2011 American Control Conference
on O'Farrell Street, San Francisco, CA, USA
June 29 - July 01, 2011

Data Driven Inverse-model Control of SI Engines

Dmitry N. Gerasimov¶, Hossein Javaherian§ and Vladimir O. Nikiforov†

***Abstract* – Effective control of spark ignition engines (SIE) under all operating conditions is essential for achieving high fuel economy, low emissions and high vehicle performance. Design and development of high performance control system is a challenging problem due to the variety of engine operating regimes, the complexity of nonlinear physical and chemical engine processes, a number of unmeasurable variables which directly affect important engine variables, multiplicity of control inputs and outputs, process/measurement noise and load disturbances. In this paper, the most important problems of torque tracking and air-to-fuel ratio (AFR) stabilization at the stoichiometric level are addressed. To provide a suitable solution for this problem, a data driven approach based on the design of direct and inverse models is proposed. The inverse model is represented by a grey box with a selected fixed structure, outputs which are the control variables and a set of input variables as nonlinear functions of the engine state and regulated variables. The direct model is also represented as a grey box, but the regulated variables are the model outputs and the control variables are the model inputs. The parameters of the grey box models are estimated through an offline identification procedure using vehicle data and a special representation of the models in the form of linear regressions. The controller is designed to maintain the combined gain of tandem "inverse model – direct model" close to unity at all engine operating regimes. Two approaches for parameter estimation are proposed and justified. One approach is based on the substitution of the regulated desired value in the inverse model for its current value, and the other is based on the pseudo inverse of the direct model. Both approaches result in the design of a feedforward controller. In practice, the feedforward controller is augmented by a PID controller to provide improved performance in the presence of modeling errors and external disturbances. The final controller is robust to uncontrollable disturbances. Test results demonstrating the performance of the algorithms are presented and discussed.**

I. INTRODUCTION

In spite of extensive experience, design of effective robust nonlinear multivariable control of SIE providing torque tracking and air-fuel ratio regulation remains a challenging issue in automotive industry. Proper control of important engine variables such as torque and AFR is greatly beneficial for the performance of engines in terms of fuel consumption, torque responsiveness and exhaust emissions under both steady and transient operations. The ambitious goals of engine improvement are basically dictated by the fuel source, legislations of various countries tightening the requirements for tailpipe HC, CO and NOx emissions, and the competitive position of engine manufacturers. Thus the problem of improvement of torque and AFR controller performance is practical and requires detailed attention to details of the process and measurements.

The main problems facing researchers in this area concerns the variety of engine operating regimes, nonlinear dynamics, the complexity of physical and chemical processes in the engine, uncertainties and a number of unmeasurable variables which directly affect AFR and torque, noise and disturbances. In general, there is no universal approach which can be successfully applied for all complex nonlinear systems. Therefore it is quite important and necessary to use general principles of control. One of these principles is that some problems of control theory and application can be formulated as the problems of inverse dynamics [1, 2, 3]. Approaches based on this principle allow one to successfully solve a wide array of control problems for different nonlinear systems. An application of this principle in the area of artificial neural networks has been realized and effectively developed [4, 5, 12]. In this approach, inverse models were represented as a grey box with known network architectures. In the works of Krutko [1, 2], it is shown that all well known approaches of classic control theory can be solved from the point of view of inverse dynamics, and the solution of several technical problems is much easier than in classical theory. From this perspective, promising solutions in the area of SIE control can be obtained with the use of principle of inverse dynamics, and effective controllers with principally new capabilities can be implemented.

In this paper the approach based on inverse engine models is proposed. These inverse models when properly used and adjusted can be a powerful base for effective control design. Potentials of inverse model control can be illustrated with the following simple example. Let us consider the open-loop control system presented in Figure 1. Engine controller can be designed on the basis of inverse model which is presented as the consequence of nonlinear and recursive transformations of regulated variable y to the control variable u. The substitution of y^* instead of its current value immediately gives feedforward controller. In this case, if the inverse model has absolute precision,

§ H. Javaherian is with the Propulsion Systems Research Lab, GM R&D Center, Warren MI (hossein.javaherian@gm.com).
† Vladimir O. Nikiforov is with Saint-Petersburg State University of Information Technologies, Mechanics and Optics, Saint-Petersburg, Russia (nikiforov@mail.ifmo.ru)
¶ Dmitry N. Gerasimov is with Saint-Petersburg State University of Information Technologies, Mechanics and Optics, Saint-Petersburg, Russia (gerasimovdn@mail.ru).

978-1-4577-0079-8/11/$26.00 ©2011 AACC

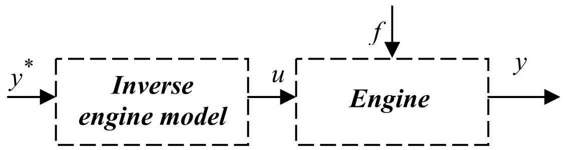

Fig. 1. Inverse controller in open-loop system (y is the regulated variable, y^* is the reference signal, u is the control variable, f is disturbance)

$y^*(0) = y(0)$ and $f(k) = 0$, the open-loop control system has absolute precision, i.e. $y^*(k) = y(k)$. But in reality there are four main problems that control designers face:

a) Initial conditions $y^*(0), y(0)$ are not equal;

b) Inverse model is not ideal and not free from errors;

c) Engine is operating subject to disturbances, but the inverse model controller does not fully take it into account. Thus feedforward loop does not compensate for disturbances;

d) Due to nonlinearities and dynamics of the inverse model, the substitution of desired value of regulated variable instead of its current value can give high deviation of current control from its desired value. As a consequence the control system may exhibit inferior performance [6];

These problems can partially be solved by the introduction of feedback loop which is based on measurement of current value of the regulated variable. Feedback controller corrects the action of feedforward controller providing at least the stability of the closed-loop system and some degree of improvement of the control system performance. However significant improvement of the control performance can be achieved by development of feedforward loop which is responsible for compensation of nonlinear dynamics of the plant. Thus the main focus of this research is on proper feedforward control design based on appropriate design and development of inverse engine model.

In this regard, special attention is paid to the problem d) outlined above, which is challenging for AFR channel due to the fast transient nonlinear dynamics and delays of AFR mixing process and measurement of $\lambda(k)$. In this respect, a simple substitution of desired value “1” instead of current value $\lambda(k)$ will lead to low efficiency of control. Therefore, in this research a new approach for inverse model adjustment for the AFR channel is proposed. This approach is based on the pseudo inversion of the direct model, and proper parameter adjustment of inverse model is achieved with the minimization of a performance index rigidly connected with the error of control.

The organization of the paper is as follows. In the first section the problem of torque and AFR control is formulated, and control variables for both channels are derived. In section 2, the structure of inverse models is described. In the third and forth sections the controllers of torque tracking and AFR stabilization are designed. In section 5, the experimental results obtained after practical implementation of the dual channel controller are presented.

II. Problem Statement

The objective of control is to compensate engine nonlinear dynamics, uncertainties of the engine model, disturbances and to provide the following inequalities under all operating regimes:

$$\left| M(k) - M^*(k) \right| < \Delta_M \text{ for all } t > T_M, \tag{1}$$

where $M(k)$ is the averaged for one engine cycle crankshaft torque, $M^*(k)$ is the reference torque, T_M is the transient time of torque control channel, Δ_M is the precision of tracking, k is event-based sampling time (1 sample corresponds to 1/4th of crankshaft revolution),

$$\left| \lambda(k) - 1 \right| < \Delta_\lambda \qquad \text{for all } t > T_\lambda, \tag{2}$$

where $\lambda(k)$ is the current normalized AFR, "1" is the normalized desired AFR, T_λ is the transient time of AFR control channel, Δ_λ is the precision of stabilization.

Acceptable precision is supposed to be reached, if $\Delta_M \approx 25\, N \cdot m,\ \Delta_\lambda \approx 8\%$ for all operating conditions.

The control variable for torque channel is the angle $\alpha(k)$ of throttle actuated by the throttle drive which in turn is related to the pedal position controlled by the driver. The control variable for AFR channel is the pulse width of fuel injected $\Delta_{inj}(k)$.

III. Inverse Engine Model Formulation

The inverse multi input – multi output (MIMO) model with torque and AFR channels is presented as superposition of empirically chosen nonlinear functions of state and regulated variables passed through linear digital filters with identified parameters. The outputs of the inverse model are the control variables $\alpha(k)$ and $\Delta_{inj}(k)$. The choice of the input variables and the structure was motivated in the course of detailed investigation of direct mean-value mathematical models [7, 8, 9, 10].

The proposed dual channel model has the following form:

$$\alpha(k + m1) = \sum_{i=1}^{L} H_i(z)\varphi_i(k) + g1, \tag{3}$$

$$1/\Delta_{inj}(k) = \sum_{j=1}^{N} W_j(z)\xi_j(k) + g2, \tag{4}$$

where $g1$, $g2$ are the biases, L, N are the numbers of the input variables for corresponding channel,

$$H_i(z)=\frac{b_{n1,i}z^{n1}+b_{n1-1,i}z^{n1-1}+...+b_{1,i}z+b_{o,i}}{z^{n1}+a_{n1-1}z^{n1-1}+...+a_1 z+a_o}, \quad (5)$$

$$W_i(z)=\frac{d_{n2,i}z^{n2}+d_{n2-1,i}z^{n2-1}+...+d_{1,i}z+d_{o,i}}{z^{n2}+h_{n2-1}z^{n2-1}+...+h_1 z+h_o} \quad (6)$$

are the discrete filters with constant parameters a_j, $b_{j,i}$, $d_{j,i}$, h_j to be identified, z is the forward shift operator, $n1$, $n2$ are the orders of corresponding channel of the model,

$$\varphi^T(k)=\left[\theta_{ign}(k),\ \theta_{ign}{}^2(k),\ 0.1M(k+m1),\ 0.01M^2(k+m1),\right.$$
$$\omega(k),\ \omega^2(k),\ P(k), P^2(k), 0.1\theta_{ign}(k)\cdot M(k+m1),$$
$$\theta_{ign}(k)\cdot\omega(k),\ \theta_{ign}(k)\cdot P(k),\ 0.1M(k+m1)\cdot\omega(k),$$
$$\left.0.1M(k+m1)\cdot P(k),\ \omega(k)\cdot P(k)\right]^T,$$
$$\xi^T(k)=\left[P(k),\ P^2(k),\ \omega(k),\ \omega^2(k),\ P(k)\cdot\omega(k),\right.$$
$$P^2(k)\cdot\omega(k),\ P(k)\cdot\omega^2(k), P^2(k)\cdot\omega^2(k),$$
$$\left.P^3(k)\cdot\omega(k),\ P(k)\cdot\omega^3(k)\right]^T\lambda(k+m2),$$

where $m1$, $m2$ are the sample time delays for each channel, P is the air pressure in the intake manifold, ω is the averaged for one engine cycle crankshaft speed, θ_{ign} is the spark advance. The output of AFR channel (4) is presented as the inverse of control signal $1/\Delta_{inj}$ due to its direct proportionality to regulated variable λ. Delay $m1$ is caused by the dynamics of crankshaft, while delay $m2$ is caused by delay of combustion process and exhaust gases transportation from cylinders to sensitive element of oxygen sensor generating λ.

The main advantage of these models is in the possibility of their transformation to the form of linear regression**:**

$$Y(k+n)=\vartheta^T(k)\theta, \quad (7)$$

$$\vartheta^T(k)=\left[y(k+n-1)\ \ y(k+n-2)\ \dots\ y(k)\right.$$
$$u_1(k+n-m)\ u_1(k+n-m-1)\ u_1(k+n-m-2)\ \dots\ u_1(k-m)$$
$$u_2(k+n-m)\ u_2(k+n-m-1)\ u_2(k+n-m-2)\ \dots\ u_2(k-m)$$
$$\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots$$
$$\left.u_s(k+n-m)\ u_s(k+n-m-1)\ u_s(k+n-m-2)\ \dots\ u_s(k-m)\right],$$

where Y is the output of a channel, u_i are the input variables of each channel (φ_i or ξ_j), n is the dynamical order of the channel (n_1 or n_2), m is the delay between input variables and output variable (m_1 or m_2), $\theta\in R^{(s+1)\cdot n-1\times 1}$ is the vector of the filters parameters (a_j, $b_{j,i}$, $g1$ or $d_{j,i}$, h_j, $g2$), s is the number of the channel inputs (L or N).

Representation (7) allows to estimate the unknown model parameters with the use of standard techniques of identification theory [11].

The main problem, the authors focus central attention, is the proper adjustment of the unknown vector of models parameters θ which can provide control objectives (1) and (2).

IV. Torque Controller Design

The proposed algorithm of the torque controller design includes four stages.

First of all inverse model of torque channel (3), (5) was designed, and its parameters were identified. The identification of the parameters was conducted with the use of representation (7), least squares approach and data collected during FTP18 test for a vehicle with a V8 engine with volume 5,3L. Data bank includes all state, regulated and control variables which are used in the research. These variables were measured every event (1/4th of crankshaft revolution) during all FTP cycles and saved in data file prepared for Matlab environment.

The results of model verification for $n1=6$, $m1=4$ are presented in Figure 2.

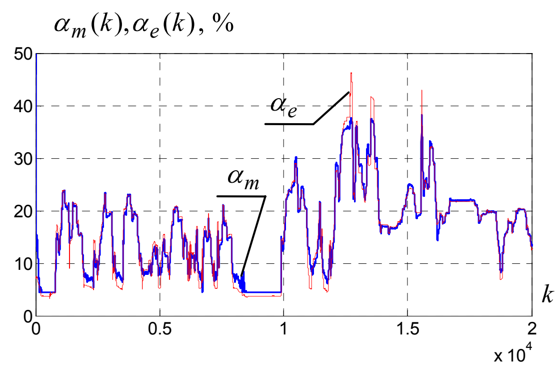

Fig. 2. Results of the inverse torque model verification in the vehicle (α_m is the output of the model, α_e is the experimental data).

Results show acceptable performance of the inverse model which is used as the base for the further control design.

At the second stage desired value of regulated variable $M^*(k)$ was substituted for its current value $M(k)$ and feedforward controller design.

$$\alpha_{ff}(k)=sat\left\{\sum_{i=1}^{14}H_i(z)\varphi_i(k)\Big|_{M(k)=M^*(k)}+g1\right\}, \quad (8)$$

$$sat\{u(k)\}=\begin{cases}55, & if\ \ u(k)\ge 55;\\ u(k), & if\ \ u(k)\in(2,\ 55);\\ 2, & if\ \ u(k)\le 2,\end{cases} \quad (9)$$

where 2 and 55 are the percentage minimum and maximum throttle plate positions correspondingly.

Such a simple procedure of feedforward controller design was motivated by relatively slow crankshaft dynamics and relatively small difference between $M^*(k)$ and $M(k)$ (about 20%).

At the third stage feedback loop was designed and adjusted. Feedback loop is represented as a PID controller with empirically adjusted coefficients:

$$\alpha_{fb}(k) = \left[k_1 + k_2 \frac{1}{z-1} + k_3 \frac{z-1}{z} \right] \varepsilon_M(k), \qquad (10)$$

where k_1, k_2, k_3 are the design parameters chosen empirically,

$$\varepsilon_M(k) = M^*(k) - M(k); \qquad (11)$$

At the last stage the closed-loop system was created and implemented. Final controller is represented as:

$$\alpha(k) = \alpha_{ff}(k) + \alpha_{fb}(k), \qquad (12)$$

where $\alpha_{ff}(k)$ and $\alpha_{fb}(k)$ are defined by (8) and (10) correspondingly.

V. AFR Controller Design

It is well known that for internal combustion engines the processes of air and fuel mixing, fuel burning and exhaust gases outflow are very complex, nonlinear and relatively fast. In fact fast transients of nonlinear aerodynamics effects in the intake manifold, fuel evaporation process, fuel combustion and exhaust gases outflow are challenging obstacles which should be overcome in the procedure of AFR control synthesis. Therefore an analog idea forming the basis for torque control does not work for AFR controller design. This idea was modified in terms of identification of inverse model parameters. Identification of the parameters was based on minimization of performance index depending on the control error $\varepsilon_\lambda(k) = 1 - \lambda(k)$, where the current value of AFR is generated by direct AFR model. The corresponding modified algorithm has the several stages.

At the first stage AFR direct model was designed and verified. Basically this model is needed to analyze the open-loop system and design the algorithm generating feedforward controller parameters to provide both the open-loop gain (see example in Figure 1) closed to "1" for all operating regimes and objective (2).

The choice of the input variables and the structure was also motivated in the course of detailed investigation of direct mean-value mathematical models [7, 8, 10]. The proposed model has the following form:

$$\lambda(k) = \sum_{i=1}^{P} \Phi_i(z) \upsilon_i(k - m2) + f1, \qquad (13)$$

where $f1$ is the bias, P is the quantity of the input variables,

$$\upsilon^T(k) = \big[P(k),\ P^2(k)\ \ \omega(k)\ \ \omega^2(k)\ \ P(k)\omega(k)\ \ P^2(k)\omega(k)$$
$$P(k)\omega^2(k),\ P^2(k)\omega^2(k),\ P^3(k)\omega(k),\ P(k)\omega^3(k)\big]^T \frac{1}{\Delta_{inj}(k)},$$

$$\Phi_i(z) = \frac{\psi_{l,i} z^n + \psi_{l-1,i} z^{l-1} + \ldots + \psi_{1,i} z + \psi_{o,i}}{z^l + \beta_{l-1} z^{l-1} + \ldots + \beta_1 z + \beta_o}, \qquad (14)$$

l is the order of the filters, $\psi_{i,j}$, β_i are the filters parameters.

The model proposed has two useful properties which simplify the procedure of control synthesis:

— direct model (13), (14) can be also represented in the form (7). Thus parameters $\psi_{i,j}$, β_i are identified with the use of standard least squares approach and experimental data;

— the regulated variable $1/\lambda(k)$ is linear in respect to control variable $\Delta_{inj}(k)$.

However AFR model includes time varying functions $\upsilon_i(k)$ complicating the design of the control law.

The model parameters were identified with use of the data obtained during test of vehicle with the V8 engine. After identification procedure the model was verified. The results of model verification for $l = 8$, $m2 = 10$ are presented in Figure 3.

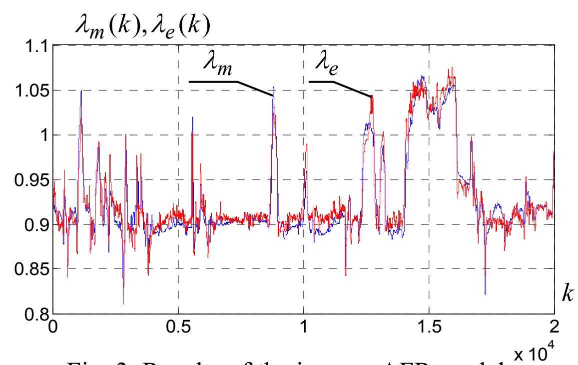

Fig. 3. Results of the inverse AFR model verification for a V8 engine (λ_m is the output of the model, λ_e is the experimental data).

The results of direct model verification illustrate high precision of the model presented and efficiency of grey box principle.

At the next stage the filters (6) of inverse AFR model (4) $W_i(z)$ were expanded to Taylor series in:

$$W_i(z) \approx c_{0,i} + c_{1,i} \frac{1}{z} + c_{2,i} \frac{1}{z^2} + \ldots + c_{fin,i} \frac{1}{z^{fin}}, \qquad (15)$$

where $c_{j,i}$ are coefficients of the expansion, fin is the final degree of the series.

Taking into account representation (15) expression (4) can be rewritten as

$$1/\Delta_{inj}(k) = \sum_{j=1}^{N} \sum_{i=0}^{fin} c_{i,j} \frac{1}{z^i} \big[\xi_j(k)\big] + g2. \qquad (16)$$

Feedforward controller can be created immediately by substitution of "1" instead of λ in vector ξ. The controller can be presented as

$$\Delta_{inj\ ff}(k)=\left(\sum_{j=1}^{N}\sum_{i=0}^{fin}c_{i,j}\frac{1}{z^i}\left[\xi_j(k)\right]+g2,\right)\Bigg|_{\lambda(k)=1} . \quad (17)$$

To estimate the coefficients $c_{j,i}$ the last expression was substituted to the direct model (13), (14). After simple algebraic transformations the model of the open-loop tandem can be represented in the form of linear regression:

$$\bar{y}=\eta^T\varpi(k)+f1\cdot(1+\beta_{l-1}+...+\beta_1+\beta_o), \quad (18)$$

where

$\bar{y}(k)=\lambda(k)+\beta_{l-1}\lambda(k-1)+...+\beta_1\lambda(k-l+1)+\beta_o\lambda(k-l)$,

$\eta^T=\big[c_{0,1},\ c_{1,1},\ ...\ c_{fin,1},\ c_{0,2},\ c_{1,2},\ ...\ c_{fin,2},\ ...,$

$\quad c_{0,N},\ c_{1,N},\ ...\ c_{fin,N}\big]^T$,

$\varpi^T(k)\ =\ \Big[\ \sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\xi_1(k)\right],$

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\xi_2(k)\right],\ ...,\ \sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\xi_N(k)\right],$

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z}\xi_1(k)\right],$

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z}\xi_2(k)\right],\ ...,\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z}\xi_N(k)\right],$

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z^2}\xi_1(k)\right],$

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z^2}\xi_2(k)\right],\ ...,\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z^2}\xi_N(k)\right],$

. . . .

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z^{fin}}\xi_1(k)\right],$

$\sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z^{fin}}\xi_2(k)\right],\ ...,\ \sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\left[\upsilon_i(k)\frac{1}{z^{fin}}\xi_N(k)\right],$

$\quad \sum_{r=0}^{l}\sum_{i=1}^{P}\psi_{r,i}\frac{1}{z^r}\upsilon_i(k)\Big]^T.$

Such representation allows us to identify unknown parameters $c_{j,i}$ in terms of minimization of performance index

$$J=\frac{1}{2k}\sum_{i=1}^{k}(\bar{y}(i)\big|_{\lambda(i)=1}-\bar{y}(i))^2 . \quad (19)$$

The minimization of this index is provided with the use of least squares algorithm which is applied to the linear regression model (18).

It can be shown that index (19) is rigidly connected with stabilization error $\varepsilon_\lambda=1-\lambda$, hence the minimization of this index is equivalent to the minimization of the stabilization error. Therefore such an optimal estimation of parameters $c_{j,i}$ improves the efficiency of the feedforward loop.

At the next stage feedback loop was designed and adjusted. Feedback loop is represented as a PID controller with empirically adjusted coefficients:

$$\Delta_{inj\ fb}(k)=\left[k_1+k_2\frac{1}{z-1}+k_3\frac{z-1}{z}\right]\varepsilon_\lambda(k), \quad (20)$$

where k_1, k_2, k_3 are the design parameters chosen empirically.

At the last stage the closed-loop system was created and implemented. Final controller is represented as:

$$\Delta_{inj}(k)=sat\left\{\left(\Delta_{inj\ ff}(k)+\Delta_{inj\ fb}(k)\right)^{-1}\right\}. \quad (21)$$

$$sat\{u(k)\}=\begin{cases}50, & if\ \ u(k)\geq 50;\\ u(k), & if\ \ u(k)\in(0,\ 50);\\ 0, & if\ \ u(k)\leq 0,\end{cases} \quad (22)$$

where 50 is the maximum fuel pulse width in milliseconds.

Thus two channel torque and AFR controller based on adjusted inverse models is presented by expressions (12) and (21).

VI. Vehicle Test Results

To verify the proposed approach, the control algorithms were tested in a vehicle with a V8 5,3L engine over several operating regimes in chassis rollers characterized by full ranges of load, crankshaft speed and desired torque.

The test duration lasted 2 minutes.

The parameters of the controller are presented in Table 1. The results of the test are presented in Figure 4.

During the test, the air pressure and reference torque were changed in wide ranges, and these changes included fast transients accompanied by the highest errors of control. The maximum error of AFR stabilization was provides at the level 8%, while torque tracking accompanied by high amplitude of measurement noise was provided at the average level 20% .

Thus it can be inferred that the test results show acceptable performance of the torque tracking and AFR stabilization according to the objectives (1) and (2) in the wide range of engine operating.

Table 1. Parameters of the dual channel controller

Torque controller parameters			AFR controller parameters			
PID			Feed-forward	PID		
k_1	k_2	k_3	fin	k_1	k_2	k_3
0.06	0.0002	0.0	25	0.2	0.001	0.0

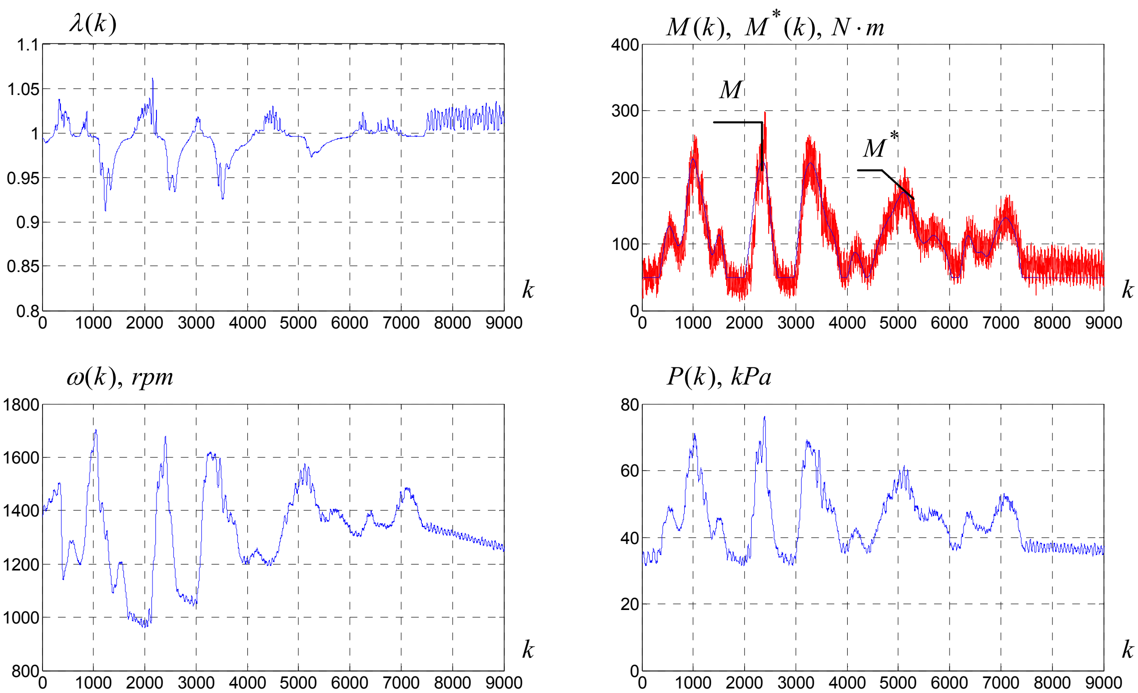

Fig. 4. Experimental results of vehicle test with the torque and AFR inverse model controller

VII. 6. Conclusion

In this paper new approaches for torque and AFR control were proposed and the corresponding control algorithms were designed and tested in a vehicle. The approaches and algorithms are based on inverse engine models which were presented as grey boxes with fixed structure and the parameters identified in the course of experimental data processing. The inverse models were used for the design of feedforward controller compensating for the nonlinear dynamics of the engine. It is worth noting that the controller designed is robust in respect to uncontrollable noise and disturbances.

The workability of the approach and the algorithm was illustrated by the experimental results. The implemented torque and AFR controller provides the control objectives (1), (2) with acceptable precision.

The proposed algorithms are also developed for the design of self-learning controllers which can adjust the inverse models and feedforward loops without the human intervention and are subjects of future publications.

On the basis of the proposed approach of AFR stabilization a theoretical approach for a class of linear time varying systems including model (13) will be created and developed .

ACKNOWLEDGMENTS

This research was supported by the Propulsion Control Systems Group at GM R&D which is gratefully appreciated.

REFERENCES

[1] Krutko, P.D. “Inverse Problems of Control System Dynamics Linear Models,” Nauka Phys. & Math. Publ., Moscow 1987 (in Russian)

[2] Krutko, P.D. “Inverse Problems of Control System Dynamics: Nonlinear Models,” Nauka Phys. & Math. Publ., Moscow 1988 (in Russian)

[3] Widrow, B. and E. Walach, Adaptive Inverse Control, New Jersey, Prentice Hall, 1996

[4] K.S. Narendra, and K. Parthasarathy,“Identification and Control of Dynamical Systems Using Neural Networks,” IEEE Transactions on Neural Networks,” vol. 1, pp. 4-27, 1990

[5] S. Haykin, Neural Networks - A Comprehensive Foundation, Prentice Hall, 1999

[6] K.A. Pupkov, N.D. Egupov “Methods of Robust, Neuro-Fuzzy and Adaptive Control,” Moscow, MSTU named after N.E. Bauman, 2001, 744p (In Russian)

[7] Park S., Yoon. M., Sunwoo M. “Feedback Error Learning Neural Networks for Air-to-fuel Ratio Control in SI Engines,” SAE paper No. 2003-01-0356, 2003

[8] Heywood J.B. Internal Combustion Engine Fundamentals, McGraw-Hill International Editions, 1988

[9] I. Kolmanovsky, M. Druzhinina, J. Sun. “Nonlinear Torque and Air to Fuel Ratio Controller for Direct Injection Stratified Charge Gasoline Engines,” Proceedings of AVEC 2000 5th Int’l symposium on advanced vehicle control. August 22-24, 2000, USA, Ann Arbor, Michigan

[10] Y.W. Kim, Rizzoni G and Utkin V. “Automotive Engine Diagnosis and Control via Nonlinear Estimation,” IEEE Control Systems Mag., October 1998, pp. 84 – 99

[11] L. Ljung, System Identification - Theory For the User, 2nd ed, PTR Prentice Hall, Upper Saddle River, N.J., 1999

[12] H. Javaherian, Huang, T., and Liu, D., “A Biologically-Inspired Adaptive Nonlinear Control Strategy with Applications to Powertrain Control,” IEEE Proceedings of the International Conference on Systems, Man and Cybernetics, San Antonio, Texas, Oct 11-14, 2009