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Research Article

Fuzzy Modelling and Control of the Air System of a Diesel Engine

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This paper proposes a fuzzy modelling approach oriented to the design of a fuzzy controller for regulating the fresh airflow of a real diesel engine. This strategy has been suggested for enhancing the regulator design that could represent an alternative to the standard embedded BOSCH controller, already implemented in the Engine Control Unit (ECU), without any change to the engine instrumentation. The air system controller project requires the knowledge of a dynamic model of the diesel engine, which is achieved by means of the suggested fuzzy modelling and identification scheme. On the other hand, the proposed fuzzy PI controller structure is straightforward and easy to implement with respect to different strategies proposed in literature. The results obtained with the designed fuzzy controller are compared to those of the traditional embedded BOSCH controller.

1. Introduction

The reduction of pollutant emissions imposed by legislation such as Euro V [1], the improvement of engine performance, the complexity of present automotive applications due to the introduction of several components made more and more necessary the use of high-performance control systems.

For diesel engines with fixed geometry compressors [2], techniques based on exhaust gas recirculation and throttle valve actuator control have been devised to face the stringent requirements. They give a great deal of freedom to control the behaviour of the engine. In general two classes of control approaches are available. Conventional strategies often treat these devices independently as Single-Input, Single-Output (SISO) systems [3]. On the other hand, in the literature multivariable strategies can be found, which exploit model-based controllers [4]. Since a complete model-based controller calibration sometimes is quite expensive and time consuming, with the present state of the art, and on-vehicle tuning cannot be bypassed, these multivariable strategies come at the cost of a quite larger number of controller parameters to tune.

It is worth noting also that the design and testing of these controls increasingly demand accurate mathematical models for the static and dynamic behavior of combustion engines. In addition to the classical engine settings injected fuel, injection angle, and engine speed, new control inputs like the variable turbine geometry of turbochargers, exhaust gas recirculation, and common rail injection offers additional commands for optimising an engine's performance. All these engine variables affect the engine torque, the specific fuel consumption, and the emissions. As a consequence, modern combustion engines have developed to complex, nonlinear multivariable systems. Due to this growing number of engine input and output variables, the state-of-the-art approach to implement an engine control, predominantly based on look-up tables, becomes very time consuming and often does not lead to optimal results. Physical modelling still requires far too long development and simulation times [3].

Since a mathematical model is a description of system behaviour, accurate modelling for a complex nonlinear system is very difficult to achieve in practice. Sometimes for nonlinear systems it can be impossible to describe them by analytical equations. Moreover, very often, the system structure or parameters are not precisely known. Thus, parametric model identification represents an alternative for developing experimental models of complex systems, such as combustion engines. An approach using quadratic regression models for emissions to find an optimal set of engine settings in each operating point can be found in the literature. In contrast to traditional nonlinear identification methods, where detailed knowledge about the model's structure is required, fuzzy systems and neural networks are capable of deriving nonlinear models directly from measured input/output data without detailed system assumptions [5, 6]. Recent publications also stress the importance of considering not only the static behavior of the combustion process, but also to implement dynamic control strategies, especially for turbocharged engines with exhaust gas recirculation [7, 8]. The development of suitable nonlinear approaches can allow adequate dynamic models of combustion engine emissions to be developed.

Because of these assumptions, this paper suggests to use the fuzzy system theory, since it seems to be a natural tool to handle complicated and uncertain conditions [6]. Thus, instead of exploiting complicated nonlinear models obtained by modelling techniques, it is suggested to describe the plant under investigation by a collection of local affine systems of the type of Takagi-Sugeno (TS) fuzzy prototypes [9], whose parameters are obtained by identification procedures. The interesting feature of fuzzy logic is that it represents a powerful tool for describing vague and imprecise fact and is therefore suited for applications where complete information about fault and system is not available to the designer. It should finally be pointed out how the fuzzy approach can solve the problem at two levels: first, fuzzy TS models are used to generate an accurate description of the monitored plant and then, the problem of the design of the control system is enhanced using again fuzzy logic [6].

Regarding the controller design, classical control methods, such as Proportional Integral Derivative (PID) control, usually do not guarantee a satisfactory behavior at each operating point of a supercharged engine, due to high system nonlinearity, ageing of mechanical parts, and environmental conditions [10]. Some multivariable PID model based controllers are compared in [11], where the authors show that more complex control structures than PID guarantee higher performances and robustness. In [12] the use of two separate adaptive PID regulators, one working at steady state and the other during fast transients, results in good dynamic responses. Clearly, nonlinear approaches can cope effectively with large system nonlinearities, often present in diesel systems [3]. For instance, in [13] it is shown how employing fuzzy control results in an improvement of the airflow response at low engine speeds and different loads, with considerable reductions in the design and implementation efforts.

In this paper a fuzzy control approach for the adjustment of the EGR and TVA valves for a diesel engine is proposed and applied to a particular engine. The resulting design criteria are independent from the engine model and allow to quickly tune the controller parameters with partial knowledge of the system characteristics. In more detail, the design of the controller is performed according to the following steps. Firstly, a PI regulator is devised using the classic Ziegler-Nichols method [14]. Then, the corresponding fuzzy PI controller is built, by means of a suitable choice of the gains. The Membership functions (MFs) and rules are derived directly from the identified TS fuzzy model.

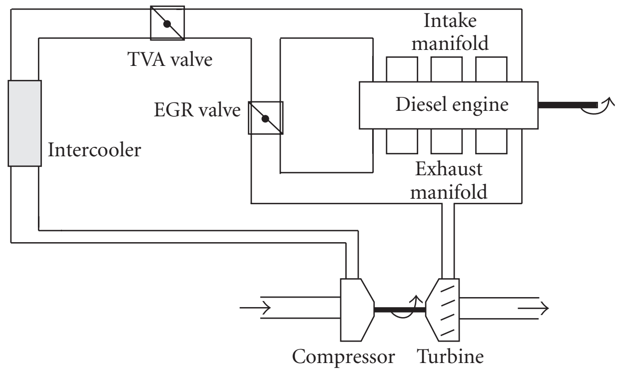

Figure 1: The diesel engine air system.

Finally, the effectiveness of the proposed fuzzy modelling and control strategies is assessed on real data sequences acquired from full European driving cycle tests. A large number of experiments provide the evidence of the superiority of the proposed fuzzy PI regulator with respect to the PI controller developed by BOSCH, with particular reference to the overall tracking capabilities.

The paper has the following structure. Section 2 provides an overview of the diesel engine system and its air system used for modelling and control purposes. The general model of the diesel engine and the standard structure of the embedded controller developed by BOSCH are summarised. The embedded BOSCH controller is considered here as it takes into account the standard instrumentation and ECU capabilities. Section 3 describes the fuzzy modelling and identification strategy exploited in this work for obtaining the input-output description of the considered diesel engine. The proposed fuzzy controller design and the tuning strategy are presented in Section 3.2. The achieved results that are summarised in Section 4 show the performances of the fuzzy modelling and control schemes, validated and compared with respect to the actual embedded strategy. Section 5 ends the paper by highlighting the main points of the work, open problems, and further investigations.

2. The Engine and Its Air System Control

Section 2.1 provides basic details regarding the diesel engine model considered in this work. It describes the classical embedded and the suggested control strategies exploided for the regulation of the air system of the considered diesel engine. In particular, the standard embedded controller developed by BOSCH and used by VM Motors S.p.A. is described in Section 2.2. The tuning procedure exploited for the calibration of the controller maps and parameters is also recalled.

2.1. The Turbocharged Diesel Engine System. In this paper, a diesel engine "Panther" RA428 equipped with a fixed geometry turbine, an external Exhaust Gas Recirculation (EGR) system, and a Throtlle Valve Actuator (TVA) is considered as shown schematically in Figure 1.

This in-line 4 cylinder (2.8 L) diesel motor is produced in Italy by VM Motors S.p.A. (Cento, Ferrara, Italy). This engine is used in the JK Jeep Wrangler outside of the U.S. market. This engine is often reffered to by its development codename: Panther. This engine main features are the following:

(i) 2776 cc of displacement;

(ii) 4 valve/per cylinder;

(iii) Double Over Head Camshaft (DOHC);

(iv) BOSCH common rail direct injection with electric piezo injectors operating at 30,000 psi;

(v) weighs 451 pounds/205 kilograms power rating of 174 horsepower, 340 foot pounds.

The turbine converts the energy of the exhaust gas into mechanical energy of the rotating turboshaft, which, in turn, drives the compressor. The compressor increases the density of air supplied to the engine. This larger mass of fresh air can be burned with a larger quantity of fuel thereby resulting in a larger output torque. By varying the TVA valve, it is possible to act on the mass flow rate through the engine intake manifold [2, 15, 16].

To reduce the emissions of harmful nitrogen oxides (NO_x) produced during combustion, a portion of the exhaust gas can be diverted back to the intake manifold to dilute the air supplied by the compressor. This process is referred to as EGR system. It is accomplished with an EGR valve that connects the intake manifold to the exhaust manifold. In the cylinders the recirculated exhaust gas acts as inert gas thus lowering the flame temperature and, hence decreasing the formation of (NO_x). The considered diesel engine air system includes a TVA valve between the compressor and the intake manifold as well. This throttle permits the air system to create a variable pressure drop through the TVA valve, thereby increasing the EGR rates [4, 15, 16].

In the following, in order to show the physical modelling procedure of a diesel engine, the case study and the diesel engine formal model are briefly described.

For the four cylinders turbocharged diesel engine under investigation, it is assumed that the working fluid is a mixture of ideal gases always in equilibrium for all chemical compositions and pressure-temperature conditions. In order to simplify the fluid dynamics description, a dynamic model relying on the filling and emptying principle is set up [17, 18]. Assuming small enough pipe dimensions, a lumped capacities representation is adopted, in which the fluid thermodynamic properties are spatially constant but time variant. In particular, this work describes the engine by means of five elements: the turbine and the compressor, the intake and exhaust manifolds, and the cylinders. Each component is characterized by a different set of thermodynamic state variables and may be described by the ideal gas law, conservation of the mass, conservation of energy, and dynamic equilibrium equations.

The principle of conservation of mass in the intake and exhaust manifolds produces the following equation:

$$\frac{V}{R}\frac{d(p/T)}{dt} = m_{\text{in}} - m_{\text{out}}, \tag{1}$$

where p and T are the gas pressure and temperature in the manifold volume V, respectively, R is the universal gas constant, m_{in} is the mass inflow, and m_{out} is the mass outflow. Neglecting heat transfers through walls, the conservation of energy equation for the intake and exhaust manifolds can be written as follows:

$$\frac{V}{R}c_v\frac{dp}{dt} = m_{\text{in}}h_{\text{in}} - m_{\text{out}}h_{\text{out}}, \tag{2}$$

where c_v is the specific heat at constant volume, calculated for the manifold under study and assumed as a time invariant, h_{in} is the input fluid enthalpy content, h_{out} is the enthalpy content of the fluid in the manifold.

The conservation of mass in the cylinders yields

$$\frac{dM_{\text{cyl}}}{dt} = m_{2a} + \dot{\mu}_f - m_{1s}, \tag{3}$$

where M_{cyl} is the overall mass in each cylinder, m_{2a} is the mass inflow from the intake valve, m_{1s} is the mass outflow to the exhaust valve, and $\dot{\mu}_f$ is the apparent burned fuel rate. The latter is calculated as the sum of two contributions under the assumption that combustion develops in three sequential steps, namely, combustion delay, premixed combustion, and diffusive combustion [17]. The gas pressure p_{cyl} in the cylinder is obtained by applying the ideal gas law:

$$p_{\text{cyl}}V_{\text{cyl}} = M_{\text{cyl}}R_{\text{cyl}}T_{\text{cyl}}. \tag{4}$$

The temperature T_{cyl} is calculated by means of the energy conservation equation:

$$\begin{aligned} M_{\text{cyl}}c_{v\text{cyl}}\frac{dT_{\text{cyl}}}{dt} &= \frac{dQ}{dt} - p_{\text{cyl}}\frac{dV_{\text{cyl}}}{dt} + m_{2a}\left(h_{va} - u_{\text{cyl}}\right) \\ &\quad - m_{1s}\left(h_{vs} - u_{\text{cyl}}\right) + \dot{\mu}_f\left(h_f - u_{\text{cyl}}\right), \end{aligned} \tag{5}$$

where R_{cyl} is the cylinder universal gas constant, $c_{v\text{cyl}}$ is the specific heat at constant volume, Q is the heat transfer in the cylinders, V_{cyl} is the instantaneous cylinder volume depending on the piston position, h_f is the fuel low calorific value, h_{va} is the input fluid enthalpy content, h_{vs} is the exhaust fluid enthalpy content, and u_{cyl} is the fluid internal energy. Neglecting the conductive contribution, for example, assuming constant cylinder walls temperature T_w, the heat transfer Q can be computed as the sum of the convective and radiative contributions. The convective term is

$$Q_c = h_c A_{sc}\left(T_w - T_{\text{cyl}}\right), \tag{6}$$

where A_{sc} is the instantaneous heat transfer surface, depending on the crankshaft angle, and h_c is a convective heat transfer coefficient, depending on the fluid working conditions. The radiative term is

$$Q_r = \beta\sigma A_{sc}\left(T_{\text{cyl}}^4 - T_w^4\right), \tag{7}$$

where σ is the Stephan-Boltzman constant and β is a coefficient computed by way of a polynomial fit or experimental data, depending on the engine speed and the equivalence ratio.

The cylinders intake and exhaust valves are represented as converging nozzles. Assuming stationary flow, two gas conditions are distinguished, which can be described by the following dynamic equations, depending on the output/input pressure ratio $p_{\text{out}}/p_{\text{in}}$:

$$m = \begin{cases} \dfrac{p_{\text{in}}}{\sqrt{RT_{\text{in}}}} A_{\text{eff}} \sqrt{\dfrac{2k}{k-1}\left[\left(\dfrac{p_{\text{out}}}{p_{\text{in}}}\right)^{2/k} - \left(\dfrac{p_{\text{out}}}{p_{\text{in}}}\right)^{(k+1)/k}\right]} \\ \qquad \text{if } \dfrac{p_{\text{out}}}{p_{\text{in}}} > \left[\dfrac{2}{k+1}\right]^{k/(k-1)} \\ \text{(subsonic flow condition in the outlet section)}, \\ \dfrac{p_{\text{in}}}{\sqrt{RT_{\text{in}}}} A_{\text{eff}} \sqrt{k\left(\dfrac{2}{k+1}\right)^{(k+1)/(k-1)}} \\ \qquad \text{if } \dfrac{p_{\text{out}}}{p_{\text{in}}} \leq \left[\dfrac{2}{k+1}\right]^{k/(k-1)} \\ \text{(sonic flow condition in the outlet section)}, \end{cases} \tag{8}$$

where k is the gas elastic constant, referred to the intake air flow, A_{eff} is the equivalent outlet section surface, evaluated by means of the valve displacemenl curve, and depends on the crankshaft angle.

The turbocharger is equipped with a turbine and a compressor. By interpolating data stored in experimental maps (or look-up tables) it is possible to calculate the turbine and compressor efficiencies and the output air flow from the compressor, corresponding to different turbocharger speeds and pressure ratios. Evaluating the power supplied by the turbine and received by the compressor is straightforward. For the compressor it can be obtained

$$P_C = m_{\text{out}} c_p T_{\text{in}} \left[\left(\frac{p_{\text{out}}}{p_{\text{in}}}\right)^{(k-1)/k} - 1\right] \frac{1}{\eta_C}, \tag{9}$$

where c_p is the specific heat at constant pressure, assumed invariant during the transformation and referred to the intake mass flow, T_{in} is the environmental temperature, and η_C is the compressor efficiency.

On the other hand, for the turbine the following relation can be written:

$$P_T = m_{\text{in}} c_p T_{\text{in}} \left[1 - \left(\frac{p_{\text{out}}}{p_{\text{in}}}\right)^{(k-1)/k}\right] \eta_T, \tag{10}$$

where η_T is the turbine efficiency.

Finally, the turbocharger speed is calculated by applying the dynamic equilibrium momentum equation:

$$J_T \frac{d\omega_T}{dt} + \nu\omega_T = \frac{P_T - P_C}{\omega_T}, \tag{11}$$

where J_T is the turbocharger moment of inertia, ν is the shaft viscous friction coefficient, and ω_T is the turbocharger speed.

Similarly, by applying the dynamic equilibrium momentum equation to the driving shaft, the engine speed ω_e can be computed

$$\left[J_e + M\left(\frac{R_p}{2\pi\tau}\right)^2\right] \frac{d\omega_e}{dt} = C_t - C_p - C_r, \tag{12}$$

where J_e and $M(R_p/2\pi\tau)^2$ are the crankshaft and the vehicle moment of inertia, respectively. M is the overall vehicle mass, R_p the tires circumference, τ the gear transmission ratio, C_t the driving torque, C_p the organic friction torque, and C_r the load torque, taking into account the road and viscous friction. Torques C_p and C_r are computed by means of polynomial fits of experimental data at different engine speeds and fuel mass introduction values.

Finally, the TVA and EGR behaviour can be described by relation of the type of (8), since for the air mass flow through throttle valves, the standard model for isentropic restriction flow is used. In this cases, (8) is corrected by means of a discharge coefficient C_d, and the term A_{eff} is the real opening throttle area. In practice, the product $C_d A_{\text{eff}}$ is defined as the effective opening throttle area and identified as a single coefficient, usually computed as a function of the valve opening control signal (angle in degrees or aperture percentage). It can exist many different models to describe this relation, in general chosen for providing the best fit on the real engine data.

In this paper, the simultaneous control of the EGR valve and the TVA throttle of the diesel engine described above are investigated. For this purpose, a mathematical model of the process under investigation is required, either in state space or input-output forms. However, in practical situations, the straightforward application of model-based controller design techniques can be difficult, due to the dynamic model complexity. In fact, the plant analytical description is usually designed to carefully capture all kinds of details relevant to the analysis and the deployment of the real system. On the other hand, this intrinsic complexity makes almost unfeasible the use of many cited control design methods, and a viable procedure for the practical application of control design techniques is really necessary in practical cases. In particular, the use of model identification is investigated here for finding a solution of the control problem. To this aim, two practical aspects of the presented work are stressed. Firstly, the system complexity may not indicate a requirement for a complex physical or thermodynamic model. In fact, as shown in this work, a dynamic model identification method can be successfully used, thus obviating the requirement for physical models. Secondly, the TS fuzzy prototype enhances the design of the control strategy. This is considered important to avoid the complexity that would otherwise be inevitable when nonlinear models are used.

2.2. Standard Embedded BOSCH Control. The standard control strategy for EGR and TVA systems uses the Proportional + Integral (PI) control structure with feed-forward terms as illustrated in Figure 2.

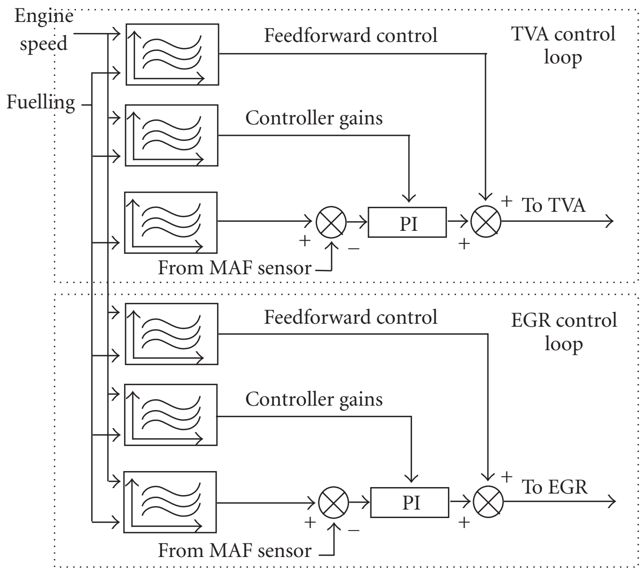

Figure 2: Standard control strategy developed by BOSCH.

Since the EGR-TVA plant is decoupled during transients, BOSCH proposed a regulation based on two Single-Input, Single-output loops [15, 16]. The Mass fresh AirFlow (MAF) is measured upstream of the compressor and is used to close the loops on the EGR and TVA systems. Therefore, the two outputs of the controller are switched by a suitable logic and divided into the EGR and TVA valve control signals, as shown in Figure 2. The gains of the two PI controllers depend on suitable maps (look-up tables), which result functions of the engine fuelling and speed.

The setpoints for these two controllers are derived from extensive engine mapping, involving the engine turbine, compressor, and EGR system positions at fixed engine speed and fuelling inputs to determine the optimum settings with respect to the desired performances. From prepositioning values, the controller drives the actuators as close as possible to the positions required to attain the desired fresh airflow.

The open-loop term (feedforward duty cycle) is valid only in steady-state conditions, but it cannot guarantee accurate setpoint tracking due to the engine variability, aging, and driving environment. The closed-loop through the PI modules is used to ensure the position convergence. The response of the MAF to the EGR and TVA systems varies with engine operating points, therefore PI controller with gain scheduling is employed extensively by the BOSCH strategy [15, 16]. By means of the considered BOSCH strategy, the gains of the PI controllers shown in Figure 2 are scheduled by means of suitable maps (look-up tables). Usually, these maps and the PI parameters are empirically determined by the calibration engineers working at the Calibration Section of VM Motors S.p.A. However, facing the future standard requirements, this tuning strategy seems to have reached its limits and should be replaced by an automatic strategy.

To improve the tracking of the setpoint, several strategies have been presented in the recent years, as described, for example, in [15, 19].

Model-based strategies require an accurate dynamic model of the diesel engine, as shown in Section 2.1. This model can be derived via the so-called “grey-box” modelling approach, which is based on the description of the input-output behaviour of the diesel engine from the *first principle*, that is, starting directly at the level of established laws of physics. Also the parameters of the physical laws have to be empirically estimated. Both steps are complex and time consuming (several months on a test bed). The high value variability of engine parameters makes necessary, in the ideal case, an individual modelling for each produced engine. Sometimes such parameter estimation cannot be applied to standard engines. Moreover, these algorithms cannot be nowadays supported by standard Electronic Control Unit (ECU) in terms of calculation power [15, 19].

As an example, predictive controllers and robust controllers have the advantage that the actuator prepositioning is no more needed. In general, this would be interesting if both the intake manifold pressure and the fresh airflow setpoints could be always reached simultaneously. Regarding the diesel engine considered in this work, and its own characteristics, this is not possible for all operating points. For example at idle speed, any position combination of the two EGR and TVA actuators could allow the tracking of the MAF setpoint. To improve the air system control, a strategy taking into account the engine characteristics, without an internal model and with a very low calculation need, should be provided. To meet these requirements, a strategy relying on the fuzzy modelling for control design is proposed in this paper.

3. Fuzzy Modelling for Control

This section describes the approaches exploited for obtaining the mathematical description of the diesel engine system and the control strategy used for the regulation of its air system. In particular, the fuzzy modelling and identification scheme, which is reported in Section 3.1, enhances the design procedure of the proposed fuzzy controller, as shown in Section 3.2.

3.1. Fuzzy Identification from Data. The modelling approach exploited in this work relies on the identification of transparent rule-based fuzzy models, which can accurately predict the quantities of interest, and at the same time provides insight into the system that generated the data. Attention is paid to the selection of appropriate model structures in terms of the dynamic properties, as well as the internal structure of the fuzzy rules (in particular, Takagi-Sugeno type) [9]. From the system identification point of view, a fuzzy model is regarded as a composition of local affine submodels. Fuzzy sets naturally provide smooth transitions between the submodels and enable the integration of various types of knowledge within a common framework.

In order to generate fuzzy models automatically from measurements, a comprehensive methodology is used. This employs fuzzy clustering techniques to partition the available data into subsets characterised by a linear behaviour. The relationships between the presented identification method and linear regression are exploited, allowing for the combination of fuzzy logic techniques with system identification tools. In addition, an implementation in a *MATLAB Toolbox* of the Fuzzy Modelling and IDentification (FMID) techniques presented in the following is available [20]. Fuzzy identification usually refers to techniques and algorithms for constructing fuzzy models from data.

The modelling approach suggested in this paper is used for achieving the integration of knowledge and data in a fuzzy model. In particular, no prior knowledge about the system under investigation is initially used to formulate the rules, and a fuzzy model is constructed using numerical data only. It is expected that the extracted rules and membership functions can provide an a posteriori interpretation of the system's behaviour. An expert can compare this information with his own knowledge, can modify the rules, or supply new ones, and can design additional experiments in order to obtain more informative data. This technique is proposed here as it can obviate the process of knowledge acquisition which is a well-known bottleneck for the practical applications of knowledge-based systems [21]. Instead, the expert is invited to assume a more active role of model analysis and validation, which may lead to revealing new pieces of information, and may result in a kind of emergent knowledge acquisition.

To date, relatively little attention has been devoted to the identification of transparent fuzzy models from data. Most of the techniques reported in the literature aim at obtaining numerical models that simply fit the data with the best possible accuracy, without paying attention to the interpretation of the results [22, 23]. Many other identification techniques can be used for completely "grey-box" modelling, such as standard nonlinear regression [24], spline techniques [25], or neural networks [26]. In many cases, a natural requirement is that a model not only predicts accurately the system's outputs but also provides some insights into the working of the system. Such a model can be used not only for the given situation, but can also be more easily adapted to changing design parameters and operating conditions.

In this section, fuzzy models are viewed as a class of local modelling approaches, which attempt to solve a complex modelling problem by decomposing it into a number of simpler subproblems. The theory of fuzzy sets offers an excellent tool for representing the uncertainty associated with the decomposition task, for providing smooth transitions between the individual local submodels, and for integrating various types of knowledge within one common framework. In particular, fuzzy logic is exploited to define a TS fuzzy model [9]. The TS fuzzy model for nonlinear dynamic systems is described by a collection of local linear or affine submodels, each one approximating the system behaviour around a single working point. The scheduling of the submodels is achieved through a smooth function of the system state, the behaviour of which is defined using fuzzy set theory [27].

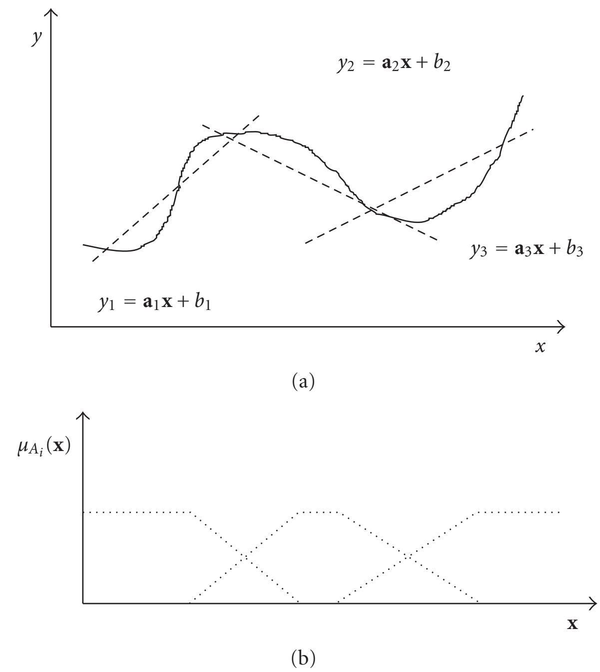

Figure 3: Fuzzy model diagram.

A large part of fuzzy modelling and identification algorithms (see [6] and references therein) share a common two-step procedure, in which at first, the operating regions are determined using heuristics or data clusterings techniques. Then, in the second stage, the identification of the parameters of each submodel is achieved using Least-Squares algorithm. From this perspective, fuzzy identification can be regarded as a search for a decomposition of a nonlinear system, which gives a desired balance between the complexity and the accuracy of the model, effectively exploring the fact that the complexity of systems is usually not uniform. Since it cannot be expected that sufficient prior knowledge is available concerning this decomposition, methods for automated generation of the decomposition, primarily from system data, are developed. A suitable class of fuzzy clustering algorithms is used for this purpose.

3.1.1. Takagi-Sugeno Multiple-Model Paradigm. A fuzzy rule-based model suitable for the approximation of a large class of nonlinear systems was introduced by Takagi and Sugeno [9].

In the TS fuzzy model 3, the rule consequents are crisp functions of the model inputs:

$$R_i : \text{IF } \mathbf{x}(k) \text{ is } A_i \text{ THEN } y_i = f_i(\mathbf{x}(k)), \quad i = 1, 2, \ldots, K, \tag{13}$$

where $\mathbf{x}(k) \in \Re^p$ is the input (antecedent) variable and $y_i \in \Re$ is the output (consequent) variable. R_i denotes the ith rule, and K is the number of rules in the rule base. A_i is the antecedent fuzzy set of the ith rule, defined by a (multivariate) membership function:

$$\mu_{A_i}(\mathbf{x}) : \Re^p \longrightarrow [0, 1]. \tag{14}$$

As in the linguistic model, the antecedent proposition "$\mathbf{x}(k)$ is A_i" is usually expressed as a logical combination of simple propositions with univariate fuzzy sets defined for the individual components of $\mathbf{x}(k)$, often in the conjunctive form

$$R_i : \text{IF } x_1 \text{ is } A_{i1},\ x_2 \text{ is } A_{i2}, \ldots,\ x_p \text{ is } A_{ip}, \quad \text{THEN } y_i = f_i(\mathbf{x}), \quad i = 1, 2, \ldots, K. \tag{15}$$

The consequent functions f_i are typically chosen as instances of a suitable parameterised function, whose structure remains equal in all the rules and only the parameters vary. A simple and practically useful parametrisation is the affine linear form

$$y_i = \mathbf{a}_i\mathbf{x} + b_i, \tag{16}$$

where a_i is a parameter vector and b_i is a scalar offset. This model is referred to as *affine TS model*. The consequents of the affine TS model are hyperplanes (p-dimensional linear subspaces) in $\Re^{p+1}$. The antecedent of each rule defines a (fuzzy) validity region for the corresponding affine consequent model. The global model is composed of a concatenation of the local models and can be seen as a smoothed piecewise approximation of a nonlinear surface. Approximation properties of the affine TS model were investigated, for example, in [28, 29].

Before the output can be inferred, the degree of fulfilment of the antecedent denoted by $\beta_i(\mathbf{x})$ must be computed. For rules with multivariate antecedent fuzzy sets given by (13) and (14), the degree of fulfilment is simply equal to the membership degree of the given input $\mathbf{x}$, that is, $\beta_i = \mu_{A_i}(\mathbf{x})$. When logical connectives are used, the degree of fulfilment of the antecedent is computed as a combination of the membership degrees of the individual propositions using the fuzzy logic operators [6].

In the Takagi-Sugeno model, the inference is reduced to a simple algebraic expression, similar to the fuzzy-mean defuzzification formula [9]

$$y = \frac{\sum_{i=1}^{K} \beta_i(\mathbf{x}) y_i}{\sum_{i=1}^{K} \beta_i(\mathbf{x})}. \tag{17}$$

By denoting the normalised degree of fulfilment

$$\lambda_i(\mathbf{x}) = \frac{\beta_i(\mathbf{x})}{\sum_{j=1}^{K} \beta_j(\mathbf{x})}, \tag{18}$$

the affine TS model with a common consequent structure can be expressed as a pseudolinear model with input-dependent parameters:

$$y = \left(\sum_{i=1}^{K} \lambda_i(\mathbf{x})\mathbf{a}_i^T\right)\mathbf{x} + \sum_{i=1}^{K} \lambda_i(\mathbf{x}) b_i = \mathbf{a}^T(\mathbf{x})\mathbf{x} + b(\mathbf{x}). \tag{19}$$

The parameters $\mathbf{a}(\mathbf{x})$, $b(\mathbf{x})$ are convex linear combinations of the consequent parameters a_i and b_i, that is,

$$\mathbf{a}(\mathbf{x}) = \sum_{i=1}^{K} \lambda_i(\mathbf{x})\mathbf{a}_i^T, \qquad b(\mathbf{x}) = \sum_{i=1}^{K} \lambda_i(\mathbf{x}) b_i. \tag{20}$$

Because of this property, a TS model can be regarded as a mapping from the antecedent (input) space to a convex region (polytope) in the space of the parameters of a quasilinear system of (19).

Consider, for instance, the dynamic system of (13), that can be rewritten in the following form:

$$\begin{aligned} R_i : \text{IF } & y(k-1) \text{ is } A_{i1},\ y(k-2) \text{ is } A_{i2}, \ldots,\ y(k-n) \text{ is } A_{\text{in}}, \\ & u(k-1) \text{ is } B_{i1},\ u(k-2) \text{ is } B_{i2}, \ldots,\ u(k-n) \text{ is } B_{\text{in}}, \\ \text{THEN } & y(k) = \sum_{j=1}^{n} \alpha_j^{(i)} y(k-j) + \sum_{j=1}^{n} \delta_j^{(i)}\ u(k-j), \end{aligned} \tag{21}$$

where the consequents are *linear* ARX models, n is the order of the ARX dynamic system, $\mathbf{x}(k) = [y(k-1), \ldots, y(k-n), u(k-1), \ldots, u(k-n)]^T$, and $\mathbf{a}_i = [\alpha_1^{(i)}, \ldots, \alpha_n^{(i)}, \delta_1^{(i)}, \ldots, \delta_n^{(i)}]$.

3.1.2. Fuzzy Clustering for Fuzzy Identification. An effective approach to the identification of complex nonlinear systems is to partition the available data into subsets and approximate each subset by a simple model [30]. Fuzzy clustering can be used as a tool to obtain a partitioning of data where the transitions between the subsets are gradual rather than abrupt. This section recalls the basic concepts of fuzzy clustering [6] at a level necessary to understand the subsequent applications. For a more detailed treatment of the subject, the reader may refer to the classical monographs by Duda and Hart [31], Bezdek [32], and Jain and Dubes [33]. A more recent overview can be found in a collection of Bezdek and Pal [34], and the monograph by Backer [35]. The notation and terminology in this section closely follows [32].

The aim of cluster analysis is the classification of objects according to similarities among them, and the organising of data into groups. Clustering techniques are among the unsupervised (learning) methods, since they do not use prior class identifiers. Most clustering algorithms also do not rely on assumptions common to conventional statistical methods, such as the underlying statistical distribution of data, and therefore they are useful in situations where little prior knowledge exists. The potential of clustering algorithms to reveal the underlying structures in data can be exploited, not only for classification and pattern recognition, but also for the reduction of complexity in modelling and optimisation. Clustering techniques can be applied to data which are typically observations of some physical process. Generally, a cluster is a group of objects that are more similar to one another than to members of other clusters [32, 33]. In metric spaces, similarity is often defined by means of a distance norm. Distance can be measured among the data vectors themselves, or as a distance from a data vector to some prototypical object of the cluster. The prototypes are usually not known beforehand and are sought by the clustering algorithms simultaneously with the partitioning of the data. The prototypes may be vectors of the same dimension as the data objects, but they can also be defined as geometrical objects, such as linear or nonlinear subspaces or functions. Data can reveal clusters of different geometrical shapes, sizes, and densities. Algorithms that can detect subspaces of the data space are of particular interest for identification and will be summarised in the following.

Many clustering algorithms have been introduced in the literature. Since clusters can formally be seen as subsets of the data set, one possible classification of clustering methods can be according to whether the subsets are fuzzy or crisp (hard). Hard clustering methods are based on classical set theory and require that an object either does or does not belong to a cluster. The *fuzzy clustering* methods, however, allow the objects to belong to several clusters simultaneously, with different degrees of membership. In many situations, fuzzy clustering is more natural than hard clustering, as objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial memberships.

Another classification of clustering techniques can be related to the algorithmic approach of the different techniques [32]. In particular, the class of clustering algorithms presented here exploits an objective function to measure the desirability of partitions. Nonlinear optimisation algorithms are used to search for local extrema of the objective function. In general, the fuzzy clustering algorithms are developed in connection with suitable objective functions. These methods lead to least-squares optimisation, and hence there are close relationships between clustering with fuzzy objective function and statistical regression and systems identification methods [6]. In more detail, the clustering algorithm exploited in this work is based on optimisation of the basic *c-means* objective function and it is known as *fuzzy c-means clustering* algorithm [36].

When considering fuzzy identification via data clustering, an important point concerns the determination of the optimal number of clusters. When clustering real data without any a priori information about the data structure, one usually has to make assumptions about the number of underlying subgroups (clusters) K in the data. The chosen clustering algorithm then searches for K clusters, regardless of whether they are really present in the data or not. Two main approaches to determining the appropriate number of clusters in data can be distinguished [6]. The first one consists of clustering data for different values of K, and using validity measures to assess the goodness of the obtained partitions. Different scalar validity measures have been proposed in the literature. The second approach starts with a sufficiently large number of clusters, and successively reduces this number by merging clusters that are similar (compatible) with respect to some predefined criteria.

3.1.3. Fuzzy Model Identification from Clusters. As shown in the previous sections, fuzzy clustering algorithms can be used to approximate a set of data by local linear models. Each of these models is represented by a fuzzy subset in the data set available for identification. In order to obtain a model useful for prediction, an additional step must be applied to generate a model independent of the identification data. Such a model can be represented either as a rule base or as a fuzzy relation [6]. This section recalls the algorithms for constructing fuzzy TS models from the fuzzy partitions obtained by product space clustering. In particular, the construction of Takagi-Sugeno models is addressed and the methods for generating the antecedent membership functions and estimating the consequent parameters are summarised below.

Each cluster obtained by product space clustering of the identification data set can be regarded as a local linear approximation of the regression hypersurface. The global model can be conveniently represented as a set of affine Takagi-Sugeno rules:

$$R_i: \quad \text{IF } \mathbf{x} \text{ is } A_i \text{ THEN } y_i = \mathbf{a}_i^T \mathbf{x} + b_i, \quad i = 1, 2, \ldots, K. \tag{22}$$

The *antecedent* fuzzy sets A_i can be computed analytically in the antecedent product space, or can be extracted from the fuzzy partition matrix. The *consequent parameters* $\mathbf{a}_i$ and b_i are estimated from the data using the method sketched in the following, or they can be extracted from the eigenstructure of the cluster covariance matrices. The antecedent membership functions can be obtained by projecting the fuzzy partition onto the antecedent variables, or by computing the membership degrees directly in the product space of the antecedent variables. These two methods are described in the following but the second one will be exploited for the identification of the TS models by means of the Fuzzy Modelling and Identification Toolbox (*FMID*), for Matlab [20] developed by Robert Babuška [6].

The first method estimates the antecedent membership function by *projection*. The principle of this method consists of projecting the multidimensional fuzzy sets defined pointwise onto the individual antecedent variables of the rules. These variables can be the original regression variables, in which case the projection is an orthogonal projection of the data. Then, the transformed antecedent variables can be obtained by means of eigenvector projection, using the p largest eigenvectors of the cluster covariance matrices. The eigenvector projection is useful for clusters which are opaque to the axis of the regression space, and cannot be represented by axis-orthogonal projection with a sufficient accuracy. By projecting the fuzzy partition matrix onto the antecedent variable x_i, a pointwise definition of the fuzzy set A_i is obtained. In order to obtain a prediction model, the antecedent membership functions must be expressed in a form that allows computation of the membership degrees, also for input data not contained in the data set. This is achieved by approximating the pointwise defined membership function by some suitable parametric function. The piecewise exponential membership functions proved to be suitable for the accurate representation of the actual cluster shape. This function is fitted to the envelope of the projected data by numerically optimising its parameters. An advantage of this method over the *multi-dimensional membership functions*, summarised below, is that the projected membership functions can always be approximated such that convex fuzzy sets are obtained. Moreover, asymmetric membership functions can be used to reflect the actual partition of the considered nonlinear regression problem. The second method considers *multi-dimensional antecedent membership functions*, which are represented analytically by computing an inverse of the distance from the cluster prototype. The membership degree is computed directly for the entire input vector (without the decomposition). The antecedents of the TS rules are simple propositions with multi-dimensional fuzzy sets given by (22), and $\beta_i(\mathbf{x}) = \mu_{A_i}(\mathbf{x})$.

Regarding the estimation of the *consequent parameters*, there are several methods of obtaining them. Based on the geometrical interpretation of the TS model, the consequent parameters can be directly computed from the cluster prototypical points and the smallest eigenvectors of the cluster covariance matrices. This method assumes that errors are present in both the regressors and the regressand, and corresponds to the total least-squares solution of the local linearisation around the cluster centre [37]. A set of optimal parameters with respect to the model output can also be estimated from the identification data set by ordinary least-squares methods or by using the procedure recalled in the following [38]. This approach can be formulated as minimisation of the total prediction error using the TS defuzzification formula of (17), or as minimisation of the prediction errors of the individual local models, solved as a set of K independent, weighted least-squares problems.

In the following, an example of identification of the consequent TS parameters by exploiting an algorithm developed by one of the author is summarised. This approach is usually preferred when the TS model should serve as predictor [38] and it computes the consequent parameters by the so-called *Frisch scheme*. After the clustering of the data has been obtained, data subsets can be processed according the Frisch scheme identification procedure [39, 40], in order to estimate the TS parameters for each affine submodels, according to the rules presented in [38].

Thus, in order to identify the structure of the TS SISO model of (17) in the ith cluster with $i = 1, \dots, K$ and K clusters, the following matrices can be defined:

$$X_n^{(i)} = \begin{bmatrix} y(k) & \mathbf{x}_n^T(0) & 1 \\ y(k+1) & \mathbf{x}_n^T(1) & 1 \\ \vdots & \vdots & \\ y(k+N_i-1) & \mathbf{x}_n^T(N_i-1) & 1 \end{bmatrix}, \quad (23)$$

where the subscript n represents the order of the considered dynamic model (number of regressors), that is, $\mathbf{x}_n(h) = [y(h-1), \dots, y(h-n), u(h-1), \dots, u(h-n)]^T$. Therefore:

$$\Sigma_n^{(i)} = \left(X_n^{(i)}\right)^T X_n^{(i)}. \quad (24)$$

In order to solve the noise-rejection problem in a mathematical framework, it is necessary to follow the assumptions [39, 40] that the noises $\tilde{u}(k)$ and $\tilde{y}(k)$ are additive on the input-output data $u^*(k)$ and $y^*(k)$ are region independent $(k = 1, 2, \dots, N)$.

Under these assumptions, a positive-definite matrix $\Sigma_n^{(i)}$ associated to the sequences belonging to the ith cluster can be expressed as the sum of two terms $\Sigma_n^{(i)} = \Sigma_n^{*(i)} + \overline{\widetilde{\Sigma}}_n$, where

$$\overline{\widetilde{\Sigma}}_n = \operatorname{diag}\left[\overline{\widetilde{\sigma}}_y I_{n+1}, \overline{\widetilde{\sigma}}_u I_n, 0\right] \geq 0. \quad (25)$$

The solution of the above identification problem requires the computation of the unknown noise covariances $\overline{\widetilde{\sigma}}_u$ and $\overline{\widetilde{\sigma}}_y$, that can be achieved solving the following relation:

$$\Sigma_n^{*(i)} = \Sigma_n^{(i)} - \widetilde{\Sigma}_n \geq 0 \quad (26)$$

in the variables $\widetilde{\sigma}_u, \widetilde{\sigma}_y$, where $\widetilde{\Sigma}_n = \operatorname{diag}[\widetilde{\sigma}_y I_{n+1}, \widetilde{\sigma}_u I_n, 0]$. It is worth noting that all the surfaces of type as defined by (26) have necessarily at least one common point, that is, point $(\overline{\widetilde{\sigma}}_u, \overline{\widetilde{\sigma}}_y)$ corresponding to the true variances of the noise affecting the input and the output data.

The search for a solution for the identification problem can therefore start from the determination of this point in the noise space, if the noise characteristics are common to all the clusters and all assumptions regarding the Frisch scheme are satisfied (independence between input-output sequences, additive noise, noise whiteness).

In real cases, these assumptions have to be relaxed, thus no common point can be determined among surfaces $\Gamma_n^{(i)} = 0$ in the noise plane and a unique solution to the identification problem cannot be obtained. In this situation, the local fuzzy model identification can be performed by finding the point $(\widetilde{\sigma}_u, \widetilde{\sigma}_y) \in \Gamma_{n+1}^{(i)} = 0$ that makes $\Sigma_{n+1}^{*(i)}$ closer to the double singular condition. It leads to determine the common point of the surfaces when the assumptions of the Frisch scheme are not violated. Moreover, for each cluster, different noises $(\overline{\widetilde{\sigma}}_u^{(i)}, \overline{\widetilde{\sigma}}_y^{(i)})$ and the following relation should be rewritten as

$$\Sigma_n^{*(i)} = \Sigma_n^{(i)} - \widetilde{\Sigma}_n^{(i)} \geq 0, \quad (27)$$

where $\widetilde{\Sigma}_n^{(i)} = \operatorname{diag}[\overline{\widetilde{\sigma}}_u^{(i)} I_{n+1}, \overline{\widetilde{\sigma}}_y^{(i)} I_n, 0] \geq 0$ whilst $(\overline{\widetilde{\sigma}}_u^{(i)}, \overline{\widetilde{\sigma}}_y^{(i)})$ represent the variances of input and output additive noises in the ith cluster.

Finally, the matrices $\widetilde{\Sigma}_n^{(i)}$ can therefore be built and the parameter of the model in each cluster determined by means of relation

$$\left(\Sigma_n^{(i)} - \widetilde{\Sigma}_n^{(i)}\right)\mathbf{a}^i = \mathbf{0}, \quad \text{for } i = 1, \dots, K, \quad (28)$$

for a number of K clusters. This completes the multiple-model identification procedure in the fuzzy environment.

In Section 4 the example concerning the fuzzy modelling and identification from real data of the considered diesel engine by means of TS models will be presented.

3.2. Fuzzy Controller Design. The structure of the control system with the proposed fuzzy PI (FPI) controller is shown in Figure 4, where the proposed fuzzy controller is based on Sugeno's fuzzy technique.

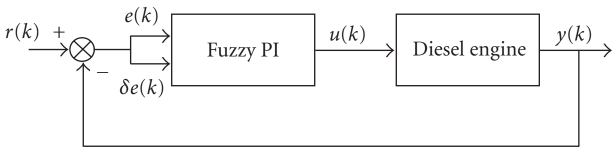

FIGURE 4: The structure of the control system with the proposed fuzzy PI controller.

The proposed fuzzy logic controller works with input signals of the system error $e(k)$. This system or tracking error is defined as the difference between the set point $r(k)$ and the plant output $y(k)$ at the sample k, or

$$e(k) = r(k) - y(k). \tag{29}$$

As shown in Figure 4, the fuzzy PI controller uses a second input signal, defined as the sum of the system errors, which is computed using

$$\delta e(k) = \sum_{i=1}^{k} e(i). \tag{30}$$

It is known from digital control theory that the most frequently used digital PI control algorithm can be described with the well-known discrete equations as follows [14]:

$$u(k) = k_p e(k) + k_i \delta e(k), \tag{31}$$

where $k_i = k_p(T_s/T_i)$, T_s is the sample time of the discrete system, T_i is the integral time constant of the conventional controller, k_p is the proportional gain, and $u(k)$ is the output control action.

The Sugeno's fuzzy rules into the fuzzy PI controller can be composed in the generalized form of "IF-THEN" composition with a premise and an antecedent part to describe the control policy. The rule base comprises a collection of K rules, where the upper index (j) represents the rule number:

$$R_j : \text{IF } \mathbf{x}(k) \text{ is } A_j \text{ THEN } f_u^{(j)}(k) = K_P^{(j)} e(k) + K_I^{(j)} \delta e(k), \quad j = 1, 2, \ldots, K, \tag{32}$$

where $e(k)$ and $\delta e(k)$ are the input variables. This way a similarity between the equation of the conventional digital PI controller 31 and the Sugeno's output function (32) could be found. In this case, the fuzzy PI controller is considered as a collection of many local PI controllers, which are represented by the Sugeno's functions into the different fuzzy rules, and this way it is possible to approximate the nonlinear characteristic of the controlled plant.

For a discrete universe with K quantisation levels in the fuzzy output, the control action $u = u_F$ is expressed as a weighted average of the Sugeno's output functions f_u and their membership degrees β_i of the quantisation levels. Also in this case, before the output can be inferred, the degree of fulfilment of the antecedent denoted by $\beta_i(\mathbf{x})$ must be computed. Thus, as for the case of (13) and (14), the degree of fulfilment is simply equal to the membership degree of the given input $\mathbf{x}$, that is, $\beta_i = \mu_{A_i}(\mathbf{x})$. By recalling the identified Takagi-Sugeno model, the inference is reduced to a simple expression, similar to the fuzzy-mean defuzzification formula [9]

$$u_F = \frac{\sum_{j=1}^{K} \beta_j(\mathbf{x}) f_u^{(j)}}{\sum_{i=1}^{K} \beta_j(\mathbf{x})}, \tag{33}$$

or by substituting the expression of the fuzzy PI terms:

$$u_F(k) = \frac{\sum_{j=1}^{K} \beta_j(\mathbf{x}(k)) \left(K_P^{(j)} e(k) + K_I^{(j)} \delta e(k) \right)}{\sum_{i=1}^{K} \beta_j(\mathbf{x}(k))}, \tag{34}$$

where the time dependence at the instant k has been highlighted.

It is worth noting that the PI controller parameters $K_P^{(j)}$ and $K_I^{(j)}$(with $j = 1, \ldots, K$) are settled according to the Ziegler-Nichols rules [14] applied to the identified local linear submodels of (22). Then, in order to obtain a quick reaction to set-point variations, gain scheduling of the fuzzy regulator parameters is performed depending on the error, as shown by (34).

The second step consists in building the fuzzy controller of (34). The input MFs $\beta_j(\mathbf{x})$ coincide with the ones of the identified TS model, as described in Section 3.1.3. The output MFs are equally spaced singletons. The number of the input MFs determines the number of rules and output MFs. In this work, the optimal number of rules K is equal to the minimal number of clusters used to identify the nonlinear diesel engine system, as recalled in Section 3.1.3. Finally, the adopted fuzzy operators are the product as AND operator, the bounded sum as OR operator, min as implication method, the Center of Gravity (COG) as defuzzification method.

4. Experimental Results

This section describes the experimentations with the method proposed for the fuzzy modelling techinque oriented to the design of the controller relying on the multiple-model approach.

As described in Section 1, theoretical models of the diesel engine air system are too complex and labor intensive for control design. The reason is that complex thermodynamic, chemical equations, and side-effects have to be taken into account. Therefore, diesel engine models are mostly experimental. In contrast to this physical modelling, dynamic fuzzy models can easily be exploited in order to represent all relevant variables influencing the diesel engine air system. Depending on the complexity of the engine, more than 5 inputs might be necessary to consider the most relevant variables concerning the air system.

Thus, the fuzzy identification procedure recalled in Sections 3.1.3, 3.1.2, 3.1.1, and 3.1 exploits the identification of a nonlinear dynamic system based on TS fuzzy models. According to this procedure, the nonlinear dynamic process can be described as a composition of several TS models selected according to process operating conditions. In particular, Section 3.1 addresses the method for the identification and the optimal selection of the local TS models from a sequence of noisy input-output data acquired from the process.

It is assumed that the monitored system, depicted in Figure 1, can be described by a model of the type given by (21). The problem considered here thus regards the fuzzy system identification on the basis of the knowledge of the measured sequences $\mathbf{u}(k)$ and $y(k)$ acquired from the input-output sensors of the considered diesel engine. As stated in Section 2.1, in general the process operates in different working conditions and the 7 measurements, including temperatures, flows, control signals, and speed can be acquired with a sampling rate $T_s = 0.1$ s. Because of the underlying physical mechanisms and because of the modes of the control signals, the process has nonlinear steady state as well as dynamic characteristics.

In more detail, the acquired inputs $\mathbf{u}(k) = [u_1(k), \dots, u_6(k)]$ and the output $y(k)$ (with $k = 1, 2, \dots, N$) of the diesel engine are summarised in the following.

u_1: engine fuelling;

u_2: engine speed;

u_3: intake air flow temperature;

u_4: engine oil temperature;

u_5: EGR command;

u_6: TVA command;

y: intake air flow (for each cylinder).

The clustering algorithm recalled in Section 3.1.1 was used and it provides an optimal number of $K = 9$ clusters (operating conditions) and $n = 2$ the number of sample delays of the inputs and outputs for a model of the type of (21). After clustering, the system structure and its parameters $\mathbf{a}_i = \{\alpha_j^{(i)}, \delta_j^{(i)}\}$, with $i = 1, \dots, K$ and $j = 1, 2$, were estimated using the Frisch scheme. The reconstructed output $y(k)$ of the plant is characterised as a TS fuzzy multiple-input single-output (MISO) model 17 with 6 inputs. As an example, the actual output measurement compared with the reconstructed signal is reported in Figure 5.

The identified model capabilities and reliability were then validated by testing it on many different separate real data sets, acquired from a Jeep Wrangler under emission test, according the European Union Driving Cycle (EUDC). This test is based on the prescribed vehicle velocity profile shown in Figure 6.

By considering different test data sequences, which consist of a number of samples $N > 30000$, Table 1 reports the Predicted PerCent Reconstruction Error (PPCRE). This performance index is defined as

$$\text{PPCRE} = 100\sqrt{\frac{\sum_{k=1}^{N} \epsilon^2(k)}{\sum_{k=1}^{N} y^2(k)}}, \tag{35}$$

where the prediction error $\epsilon(k)$ is computed as the difference between the actual diesel engine output $y(k)$ and the output from the TS fuzzy model. Since this error is normalised with respect to the output standard deviation, it can represent the percentage of data that are not correctly explained by the identified TS model. The results summarised in Table 1 indicate how the fuzzy multiple-model approximates the real process very accurately and that the composite model can serve as a reliable predictor for the real diesel engine.

Using this identified TS fuzzy prototype, a model-based approach for the diesel engine controller design can be exploited and applied to the actual process.

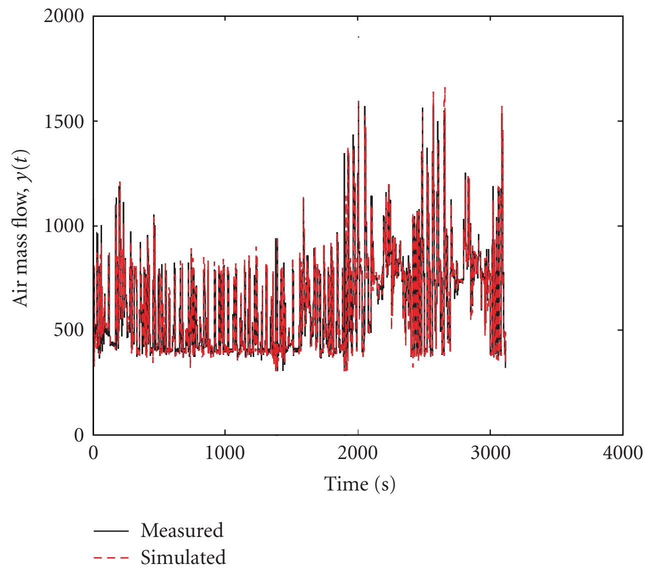

Figure 5: Compared actual and simulated intake air flow.

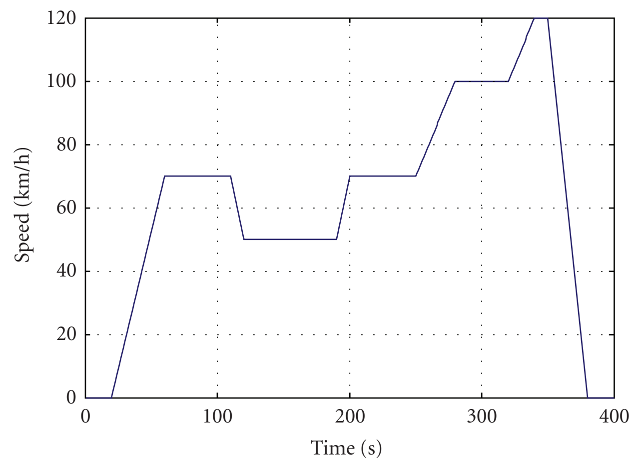

Figure 6: European Union Driving Cycle velocity profile.

Table 1: Output estimation errors of the TS fuzzy model for different data sets.

Data Set	PPCRE
Estimation data set	0.90%
Validation data set	2.80%
Test data set	4.20%

According to Section 3.2, the parameters of the fuzzy PI controllers have been computed. In particular, as the identified TS model consists of a fuzzy collection of 9 ARX MISO 2nd order ($n = 2$) models, the regulator parameters in (32) can be computed analitically.

In more detail, by considering a second-order local model described by its identified parameters $\mathbf{a}_i = [\alpha_1^{(i)}, \alpha_2^{(i)}, \delta_1^{(i)}, \delta_2^{(i)}]$ from (28), the critical gain $K_0^{(i)}$ and the critical period of oscillations $T_0^{(i)}$ required by the Ziegler-Nichols method [41] are computed from the following relations [42]:

$$K_0^{(i)} = \frac{\alpha_1^{(i)} - \alpha_2^{(i)} - 1}{\delta_2^{(i)} - \delta_1^{(i)}},$$
$$T_0^{(i)} = \frac{2\pi T_s}{\arccos \gamma^{(i)}} \quad \text{with } \gamma^{(i)} = \frac{\alpha_2^{(i)}\delta_1^{(i)} - \alpha_1^{(i)}\delta_2^{(i)}}{2\delta_2^{(i)}}. \tag{36}$$

The following relations are recommended to calculate the parameters $K_P^{(i)}$ and $K_I^{(i)}$ for the (local) ith PI controller of (32):

$$K_P^{(i)} = 0.6\, K_0^{(i)} \left(1 - \frac{T_s}{T_0^{(i)}}\right), \qquad K_I^{(i)} = \frac{1.2\, K_0^{(i)}}{K_P^{(i)}\, T_0^{(i)}}, \tag{37}$$

where T_s is the sampling time.

In the following, the suggested fuzzy PI controller and the embedded BOSCH controller have been developed and compared in the Matlab and Simulink environments.

The experimental setup employs 2 MISO fuzzy PI regulators used for the control of the EGR and TVA valves, respectively. As an example, by using the previous relations of (36) and (37), the following tuned parameter sets have been computed for the EGR valve control:

$$\left\{K_P^{(1)}, \dots, K_P^{(9)}\right\} = \{7.1, 10.2, 17.1, 20.1, 12.2, 14.3, 5.1, 8.5, 22.3\},$$
$$\left\{K_I^{(1)}, \dots, K_I^{(9)}\right\} = \{0.2, 0.15, 0.50, 0.60, 0.35, 0.40, 0.15, 0.30, 0.65\}. \tag{38}$$

In order to compare the advantages of the proposed fuzzy PI strategy, the obtained results are compared with the ones achieved by using the embedded BOSCH regulator described in Section 2.2. The embedded controller parameters were empirically tuned by the calibration engineers of the VM Motors S.p.A., and experimentally optimised on a test-bed to ensure the best controller performances.

Figure 7 reports the desired fresh air setpoint $r(k)$ (blue curve) and shows the air flow $y(k)$ from the identified TS model with the proposed fuzzy PI controller (green line), whilst the red curve is the TS model response obtained with the embedded PI-based strategy by BOSCH. As shown in Figure 7, the tracking performances achieved by the proposed fuzzy PI controller are better than the ones obtained with the standard regulator.

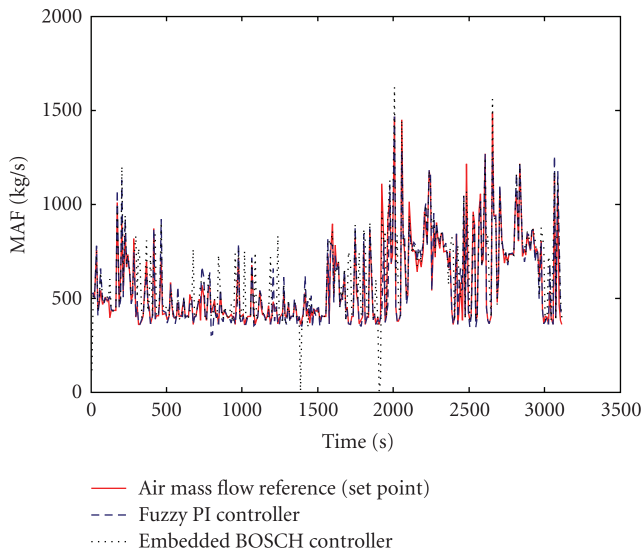

Figure 7: Responses with the fuzzy PI and the standard embedded BOSCH controllers.

Because of the lack of theoretical methods suited to such complex system, the controller robustness has been assessed in simulation by considering different data sequences, corresponding to different driving cycles on the test vehicle. This situation should correspond to the variabilities generally encountered on the engine, and due for example to variations of the engine volumetric efficiency, or turbocompressor efficiency. In Table 2, the percentage Normalised Sum of Squared tracking Error (NSSE) defined as:

$$\text{NSSE} = 100\sqrt{\frac{\sum_{k=1}^{N}\left(r(k) - y(k)\right)^2}{\sum_{k=1}^{N} r^2(k)}} \tag{39}$$

is computed for the controllers and for different data sequences. According to these simulation results, the robustness of the suggested fuzzy PI controller seems to be reached.

4.1. Real-Time Validation. Clearly, the presented fuzzy identification and model-based controller design algorithms require a considerable calculation effort. State-of-the-art Engine Control Units (ECUs) would not be able to calculate these algorithms in an appropriate time. Assuming that the growth in calculation power proceeds at the high speed of the last few years, future ECUs should make sufficient calculation time available within some years, where very simple adaptation or identification algorithms could be implemented. However, it is worth noting that the complete fuzzy modelling for control strategy suggested in this work was computed off-line.

Special real-time computer systems based on digital signal processors already allow an implementation and testing of the model-based controllers in vehicles or engine test stand. In order to operate the designed fuzzy regulator under realistic conditions, a real-time system was implemented at a dynamic engine test stand where it could be run parallel to

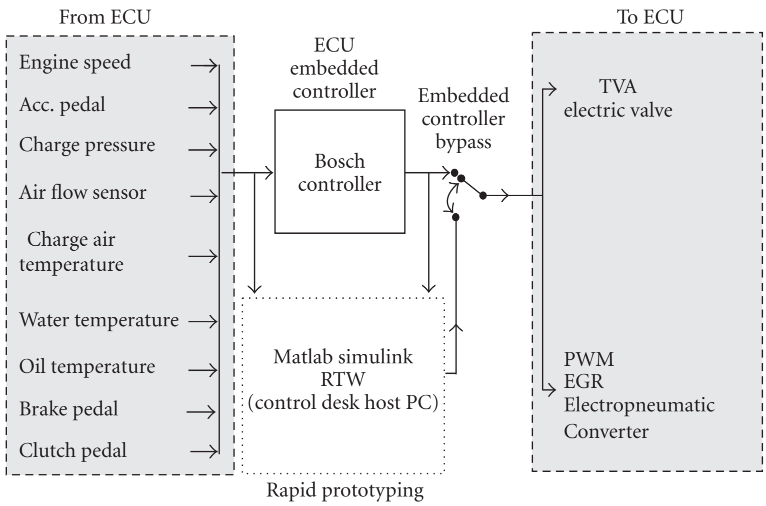

Figure 8: Integration of the real-time system with the test vehicle.

Table 2: Performances of the simulated controllers.

Data set	BOSCH controller NSSE	Fuzzy PI NSSE
Identification data set	24.70%	10.60%
Validation data set	29.80%	12.70%
Test data set	33.50%	14.70%

the production car's ECU. This system uses the production car sensors, and the input-output messages of the ECU.

The controller actuated signals, which are calculated in real-time, are then sent to the actual actuators by means of a suitable electronic interface. Thus, this system, whose logic diagram is reported in Figure 8, allows to test the capabilities of both the embedded BOSCH controller and the suggested fuzzy controller.

In this application, the test system is used as a rapid prototyping environment. The goal of this structure is to enable a very fast and easy implementation and testing of new control concepts on real-time hardware. The user is enabled to code newly developed algorithms from block diagrams via the Matlab and Simulink environments, and download the code by means of an automatic code generation software to the real-time hardware (e.g., the well-known Real-Time Workshop of Matlab). In this way, a complete design iteration can thus be accomplished very easily.

The described real-time hardware system shown in Figure 8 enables very fast and easy implementation and testing of complex control strategies, even under the harsh real-time conditions of diesel engines.

5. Conclusion

In this paper, a fuzzy modelling procedure oriented to the design of a fuzzy controller has been presented. The proposed fuzzy identification strategy relying on local linear models has the advantages of automatically finding the fuzzy model optimal structure and a straightforward estimation of the model parameters in the relatively small computation time. On the other hand, the suggested fuzzy controller allows the regulation of the intake fresh airflow without using a physical model of the diesel engine air system. Its structural simplicity and straightforward design derived from an identified fuzzy prototype distinguishes it from predictive and robust controller strategies, sometime inapplicable in standard cars. The use of the suggested fuzzy controller allowed to track with good accuracy the reference fresh mass airflow signal, thus assuring the minimisation of NO_x emissions and avoiding exhaust visible smoke. In comparison to the current PID embedded strategy developed by BOSCH, a significant improvement in desired setpoint tracking is obtained as highlighted by the experimental results obtained from real data shown in this work. In order to validate the optimization results, a real-time rapid control prototyping system was exploited, which allows the evaluation of the model-based design technique directly at the real process. Further investigations will be performed for implementing this controller in an electronic control unit and tested on an engine test-bed in order to finally assess its performances.

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