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FLATNESS-BASED ADAPTIVE FUZZY CONTROL OF SPARK-IGNITED ENGINES

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Abstract

An adaptive fuzzy controller is designed for spark-ignited (SI) engines, under the constraint that the system's model is unknown. The control algorithm aims at satisfying the H_∞ tracking performance criterion, which means that the influence of the modeling errors and the external disturbances on the tracking error is attenuated to an arbitrary desirable level. After transforming the SI-engine model into the canonical form, the resulting control inputs are shown to contain nonlinear elements which depend on the system's parameters. The nonlinear terms which appear in the control inputs are approximated with the use of neuro-fuzzy networks. It is shown that a suitable learning law can be defined for the aforementioned neuro-fuzzy approximators so as to preserve the closed-loop system stability. With the use of Lyapunov stability analysis it is proven that the proposed adaptive fuzzy control scheme results in H_∞ tracking performance. The efficiency of the proposed adaptive fuzzy control scheme is checked through simulation experiments.

1 Introduction

In the last years there has been significant research effort in the development of embedded control systems for the automotive industry, aiming at improving the performance of vehicle's engines in terms of produced power, at reducing fuel consumption and at elimination the emission of exhaust gases. In particular, the problem of control of the rotation speed of SI-engines as well as the problem of control of the engine's pressure manifolds has been approached with different methods [1-2]. In [3] a nonlinear state space controller for turn speed (and consequently the torque) of a spark-ignited engine is proposed. The controller design is based on feedback linearization in combination with pole placement. In [4] time-varying internal model-based design is applied to compensate for the time-varying but angle dependent pressure pulsations in the fuel injection system of SI-engines. In [5] a control method for the air-path system of SI-engines is presented. The first part considers generation of the motion-planning trajectory of the intake manifold pressure from a torque set point. Then, feedforward and feedback control laws are presented. In [6] a feedback linearization approach based on differential flatness theory is proposed for the control of the air system of a turbocharged gasoline engine. Finally, in [7] a model-based approach is pursued to maximize an SI-engine's torque through optimal control of the variable valve timing (VVT) and the variable gas turbine (VGT).

To make embedded control systems capable of functioning efficiently under variable operating conditions and despite modeling uncertainties and external perturbations, robustness of the control algorithm has become a prerequisite [8-10]. An approach for obtaining such robustness has been the development of adaptive neurofuzzy control methods [11-12]. It has been shown through theoretical stability analysis and confirmed through experimental tests that neurofuzzy approximators can be used in indirect adaptive control schemes where their role is to identify online the unknown system dynamics and to provide the control with this information that is used for generating the control inputs [13-17]. Moreover, in the last years specific results have produced about the use of neurofuzzy adaptive controllers in embedded control systems for combustion engines [20-25]. In this paper a new nonlinear adaptive-fuzzy control scheme based on differential flatness theory is proposed for SI-engines. The new results come to extend the method presented in [26-30]. By showing that the SI-engine model is a differentially flat one it becomes possible to transform it to the linear canonical form. For the latter description of the system's dynamics the design of a state feedback controller becomes easier. After transformation to the linear canonical form, the resulting control input for the engine is shown to contain nonlinear elements which depend on the system's parameters. If the parameters of the system are unknown, then the nonlinear terms which appear in the control signal can be approximated with the use of neuro-fuzzy networks [18-19]. In the paper it is shown that a suitable learning law can be defined for the aforementioned neuro-fuzzy approximators so as to preserve the closed-loop system stability. Lyapunov stability analysis proves also that the proposed flatness-based adaptive fuzzy control scheme results in H_∞ tracking performance.

The paper proposes nonlinear feedback control for SI engines of an unknown dynamical model with the use of a differential flatness theory adaptive fuzzy control method. On the one side, adaptive fuzzy control has been proven to be an efficient nonlinear control method [31-35]. On the other side, differential flatness theory stands for a major direction in the design of nonlinear control systems [36-45]. Adaptive fuzzy control system based on differential flatness theory extends the class of systems to which indirect adaptive fuzzy control can be applied. This is important for the design of controllers, capable of efficiently compensating for modeling uncertainties and external disturbances in nonlinear dynamical systems. Unlike other adaptive fuzzy control schemes which are based on several assumptions about the structure of the nonlinear system as well as about the uncertainty characterizing the system's model, the proposed adaptive fuzzy control scheme based on differential flatness theory offers an exact solution to the design of fuzzy controllers for unknown dynamical systems. The only assumption needed for the design of the controller and for succeeding H_∞ tracking performance for the control loop is that there exists a solution for a Riccati equation associated to the linearized error dynamics of the differentially flat model. This assumption is quite reasonable for several nonlinear systems, thus providing a systematic approach to the design of reliable controllers for such systems [29], [34].

The structure of the paper is as follows: in Section 2 the dynamic model of the SI-engine is analyzed and its state-space description is given. In Section 3 feedback linearizing control of the SI-engine using Lie algebra is introduced. In Section 4 Feedback linearizing control of the SI engine using differential flatness theory is analyzed. In Section 5 flatness-based adaptive fuzzy control for the spark ignited engine is analyzed. In Section 6 Lyapunov stability analysis is given. In 7 simulation tests are carried out to evaluate the performance of the control loop. Finally, in Section 8 concluding remarks are stated.

2 Dynamic model of the SI engine

2.1 State-space description of the SI-engine

It is possible to control the intake pressure p_m and the rotational speed of the engine's shaft ω by adjusting the angle of the air throttle. It is considered that the associated control loop is independent from the loops of the fuel injection control and spark timing control (Fig. 1)

The basic equations of the system are:

$$\begin{aligned} \dot{\omega} &= k_{\omega_1} p_m(t-\tau_d) + k_{\omega_2} + k_{\omega_3} T_{f_m} \\ \dot{p}_m &= k_{p_1}\omega p_m + k_{p_2}\omega + k_{p_3} u \\ y_1 &= \omega \end{aligned} \tag{1}$$

The variable of the intake pressure appears with time delay in the equation of the turn speed in the

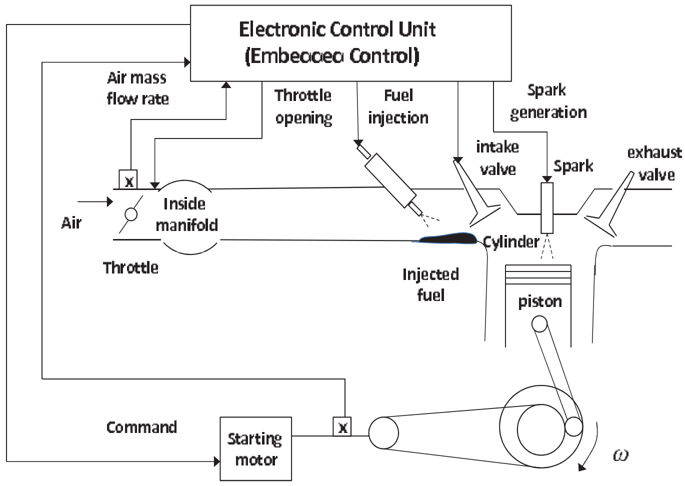

Figure 1. Diagram of the spark-ignited engine

second row of the model of the SI engine. Using that $p_{md} = p_m(t-\tau_d)$ and

$$p_m(t-\tau_d) = \frac{1}{\tau s+1} p_m \tag{2}$$

while $\tau = a_d/\omega$ and a_d is a parameter that is measured in radians. Denoting $k_d = -1/a_d$ one has about the dynamics of the delayed intake pressure variable

$$p_{md} = k_d \omega (p_{m_d} - p_m) \tag{3}$$

Using the previous formulation, and defining the state variables $x_1 = \omega$, $x_2 = p_{m_d}$ and $x_3 = p_m$, the dynamics of the SI engine is written as

$$\begin{matrix} \dot{x}_1 = k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m} \\ \dot{x}_2 = K_d x_1 (x_2 - x_3) \\ \dot{x}_3 = k_{p_1} x_1 x_3 + k_{p_2} x_1 + k_{p_3} u \end{matrix} \tag{4}$$

where T_{f_m} are friction torques, which can be also perceived as disturbances. In the above equations coefficients k_{p_i}, $i = 1,2,3$, k_{ω_i}, $i = 1,2,3$ and K_d are associated with the combustion cycle of the SI-engine and are defined in [1-2].

The model also takes the matrix form

$$\dot{x} = f(x) + g(x)u \tag{5}$$

with

$$f(x) = \begin{pmatrix} k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m} \\ k_d x_1 (x_2 - x_3) \\ k_{p_1} x_1 x_3 + k_{p_2} x_1 \end{pmatrix} \quad g(x) = \begin{pmatrix} 0 \\ 0 \\ k_{p_3} \end{pmatrix} \tag{6}$$

3 Feedback linearizing control of the SI-engine using Lie algebra

Using Lie derivatives, the following state variables are defined for the SI-engine model of Eq. (4): $z_1 = h_1(x) = x_1$, $z_2 = L_f h_1(x)$ and $z_3 = L_f^2 h_1(x)$. It holds that

$$\begin{matrix} z_2 = L_f h_1(x) = \frac{\partial h_1}{\partial x_1} f_1 + \frac{\partial h_1}{\partial x_2} f_2 + \frac{\partial h_1}{\partial x_3} f_3 \Rightarrow \\ z_2 = f_1 \Rightarrow z_2 = k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m} \end{matrix} \tag{7}$$

In a similar manner one obtains (8)
Moreover, it holds that (9)

Additionally, it holds that (10)

while one also obtains (11)

which also shows that the relative degree of the SI-engine model is $n = 3$. It can be also confirmed that it holds

$$\begin{matrix} \dot{z}_1 = z_2 \\ \dot{z}_2 = z_3 \\ \dot{z}_3 = L_f^3 h_1(x) + L_g L_f^2 h_1(x) u \end{matrix} \tag{12}$$

which after defining the new control input $v = L_f^3 h_1(x) + L_g L_f^2 h_1(x) u$ can be written in the linear canonical (Brunovsky) form

$$\begin{array}{c} z_3 = L_f^2 h_1(x) = \frac{\partial z_2}{\partial x_1} f_1 + \frac{\partial z_2}{\partial x_2} f_2 + \frac{\partial z_2}{\partial x_3} f_3 \Rightarrow \\ z_3 = f_1 \Rightarrow z_2 = k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m} \Rightarrow \\ z_3 = k_{\omega_1} f_2 \Rightarrow z_3 = k_{\omega_1} k_d x_1 (x_2 - x_3) \end{array} \quad (8)$$

$$\begin{array}{c} L_f^3 h_1(x) = \frac{\partial z_3}{\partial x_1} f_1 + \frac{\partial z_3}{\partial x_2} f_2 + \frac{\partial z_3}{\partial x_3} f_3 \Rightarrow \\ L_f^3 h_1(x) = k_{\omega_1} k_d (x_2 - x_3) f_1 + k_{\omega_1} k_d x_1 f_2 - k_{\omega_1} k_d x_1 f_3 \Rightarrow \\ L_f^3 h_1(x) = k_{\omega_1} k_d (x_2 - x_3) [k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m}] + \\ + k_{\omega_1} k_d x_1 [k_d x_1 (x_2 - x_3)] - k_{\omega_1} k_d x_1 [k_{p_1} x_1 x_3 + k_{p_2} x_1] \end{array} \quad (9)$$

$$\begin{array}{c} L_g L_f h_1(x) = L_g z_2 \Rightarrow L_g L_f h_1(x) = \frac{\partial z_2}{\partial x_1} g_1 + \frac{\partial z_2}{\partial x_2} g_2 + \frac{\partial z_2}{\partial x_3} g_3 \Rightarrow \\ L_g L_f h_1(x) = \frac{\partial z_2}{\partial x_3} k_{p_3} \Rightarrow L_g L_f h_1(x) = \frac{\partial f_2}{\partial x_3} k_{p_3} \\ \Rightarrow L_g L_f h_1(x) = 0 \end{array} \quad (10)$$

$$\begin{array}{c} L_g L_f^2 h_1(x) = L_g z_3 \Rightarrow L_g L_f^2 h_1(x) = \frac{\partial z_3}{\partial x_1} g_1 + \frac{\partial z_3}{\partial x_2} g_2 + \frac{\partial z_3}{\partial x_3} g_3 \Rightarrow \\ L_g L_f^2 h_1(x) = -k_{\omega_1} k_d k_{p_1} x_1 \end{array} \quad (11)$$

$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} v \quad (13)$$

From the relation $z_1^{(3)} = v$ the state feedback control law for the SI-engine that assures asymptotic convergence of the state vector z to the desirable setpoint z_d is given by

$$v = z_{1d}^{(3)} - k_1(\ddot{z}_1 - \ddot{z}_{1,d}) - k_2(\dot{z}_1 - \dot{z}_{1,d}) - k_3(z_1 - z_{1,d}) \quad (14)$$

Using that the control input for the linearized model is $v = L_f^3 h_1(x) + L_g L_f^2 h_1(x) u$ the control input that is finally applied to the SI-engine is

$$u = \frac{1}{L_g L_f^2 h_1(x)} [v - L_f^3 h_1(x)] \quad (15)$$

4 Feedback linearizing control of the SI-engine using differential flatness theory

The state-space description of the SI-engine dynamics given in Eq. (4) is considered again

$$\dot{x}_1 = k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m} \quad (16)$$

$$\dot{x}_2 = K_d x_1 (x_2 - x_3) \quad (17)$$

$$\dot{x}_3 = k_{p_1} x_1 x_3 + k_{p_2} x_1 + k_{p_3} u \quad (18)$$

The flat output of the SI-engine model is taken to be $y = x_1$, which is the engine's turn speed. It will be shown that all state variables of the system and the control input can be written as functions of the flat output and its derivatives, and thus the SI-engine model is a differentially flat one.

Eq. (16) is solved with respect to x_2. This gives

$$\begin{array}{c} x_2 = \frac{\dot{x}_1 - k_{\omega_2} - k_{\omega_3} T_{f_m}}{k_{\omega_1}} \Rightarrow x_2 = \frac{\dot{y} - k_{\omega_2} - k_{\omega_3} T_{f_m}}{k_{\omega_1}} \Rightarrow \\ x_2 = f_2(y, \dot{y}) \end{array} \quad (19)$$

Eq. (17) is solved with respect to x_3. This gives

$$\begin{array}{c} x_3 = \frac{k_d x_1 x_2 - \dot{x}_2}{k_d x_1} \Rightarrow x_3 = \frac{k_d y f_2(y, \dot{y}) - \dot{f}_2(y, \dot{y})}{k_d y} \Rightarrow \\ x_3 = f_3(y, \dot{y}) \end{array} \quad (20)$$

Moreover, from Eq. (18) it holds

$$u = \frac{\dot{x}_3 - k_{p_1} x_1 x_3 - k_{p_2} x_1}{k_{p_3}} \Rightarrow u = \frac{\dot{f}_3(y, \dot{y}) - k_{p_1} y f_3(y, \dot{y}) - k_{p_2} y}{k_{p_3}} \quad (21)$$

Therefore, all state variables and the control input in the model of the SI-engine are described as functions of the flat output and its derivatives. Consequently, the SI-engine model is a differentially flat one. It holds that

$$\begin{gathered} y = x_1 \\ \dot{y} = \dot{x}_1 \Rightarrow \dot{y} = k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{f_m} \end{gathered} \tag{22}$$

Differentiating once more with respect to time gives

$$\begin{gathered} \ddot{y} = k_{\omega_1} \dot{x}_2 + k_{\omega_3} \dot{T}_{f_m} \Rightarrow \\ \ddot{y} = k_{\omega_1} k_d x_1 (x_2 - x_3) + k_{\omega_3} \dot{T}_{f_m} \end{gathered} \tag{23}$$

By deriving once more with respect to time one gets (24)

Therefore one arrives at a description of the SI-engine dynamics which is equivalent to the one obtained from linearization with the use of Lie algebra

$$y^{(3)} = L_f^3 h_1(x) + L_g L_f^2 h_1(x) u \tag{25}$$

where (26) and also

$$L_g L_f^2 h_1(x) = -k_{\omega_1} k_d k_{p_3} x_1 \tag{27}$$

For the previous description of the SI-engine dynamics, the following state variables are defined $z_1 = y$, $z_2 = \dot{y}$ and $z_3 = \ddot{y}$, the following state-space model is obtained

$$\begin{gathered} \dot{z}_1 = z_2 \\ \dot{z}_2 = z_3 \\ \dot{z}_3 = L_f^2 h_1(x) + L_g L_f^2 h_1(x) u \end{gathered} \tag{28}$$

The linearized model of the SI-engine is finally written in the Brunovsky canonical form

$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} v \tag{29}$$

From the relation $z_1^{(3)} = v$ the state feedback control law for the SI-engine that assures asymptotic convergence of the state vector z to the desirable setpoint z_d is given by

$$v = z_{1d}^{(3)} - k_1(\ddot{z}_1 - \ddot{z}_{1,d}) - k_2(\dot{z}_1 - \dot{z}_{1,d}) - k_3(z_1 - z_{1,d}) \tag{30}$$

Using that the control input for the linearized model is $v = L_f^3 h_1(x) + L_g L_f^2 h_1(x) u$ the control input that is finally applied to the SI-engine is

$$u = \frac{1}{L_g L_f^2 h_1(x)} [v - L_f^3 h_1(x)] \tag{31}$$

5 Flatness-based adaptive fuzzy control

5.1 Nonlinear system transformation into the Brunovsky form

A single-input differentially flat dynamical system is considered again:

$$\dot{x} = f_s(x,t) + g_s(x,t)(u + \tilde{d}),\ x \in R^n,\ u \in R,\ \tilde{d} \in R \tag{32}$$

where $f_s(x,t)$, $g_s(x,t)$ are nonlinear vector fields defining the system's dynamics, u denotes the control input and $\tilde{d}$ denotes additive input disturbances. Knowing that the system of Eq. (32) is differentially flat, the next step is to try to write it into a Brunovsky form. It has been shown that, in general, transformation into the Brunovsky (canonical) form can be succeeded for systems that admit static feedback linearization [42]. Single input differentially flat systems, admit static feedback linearization, therefore they can be transformed into the Brunovksy form. For multi-input differentially flat systems there may also exist a transformation into the Brunovsky form [34].

The selected flat output is again denoted by y. For the state variables x_i of the system of Eq. (32) it holds

$$x_i = \phi_i(y, \dot{y}, \cdots, y^{(r-1)}),\ i = 1, \cdots, n \tag{33}$$

while for the control input it holds

$$u = \psi(y, \dot{y}, \cdots, y^{(r-1)}, y^{(r)}) \tag{34}$$

Introducing the new state variables $y_1 = y$ and $y_i = y^{(i-1)}$, $i = 2, \cdots, n$, the initial system of Eq. (32) can be written in the Brunovsky form:(35)

where $v = f(x,t) + g(x,t)(u + \tilde{d})$ is the control input for the linearized model, and $\tilde{d}$ denotes additive input disturbances. Thus one can use that

$$y^{(n)} = f(x,t) + g(x,t)(u + \tilde{d}) \tag{36}$$

$$\begin{array}{c} y^{(3)} = k_{\omega_1} k_d \dot{x}_1 (x_2 - x_3) + k_{\omega_1} k_d x_1 \dot{x}_2 - k_{\omega_1} k_d x_1 \dot{x}_3 + k_{\omega_3} \ddot{T}_{fm} \Rightarrow \\ y^{(3)} = k_{\omega_1} k_d (x_2 - x_3)[k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{fm}] + \\ + k_{\omega_1} k_d x_1 [k_d x_1 (x_2 - x_3)] - k_{\omega_1} k_d x_1 [k_{p_1} x_1 x_3 + k_{p_2} x_1] + \\ - k_{\omega_1} k_d k_{p_3} x_1 u + k_{\omega_3} \ddot{T}_{fm} \end{array} \quad (24)$$

$$\begin{array}{c} L_f^3 h_1(x) = k_{\omega_1} k_d (x_2 - x_3)[k_{\omega_1} x_2 + k_{\omega_2} + k_{\omega_3} T_{fm}] + \\ + k_{\omega_1} k_d x_1 [k_d x_1 (x_2 - x_3)] - k_{\omega_1} k_d x_1 [k_{p_1} x_1 x_3 + k_{p_2} x_1] + k_{\omega_3} \ddot{T}_{fm} \end{array} \quad (26)$$

where $f(x,t)$, $g(x,t)$ are unknown nonlinear functions, while as mentioned above $\tilde{d}$ is an unknown additive disturbance. It is possible to make the system's state vector x follow a given bounded reference trajectory x_d. In the presence of model uncertainties and external disturbances, denoted by w_d, successful tracking of the reference trajectory is provided by the H_∞ criterion [30],[17]:

$$\int_0^T e^T Q e dt \leq \rho^2 \int_0^T {w_d}^T w_d dt \quad (37)$$

where ρ is the attenuation level and corresponds to the maximum singular value of the transfer function $G(s)$ of the linearized model associated to Eq. (35) and Eq. (36).

Remark 1: From the H_∞ control theory, the H_∞ norm of a linear system with transfer function $G(s)$, is denoted by $||G||_\infty$ and is defined as $||G||_\infty = sup_\omega \sigma_{max}[G(j\omega)]$ [26-30]. In this definition *sup* denotes the supremum or least upper bound of the function $\sigma_{max}[G(j(\omega)]$, and thus the H_∞ norm of $G(s)$ is the maximum value of $\sigma_{max}[G(j(\omega)]$ over all frequencies ω. H_∞ norm has a physically meaningful interpretation when considering the system $y(s) = G(s)u(s)$. When this system is driven with a unit sinusoidal input at a specific frequency, $\sigma_{max}|G(j\omega)|$ is the largest possible output for the corresponding sinusoidal input. Thus, the H_∞ norm is the largest possible amplification over all frequencies of a sinusoidal input.

Remark 2: The input additive disturbance term $\tilde{d}$ in the dynamics of the controlled system does not affect the transformation into the canonical form that is performed according to the differential flatness theory. Such a disturbance is efficiently compensated by the proposed adaptive fuzzy control law.

5.2 Control law

For the measurable state vector x of the system of Eq. (35) and Eq. (36), and for uncertain functions $f(x,t)$ and $g(x,t)$ an appropriate control law is

$$u = \frac{1}{\hat{g}(x,t)}[y_d^{(n)} - \hat{f}(x,t) - K^T e + u_c] \quad (38)$$

with $e = [e, \dot{e}, \ddot{e}, \cdots, e^{(n-1)}]^T$ and $e = y - y_d$, $K^T = [k_n, k_{n-1}, \cdots, k_1]$, such that the polynomial $e^{(n)} + k_1 e^{(n-1)} + k_2 e^{(n-2)} + \cdots + k_n e$ is Hurwitz. The control law of Eq. (38) results into (39)

where the supervisory control term u_c aims at the compensation of the approximation error

$$w = [f(x,t) - \hat{f}(x,t)] + [g(x,t) - \hat{g}(x,t)]u \quad (41)$$

as well as of the additive disturbance term $d_1 = g(x,t)\tilde{d}$. The above relation can be written in a state-equation form. The state vector is taken to be $e^T = [e, \dot{e}, \cdots, e^{(n-1)}]$, which after some operations yields (41)

where

$$A = \begin{pmatrix} 0 & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & 1 & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & \cdots & 1 \\ 0 & 0 & 0 & \cdots & \cdots & 0 \end{pmatrix}, \quad B = \begin{pmatrix} 0 \\ 0 \\ \cdots \\ \cdots \\ 0 \\ 1 \end{pmatrix} \quad (42)$$

and $K = [k_n, k_{n-1}, \cdots, k_2, k_1]^T$. As explained above, the control signal u_c is an auxiliary control term, used for the compensation of $\tilde{d}$ and w, which can be selected according to H_∞ control theory:

$$u_c = -\frac{1}{r} B^T P e \quad (43)$$

$$\begin{pmatrix} \dot{y}_1 \\ \dot{y}_2 \\ \cdots \\ \cdots \\ \dot{y}_{n-1} \\ \dot{y}_n \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \cdots \\ \cdots \\ y_{n-1} \\ y_n \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ \cdots \\ \cdots \\ 0 \\ 1 \end{pmatrix} v \tag{35}$$

$$e^{(n)} = -K^T e + u_c + [f(x,t) - \hat{f}(x,t)] + [g(x,t) - \hat{g}(x,t)]u + g(x,t)\tilde{d} \tag{39}$$

$$\dot{e} = (A - BK^T)e + Bu_c + B\{[f(x,t) - \hat{f}(x,t)] + [g(x,t) - \hat{g}(x,t)]u + d_1\} \tag{40}$$

5.3 Approximators of unknown system dynamics

The approximation of functions $f(x,t)$ and $g(x,t)$ of Eq. (36) can be carried out with neuro-fuzzy networks (Figure 2.). The estimation of $f(x,t)$ and $g(x,t)$ can be written as [11]:

$$\hat{f}(x|\theta_f) = \theta_f^T \phi(x), \ \ \hat{g}(x|\theta_g) = \theta_g^T \phi(x), \tag{44}$$

where $\phi(x)$ are kernel functions with elements

$$\phi^l(x) = \frac{\prod_{i=1}^n \mu_{A_i}^l(x_i)}{\sum_{l=1}^N \prod_{i=1}^n \mu_{A_i}^l(x_i)} \ l = 1, 2, \cdots, N \tag{45}$$

It is assumed that the weights θ_f and θ_g vary in the bounded areas M_{θ_f} and M_{θ_g} which are defined as

$$\begin{array}{c} M_{\theta_f} = \{\theta_f \in R^h : ||\theta_f|| \leq m_{\theta_f}\}, \\ M_{\theta_g} = \{\theta_g \in R^h : ||\theta_g|| \leq m_{\theta_g}\} \end{array} \tag{46}$$

with m_{θ_f} and m_{θ_g} positive constants.

The values of θ_f and θ_g that give optimal approximation are:

$$\begin{array}{c} \theta_f^* = \arg\ \min_{\theta_f \in M_{\theta_f}} [sup_{x \in U_x} |f(x) - \hat{f}(x|\theta_f)|] \\ \theta_g^* = \arg\ \min_{\theta_g \in M_{\theta_g}} [sup_{x \in U_x} |g(x) - \hat{g}(x|\theta_g)|] \end{array} \tag{47}$$

The approximation error of $f(x,t)$ and $g(x,t)$ is given by

$$w = [\hat{f}(x, |\theta_f^*) - f(x,t)] + [\hat{g}(x|\theta_f^*) - g(x,t)]u \Rightarrow$$

$$\begin{array}{c} w = \{[\hat{f}(x|\theta_f^*) - \hat{f}(x|\theta_f)] + [\hat{f}(x|\theta_f) - f(x,t)]\} + \\ + \{[\hat{g}(x|\theta_g^*) - \hat{g}(x|\theta_g)] + [\hat{g}(x|\theta_g) - g(x,t)]u\} \end{array} \tag{48}$$

where: i) $\hat{f}(x|\theta_f^*)$ is the approximation of f for the best estimation θ_f^* of the weights' vector θ_f, ii) $\hat{g}(x|\theta_g^*)$ is the approximation of g for the best estimation θ_g^* of the weights' vector θ_g.

The approximation error w can be decomposed into w_a and w_b, where

$$\begin{array}{c} w_a = [\hat{f}(x|\theta_f) - \hat{f}(x|\theta_f^*)] + [\hat{g}(x|\theta_g) - \hat{g}(x|\theta_g^*)]u \\ w_b = [\hat{f}(x|\theta_f^*) - f(x,t)] + [\hat{g}(x|\theta_g^*) - g(x,t)]u \end{array} \tag{49}$$

Finally, the following two parameters are defined:

$$\begin{array}{c} \tilde{\theta}_f = \theta_f - \theta_f^* \\ \tilde{\theta}_g = \theta_g - \theta_g^*. \end{array} \tag{50}$$

Remark 3: A difference between the neurofuzzy approximator depicted in Figure 2 and a RBF neural network is the normalization layer that appears between the Gaussian basis functions layer and the weights output layer. After normalization, the sum (over the complete set of rules) of the fuzzy membership values of each input pattern becomes equal to 1. The neurofuzzy model provides also linguistic interpretability (in terms of fuzzy rules) about the implemented control law [18].

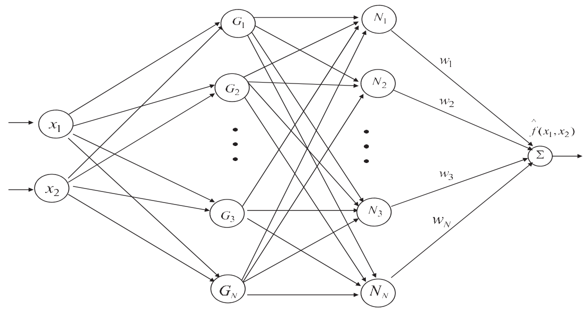

Figure 2. Neuro-fuzzy approximator: G_i Gaussian basis function, N_i: normalization unit

6 Lyapunov stability analysis

The adaptation law of the weights θ_f and θ_g as well as of the supervisory control term u_c is derived by the requirement for negative definite derivative of the quadratic Lyapunov function

$$V = \frac{1}{2}e^T Pe + \frac{1}{2\gamma_1}\tilde{\theta}_f^T\tilde{\theta}_f + \frac{1}{2\gamma_2}\tilde{\theta}_g^T\tilde{\theta}_g \quad (51)$$

Substituting Eq. (40) into Eq. (51) and differentiating gives

$$\dot{V} = \tfrac{1}{2}\dot{e}^T Pe + \tfrac{1}{2}e^T P\dot{e} + \tfrac{1}{\gamma_1}\tilde{\theta}_f^T\dot{\tilde{\theta}}_f + \tfrac{1}{\gamma_2}\tilde{\theta}_g^T\dot{\tilde{\theta}}_g \Rightarrow$$

$$\dot{V} = \tfrac{1}{2}e^T\{(A-BK^T)^T P + P(A-BK^T)\}e + \\ +B^T Pe(u_c + w + d_1) + \tfrac{1}{\gamma_1}\tilde{\theta}_f^T\dot{\tilde{\theta}}_f + \tfrac{1}{\gamma_2}\tilde{\theta}_g^T\dot{\tilde{\theta}}_g \quad (52)$$

Assumption 1: For given positive definite matrix Q and coefficients r and ρ there exists a positive definite matrix P, which is the solution of the following matrix equation (53)

Substituting Eq. (53) into $\dot{V}$ yields after some operations (54)

It holds that

$$\dot{\tilde{\theta}}_f = \dot{\theta}_f - \dot{\theta}_f^* = \dot{\theta}_f \\ \dot{\tilde{\theta}}_g = \dot{\theta}_g - \dot{\theta}_g^* = \dot{\theta}_g \quad (55)$$

The following weight adaptation laws are considered [26]

$$\dot{\theta}_f = \{ \begin{matrix} -\gamma_1 e^T PB\phi(x) \;\; if \; ||\theta_f|| < m_{\theta_f} \\ 0 \;\; ||\theta_f|| \geq m_{\theta_f} \end{matrix} \quad (56)$$

$$\dot{\theta}_g = \{ \begin{matrix} -\gamma_2 e^T PB\phi(x)u_c \;\; if \; ||\theta_g|| < m_{\theta_g} \\ 0 \;\; ||\theta_g|| \geq m_{\theta_g} \end{matrix} \quad (57)$$

$\dot{\theta}_f$ and $\dot{\theta}_g$ are set to 0, when

$$||\theta_f|| \geq m_{\theta_f}, \;\; ||\theta_g|| \geq m_{\theta_g}. \quad (58)$$

The update of θ_f stems from a LMS algorithm on the cost function $\frac{1}{2}(f-\hat{f})^2$. The update of θ_g is also of the LMS type, while u_c implicitly tunes the adaptation gain γ_2. Substituting Eq. (56) and (57) in $\dot{V}$ finally gives (59)

Denoting $w_1 = w + d_1 + w_\alpha$ one gets (60)

Lemma: The following inequality holds:

$$\tfrac{1}{2}e^T PBw_1 + \tfrac{1}{2}w_1^T B^T Pe - \tfrac{1}{2\rho^2}e^T PBB^T Pe \leq \tfrac{1}{2}\rho^2 w_1^T w_1 \quad (61)$$

Proof: The binomial $(\rho a - \frac{1}{\rho}b)^2 \geq 0$ is considered. Expanding the left part of the above inequality one gets

$$\rho^2 a^2 + \tfrac{1}{\rho^2}b^2 - 2ab \geq 0 \Rightarrow \tfrac{1}{2}\rho^2 a^2 + \tfrac{1}{2\rho^2}b^2 - ab \geq 0 \Rightarrow \\ ab - \tfrac{1}{2\rho^2}b^2 \leq \tfrac{1}{2}\rho^2 a^2 \Rightarrow \tfrac{1}{2}ab + \tfrac{1}{2}ab - \tfrac{1}{2\rho^2}b^2 \leq \tfrac{1}{2}\rho^2 a^2 \quad (62)$$

The following substitutions are carried out: $a = w_1$ and $b = e^T PB$ and the previous relation becomes

$$\tfrac{1}{2}w_1^T B^T Pe + \tfrac{1}{2}e^T PBw_1 - \tfrac{1}{2\rho^2}e^T PBB^T Pe \leq \tfrac{1}{2}\rho^2 w_1^T w_1 \quad (63)$$

The previous inequality is used in $\dot{V}$, and the right part of the associated inequality is enforced

$$(A-BK^T)^T P+P(A-BK^T)-PB(\frac{2}{r}-\frac{1}{\rho^2})B^TP+Q=0 \tag{53}$$

$$\begin{aligned}\dot{V} = -\tfrac{1}{2}e^TQe+\tfrac{1}{2}e^TPB(\tfrac{2}{r}-\tfrac{1}{\rho^2})B^TPe+B^TPe(-\tfrac{1}{r}e^TPB)+\\ +B^TPe(w+d_1)+\tfrac{1}{\gamma_1}\tilde{\theta}_f^T\dot{\tilde{\theta}}_f+\tfrac{1}{\gamma_2}\tilde{\theta}_g^T\dot{\tilde{\theta}}_g\end{aligned} \tag{54}$$

$$\dot{V} \leq -\frac{1}{2}e^TQe+\frac{1}{2}\rho^2 w_1^T w_1 \tag{64}$$

Eq. (64) can be used to show that the H_∞ performance criterion is satisfied . The integration of $\dot{V}$ from 0 to T gives

$$\begin{aligned}\int_0^T \dot{V}(t)dt \leq -\tfrac{1}{2}\int_0^T ||e||_Q^2 dt+\tfrac{1}{2}\rho^2\int_0^T ||w_1||^2 dt \Rightarrow\\ 2V(T)+\int_0^T ||e||_Q^2 dt \leq 2V(0)+\rho^2\int_0^T ||w_1||^2 dt\end{aligned} \tag{65}$$

Moreover, if there exists a positive constant $M_w > 0$ such that

$$\int_0^\infty ||w_1||^2 dt \leq M_w \tag{66}$$

then one gets

$$\int_0^\infty ||e||_Q^2 dt \leq 2V(0)+\rho^2 M_w \tag{67}$$

Thus, the integral $\int_0^\infty ||e||_Q^2 dt$ is bounded. Moreover, $V(T)$ is bounded and from the definition of the Lyapunov function V in Eq. (51) it becomes clear that $e(t)$ will be also bounded since $e(t) \in \Omega_e = \{e | e^TPe \leq 2V(0)+\rho^2 M_w\}$.

According to the above and with the use of Barbalat's Lemma one obtains $lim_{t\to\infty} e(t)=0$.

7 Simulation tests

The efficiency of the proposed control scheme was tested in the case of tracking of different setpoints. The associated results are depicted in Fig. 3 and in Fig. 4. It has been confirmed that the closed control loop succeeded fast and accurate tracking to all these setpoints while the variations of the control signal applied to the SI engine remained smooth.

8 Conclusions

In this paper, a new neurofuzzy adaptive control scheme for spark ignited (SI) engines has been developed with the use of differential flatness theory. It has been shown that the dynamic model of the SI engine is a differentially flat one, which means that all state variables and the control inputs can be expressed as functions of a unique flat output variable and its derivatives. By showing that the model satisfies differential flatness properties it has been shown that it can be transformed to the linear canonical (Brunovsky) form. For the latter description the design of a state feedback controller becomes easier. Moreover, to cope with parametric uncertainties and external disturbances for the SI model, even in the case that the system's model is completely unknown, the development of an adaptive fuzzy control scheme have been proposed.

Actually, for the description of the engine's model in the canonical form, the associated transformed inputs where shown to contain unknown nonlinear functions which had to be identified online with the use of neurofuzzy approximators. It has been proven that a convergent adaptation law for the parameters of the neurofuzzy networks exists, as a result of the requirement to have a negative definite Lyapunov function for the closed control loop. Moreover, by using such Lyapunov stability analysis methods it has been confirmed that the closed loop of the control system satisfies H_∞ tracking performance criteria, and this assures improved robustness to external perturbations affecting the combustion engine. The efficiency of the proposed control scheme has been confirmed through simulation experiments.

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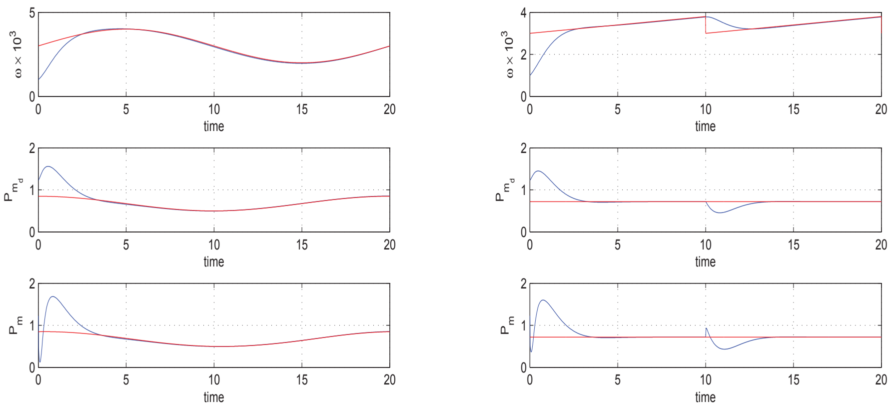
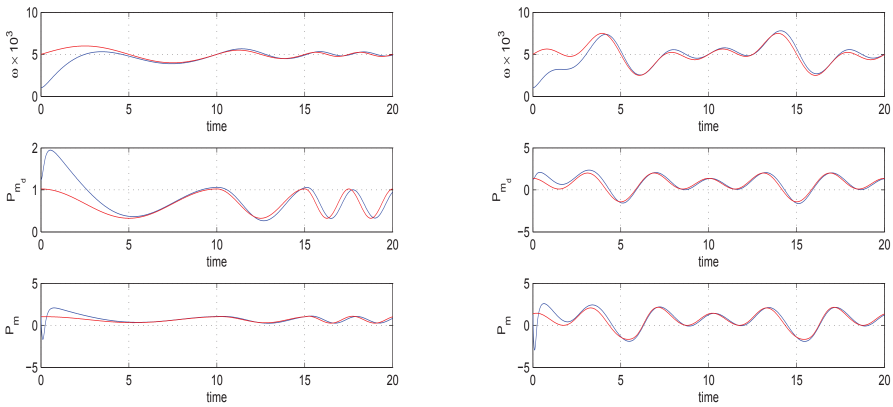
$$\begin{aligned}\dot{V} = -\tfrac{1}{2}e^TQe - \tfrac{1}{2\rho^2}e^TPBB^TPe + e^TPB(w+d_1) - \\ -e^TPB(\theta_f - \theta_f^*)^T\phi(x) - e^TPB(\theta_g - \theta_g^*)^T\phi(x)u_c \Rightarrow \\ \dot{V} = -\tfrac{1}{2}e^TQe - \tfrac{1}{2\rho^2}e^TPBB^TPe + e^TPB(w+d_1) + e^TPBw_{\alpha}.\end{aligned} \tag{59}$$

$$\begin{aligned}\dot{V} = -\tfrac{1}{2}e^TQe - \tfrac{1}{2\rho^2}e^TPBB^TPe + e^TPBw_1 \text{ or equivalently,} \\ \dot{V} = -\tfrac{1}{2}e^TQe - \tfrac{1}{2\rho^2}e^TPBB^TPe + \tfrac{1}{2}e^TPBw_1 + \tfrac{1}{2}w_1^TB^TPe\end{aligned} \tag{60}$$



(a) (b)

Figure 3. Adaptive fuzzy control of the SI engine: (a) tracking of setpoint 1 from state variables $x_i,\ i = 1,\cdots,3$, (b) tracking of setpoint 2 from state variables $x_i,\ i = 1,\cdots,3$



(a) (b)

Figure 4. Adaptive fuzzy control of the SI engine: (a) tracking of setpoint 3 from state variables $x_i,\ i = 1,\cdots,3$, (b) tracking of setpoint 4 from state variables $x_i,\ i = 1,\cdots,3$

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