exhaust mass flows can be determined by solving the following optimization problem:

$$\begin{aligned} \text{minimize : } Q_{ss}(\zeta) &= C^T C + W_{ss} \sum_{i=1}^{n-1} (\zeta_{i+1} - \zeta_i)^2 \\ \text{where : } C_i &= \left| \frac{\lambda_{out}(\zeta_i)}{\lambda_{in}^p} \right| + \left| \frac{\lambda_{out}(\zeta_i)}{\lambda_{in}^n} \right| \end{aligned} \quad (10)$$

The steady state optimization problem determines the oxygen storage levels at which some fixed positive and negative λ inlet perturbations cause minimal emissions (first term), taking into account that the distance between the neighbouring steady state ceria coverages should not be too large (second term). The steady states for exhaust mass flows that were not included by the optimization can be determined by interpolation. Note that the solution is theoretically valid at only one temperature. The controller tuning, both steady state and dynamic, was performed for two temperatures, 340 and 420°C. This temperature range is crucial as most changes of the model dynamics occur here. For a higher accuracy more temperatures can be selected, but this will increase the computational problem significantly.

The dynamic control problem is how to optimally drive the system to desired steady state with as low as possible emission (inlet lambda has to deviate from stoichiometry) but also as fast as possible. This leads to the following nonlinear optimization problem:

$$\min.: Q(\lambda_{IN}) = \sum_{i=1}^{N_{PH}} [(\zeta_{ss} - \zeta(i))^2 + W_d \lambda_{out}(i)^2 + W_{d1} \lambda_{IN}(i)^2] \quad (11)$$

subject to $q_n \leq \lambda_{IN}(i) \leq q_p$

N_{PH} stands for the prediction horizon. The number of available control moves equals N_{CH} (control horizon), and $\lambda_{\text{in}}(N_{\text{CH}}+1, \dots, N_{\text{PH}})=0$. By solving this problem at each sampling interval in the receding horizon fashion and applying the first control sample $\lambda_{\text{in}}(1)$ to the process, one actually obtains a nonlinear MPC. The known process nonlinearities can thus be used to drive the process in the most favorable manner. The larger values of the tuning parameter W_d imply lower emissions during transients but also a slower reference tracking. The last term in (11) that includes $\lambda_{\text{in}}(i)^2$ was not present in the simulation study [8]. It was found, however, that due to a low capacity of the oxygen storage and rather high reaction rates this term can serve to exclude a possible aggressive control. The constraints are set on the allowed rich and lean excursions of engine λ to avoid driveability problems but can also serve to set the maximal desired speed of the system response.

The problem (11) is computationally too demanding to be solved in the on-board computer at every sampling interval. The problem is therefore solved off-line for a number of operating points. The solutions are used to train a nonlinear function which approximates the MPC [8]. The approximator used in this case is a linear combination of weighted Gaussian radial basis functions given by:

$$\lambda_{in}(x) = \frac{\sum_{j=1}^n y_j \mu_j(x)}{\sum_{j=1}^n \mu_j(x)}$$

$$\text{where } \mu_j(x) = \exp\left(-\frac{|x - c_i|^2}{\sigma_i}\right), \quad (12)$$

$$x = \begin{bmatrix} e & \lambda_e & m_{ex} \end{bmatrix}, \quad e = \zeta_{ss} - \zeta.$$

It can be shown that a Gaussian network can be used as an universal approximator if n is large enough [15]. This function is chosen because of the parameter tuning simplicity. If fixed nodes c_i are chosen together with fixed variances σ_i the function becomes linear in parameters y_i . Hence, the batch least squares problem of fitting the function to data can be solved analytically. If the fit is not satisfactory, the whole procedure can be repeated for an increased number of network parameters. The controller proposed in [8] was a nonlinear P controller, as only the error signal was used (mass flow signal can be considered as a parameter). This was allowed because the engine dynamics could be neglected and the λ_e .

behind the engine was taken to be equal to the λ_{ref} . In this case, however, the engine dynamics is not neglected so the engine lambda signal has to be considered as a state of the system and controller becomes in fact a nonlinear PD controller. In fact, more states should be added because of the delay but that would make the problem too complex. Only cases with equal engine-out

Figure 7 The controller tuning scheme.

and catalyst-in-lambda signals are considered during tuning. The controller can be periodically updated following the model adaptation procedure to account for changes of catalytic converter dynamics due to the aging process. Figure 7 shows the scheme of the tuning procedure. Note that there are two delays present: first representing the delay from the fuel injection to the first lambda sensor placed behind the engine, and second delay from the first to the second lambda sensor placed behind the catalytic converter. To increase the system bandwidth the second delay is placed behind the catalyst model and is thus placed out of the control loop. This is allowed since the controller uses the model merely for the estimation of the oxygen storage coverage. However, when predicted and measured lambda signals behind the converter have to be compared the second delay has to be included, as shown in figure 7.

EXPERIMENTAL RESULTS AND DISCUSSION

The controller has been tested by three test cycles shown in figure 8. The engine speed was kept constant at 1200rpm, while throttle transients create intake manifold transients as shown in figure 8. The catalyst controller is compared with a $\lambda=1$ controller that only tries to keep the engine lambda value at the stoichiometry without considering the dynamics of the catalytic converter (the outer control loop is disconnected). The air/fuel ratio controller was slightly detuned so considerable lambda disturbances were present during the throttle steps.

The test 3 will be analyzed in more detail. Figure 9 shows the inlet and outlet lambda signals of the converter in both cases. It is clear that the emission level is quite high, largely due to the small oxygen storage

Figure 8 Three tests applied to validate the performance of the catalytic converter controller. The starting inlet temperature in test 1 (above) is 350°C, in tests 2 (middle) 490°C and in test 3 (below) 330°C.

Figure 9 Converter inlet (thin line) and outlet (thick line) lambda signals during the test 3. Above: catalytic converter controller, below: $\lambda=1$ controller.

capacity of the catalytic converter used (it is much smaller than the capacity of the current production catalysts), as the main goal of the study was to show possible benefits of the catalyst control in comparison with a no-control case. The predicted level of ceria coverage (ζ) is shown in figure 10. Note that this signal was used as the feedback signal only in the catalyst control case. It is clear that the coverage remains in the vicinity of the desired level (in the steady state) in the control case, while it can deviate greatly in the no-control case. The deviations toward the full oxygen storage increase the level of NOx emissions, while the deviations toward the empty storage increase the level of HC and CO emissions. This can be seen in figure 11 where the NOx and HC emissions are presented for the both cases. Response times of NOx and HC analyzers are

Figure 10 Relative oxygen storage coverage (ζ) during test 3. Thick line – catalyst controller, thin line – $\lambda=1$ controller.

Figure 11 NOx and HC emission during test 3. Thick line – catalyst controller, thin line – $\lambda=1$ controller.

around 2s. CO emissions have also been measured but the analyzer's time constant was very large and the results should be taken with a caution. The emission levels from all tests are given in table 1. The ζ signal in the case of $\lambda=1$ controller stays at higher levels than in the control case what suits mostly CO and therefore is the CO level increased with the catalyst controller. This will further be discussed in the following section. Despite this fact the accumulated emission level of HC is decreased with the catalyst controller used. Together with the large improvement in NOx emissions (which can be expected by examining the mean ζ values during the tests) this shows the usefulness of the catalytic converter controller. Note that various tests have different contribution to the total emission level: though relative CO emissions increase significantly in test 2 the overall

CO level in test 2 is very low as well as its contribution to the total figure.

Table 1 Emission levels during tests with catalytic converter controller compared with emissions of $\lambda=1$ controller (negative sign – lower emissions). Average ζ values during tests with both controllers are shown. The emission results in ‘total’ are obtained by calculating the summed change of emissions.

	NOx	HC	CO	mean ζ control	mean ζ $\lambda=1$
Test 1	-13.1%	-8.7%	-4.9%	0.57	0.61
Test 2	-33.6%	+5.2%	+54.5%	0.55	0.71
Test 3	-36.6%	-7.9%	+23.8%	0.54	0.66
Total	-32.4%	-4.3%	+14.6%		

DISCUSSION – The main question that arises is when does the application of the catalytic converter control significantly reduce the emissions. Figure 12 shows a simplified diagram in which the conversion characteristic of the converter during both lean and rich excursions is plotted. A very important variable is the ratio of the disturbance amplitude and the oxygen storage capacity, which will be called disturbance ratio. If the disturbance ratio has a high value (which is the case in this study) the overall effect of the control may not be great because larger disturbances cannot be fully buffered with the given oxygen storage capacity. This effect can be seen

Figure 12 A simplified conversion characteristic ($f(\zeta)$) and the influence of the disturbance ratio on the conversion.

after the large disturbance at 17s in test 3 (see figures 9,10).

A low disturbance ratio (which is common for today's catalytic converters) will very likely lead to a much higher improvement in the control case. The disturbance cannot produce a large emission level if the system is controlled, and the only danger is that the system drifts away from the desired coverage level, what may happen if no control is applied. Moreover, the controller offers a fast and accurate transition after fuel cut-offs and fuel enrichments. Simulation results in such a case were presented in [8]. The catalytic converter model can also be used in advance to properly select a catalytic converter for some application by estimating the emission level on the basis of known disturbance ratio. By properly controlling the system a catalyst with a lower oxygen storage capacity can be applied without increasing the emission level.

CONCLUSION

Development of the model-based controller for a catalytic converter is presented in the paper. Since the controlled variable, the relative degree of ceria coverage by oxygen, has to be estimated by the model, the accuracy of the model is crucial for a good control performance. Parameters of the nonlinear model were estimated on the basis of the converter step responses. To obtain a useful model it has to have a wide range application and should therefore contain the parameters' dependence on temperature and exhaust mass flow. The crucial parameter in the model is the oxygen storage capacity, which is a function of both parameters.

The MPC based controller is tuned off-line by solving static and dynamic optimization problems in various operating points. A Gaussian network is used to approximate the MPC on-line. The controller was tested with various dynamic tests and its performance compared to the stoichiometric engine lambda controller. It was shown that by accurately controlling the level of stored oxygen on ceria one can obtain improved performance of the exhaust system. Though the oxygen storage capacity of the converter was very low, and therefore the accurate control very difficult, the controller lead to significantly improved NOx emission while not deteriorating HC emission.

Future work is necessary to fully validate the proposed controller. Namely, tests with various catalysts have to be performed. The converter dynamics has to be further investigated, mainly the behavior after rich steps and dependence of the oxygen storage capacity on various parameters. This should be coupled with the investigation of improved correction models for the downstream lambda sensor. The controller tuning is currently performed off-line and is rather complex. Parametric optimization techniques, which are currently

being studied, should lead to a much shorter and more efficient controller tuning process.

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