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ADAPTIVE CONTROL OF THE AIR AND EGR FLOW SYSTEM IN A DIESEL ENGINE

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ABSTRACT

We apply retrospective cost adaptive control (RCAC) to command-following and disturbance-rejection problems for a diesel engine model. The engine is a multi-input, multi-output system with strong static and dynamic interactions, nonlinearities, uncertainties and nonminimum phase characteristics. We demonstrate that RCAC is effective for both the linearized and nonlinear engine models provided that two Markov parameters of the linearized engine plant model are known, either analytically or through system identification. For the command-following and disturbance-rejection problems, we consider the case when the disturbance is harmonic but otherwise unknown, and while the command signal is harmonic and known but no advance knowledge of its spectrum is assumed to be available.

INTRODUCTION

In contrast to spark-ignition engines, diesel engines use compression to initiate ignition and achieve high fuel efficiency. According to [1], diesel engines presently account for more than 50% of all new car sales in Europe. However, diesel engines present various challenges in practice, primarily with regard to emissions [2]. Motivated by this challenge, we consider a control problem for a turbocharged diesel engine (Figure 1) with Exhaust Gas Recirculation (EGR) valve, EGR throttle, and Variable Geometry Turbocharger (VGT) actuation. The turbocharger increases engine air flow by utilizing the energy of the exhaust gas. The variable-geometry actuator changes the effective flow area of the turbine as well as the angle at which the flow is directed at the turbine blades. The EGR valve and EGR throttle are used to recirculate a fraction of the burnt gas in the exhaust back to the engine cylinders in order to reduce the emission of nitrogen oxides. For background on modeling and control of diesel engines, see [3]. Several prior approaches to controlling diesel engines with EGR and VGT actuation are discussed in the survey article [4].

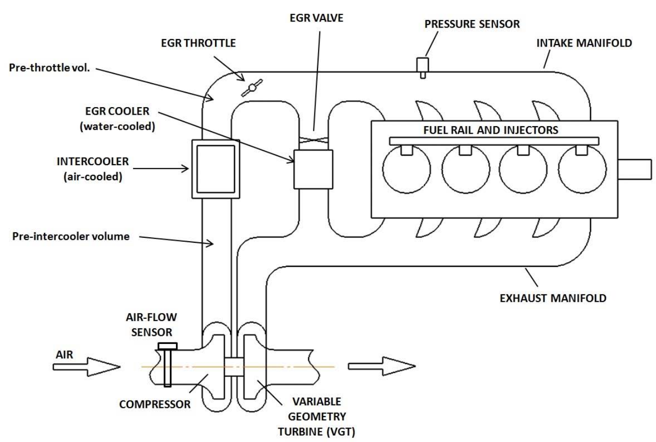

Figure 1. Schematics of a typical diesel engine.

The goal of the present paper is to develop a controller to track setpoints in the intake manifold pressure (MAP) and EGR rate. The EGR rate is defined as the percent ratio of flow through the EGR valve to the flow through the engine cylinders. The setpoints depend on operating conditions of the engine and driver inputs. The setpoint map is determined during engine calibration in order to reduce fuel consumption and emissions. The control inputs are VGT percent closed, EGR throttle percent closed, and

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EGR valve percent open. To ensure good vehicle drivability and performance, the control objectives are to achieve fast tracking of the intake manifold pressure setpoint with small overshoot. In addition, zero steady-state error is desirable for both EGR rate and intake manifold pressure outputs.

To develop a controller that achieves these objectives, we consider a mean-value model with ten states, including pressure, density, and burnt-gas fraction in the intake manifold; pressure, density, and burnt-gas fraction in the exhaust manifold; as well as turbocharger speed, pre-throttle pressure, EGR cooler temperature, and exhaust manifold heat transfer state. While the open-loop dynamics are stable, they are known to be nonlinear. In addition, the linearized model possesses a nonminimum-phase zero in one of the input-output channels [3].

To control the diesel air-flow system, we apply retrospective-cost adaptive control (RCAC) to the linearized model. RCAC is a discrete-time approach to adaptive stabilization, command following, and disturbance rejection for systems that are SISO or MIMO and possibly nonminimum phase [5]-[8]. The modeling information that RCAC requires consists of Markov parameters of the plant transfer function from the control input to the performance variables. For SISO systems, a single Markov parameter typically provides sufficient modeling information, even for nonminimum-phase plants [9, 10]. The Markov parameters provide a finite-impulse-response (FIR) approximation of the plant that is used for controller update. In some cases, a more efficient approximation can be constructed based on frequency-domain data; the robustness of RCAC to uncertainty in these data is discussed in [11]. From an identification perspective, RCAC provides guidance on the plant modeling information needed for adaptive control and the required accuracy of that modeling data.

In the present paper we apply RCAC to the linearized mean-value model, and we consider a command-following problem involving intake manifold pressure. Since the plant has two outputs and three inputs, RCAC requires two Markov parameters, which are obtained from the linearized state space model. In practice, these data could be obtained using system identification techniques [12]. To demonstrate the operation of the closed-loop system, we simulate the RCAC controller with a model linearized at a chosen operating point. We also demonstrated that RCAC is able to follow step commands for the nonlinear diesel engine model, provided two Markov parameters of the linearized engine plant model are known.

The contents of the paper is as follows. In Section 2 we present the adaptive controller design for both command following and disturbance rejection. Numerical results are presented in Section 3, and conclusions are given in Section 4.

ADAPTIVE CONTROLLER DESIGN

In this section, we briefly review RCAC method developed in [10] for command following and disturbance rejection.

Problem Formulation

Consider the MIMO discrete-time system

$$x(k+1) = Ax(k) + Bu(k) + D_1 w(k), \tag{1}$$
$$y(k) = Cx(k) + D_2 w(k), \tag{2}$$
$$z(k) = E_1 x(k) + E_0 w(k), \tag{3}$$

where $x(k) \in \mathbb{R}^n$, $y(k) \in \mathbb{R}^{l_y}$, $z(k) \in \mathbb{R}^{l_z}$, $u(k) \in \mathbb{R}^{l_u}$, $w(k) \in \mathbb{R}^{l_w}$, and $k \geq 0$. Our goal is to develop an adaptive output feedback controller that minimizes the performance variable z in the presence of the exogenous signal w with minimal modeling information about the dynamics and w. Note that w can represent either a command signal to be followed, an external disturbance to be rejected, or both. The system (1)–(3) can represent a sampled-data application arising from a continuous-time system with sample and hold operations.

If $D_1 = 0$ and $E_0 \neq 0$, then the objective is to have the output $E_1 x$ follow the command signal $-E_0 w$. On the other hand, if $D_1 \neq 0$ and $E_0 = 0$, then the objective is to reject the disturbance w from the performance measurement $E_1 x$. Furthermore, if $D_1 = \begin{bmatrix} \hat{D}_1 & 0 \end{bmatrix}$, $E_0 = \begin{bmatrix} 0 & \hat{E}_0 \end{bmatrix}$, and $w(k) = \begin{bmatrix} w_1(k)^{\mathrm{T}} & w_2(k)^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}$, then the objective is to have $E_1 x$ follow the command $-\hat{E}_0 w_2$ while rejecting the disturbance w_1. Lastly, if D_1 and E_0 are empty matrices, then the objective is output stabilization, that is, convergence of z to zero.

Retrospective Cost

For $i \geq 1$, we define the Markov parameter of G_{zu} given by

$$H_i \stackrel{\triangle}{=} E_1 A^{i-1} B. \tag{4}$$

For example, $H_1 = E_1 B$ and $H_2 = E_1 AB$. Let r be a positive integer. Then, for all $k \geq r$,

$$x(k) = A^r x(k-r) + \sum_{i=1}^{r} A^{i-1} Bu(k-i) + \sum_{i=1}^{r} A^{i-1} D_1 w(k-i), \tag{5}$$

and thus

$$z(k) = E_1 A^r x(k-r) + \sum_{i=1}^{r} E_1 A^{i-1} D_1 w(k-i) + E_0 w(k) + \bar{H}\bar{U}(k-1), \tag{6}$$

where

$$\bar{H} \stackrel{\triangle}{=} \begin{bmatrix} H_1 & \cdots & H_r \end{bmatrix} \in \mathbb{R}^{l_z \times r l_u}$$

and

$$\bar{U}(k-1) \triangleq \begin{bmatrix} u(k-1) \\ \vdots \\ u(k-r) \end{bmatrix}.$$

Next, we rearrange the columns of $\bar{H}$ and the components of $\bar{U}(k-1)$ and partition the resulting matrix and vector so that

$$\bar{H}\bar{U}(k-1) = \mathcal{H}'U'(k-1) + \mathcal{H}U(k-1), \tag{7}$$

where $\mathcal{H}' \in \mathbb{R}^{l_z \times (rl_u - l_U)}$, $\mathcal{H} \in \mathbb{R}^{l_z \times l_U}$, $U'(k-1) \in \mathbb{R}^{rl_u - l_U}$, and $U(k-1) \in \mathbb{R}^{l_U}$. We partition $\bar{H}$ into two parts, where $\mathcal{H}$ are the known Markov parameters and $\mathcal{H}'$ are unknown. Then, we can rewrite (6) as

$$z(k) = \mathcal{S}(k) + \mathcal{H}U(k-1), \tag{8}$$

where

$$\mathcal{S}(k) \triangleq E_1A^r x(k-r) + \sum_{i=1}^{r} E_1 A^{i-1} D_1 w(k-i) + E_0 w(k) + \mathcal{H}'U'(k-1). \tag{9}$$

Next, for $j = 1, \ldots, s$, we rewrite (8) with a delay of k_j time steps, where $0 \le k_1 \le k_2 \le \cdots \le k_s$, in the form

$$z(k-k_j) = \mathcal{S}_j(k-k_j) + \mathcal{H}_j U_j(k-k_j-1), \tag{10}$$

where (9) becomes

$$\begin{aligned} \mathcal{S}_j(k-k_j) \triangleq\ & E_1A^r x(k-k_j-r) \\ & + \sum_{i=1}^{r} E_1A^{i-1}D_1 w(k-k_j-i) + E_0 w(k-k_j) \\ & + \mathcal{H}_j' U_j'(k-k_j-1) \end{aligned}$$

and (7) becomes

$$\bar{H}\bar{U}(k-k_j-1) = \mathcal{H}_j'U_j'(k-k_j-1) + \mathcal{H}_j U_j(k-k_j-1), \tag{11}$$

where $\mathcal{H}_j' \in \mathbb{R}^{l_z \times (rl_u - l_{U_j})}$, $\mathcal{H}_j \in \mathbb{R}^{l_z \times l_{U_j}}$, $U_j'(k-k_j-1) \in \mathbb{R}^{rl_u - l_{U_j}}$, and $U_j(k-k_j-1) \in \mathbb{R}^{l_{U_j}}$. Now, by stacking $z(k-k_1), \ldots, z(k-k_s)$, we define the *extended performance*

$$Z(k) \triangleq \begin{bmatrix} z(k-k_1) \\ \vdots \\ z(k-k_s) \end{bmatrix} \in \mathbb{R}^{sl_z}. \tag{12}$$

Therefore,

$$Z(k) \triangleq \tilde{\mathcal{S}}(k) + \tilde{\mathcal{H}}\tilde{U}(k-1), \tag{13}$$

where

$$\tilde{\mathcal{S}}(k) \triangleq \begin{bmatrix} \mathcal{S}_1(k-k_1) \\ \vdots \\ \mathcal{S}_s(k-k_s) \end{bmatrix} \in \mathbb{R}^{sl_z}, \tag{14}$$

$\tilde{U}(k-1)$ has the form

$$\tilde{U}(k-1) \triangleq \begin{bmatrix} u(k-q_1) \\ \vdots \\ u(k-q_{l_{\tilde{U}}}) \end{bmatrix} \in \mathbb{R}^{l_{\tilde{U}}}, \tag{15}$$

where, for $i = 1, \ldots, l_{\tilde{U}}$, $k_1 \le q_i \le k_s + r$, and $\tilde{\mathcal{H}} \in \mathbb{R}^{sl_z \times l_{\tilde{U}}}$ is constructed according to the structure of $\tilde{U}(k-1)$. The vector $\tilde{U}(k-1)$ is formed by stacking $U_1(k-k_1-1), \ldots, U_s(k-k_s-1)$ and removing copies of repeated components.

Next, we define the *retrospective performance*

$$\hat{z}(k-k_j) \triangleq \mathcal{S}_j(k-k_j) + \mathcal{H}_j \hat{U}_j(k-k_j-1), \tag{16}$$

where the past controls $U_j(k-k_j-1)$ in (10) are replaced by the surrogate controls $\hat{U}_j(k-k_j-1)$. In analogy with (12), the *extended retrospective performance* for (16) is defined as

$$\hat{Z}(k) \triangleq \begin{bmatrix} \hat{z}(k-k_1) \\ \vdots \\ \hat{z}(k-k_s) \end{bmatrix} \in \mathbb{R}^{sl_z} \tag{17}$$

and thus is given by

$$\hat{Z}(k) = \tilde{\mathcal{S}}(k) + \tilde{\mathcal{H}}\hat{\tilde{U}}(k-1), \tag{18}$$

where the components of $\hat{\tilde{U}}(k-1) \in \mathbb{R}^{l_{\tilde{U}}}$ are the components of $\hat{U}_1(k-k_1-1), \ldots, \hat{U}_s(k-k_s-1)$ ordered in the same way as the components of $\tilde{U}(k-1)$. Subtracting (13) from (18) yields

$$\hat{Z}(k) = Z(k) - \tilde{\mathcal{H}}\tilde{U}(k-1) + \tilde{\mathcal{H}}\hat{\tilde{U}}(k-1). \tag{19}$$

Finally, we define the *retrospective cost function*

$$J(\hat{\tilde{U}}(k-1),k) \triangleq \hat{Z}^{\mathrm{T}}(k)R(k)\hat{Z}(k), \tag{20}$$

where $R(k) \in \mathbb{R}^{l_z s \times l_z s}$ is a positive-definite performance weighting. The goal is to determine refined controls $\hat{\tilde{U}}(k-1)$ that would have provided better performance than the controls $U(k)$ that were applied to the system. The retrospectively optimized control values $\hat{\tilde{U}}(k-1)$ are subsequently used to update the controller.

Cost Function Optimization with Adaptive Regularization

To ensure that (20) has a global minimizer, we consider the regularized cost

$$\bar{J}(\hat{\tilde{U}}(k-1),k) \triangleq \hat{Z}^{\mathrm{T}}(k)R(k)\hat{Z}(k) + \eta(k)R_2\hat{\tilde{U}}^{\mathrm{T}}(k-1)\hat{\tilde{U}}(k-1), \tag{21}$$

where $\eta(k) \geq 0$, and $R_2 \in \mathbb{R}^{\hat{\tilde{U}}} \geq 0$. Substituting (19) into (21) yields

$$\begin{aligned}\bar{J}(\hat{\tilde{U}}(k-1),k) = \hat{\tilde{U}}(k-1)^{\mathrm{T}}\mathcal{A}(k)\hat{\tilde{U}}(k-1)\\ + \hat{\tilde{U}}^{\mathrm{T}}(k-1)\mathcal{B}^{\mathrm{T}}(k) + \mathcal{C}(k),\end{aligned} \tag{22}$$

where

$$\mathcal{A}(k) \triangleq \tilde{\mathcal{H}}^{\mathrm{T}}R(k)\tilde{\mathcal{H}} + \eta(k)R_2 I_{l_{\tilde{U}}}, \tag{23}$$

$$\mathcal{B}(k) \triangleq 2\tilde{\mathcal{H}}^{\mathrm{T}}R(k)[Z(k) - \tilde{\mathcal{H}}\tilde{U}(k-1)], \tag{24}$$

$$\begin{aligned}\mathcal{C}(k) \triangleq Z^{\mathrm{T}}(k)R(k)Z(k) - 2Z^{\mathrm{T}}(k)R(k)\tilde{\mathcal{H}}\tilde{U}(k-1)\\ + \tilde{U}^{\mathrm{T}}(k-1)\tilde{\mathcal{H}}^{\mathrm{T}}R(k)\tilde{\mathcal{H}}\tilde{U}(k-1).\end{aligned} \tag{25}$$

If either $\tilde{\mathcal{H}}$ has full column rank or $\eta(k) > 0$ and $R_2 > 0$, then $\mathcal{A}(k)$ is positive definite. In this case, $\bar{J}(\hat{\tilde{U}}(k-1),k)$ has the unique global minimizer

$$\hat{\tilde{U}}(k-1) = -\frac{1}{2}\mathcal{A}^{-1}(k)\mathcal{B}(k). \tag{26}$$

Controller Construction

The control $u(k)$ is given by the strictly proper time-series controller of order n_{c} given by

$$u(k) = \sum_{i=1}^{n_{\mathrm{c}}} M_i(k)u(k-i) + \sum_{i=1}^{n_{\mathrm{c}}} N_i(k)y(k-i), \tag{27}$$

where, for all $i = 1,\ldots,n_{\mathrm{c}}$, $M_i(k) \in \mathbb{R}^{l_u \times l_u}$ and $N_i(k) \in \mathbb{R}^{l_u \times l_y}$. The control (27) can be expressed as

$$u(k) = \theta(k)\phi(k-1), \tag{28}$$

where

$$\begin{aligned}\theta(k) \triangleq [M_1(k)\ \cdots\ M_{n_{\mathrm{c}}}(k)\\ N_1(k)\ \cdots\ N_{n_{\mathrm{c}}}(k)] \in \mathbb{R}^{l_u \times n_{\mathrm{c}}(l_u+l_z)}\end{aligned} \tag{29}$$

and

$$\phi(k-1) \triangleq \begin{bmatrix} u(k-1) \\ \vdots \\ u(k-n_{\mathrm{c}}) \\ y(k-1) \\ \vdots \\ y(k-n_{\mathrm{c}}) \end{bmatrix} \in \mathbb{R}^{n_{\mathrm{c}}(l_u+l_y)}. \tag{30}$$

Recursive Least Squares Update of $\theta(k)$

Let d be a positive integer such that $\tilde{U}(k-1)$ contains $u(k-d)$. Next, we define the cumulative cost function

$$\begin{aligned}J_{\mathrm{R}}(\theta(k)) \triangleq \sum_{i=d+1}^{k} \lambda^{k-i}\|\phi^{\mathrm{T}}(i-d-1)\theta^{\mathrm{T}}(k)\\ - \hat{u}^{\mathrm{T}}(i-d)\|^2 + \lambda^k(\theta(k)-\theta(0))P^{-1}(0)(\theta(k)-\theta(0))^{\mathrm{T}},\end{aligned} \tag{31}$$

where $\|\cdot\|$ is the Euclidean norm, and $\lambda \in (0,1]$ is the forgetting factor. Minimizing (31) yields

$$\begin{aligned}\theta^{\mathrm{T}}(k) \triangleq \theta^{\mathrm{T}}(k-1) + \beta(k)P(k-1)\phi(k-d-1)\\ \cdot[\phi^{\mathrm{T}}(k-d)P(k-1)\phi(k-d-1)+\lambda]^{-1}\\ \cdot[\phi^{\mathrm{T}}(k-d-1)\theta^{\mathrm{T}}(k-1) - \hat{u}^{\mathrm{T}}(k-d)],\end{aligned} \tag{32}$$

where $\beta(k)$ is either 0 or 1. When $\beta(k)$ is 1, the controller is allowed to adapt, when $\beta(k)$ is 0, the controller adaption is off.

The error covariance is updated by

$$P(k) \triangleq (1-\beta(k))P(k-1)+\beta(k)\lambda^{-1}P(k-1) \\ -\beta(k)\lambda^{-1}(k)P(k-1)\phi(k-d-1) \\ \cdot[\phi^{\rm T}(k-d-1)P(k-1)\phi(k-d)+\lambda]^{-1} \\ \cdot\phi^{\rm T}(k-d-1)P(k-1). \quad (33)$$

We initialize the error covariance matrix as $P(0)=\gamma I$, where $\gamma>0$. RCAC is a direct digital control approach that requires minimal modeling information about the plant. For other choices of the parameters and the stability analysis, see [6–8].

APPLICATION TO TURBOCHARGED DIESEL ENGINES

To apply RCAC to a turbocharged diesel engine, we control VGT percent closed V, EGR throttle percent closed $E_{\rm t}$, and EGR valve percent open $E_{\rm v}$ using measurements of the intake manifold pressure $P_{\rm i}$ and an estimate of the EGR rate $E_{\rm r}$. The Markov parameters are based on the state-space matrices of the linearized diesel engine model.

We linearize the nonlinear engine model at engine speed of 1671 RPM. For the linearized diesel engine, the discrete state-space form of the model with a sample time $T_{\rm s}=0.01$ sec is given by

$$\tilde{x}(k+1)=\tilde{A}\tilde{x}(k)+\tilde{B}\tilde{u}(k)+\tilde{D}_1\tilde{w}(k), \quad (34)$$

$$\tilde{y}(k)=\tilde{C}\tilde{x}(k)+\tilde{D}\tilde{u}(k), \quad (35)$$

$$\tilde{z}(k)=\tilde{r}(k)-\tilde{y}(k), \quad (36)$$

where $\tilde{x} \triangleq \begin{bmatrix} P_{\rm i} & P_{\rm e} & \omega_{\rm tc} & P_{\rm p} & T_{\rm d} & \rho & C_{\rm m} & \rho_{\rm e} & F_{\rm i} & F_{\rm e}\end{bmatrix}^{\rm T}$, $\tilde{u} \triangleq \begin{bmatrix} V & E_{\rm t} & E_{\rm v}\end{bmatrix}^{\rm T}$, $\tilde{y} \triangleq \begin{bmatrix} P_{\rm i} & E_{\rm r}\end{bmatrix}^{\rm T}$, $\tilde{r}$ is the vector of the commands, and $\tilde{w}$ is the unknown disturbance. The states are intake manifold pressure $P_{\rm i}$ (kPa), exhaust manifold pressure $P_{\rm e}$ (kPa), turbo rotational speed $\omega_{\rm tc}$, prethrottle manifold pressure $P_{\rm p}$ (kPa), EGR cooler temperature $T_{\rm d}$, intake manifold density ρ (kg/m^3), exhaust heat transfer state $C_{\rm m}$, exhaust manifold density $\rho_{\rm e}$ (kg/m^3), intake manifold burnt gas fraction $F_{\rm i}$, and exhaust manifold burnt gas fraction $F_{\rm e}$. The inputs are VGT percent closed V, EGR throttle percent closed $E_{\rm t}$, and EGR valve percent open $E_{\rm v}$, while the available measurements are $P_{\rm i}$ and $E_{\rm r}$. The matrices $\tilde{A}\in\mathbb{R}^{10\times10}$, $\tilde{B}\in\mathbb{R}^{3\times10}$, $\tilde{C}\in\mathbb{R}^{2\times10}$, and $\tilde{D}\in\mathbb{R}^{2\times3}$ are given by (37)-(38). Note that all the eigenvalues of $\tilde{A}$ are within the unit circle, and thus the linearized diesel engine plant is asymptotically stable. However, the transfer function of the linearized engine model from $E_{\rm v}$ to $E_{\rm r}$ is nonminimum phase at all operation points.

Since the linearized model is exactly proper, that is, $\tilde{D}$ in (35) is nonzero, we add a unit delay to the output $\tilde{y}(k)$ such that $y(k)=\tilde{y}(k-1)$, and therefore the first two nonzero Markov parameters used to implement (26) in RCAC are $H_1 \triangleq \tilde{C}\tilde{B}$ and $H_2 \triangleq \tilde{C}\tilde{A}\tilde{B}$. RCAC generates a control signal $u(k)$ that attempts to minimize the performance variable $\tilde{z}(k)$, which is the command-following error based on the intake manifold pressure and EGR rate. We assume that measurements of only $\tilde{z}(k)$ are available for feedback. We initialize the adaptive control gains to zero, that is, $\theta(0)=0$, and we choose the controller order $n_{\rm c}=12$ and the covariance matrix $P(0)=10^{-3}I_{5n_{\rm c}}$. These values are found by trial and error. Furthermore, since the linearized model is nonminimum phase, we choose the regularization $\eta(k)=z^{\rm T}(k)z(k)$ [9] and $R_2=\begin{bmatrix}0&0&0\\0&0&0\\0&0&1\end{bmatrix}$ for the input from EGR $E_{\rm v}$ to $E_{\rm r}$. Finally we do not use a forgetting factor in the adaptive controller, that is, $\lambda=1$. Figure 2 and 3 show the time history of the intake manifold pressure $P_{\rm i}$ and EGR rate $E_{\rm r}$ in response to step commands. The numerical results show the ability of RCAC to make the outputs $P_{\rm i}$ and $E_{\rm r}$ follow the commands, while Figure 4 shows the time history of the control inputs V, $E_{\rm t}$, and $E_{\rm v}$ from RCAC. Note that zero steady-state tracking errors are achieved for both the intake manifold pressure and EGR rate outputs with satisfactory transient behavior. However, as shown in Figure 4(b), the adaptive controller uses large control signals in the EGR throttle percent closed ($E_{\rm t}\in(-580,520)$), that exceeds the actuator range of travel ($E_{\rm t}\in[0,100]$.) We note that the controller does not use the EGR valve extensively, which is reasonable given that at this operating point the pressure drop across the EGR valve is small and throttle authority is essential for following the commands.

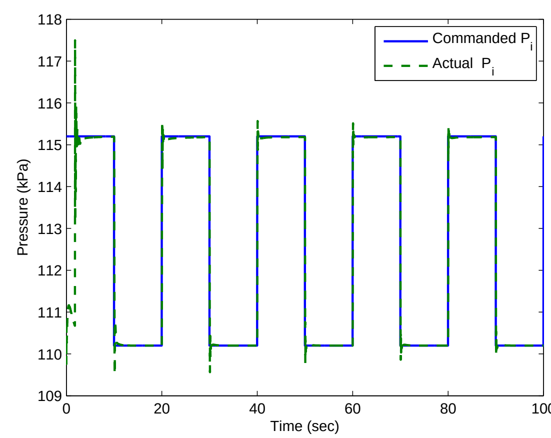

Figure 2. *Command following for the linearized diesel engine model:* Intake manifold pressure $P_{\rm i}$ in response to step changes in the setpoint. Note that zero steady-state tracking error is achieved for the intake manifold pressure outputs.

Next, we implement the adaptive controller with saturated outputs. To do this, we set three different saturation levels based on the trim conditions of the control inputs V, $E_{\rm t}$, and $E_{\rm v}$. In particular, we choose $\eta(k)=z^{\rm T}(k)z(k), n_{\rm c}=12, P(0)=10^{-4}I_{5n_{\rm c}}$,

$$\tilde{A}=\begin{bmatrix} 0.1962 & 0.0437 & 0.0033 & 0.1305 & 0.0024 & 0.7039 & 0.0011 & -0.1524 & -0.0098 & -0.0000 \\ 0.0271 & 0.2926 & 0.0005 & 0.0860 & -0.0050 & 13.4343 & 0.0182 & 28.5360 & -0.2668 & -0.0014 \\ 1.5911 & 1.9022 & 0.9702 & 1.2428 & -0.0018 & 23.8505 & 0.0427 & -30.0380 & -0.3285 & -0.0012 \\ 0.1861 & 0.0403 & 0.0034 & 0.1236 & 0.0022 & 0.6248 & 0.0010 & -0.1527 & -0.0083 & -0.0000 \\ 0.0667 & 1.9737 & 0.0001 & 0.0456 & 0.3653 & 1.0430 & 0.0487 & -390.9750 & -0.3967 & -0.0015 \\ -0.0059 & -0.0001 & 0.0000 & 0.0012 & -0.0000 & 0.9401 & -0.0000 & 0.0055 & -0.0000 & -0.0000 \\ 2.4830 & 0.0724 & -0.0022 & -0.2249 & 0.0083 & -344.6835 & 0.3690 & -1.0773 & -12.2236 & -0.0934 \\ -0.0001 & -0.0019 & 0.0000 & 0.0004 & -0.0000 & 0.0887 & -0.0000 & 0.9196 & 0.0003 & 0.0000 \\ 0.0005 & 0.0002 & -0.0000 & -0.0002 & 0.0000 & 0.0023 & 0.0000 & 0.0017 & 0.9412 & 0.0122 \\ 0.0003 & 0.0000 & -0.0000 & -0.0001 & 0.0000 & -0.0533 & 0.0000 & -0.0000 & 0.1646 & 0.8275 \end{bmatrix}, \quad (37)$$

$$\tilde{B}=\begin{bmatrix} 0.0246 & -0.0061 & 0.0438 \\ 0.6297 & -0.0021 & -0.1892 \\ -1.2203 & 0.0120 & -0.1701 \\ 0.0206 & 0.0022 & 0.0391 \\ 0.2814 & -0.0009 & -0.0846 \\ -0.0000 & -0.0001 & -0.0001 \\ 0.0262 & 0.0053 & 0.0670 \\ 0.0027 & -0.0000 & -0.0008 \\ 0.0001 & 0.0000 & 0.0002 \\ 0.0000 & 0.0000 & 0.0000 \end{bmatrix}, \tilde{C}=\begin{bmatrix} 1.0000 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.8792 & 0.8687 & -0.0284 & 5.3820 & 0.0337 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \tilde{D}=\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0.7219 \end{bmatrix}. \quad (38)$$

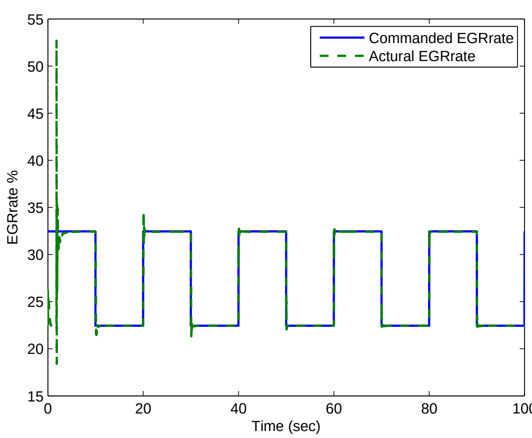

Figure 3. *Command following for the linearized diesel engine model:* EGR rate E_r in response to step changes in the setpoint. Note that zero steady-state tracking error is achieved for EGR rate.

R_2 as above, and initialize the control gains to zero. Figures 5 and 6 show that the output of the linearized model follows the step commands; however, the transient response is degraded due to the limits imposed on the control inputs. Figure 7 shows the time history of the control inputs V, E_t, and E_v. Note that, in this case, all the control signals are within the admissible range, that is, between 0 and 100 percent.

Next, we consider a disturbance rejection problem, where the control objective is to drive z to zero in the presence of the sinusoidal disturbance $w(k)=0.01\sin(0.25\pi k)$, whose frequency, phase, and amplitude are unknown to the controller. We assume that the first two nonzero Markov parameters are known, but no other information about the system is assumed to be known. Figure 8 shows that RCAC rejects the disturbance and drives z to zero.

Finally, we include preliminary results where we apply RCAC to the nonlinear diesel engine system. The first two nonzero Markov parameters $H_1=\tilde{C}\tilde{B}$ and $H_2=\tilde{C}\tilde{A}\tilde{B}$ of the linearized diesel engine (37)-(38) are used as the only model information for the nonlinear engine plant for the controller. We implement the RCAC controller with saturated outputs, and we set three different saturation levels based on the trim conditions of the control inputs V, E_t and E_v. Measurements of only $z(k)$ are available for feedback. In particular, we choose $\eta(k)=0.01, n_c=12, P(0)=10^{-3}I_{5n_c}$, R_2 as above, and initialize the control gains to zero. Figures 9(a) and Figures 9(b) show that the output of the nonlinear diesel model follow the step commands. Figures 9(c), (d), and (e) show the time history of the control inputs V, E_t, and E_v. Note that, since we saturate the RCAC control, all of the control outputs are within the admissible range, that is, between 0 and 100 percent.

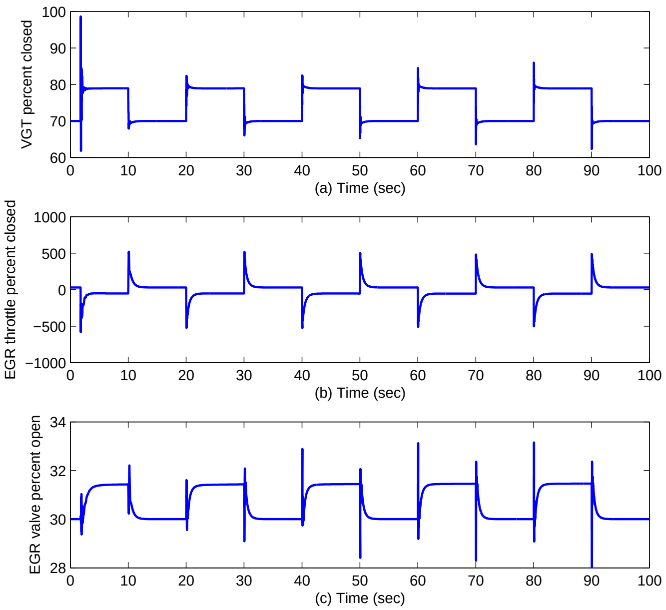

Figure 4. Control inputs VGT percent closed V (a), EGR throttle percent closed E_t (b), and EGR valve percent open E_v (c) corresponding to the closed-loop response shown in Figure 2 and Figure 3. Note that in this case, the adaptive controller uses large control authority in the EGR throttle percent closed ($E_t \in (-580, 520)$), which exceeds the limits $E_t \in [0, 100]$.

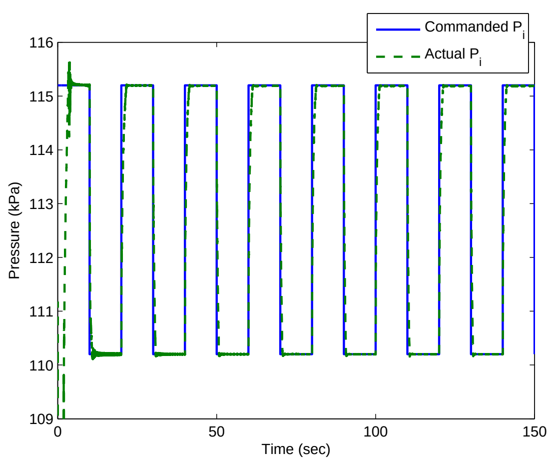

Figure 5. *Command following for the linearized diesel engine model*: Intake manifold pressure P_i in response to step commands. Note that zero steady-state tracking error is achieved for the intake manifold pressure outputs. In this case, where the control signals are saturated, the transient response is degraded relative to Figure 2.

CONCLUSION

In this paper, we considered command-following and disturbance-rejection problems for a diesel engine. RCAC was

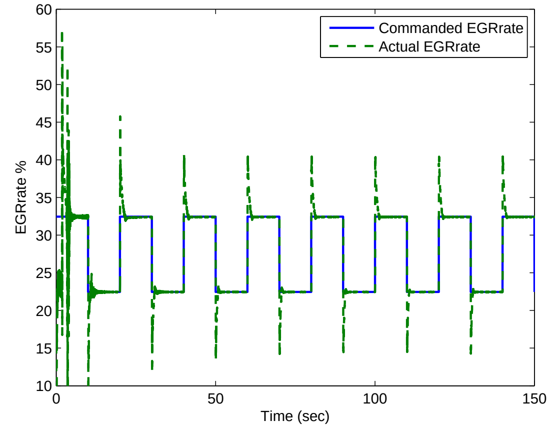

Figure 6. *Command following for the linearized diesel engine model:* EGR rate E_r in response to steps in the setpoint. Note that zero steady-state tracking error is achieved for EGR rate. In this case, where the control signals are saturated, the transient response is worse than the response in Figure 3.

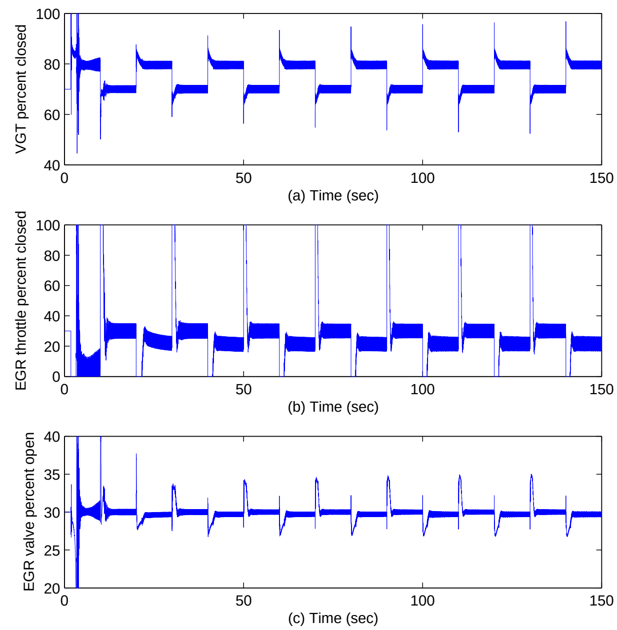

Figure 7. Control inputs VGT percent closed V (a), EGR throttle percent closed E_t (b), and EGR valve percent open E_v (c) corresponding to the closed-loop response shown in Figures 5 and 6. Note that in this case, all of the control signals are within the admissible range, that is, between 0 and 100. Compared with Figure 4, the response is degraded due to the limits imposed on the control input E_t and high gains of the controllers. Note that E_v to P_i is of nonminimum-phase.

used with limited modeling information, namely, the first two nonzero Markov parameters of the linearized plant. The prob-

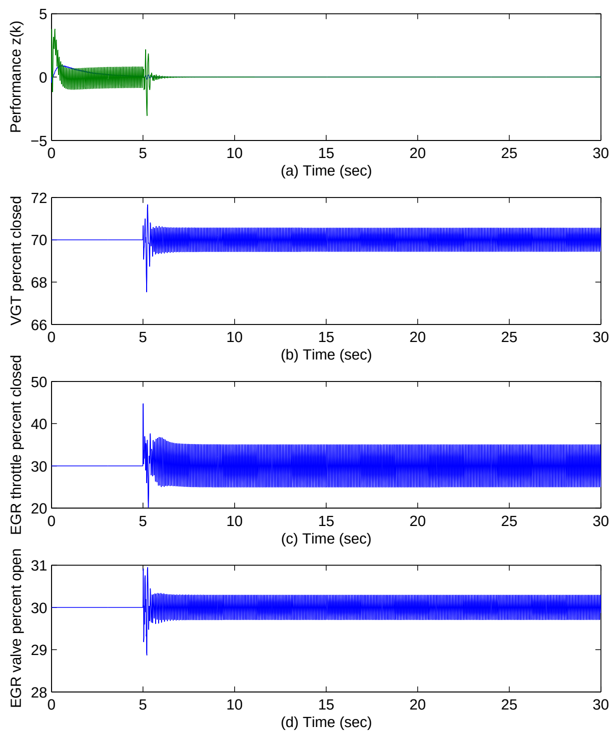

Figure 8. *Disturbance rejection for the linearized diesel engine model:* The adaptive control uses knowledge of the first two nonzero Markov parameters to reject a sinusoidal disturbance acting on the linearized engine model. The frequency, phase, and amplitude of the disturbance are assumed to be unknown. The adaptive control is turned on after 5 seconds and drives the performance z (a) to zero. Time history of control inputs VGT percent closed V, EGR throttle percent closed $E_{\rm t}$, and EGR valve percent open $E_{\rm v}$ are shown in (b), (c), and (d), respectively.

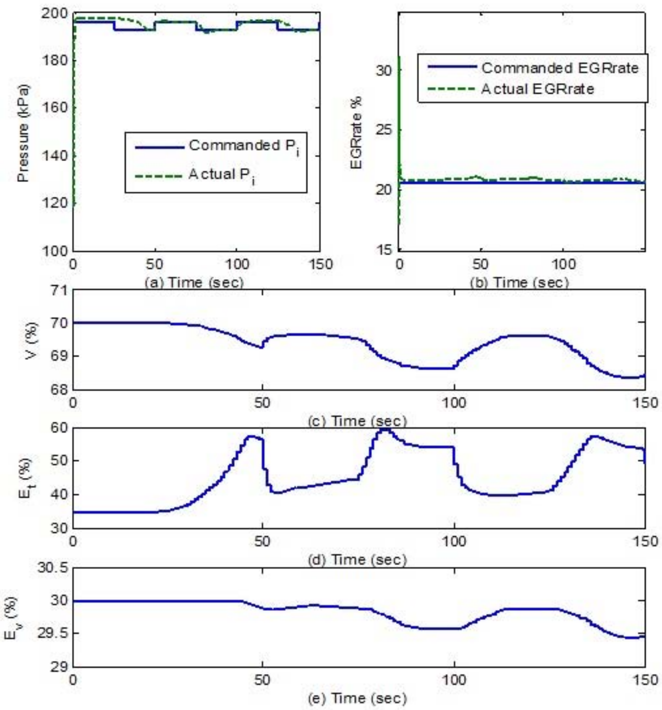

Figure 9. *Command following for the nonlinear diesel engine model:* (a) shows the intake manifold pressure $P_{\rm i}$ in response to a step command. (b) shows the EGR rate $E_{\rm r}$ in response to a step command. Figures 9(c), (d), and (e) show the time history of the control inputs V, $E_{\rm t}$, and $E_{\rm v}$. Note that, since we saturated the RCAC controller, all the control outputs are within the admissible range, that is, between 0 and 100 percent.

lem is challenging as the engine exhibits nonminimum phase characteristics. First, we assumed there is no bound on the control inputs. Then, we considered the more realistic case where we saturate the control outputs using physical bounds. In both cases, RCAC was able to follow the reference commands. Finally, we demonstrated disturbance rejection for disturbances with unknown spectra. Future research will focus on robustness of RCAC to uncertainty in the Markov parameters as well as completing the development of RCAC for the full operating rangel of the diesel engine based on the nonlinear model.

REFERENCES

[1] "Diesel engine," avilable at http://en.wikipedia.org/wiki/Diesel_engine (visited 12, June, 2012).

[2] "Deltaexpo," available at http://www.deltaexpo.com/content/view/118/35/ (visited 12, June, 2012).

[3] I.V. Kolmanovsky, P. Moral, M. van Nieuwstadt, A. Stefanopoulou, "Issues in Modelling and Control of Intake Flow in Variable Geometry Turbocharged Engines," in: *Systems Modelling and Optimization.* Edited by M.P. Polis et al. published by Chapman and Hall/ CRC, Chapman Hall/CRC Research Notes in Mathematics, vol. 396, pp. 436-445, 1999.

[4] J. Cook, J. Sun, J. H. Buckland, I.V. Kolmanovsky, H. Peng, and J. W. Grizzle, "Automotive Powertrain Control - A Survey," *Asian Journal of Control,* Special Issue on New Trends in Automotive Powertrain Systems, vol. 8, no. 3, pp. 237-261, 2006.

[5] J. B. Hoagg, M. A. Santillo, and D. S. Bernstein, "Discrete-Time Adaptive Command Following and Disturbance Rejection for Minimum Phase Systems with Unknown Exogenous Dynamics," *IEEE Trans. Autom. Contr.*, Vol. 53, pp. 912-928, 2008.

[6] M. A. Santillo and D. S. Bernstein, "Adaptive Control Based on Retrospective Cost Optimization," *AIAA J. Guid.*

Contr. Dyn., Vol. 33, pp. 289–304, 2010.

[7] J. B. Hoagg and D. S. Bernstein, "Retrospective Cost Adaptive Control for Nonminimum-Phase Discrete-Time Systems Part 1: The Ideal Controller and Error System; Part 2: The Adaptive Controller and Stability Analysis," *Proc. Conf. Dec. Contr.*, pp. 893–904, Atlanta, GA, December 2010.

[8] J. B. Hoagg and D. S. Bernstein, "Retrospective Cost Model Reference Adaptive Control for Nonminimum-Phase Discrete-Time Systems, Part 1: The Adaptive Controller; Part 2: Stability Analysis," *Proc. Amer. Contr. Conf.*, pp. 2927–2938, San Francisco, CA, June 2011.

[9] A. M. D'Amato, E. D. Sumer, and D. S. Bernstein, "Frequency-Domain Stability Analysis of Retrospective-Cost Adaptive Control for Systems with Unknown Nonminimum-Phase Zeros," *Proc. Conf. Dec. Contr.*, pp. 1098–1103, Orlando, FL, December 2011.

[10] A. M. D'Amato, E. D. Sumer, and D. S. Bernstein, Retrospective cost adaptive control for systems with unknown nonminimum-phase zeros, *Proc. AIAA Guid. Nav. Contr. Conf.*, August 2011, AIAA-2011-6203.

[11] E. D. Sumer, A. M. D'Amato, A. M. Morozov, J. B. Hoagg, and D. S. Bernstein, "Robustness of Retrospective Cost Adaptive Control to Markov-Parameter Uncertainty," *Proc. Conf. Dec. Contr.*, pp. 6085–6090, Orlando, FL, December 2011.

[12] M. S. Fledderjohn, M. S. Holzel, H. Palanthandalam-Madapusi, R. J. Fuentes, and D. S. Bernstein, "A Comparison of Least Squares Algorithms for Estimating Markov Parameters," *Proc. Amer. Contr. Conf.*, pp. 3735–3740, Baltimore, MD, June 2010.