Spark-Ignition-Engine Idle Speed Control: An Adaptive Control Approach

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Abstract—The paper presents an application of a recently developed adaptive posicast controller (APC) for time-delay systems to the idle speed control (ISC) problem in spark ignition (SI) internal combustion (IC) engines. The objective is to regulate the engine speed to a prescribed set-point in the presence of accessory load torque disturbances such as those due to air conditioning and power steering. The adaptive controller, integrated with the existing proportional spark controller, is used to drive the electronic throttle actuator. We present both simulation and experimental results demonstrating the performance improvement by employing the adaptive controller. We also present the modifications and improvements to the controller structure which were developed during the course of experimentation to solve specific problems. In addition, the potential for the reduction in calibration time and effort which can be achieved with our approach is discussed.

Index Terms—Adaptive control, delay effects, internal combustion (IC) engines, road vehicles.

I. INTRODUCTION

The basic problem of idle speed control (ISC) is to maintain the engine speed at a prescribed set-point in the presence of various disturbances such as those due to air conditioning, transmission engagement or power steering accessory load torques [1]. There are several well-known challenges in this control problem, one of the most important of which is the time delay between the intake event and combustion event of the engine. This time delay limits the achievable performance in the electronic throttle control loop. The second challenge is that the controller performance must be robust to changes in the idle-speed set-point, operating conditions (e.g., varying altitude, engine temperature, and/or ambient temperature), and part-to-part and aging-caused variability. Finally, obtaining an accurate and simple model that is appropriate for control design can be both difficult and time-consuming.

ISC has been a classical problem in automotive control, and the celebrated Watt’s governor (1796) was, in fact, a speed controller for a steam engine. Even though ISC is implemented in most of the vehicles on the road today, increasingly stringent regulatory and customer requirements necessitate its continuing improvement. For instance, a better performing ISC can improve fuel economy by reducing spark reserve and lowering idle-speed set-point, and it can also accommodate changes in sensors and actuators (e.g., a replacement of an air-bypass valve by the electronic throttle or reduction in sensor or actuator cost). Finally, ISC designs that can lower calibration time and effort can help reduce time-to-market, which is a key priority for automotive manufacturers.

The ISC problem is typically addressed by combining some form of a feedforward control with a closed-loop compensation based on the engine speed error. The feedforward controller may consist of multiple lookup tables (LUTs) which may, for instance, predict the loads due to accessories for different operating conditions. A closed-loop controller determines the compensation with electronic throttle and spark timing actuators for the engine speed tracking error and is typically gain-scheduled on operating conditions where nonlinear maps are used to determine the gains. The major effort in the calibration, which is the process of determining the appropriate entries in the LUTs, is spent in determining the gains of the feedforward controller. One of the main reasons for this may be due to the inadequacy of the closed-loop controller, which in turn requires very accurate tuning of the feedforward controller. Therefore, if a high-performing feedback controller exists that is sufficiently capable to compensate for the uncertainties, even a not-so-precise feedforward controller may be sufficient. As a result, the calibration time and effort, which is mostly spent in the design of the feedforward controller, can be reduced.

Many different closed-loop designs for ISC have been proposed in the literature, including $H_\infty$ control [2], $H_2$ control [3], sliding mode control [4], [5], $\ell_1$ optimization [6], feedback linearization [7], proportional-integral (PI) and proportional-integral-derivative (PID) control [8]–[12], linear quadratic control (LQ) [13], [11], [14], model predictive control (MPC) [15], adaptive control [16]–[18], and estimation-based control [19]–[21], to name a few. A comparison between different control algorithms for the ISC problem can be found in [22]. A comprehensive survey of engine models and control strategies developed for ISC can be found in [1].

The literature given above regarding classical and advanced control applications to the ISC problem proves the success of an automatic model-based control approach, and our work built upon these results by eliminating the need of a precise engine model for classical or optimization-based algorithms and by eliminating the conservatism introduced by the robust control approaches. This is achieved by using the adaptive posicast controller (APC) [23], [24], which is an adaptive controller for...
time-delay systems. Successful adaptive control approaches are presented also in [16]–[18], but our approach is different from them. In [16], the adaptation is used to select the idle-speed set point and, in [17], the torque differences among the cylinders are estimated to reduce the short-term fluctuations caused by them. Finally, in [18], simulation results of ISC by online estimation of the plant parameters and using these estimates in the control scheme using two actuators, spark and bypass valve, are given. In our approach, we apply APC, a model reference adaptive controller developed for time-delay systems, to control the idle speed at a prescribed set point, in the presence of external disturbances like power steering disturbance and uncertainties due to modeling inaccuracies and operating point changes. We do not employ an online parameter estimation algorithm which may require additional computation power. In addition, we present experimental results showing the success of the algorithm over the baseline controller existing in the vehicle, as well as the robustness of the algorithm by showing the parameter evolution during the course of the experiment.

The authors have previously published preliminary results of APC application to ISC and fuel-to-air ratio control problems in conference papers [25], [26] and [27]. This paper expands on those results with further theoretical improvements, new experimental results, and more detailed explanations of the experimental issues. The APC approach addresses the key challenges due to uncertainties and time delay that are important for ISC application. The underlying control architecture includes several components including the classical Smith Predictor [28], its variant reported in [29] based on finite-spectrum assignment, and adaptation [30], [31]. The controller is modified from its original design to take care of the specific needs of the ISC application, and additional design methods are developed to facilitate the controller development. First, an adaptive feedforward term is added which is crucial for disturbance rejection. Second, an algorithm is developed for the adaptation rate selection. Third, a fine-tuning method is introduced to minimize the controller tuning. Finally, a robustifying scheme is used to prevent the drift of the adaptive parameters. Our main contribution is the demonstration of the potential of this adaptive controller to improve the performance and to reduce the time and effort required for the controller calibration. This is achieved by the help of modifications and improvements that are listed above.

The experimental results obtained using a Ford F-150 test vehicle are repeated. These results demonstrate the capability of the controller to improve performance and decrease the calibration time and effort.

The adaptive postcast ISC approach represents a step towards a fully self-calibrating ISC because less reliance on feedforward characterization of accessory loads is required and because the controller gains are automatically tuned online.

While our control approach is adaptive, its development both benefits from and depends on the structural properties of the underlying plant model. This plant model for ISC control is briefly discussed next, while the reader is referred to [32] for a more extended treatment of the underlying modeling techniques.

II. PLANT MODEL

The plant model for ISC explained here is standard [32]. The control input in the model is the throttle position in degrees and the output is the engine speed in revolutions per minute (rpm). Below, the modeling aspects are discussed for each subsystem.

A. Throttle Mass Flow

The air mass flow thorough the throttle opening during idling can be modeled using the choked flow equation

\[ \dot{w}_{th} = A_{th} \frac{p_h}{\sqrt{2RT_a}} \]  (1)

where \( \dot{w}_{th} \) is the air mass flow rate passing thorough the throttle opening, \( A_{th} \) is the effective area of the throttle, \( p_h \) is the ambient pressure, \( T_a \) is the ambient temperature, and \( R \) is the gas constant. Note that the throttle area is a nonlinear function of the throttle position, but, given that during idling the throttle movement is very small, a linear relationship between throttle position and throttle effective flow area can be assumed.

B. Intake Manifold

Assuming isothermal conditions, the intake manifold pressure dynamics can be modeled as

\[ \frac{d}{dt}p_m = \frac{RT_m}{V_m} (\dot{w}_{th} - \dot{w}_\text{eng}) \]  (2)

where \( p_m \), \( T_m \), and \( V_m \) are the manifold pressure, temperature, and volume, respectively, and \( \dot{w}_\text{eng} \) is the air-mass flow rate exiting the intake manifold and entering the engine.

C. Engine Air Mass Flow

The mean value of the fuel–air mixture flow rate entering the engine cylinders can be approximated using the following equation:

\[ \dot{w}_\text{max} = \eta_v \frac{p_m}{RT_m} \frac{V_\text{displacement} \cdot \omega_c}{4\pi} \]  (3)

where \( \eta_v \) is the volumetric efficiency, \( V_\text{displacement} \) is the displacement volume, and \( \omega_c \) is the engine speed in radians per second. Air-mass flow rate entering the cylinders can be found using the formula \( \dot{w}_\text{eng} = \dot{w}_\text{max}/[1 + \Phi (F/A)_0] \), where \( (F/A)_0 \) and \( \Phi \) represent the stoichiometric fuel-to-air ratio and fuel-to-air ratio normalized by the stoichiometric fuel-to-air ratio, respectively. \( \Phi \) is referred to as the equivalence ratio.

D. Torque Generation

In general, generated torque is a nonlinear function of engine speed, mass flow rate into the engine cylinders, equivalence ratio, and spark advance

\[ T_e = f(N, \dot{w}_\text{max}, \Phi, SA) \]  (4)

where \( SA \) represents the spark advance. This nonlinear relationship can be found with a least-squares method using engine data. Also note that the induction to power (IP) delay enters into system dynamics through (4) as the torque depends on the delayed value of the mass flow rate into the engine cylinders.

E. Engine Rotational Dynamics

The equation of engine rotational dynamics is as follows:

\[ \frac{d}{dt}\omega_c = \frac{1}{J}(T_e - T_i) \]  (5)
where $J$ is the engine inertia in neutral and $T_l$ is the load torque on the engine including the internal engine friction.

**F. Final Model for ISC**

For ISC design, a nonlinear mean value engine model based on the above subsystem models was linearized around the nominal idle speed value (650 rpm) to obtain a linear plant model. Considering the deviation in the throttle position in degrees as the input and the deviation in engine speed in rpm as the output, the parametric transfer function of this linear model was

$$G(s) = K \frac{s^2 + n_1 s + n_2}{s^3 + d_1 s^2 + d_2 s + d_3} e^{-0.15 s}, \quad (6)$$

Note that the delay-free part of the transfer function in (6) is third-order and relative degree one. The simplicity of (6) will subsequently be useful in determining the structure of the APC. The main reason for the transfer function order is the linearization process followed to obtain the model from the nonlinear empirical model. The nonlinear model, containing time delays, was first linearized using standard MATLAB routines which approximated the time delay using a second-order Padé approximation. Hence, the resulting transfer function was fourth-order (there are two integrators in the plant delay-free dynamics).

Then, to obtain a transfer function with a time delay in series, we divided this transfer function with a second-order Padé approximation of the nominal system delay. It is reminded that the time delay is actually in the states and not in the input, and thus the original transfer function did not include the time delay in series. In the end, we obtained the third-order transfer function with relative degree one. If one checks the location of the nominal poles, he/she will notice that the third pole is far away (approximately 20 times larger) from the complex poles. This shows that it actually could be ignored.

The IP delay at the nominal idle speed of 650 rpm is 90 ms, assuming that this delay is the result of 360$^\circ$ of crank rotation or one revolution of the crank shaft. However, it is known that one revolution is only an approximation, since, for example, the maximum torque production does not occur exactly at the top dead center. In addition, the actuator delay and computational delays also contribute to the overall delay value. Time delay of 150 ms seen in (6) is a combined result of all of these effects.

The parameter values for this nominal operating point were $K = 29.8$, $n_1 = 50$, $n_2 = 833$, $d_1 = 21.2$, $d_2 = 51.3$, and $d_3 = 180.5$. One should also note that these parameter values are valid only for the nominal operating point and, thus, are specific to certain values of engine speed, load torque, ambient pressure, ambient temperature, and engine temperature. In the adaptive controller design, only the structure of the transfer function is used, and the parameter values are assumed to be unknown. The input delay is used to approximate the effect of state delay in the model (1)–(5). Bode plots of the plant transfer function (6) with and without the delay, $G(s)$ and $G_0(s)$, are presented in Fig. 1, assuming the nominal parameter values. This figure clearly shows the rapid phase decrease with increasing frequency due to the time delay. For the importance of the time delay in idle speed applications, see [33].

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Fig. 1. Bode plots of $G(s)$ and $G_0(s)$. 

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III. APC DESIGN

A. Initial Design

APC is a model reference adaptive controller for systems with known input delay. Below, we summarize the main idea behind the APC. The reader is referred to [24] for additional details. Consider a linearized plant with input–output description given as

\[ y(t) = W_p(s)u(t - \tau), \quad W_p(s) = \frac{k_p Z_p(s)}{R_p(s)} \tag{7} \]

where \( y \) is the measured plant output, \( u \) is the control input, and \( W_p(s) \) is the delay-free part of the plant transfer function. \( R_p(s) \) is the \( n \)-th order denominator polynomial, not necessarily stable, and the numerator polynomial \( Z_p(s) \) has only minimum phase zeros. The relative degree \( n^* \), which is equal to the order of the denominator minus the order of the numerator, is assumed to be smaller than or equal to two. It is also assumed that the delay and the sign of the high-frequency gain \( k_p \) are known, but otherwise \( W_p(s) \) may be unknown. Suppose that the reference model, reflecting desired response characteristics, is given as

\[ y_m(t) = W_m(s)r(t - \tau), \quad W_m(s) = \frac{k_m}{R_m(s)} \tag{8} \]

where \( R_m(s) \) is a stable polynomial with degree \( n^* \), \( k_m \) is the high-frequency gain, and \( \tau \) is the desired reference input.

Consider the following state-space representation of the plant dynamics (7), together with two “signal generators” formed by a controllable pair \( \Lambda I \):

\[
\begin{align*}
\dot{x}_p(t) &= A_p x_p(t) + b_p u(t - \tau), \quad y(t) = h_p^T x_p(t) \tag{9} \\
\dot{\omega}_1(t) &= \Lambda \omega_1(t) + bu(t - \tau) \tag{10} \\
\dot{\omega}_2(t) &= \Lambda \omega_2(t) + by(t) \tag{11}
\end{align*}
\]

where \( \Lambda \in \mathbb{R}^{2n \times n^*} \) and \( I \in \mathbb{R}^{n^*} \). It follows [34] that there exist \( k^* \in \mathbb{R}^{n^*} \), \( \alpha_1 \in \mathbb{R}^{n^*} \), \( \alpha_2 \in \mathbb{R}^{n^*} \), and \( \lambda^*(\sigma) : [-\sigma, 0] \rightarrow \mathbb{R} \) such that the control law

\[ u(t) = \alpha_1^T \omega_1(t) + \alpha_2^T \omega_2(t) + \int_{-\tau}^{0} \lambda^*(\sigma) u(t + \sigma) d\sigma + k^* r(t) \tag{12} \]

satisfies the exact model matching condition

\[ \frac{y(t)}{r(t)} = \frac{k_m}{R_m(s)} e^{-\tau s}. \tag{13} \]

We now consider the control of the plant (7) when the transfer function \( W_p(s) \) has unknown coefficients and the time delay \( \tau \) is known. Consider the following adaptive controller [24]:

\[
\begin{align*}
\dot{u}(t) &= \alpha_1^T \omega_1(t) + \alpha_2^T \omega_2(t) + \int_{-\tau}^{0} \lambda(t, \sigma) u(t + \sigma) d\sigma + k(t) r(t) \\
\dot{\omega}_1(t) &= -\Gamma \epsilon_1(t) \beta(t - \tau) \\
\dot{\omega}_2(t) &= \Lambda \omega_2(t) + by(t) \\
\dot{\theta}(t) &= -\Gamma \epsilon_1(t) \beta(t - \tau) \\
\frac{\partial \lambda(t, \sigma)}{\partial t} &= -\gamma(\lambda) \epsilon_1(t) u(t + \sigma - \tau) \tag{14}
\end{align*}
\]

where

\[ \theta = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ k \end{bmatrix}, \quad \Omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \tau \end{bmatrix}, \quad e_1 = y - y_m. \tag{15} \]

\( \Gamma \) is a diagonal matrix, the entries of which represent the adaptation rate of the corresponding controller parameter, and \( \gamma(\lambda) \) is the adaptation rate for the controller parameter \( \lambda(t, \sigma) \). Defining the parameter errors as \( \dot{\theta}(t) = \theta(t) - \dot{\theta}^* \) and \( \dot{\lambda}(t, \sigma) = \lambda(t, \sigma) - \dot{\lambda}(t, \sigma) \), the control signal \( u \) in (14) can be rewritten as

\[
\begin{align*}
u(t) &= \alpha^T \omega(t) + \int_{-\tau}^{0} \lambda(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \alpha^T \omega(t) + \int_{-\tau}^{0} \dot{\lambda}(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\lambda}(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\lambda}(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\theta}(t) \tag{16}
\end{align*}
\]

where \( \alpha \triangleq \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \). It is shown in [24] that the differential equations (9)–(11) together with the control signal equation (16) describe the closed-loop dynamics as

\[
\begin{align*}
\dot{X}_p(t) &= A_m X_m(t) \\
+ b_m \left[ \dot{\alpha}^T (t - \tau) \omega(t - \tau) + \int_{-\tau}^{0} \lambda(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\lambda}(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\lambda}(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\lambda}(t, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\theta}(t) \right] \\
y_p(t) &= h_m^T X_m(t) \tag{17}
\end{align*}
\]

where \( X_p \triangleq \begin{bmatrix} x_1^T \\ \omega_1^T \\ \omega_2^T \end{bmatrix} \), \( h_m \triangleq \begin{bmatrix} 0 \\ 0 \end{bmatrix} \), \( y_p = y \), and \( A_m \) is a constant Hurwitz matrix. From the model matching condition, we know that, when the parameter errors are equal to zero, the closed-loop transfer function is identical to that of the reference model. Therefore, the reference model can be described by the \((3n)\)-th order differential equation (where \( n \) is the order of the plant)

\[
\begin{align*}
\dot{X}_m(t) &= A_m X_m(t) + b_m k^* r(t - \tau) \\
y_m(t) &= h_m^T X_m(t) \tag{18}
\end{align*}
\]

where

\[
\begin{align*}
x_m(t) &= \begin{bmatrix} x_1 \omega_1^T \omega_2^T \end{bmatrix} \tau \\
h_m^T(s I - A_m)^{-1} b_m k^* = \frac{k_m}{R_m(s)}. \tag{19}
\end{align*}
\]

Note that \( x_p^T(t) \omega_1^T \omega_2^T \), and \( \omega_2^T(t) \) can be considered as the signals in the reference model corresponding to \( x_p^T(t) \omega_1^T \omega_2^T \) in the closed-loop system. Therefore, subtracting (18) from (17), we get the following error equation for the overall system:

\[
\begin{align*}
\dot{e}(t) &= A_m e(t) \\
+ b_m \left[ \dot{\alpha}^T (t - \tau) \omega(t - \tau) + \int_{-\tau}^{0} \lambda(t - \tau, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\lambda}(t - \tau, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\lambda}(t - \tau, \sigma) u(t + \sigma + k^* r(t) \\
+ \dot{\theta}(t) + \int_{-\tau}^{0} \dot{\theta}(t) \right] \\
e_1(t) &= h_m^T e(t) \tag{20}
\end{align*}
\]
where $e(t) = X_p - X_m$ and $e_1(t) = y_p(t) - y_m(t)$. Equation (20) can be written in a more compact form as

$$
\dot{e}(t) = A_m e(t) + b_m \left[ \int_{t-\tau}^{t} \lambda(t-\tau, \sigma)u(t-\tau + \sigma) d\sigma \right] + h_m(T_m e(t)),
$$

(21)

Using the error model (21) and defining an appropriate Lyapunov-Krasovskii functional, it can be shown [24] that the plant (7), adaptive controller, and the adaptive laws given in (14) have bounded solutions for all $t \geq t_0$ and $\lim_{t \to \infty} e_1(t) = 0$. It is noted that the stability result given in [24] is semiglobal, i.e., the stability of the closed-loop system can be shown for any compact set by changing the allowable delay value. The experimental results show that, for the studied ISC problem, the delay values are such that the APC always provide stable solutions.

**B. Implementation Enhancements**

In order to apply the APC specified by (10), (11), and (14), one has to address several issues which were not taken into account during the initial design but arise in the implementation. Below, we explain these issues and how we address them.

1) **Disturbance Rejection:** Controller (14) is a model reference adaptive controller where the goal is to force the plant output follow the reference model output. In the design stage, the input disturbances are not explicitly taken into account. However, in the idle speed application, where $r(t) = r_0$ is constant, it can be shown that the controller is rejecting constant input disturbances, with the feedforward term $k(t)r(t)$ turning into a pure integrator. Please see Appendix A for the proof of the disturbance rejection.

2) **Approximation of the Finite Integral Term:** The finite integral term in the control signal $u$ given in (14) is implemented by using a set of point-wise delays [29] as follows:

$$
\int_{t-\tau}^{t} \lambda(\sigma, t)u(t + \sigma) d\sigma = \lambda_1(t)u(t - dt) + \cdots + \lambda_m(t)u(t - mdt)
$$

(22)

where $dt$ is the sampling interval and $mdt = \tau$. In the experiments, $dt = 30$ ms, so $m = 0.15/0.03 = 5$. With this approximation, the adaptive laws given in (14) can be represented as

$$
\dot{\theta}(t) = -\Gamma e_1(t)\Omega(t - \tau)
$$

(23)

where

$$
\theta = \begin{bmatrix}
\theta_1 \\
\theta_2 \\
\lambda_1 \\
\lambda_2 \\
k
\end{bmatrix}, \quad \Omega = \begin{bmatrix}
\omega_1 \\
\omega_2 \\
u(t - dt) \\
u(t - mdt) \\
r
\end{bmatrix}
$$

(24)

and $\Gamma > 0$ is a diagonal adaptation rate matrix.

In [35], the limitations of this approximation have been pointed out together with an example of unstable behavior arising due to numerical integration. In the powertrain control problem considered here, both in the experiments and in the simulations, the values of coefficients $\lambda_i$ are of the order of $10^{-1}$, and, for these values, we have been able to confirm that the danger of the instabilities due to numerical approximation does not arise. In addition, the stability margin for different values of $\lambda_i$’s is quite large. This is discussed in greater detail in Appendix C.

3) **Robustness:** The adaptive controller design presented in Section III-A portrayed an idealized situation. The delay-free part of the plant dynamics, $W_p(s)$, is assumed to be finite dimensional, linear, and time-invariant with unknown parameters. It is also assumed that the inputs and outputs to the plant can be measured exactly. However, in the real implementation, no plant is truly linear or finite dimensional. Plant parameters may vary with time and operating conditions, and measurements may be contaminated by noise. The plant model is almost always approximate. It is precisely in these cases that adaptive control is most needed [34].

Due to the above possible violations of the assumptions, the controller parameters may drift without converging to a bounded region. One of the remedies to this problem is the use of $\sigma$-modification robustness scheme [34], which mainly adds a damping term to adaptation laws. With the $\sigma$-modification, the adaptive law given in (23) is modified as

$$
\dot{\hat{\theta}}(t) = -\Gamma e_1(t)\Omega(t - \tau) - \sigma \bar{\theta}(t)
$$

(25)

where $\sigma$ is a constant. The drawback of this adaptive law is that the origin is no longer an equilibrium point of (34) and (25). This implies that, even when all of the assumptions are perfectly satisfied, the errors do not converge to zero. One way to remedy this drawback is to use a conditional $\sigma$-modification scheme

$$
\dot{\hat{\theta}}(t) = \begin{cases}
-\Gamma e_1(t)\Omega(t - \tau) - \sigma \bar{\theta}(t), & \text{if } |\bar{\theta}| \geq \bar{\theta}_i \\
-\Gamma e_1(t)\Omega(t - \tau), & \text{otherwise}
\end{cases}
$$

(26)

where $\bar{\theta}_i$ is a predetermined constant. Although we observed in our vehicle experiments that this method is working well for the ISC application, one limitation of this method is a lack of automatic procedure to predetermine the value of $\bar{\theta}_i$. Several approaches to selecting $\bar{\theta}_i$ have been proposed. In the first approach, one may fix the value of $\bar{\theta}_i$ as the corresponding controller parameter vector, which will satisfy the model matching condition for the worst case uncertainty in the plant parameters. A second approach is to conduct experiments without using $\sigma$-modification, and the controller parameters can be observed after which a reasonable value for the $\bar{\theta}_i$ can be selected depending on these observations. For example, one can observe the values of $\bar{\theta}_i$ at different operating points and then select $\bar{\theta}_i$ that prevents the $\bar{\theta}_i$ from drifting away from a certain range from these observed values. A third method is to first set the initial values of the controller parameters in such a way that model matching is satisfied for nominal plant parameters, following which $\bar{\theta}_i$ can be set at a certain percentage higher than the absolute value of these initial conditions. In our experiments, we used the second proposed method.

4) **Adaptation Rate Selection:** We choose the adaptation gain $\Gamma_i$ for a particular controller parameter $\hat{\theta}_i$ using the following empirical rule:

$$
\Gamma_i = \frac{|\hat{\theta}_i|}{3m|e_1(t)\Omega(t - \tau)|} \approx \frac{|\hat{\theta}_i|}{3m|^r|^2}
$$

(27)
where \( \tilde{h}_k \) is an estimate of the desired control parameter, \( \tau_m \) is the time constant of the reference model, and \( \gamma^* \) is a characteristic value of the reference signal. The rationale for the above is that the desired speed of adaptation is determined by the value that the parameter \( \tilde{h}_k \) must reach in a time \( 3\tau_m \), which corresponds to the settling time. Since the assumption is that the plant parameters are unknown, the actual desired control parameter vector \( \tilde{h}_k^0 \) is unknown. \( \tilde{h}_k^0 \) used in \((27)\) should therefore be viewed as an estimate of \( \tilde{h}_k^0 \) derived from the matching condition using a nominal plant model. It is assumed that the control parameters start from zero and that the orders of magnitude of \( e_1(t) \) and \( \Omega_k(t) \) are close to that of the reference signal. This last assumption can be verified at the first few instants of the operation where the error is approximately equal to the reference signal. So, in a sense, the \( \Gamma_R \) selection is based on worst condition where adaptation has just begun.

5) Fine-Tuning: Equations \((22)\) and \((27)\) imply that \( \tilde{h}_k^0 \) need to be estimated to determine \( \Gamma \). Since the \( \lambda_i \)'s were observed to be small in the simulations, we determined the ideal values of the controller parameters neglecting the delay in the plant and using a pole placement procedure \([34]\). Also, \( \lambda_i \)'s were observed to have the same order of magnitude for all \( i \), which suggests that the same adaptation gain \( \Gamma_{\lambda_i} \) for \( \lambda_i, i = 1, \ldots, 5 \) can be used in \((23)\). The value of \( \Gamma_{\lambda_i} \) was determined using simulation studies of the linearized model.

Due to the approximations discussed above, the resulting \( \Gamma \) may be nonideal. Therefore, a weighting matrix \( M \) was included as \( \Gamma_w = \Gamma M \) with

\[
M = \begin{bmatrix}
z_1 I_{n \times n} & 0 & 0 & 0 \\
0 & z_2 I_{n \times n} & 0 & 0 \\
0 & 0 & I_{m \times m} & 0 \\
0 & 0 & 0 & z_\tau
\end{bmatrix}
\]

(28)

where \( z_1, z_2, \) and \( z_\tau \) are constants that are used to fine-tune the adaptation gains. Extensive simulations and experiments on the F-150 test vehicle revealed that setting \( z_1 = z_\tau = 1 \) and increasing \( z_2 \) made the response faster and improved the disturbance rejection performance by decreasing the overshoots and undershoots after introducing/removing the disturbances.

The above discussion implies that the selection of \( \Gamma \) requires only two free parameters, \( \Gamma_{\lambda_i} \) and \( z_\lambda \), that are to be empirically determined.

6) Antiwindup Logic: The actuator, electronic throttle, has its hard limits, and the calculated control signal may sometimes exceed these limits, either from below or from above. In the case of idle speed control application, the desired throttle angle is small and thus the saturation may occur due to the control signal hitting the lower limit of the saturation. Consequently, an add-on algorithm needs to be integrated with the controller that prevents the winding up of the integrators resulting from the adaptation laws in \((14)\).

We use antiwindup logic where the main goal is to stop the adaptation if the control signal saturates and if the tracking error, \( e_1 = y_m - y_p \), is not favorable. Calling the control signal before the saturation block as \( u \) and after the saturation as \( u_{\text{sat}} \), the antiwindup algorithm can be expressed as follows:

\[
\dot{\tilde{h}}_i(t) = \begin{cases}
0, & \text{if } u > u_{\text{sat}} \text{ and } e_1 < 0 \\
-\Gamma_{\text{sat}} e_1(t) \tilde{h}_i(t - \tau), & \text{otherwise}.
\end{cases}
\]

(29)

The additional tracking error based condition for not suspending the adaptation during saturation improved the speed of the transient response as has been demonstrated in our vehicle experiments.

The presented antiwindup approach proved to be sufficient for the experiments conducted and therefore was satisfactory for this application. However, there are other theoretically proven antiwindup methods that are specifically developed for adaptive controllers \([36]\), which may produce better results in general. We plan to apply these methods in our future research.

C. Final Design and Calibration

A control design that is meant to be used in a mass-production application must be accessible and easy to use by the engineers who implement and support the control strategy in production. This is important, given that these engineers may not be highly skilled and experienced in advanced control methods. Motivated by these considerations, below we give a step-by-step design procedure to obtain a transparent and streamlined design process. We assume that a linear plant model with uncertain parameters and a known time delay is available.

Step 1) Select \( L \) and \( I \) of the signal generators defined in \((10)\) and \((11)\). These signal generators act like state observers, and it is suggested that their eigenvalues are selected much faster than the reference model pole. Note that the \( \Delta-I \) pair must be controllable.

Step 2) Set the initial value of the controller parameters to zero except for the feedforward term \( k(t) \). It is suggested that this parameter is initialized such that \( k(0) \in (0, 1) \).

Step 3) Set the time constant of the reference model at least two times faster than that of the nominal plant time constant.

Step 4) Set the adaptation rate matrix \( \Gamma \) according to the algorithm given in \((27)\).

Step 5) Tune the parameter \( z_\lambda \), until the highest unmeasured load is rejected according to the requirements. Note that increasing \( z_\lambda \) decreases transient excursions, however, higher gains might cause undesired oscillations.

Apart from these five easy steps, the design must be integrated with the robustness scheme presented in \((26)\) and the antiwindup scheme presented in \((29)\).

Note that the controller needs only about 0.35 KB of memory for the data storage and requires less than 83 operations per computation cycle. This corresponds to less than \( 2.8 \times 10^5 \) floating point operations per second (flips). For conventional ECUs, the APC controller use around 0.028% of the total computational power, which is negligible. Please see Appendix B for the calculation of the memory requirements and computational complexity.
IV. SIMULATIONS

Here, we present the simulation results using the nonlinear engine model. We note that the simulation model was available for a similar, but not exactly identical, engine as used in the experimental vehicle.

Fig. 2 shows the response of the nonlinear engine model to step changes in the idle speed set point. The adaptation rates were calculated setting $M = I$. Although the response is sluggish, this figure demonstrates that the rule (27) produces reasonable initial estimates for the adaptation rates.

Fig. 3 shows the response of the nonlinear model to step changes in the idle speed set-point by changing $z_v$ to 220. By changing just this single parameter, the increase in the adaptation gain is attained which provides a much faster yet still well-damped response.

All initial conditions for the controller parameters were set to zero except for the feedforward term $k(t)$. It was found that any value of $k(0)$ chosen from the interval $(0, 1)$ gave a reasonable performance. Results given in the simulations correspond to the case when $k(0) = 0.3$.

V. EXPERIMENTS

The experimental results given in this section were obtained using an F-150 test vehicle provided by Ford Motor Company.

The vehicle has a 4.6-l V-8 front engine with a multiport fuel-injection system. The engine has two valves per cylinder and can achieve 231 Hp at 4750 rpm and 397 Nm at 3500 rpm. The air intake is controlled with an electronic throttle. A dSPACE MicroAutoBox, communicating with the engine control unit (ECU) via CAN bus was used for real-time controller rapid prototyping. This system is used to implement the controller and monitor the performance. Fig. 4 shows the hardware wiring.

In the production environment, the engine is controlled by the ECU. The ECU normally also controls the other actuators of the engine, monitors the health of the engine, and processes sensor inputs [37].

In our setup, we override the ISC commands coming from the ECU with our adaptive control signal using the rapid prototyping system (see Fig. 4). This system has the engine speed as the measured input and calculates the throttle command as the control input.

The existing controller on the test vehicle (which we refer to as the baseline controller) consists of a feedforward controller in parallel with a closed-loop controller of PID type. The adaptive controller overrides this feedback controller while the feedforward controller is retained “as is.” Thus, our results compare the performance of the existing closed-loop controller in the test vehicle with the adaptive controller.
The same adaptation gains used in the simulation shown in Fig. 3 were used for all in-vehicle experiments, without further tuning. The controller designed for the simulations was kept the same, (same nominal model structure, same reference model, same delay value) for all of the experiments that are presented. It was observed that the APC performed uniformly better when compared with the existing baseline controller, in all experiments.

A. Set-Point Tracking

Fig. 5 shows the set-point tracking performance for both the baseline controller and for the APC. This experiment was repeated for 3 min and the improvement over the baseline controller in rms error was found to be 6%. Note that, since almost always the desired idle speed is constant, the tracking is not the main concern in idle speed control. It is also noted that the response of the system with the adaptive controller in Fig. 5 starts just before the reference input. The main reason for this is that the reference input plotted in the figure was used for the baseline controller experiment. The response of the adaptive system is superimposed on the baseline tracking plot. The adaptive system response starts a little earlier than the reference plot in the figure since the adaptive system reference (not shown in the figure) is given a little earlier than the baseline reference. The two references, adaptive and baseline, could not be given exactly at the same time due to experimental conditions. However, this does not have any effect on the outcome of the experiment.

B. Disturbance Rejection

We next introduced various disturbances into the picture to evaluate the disturbance rejection properties of the APC. Fig. 6 shows the deviation from the idle speed (650 rpm) when power steering load is applied repetitively, for two different controllers. The introduction of the disturbance causes the excursions below the set-point and its release results in the ones above the set-point. This experiment was conducted for 3 min and the rms error improvement over the existing baseline controller was 35%.

In real driving, idle speed set point may change as required to accommodate the states of accessories or changes in the battery voltage. Thus, it is worth comparing the performance of the controllers for different operating points. Fig. 7 shows the deviation from the idle speed set point when a power steering disturbance is introduced at 900 rpm, for two different controllers. The
dips correspond to the introduction of the disturbance and flares correspond to the release. This experiment was conducted for 3 min, and rms error improvement over the existing controller was found to be 48%. Similarly, Fig. 8 shows the deviation from the idle speed set point when a power steering disturbance is introduced at 590 rpm, for two different controllers. This experiment was also conducted for 3 min, and rms error improvement over the existing controller was found to be 33%. The first 30 s of this experiment are presented in Fig. 9 to show the controller performance at the beginning of the experiment.
Fig. 9. First 30 s of the experiment presented in Fig. 8.

Fig. 10. Top: Adaptive controller performance for power steering disturbance. Bottom: Evolution of the controller parameters.

C. Robustness

Fig. 10 shows the result of the 3-min disturbance rejection experiment, a section of which was presented in Fig. 6. In the bottom figure of Fig. 10, the evolution of the adaptive parameters that are two of the three components of $\alpha_2$, is presented. The adaptive parameters have nonzero value in the beginning of the experiment because they adjust themselves until the idle speed first converges to its steady state value before the experiment starts. Note that the parameters continue to adapt during the course of the experiment and they seem to keep decreasing with a certain slope. As we discussed previously, there may be many reasons for this parameter drift, some of which can be unmodeled dynamics, noise, and measurement errors. Another possibility is that the parameters would converge to a bounded region after a long time period. In any case, it is not practical to apply the adaptive controller without a robustness scheme which will make sure that the parameters stay in a predetermined bounded region so that the possibility of instability is prevented.

Fig. 11 presents the disturbance rejection experimental result where we applied the robustness scheme, which is explained in (26). Note that the adaptive parameters continue to decrease until they hit their predetermined values and then continue to adapt without leaving that region and stay bounded. An interesting point here is that although the adaptation is restricted in a certain region, the performance improvement is still more or less the same, 38%, as in the case without any restrictions (36%).

VI. SUMMARY

We successfully applied the APC for time-delay systems proposed in [23] and [24] to the ISC problem in an internal combustion engine. In addition to initial controller design, presented in Section III-A, we enhanced the controller with a robustifying scheme, an adaptation rate-selection algorithm, a fine-tuning procedure, and an antiwindup logic, and we demonstrated the disturbance rejection properties of the controller. Note that all of these enhancements are built hand in
hand with the implementation since they all stemmed from the implementation requirements.

Simulations and in-vehicle experimental results confirm that performance improvements can be attained using this approach. In addition, the approach has a potential to reduce calibration time and effort due to two reasons. First, the controller performs better than the existing baseline controller which suggests that the overall controller (feedforward + closed loop) can be de
ing (31). We (34) and (31) are presented in the overall controller (feedforward better than the existing baseline controller which suggests that performance improvements can be attained using this approach.

Fig. 11. Top: Adaptive controller performance for power steering disturbance. Bottom: Evolution of the controller parameters with $\sigma$-modification.

Note that, in idle speed application, the idle speed reference $r_0 \in \mathcal{R}$ is constant and, therefore, we have $r(t-\tau) = r_0$ in (31). We define a new variable $\tilde{k}'$ as

$$\tilde{k}' = k + \frac{d}{\dot{m}_0}.$$  

Hence, (31) reduces to

$$\dot{e}(t) = A_m e(t) + b_m \left[ \tilde{\alpha}^T(t-\tau)\omega(t-\tau) \\
+ \int_{t-\tau}^{0} \tilde{\lambda}(t-\tau,\sigma)u(t-\tau+\sigma)d\sigma + \tilde{k}'\tau_0 \right]$$

$$e_1(t) = h_m^T e(t).$$  

which can also be written as

$$\dot{e}(t) = A_m e(t) + b_m \left[ \tilde{\gamma}^T(t-\tau)\Omega(t-\tau) \\
+ \int_{t-\tau}^{0} \tilde{\lambda}(t-\tau,\sigma)u(t-\tau+\sigma)d\sigma \right]$$

$$e_1(t) = h_m^T e(t).$$  

APPENDIX A

DISTURBANCE REJECTION PROOF

When there is a constant disturbance $d \in \mathcal{R}$ present in the system, the state space description of the plant (9) is modified as

$$A_p(t) = A_p x_p(t) + b_p(u(t-\tau) + d), y(t) = h_p^T x_p(t).$$  

This, in turn, modifies the error (20) as

$$\dot{e}(t) = A_m e(t) + b_m \left[ \tilde{\alpha}^T(t-\tau)\omega(t-\tau) \\
+ \int_{t-\tau}^{0} \tilde{\lambda}(t-\tau,\sigma)u(t-\tau+\sigma)d\sigma \\
+ \tilde{k}'(t-\tau) + d \right]$$

$$e_1(t) = h_m^T e(t).$$  

where $\tilde{\gamma}' = [\tilde{\alpha}_1 \tilde{\alpha}_2 \tilde{k}']^T$. Equations (34) and (31) are exactly the same equations written using different variables, meaning that the definition of the new variable does not alter the equilibrium position of the differential equation. In addition, (34) is in the same form as in the case of disturbance-free system (21), so the stability proof follows the same lines and $\lim_{t \to \infty} e_1(t) \to 0$. So, the system is stable, the disturbance is rejected, and the plant output follows the reference model output asymptotically.

To conclude, disturbance rejection is achieved by eliminating the disturbance term in the error equation, and this is done by introducing a new variable defined by shifting the feedforward controller term $k$ by a constant.
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REFERENCES


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