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Neuro-Hybrid Models for Automotive System Identification

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***Abstract*—**In automotive systems almost all steps concerning the calibration of several control systems, e.g., low idle governor or boost pressure governor, are made with the vehicle because the time-to-production and cost requirements on the projects do not allow for the vehicle analysis necessary to build reliable models. Here is presented a procedure using parametric and NN (neural network) models that enables the generation of vehicle system models based on normal ECU engine control unit) vehicle measurements. These models are locally valid and permit pre and follow-up calibrations so that, only the final calibrations have to be done with the vehicle.

***Keywords*—**Automotive systems, neuro-hybrid models, demodulator, nonlinear systems, identification, and neural networks.

I. Introduction

IN the automotive industry the systems of interest are almost of nonlinear nature [1]-[3]. These systems can be taken for identification using linear or nonlinear models. A linear model will not be a so good approximation as when employing a nonlinear one but makes the identification procedure a lot more simpler. It is then possible to get advantage of well proved identification tools like the least squares estimation (LSE) algorithm [4]-[5]. This algorithm is a very known algorithm for parametric models and can be also extended to provide reliable results when nonlinearities are added to models. Other way is to use nonparametric models as the series expansion (SE) or neural networks (NN) [6]-[7]. Series expansion like the Volterra expansion permits a good description of the systems dynamics, but also very attractive is the use of neural networks. This comes from the availability of tools that make it easier to identify a system from set of measurements done on that system's variables, e.g., the program Matlab with its Neural Network toolbox. Without going into details neural networks can be built on very different structures which give them the ability to approximate any function with a finite number of discontinuities.

Nevertheless the quality of the identification of a dynamic system is strongly dependent on the type of signals that are employed for that purpose. These signals must be able to excite the relevant system dynamics in a way that this information can be later extracted from the system variables and brought into the chosen model structure. This is achieved by fulfillment of the so called persistence of excitation condition, that for linear systems implies, that for one parameter models a sinus exciting signal is enough for a complete system identification. Of course, for several kinds of dynamic systems the achievement of this condition can be very difficult or impractical at least if one is seeking for a global model of the system. Help can be obtained by looking for identification strategies that take advantage of the use of local models which may also have, if necessary, different structures, i.e., be of parametric or nonparametric nature.

This possibility turns to be important when trying to model dynamic systems that are usually of interest in the automotive industry. Here to obtain the best performance of the integration engine, car body parts and auxiliary systems distinct control systems are employed and provide for the desired behavior at various motor operating points such as idle speed or full load. In these cases the encountered dynamics shows a variety of nonlinear characteristics that are better captured when utilizing local nonlinear models and this bring with it the challenge of how to perform data acquisition for identification purposes, i.e., system excitation in a local dynamic region. This is also true when analyzing the idle speed control system or idle speed governor system and it is more noticeable if one takes only into consideration the measurements that are available through the vehicle's engine control unit (ECU). A solution out of these difficulties is achieved by combining a parametric model with a nonparametric neural network model that is itself supported by a so called signal demodulator. The underlying idea is to separate linear and nonlinear dynamics when performing identification with the nonlinear dynamics described by a static map whose inputs contain transformed versions of the input of the identified system, allowing for greater retention in the model of the information available in the used measurements. This procedure will be the subject of the next paragraphs. First the concept of neuro-hybrid models will be presented and analyzed within the settings and methods normally used for system identification. After that it will be given an application example regarding an automotive system which will be followed by a conclusion.

II. System Identification with Neuro-Hybrid Models

A nonlinear dynamic system can be defined using either a state variable or an input-output representation. In any case

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and without lose of generality an input-output representation can be extended in order to distinguish between nonlinear and linear behaviors when restricting the dynamic system to some particular region of its state variables. For such regions or domains, $U_i = \{x \in \{[x_{1i_{\min}}, x_{1i_{\max}}], \ldots, [x_{ni_{\min}}, x_{ni_{\max}}]\}\}$ where x stands for the system's state variables, the output of the system, y, when the system is subjected to the input u will be given by

$$y = f_{nl}(x,u) + f_l(x)u \tag{1}$$

Taking in consideration (1) the identification of the dynamic system can be done by performing first the identification of its linear part, $f_l(x)$, using a linear model of appropriate order and then identifying its nonlinear part, $f_{nl}(x,u)$, by employing a static map. This strategy simplifies the identification procedure by allowing the choice of well known methods and models, i.e., linear parametric models together with least squares estimation algorithms and nonparametric models defined by neural networks. Nevertheless in this strategy the static map is also expected to capture all the system's dynamics that was not taken by the linear model. The fulfillment of such request is very dependent on the characteristics of the signal applied to the system's input and difficult to achieve when that signal is considered almost constant because it contains only a limited number of step changes in value. For such signals the normally used training algorithms for neural networks like the backpropagation algorithm are not able to extract enough information from its input-output vectors to reproduce accurately the relationship that exists between these two vectors. Given this fact a solution to allow for the correct learning of this relationship by the neural networks can be found having as reference the theory of Fourier regarding signal decomposition. According with this theory non-sinusoidal signals, $f(t)$, have a frequency content or spectrum, $F(j\omega)$, given by

$$F(j\omega) = \int_{-\infty}^{+\infty} f(t) e^{-j\omega t} dt \tag{2}$$

where ω represents an angular frequency and once known its spectrum it can always be reconstructed as a summation of sinus and cosine signals each of one with a magnitude defined by $F(j\omega)$, i.e.,

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(j\omega) e^{j\omega t} d\omega \cdot \tag{3}$$

So, it can be said that the information contained around an instant of time, e.g., step change of value in a signal, can be expanded in time by doing a spectrum analysis and generating the corresponding sinus and cosine signals for each frequency in the spectrum. In practical terms this can be performed by employing several filters each of them tuned for a particular frequency of the signal to be analyzed. This set of signals represents then in an unique way in time the analyzed signal.

The approach just presented is used in the identification of the nonlinear part of the dynamic system with the neural networks model becoming as its input a set of filtered versions of the system's input more the state variables of the parametric model that was identified in first place. This approach is part essential of the so called neuro-hybrid model as shown in Fig. 1 where the demodulator block has the function already mentioned of providing a set of signals that describe in a unique way the frequency content of the input signal of the dynamic system under identification.

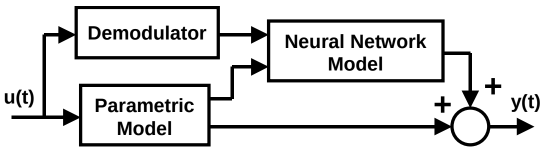

Fig. 1 Structure of a neuro-hybrid model

The neuro-hybrid model provides a flexible structure for system identification because it implements a mechanism where the system dynamics dependent on its dominant behavior and a priori knowledge can be weighed between the parametric and the neural network models. If the system dynamics is almost linear the parametric model will describe the most of it, $\hat{f}_l(\hat{x})$, with the remained dynamics given by

$$f_{error}(\hat{x},u) = y - \hat{f}_l(\hat{x})u \tag{4}$$

which will be a smooth function requiring a simple demodulator and neural network model. The opposite will happen when the system to be identified shows a strong nonlinear behavior. In any case the demodulator will generate an output vector

$$u_{dm} = [u, g_1(u), g_2(u), \ldots, g_n(u)] \tag{5}$$

where the functions, $g_i(u)$ with i = 1, …, n, can in their simplest form be taken as 1st order filters with a Laplace representation

$$G_i(s) = \frac{1}{\alpha_i s + 1} \cdot \tag{6}$$

The structure of the demodulator plays an important role in the neuro-hybrid model with the number of generated signals in its output vector directly related to the complexity of the dynamics to be approximated by the neural network, i.e., a complex dynamics requires a larger output vector than where such does not occur. The same can be stated regarding the expected similarities between the components of its output vector. For a good identification this similarity should be small and can be indirectly defined in the time domain by the so called dissimilarity index, I_{ds}, which should be as big as possible. This is in (7) formulated and if (5) is taken as reference it can be seen that $u_0 = u$ and $u_i = g_i(u)$.

$$I_{ds} = \sum_{i=0,j=0,i\neq j}^{n} \int_{-\infty}^{+\infty} \eta(u_i, u_j) \left\| (\dot{u}_i - \dot{u}_j) \right\| dt \tag{7}$$

with

$$\eta(u_i, u_j) = \begin{cases} 1 & \text{iff} \quad u_i \neq u_j \\ 0 & \text{iff} \quad u_i = u_j \end{cases}$$

The dissimilarity index, I_{ds}, can be also used to obtain information about the input signal employed to excite the dynamic system under identification. In general it can be said that a low value for this index will point out to a situation where the dynamic system is not adequately excited for identification purposes.

III. A Neuro-Hybrid Model for Idle Speed Engine Identification

The idle engine speed control system is one part essential of every vehicle control system and must be able to provide for a good engine speed regulation on different engine operating conditions such as low temperatures, gear shift and activation/deactivation of supplementary systems (air conditioning and/or heaters) without degradation of engine vibration or noise. Depending on these operating conditions the dynamic behavior of the engine changes itself in a strong way and the similar is also true regarding engine speed and load, i.e., for low engine speeds and/or loads the engine has other dynamics that when working at high engine speeds and/or loads. This latter phenomenon is very noticeable during gear shift and requires a complex structure and intensive calibration of the idle engine speed controller with the most of the calibration work usually done in the vehicle. Improvement in this calibration procedure would be achieved if a reliable engine model could be obtained from the measurements directly available on the vehicle's ECU (Engine Control Unit).

Having in mind these considerations a neuro-hybrid model is employed to describe the engine dynamic behavior during idle speed gear shift (2nd to 3rd gear). For the linear part a 2nd order discrete model was chosen and identified using a recursive least squares algorithm [8]-[9]. The remained system dynamics will be modeled by a cascade-forward neural structure with a total of 41 neurons among five layers and having an input vector with ten components. The cascade-forward neural structure was chosen because in this type of neural network there are also connections between the inputs and each of its inner layers. The implementation and learning of the neural network was done accordingly with the structure shown in Fig. 2 using the program Matlab with its Neural Network toolbox and in this case the demodulator employs seven low pass 1st order filters. This type of demodulator was chosen as a compromise between modeling accuracy, complexity and processing time.

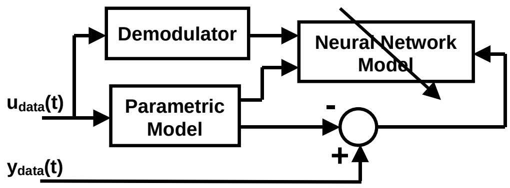

Fig. 2 Neural network training within the structure of the neuro-hybrid model for idle speed engine identification

The measurements for identification were made directly on the ECU (Engine Control Unit) of a diesel vehicle and considered the gear shift between 2nd and 3rd gears when in idle speed control. These measurements concern the torque that is calculated by the controller and the actual engine speed leaving out other influences on the vehicle such as rough roads and given so it is also expected some error between measurement and model simulation results. This error is accepted and regarded as a natural consequence of the simple resources taken to perform the system identification.

The first set of measurements was performed with a tuned idle speed controller that allows on the closed loop for a damped second order dynamic behavior. This is to be seen in Fig. 3 where first the engine speed breaks at the beginning of the gear shift and after strong intervention of the controller remains at its steady state value with small deviations that are caused by a relatively rough road. In this case the engine presents almost a linear character and the identified neuro-hybrid model is able to reproduce with a small error its dynamic behavior.

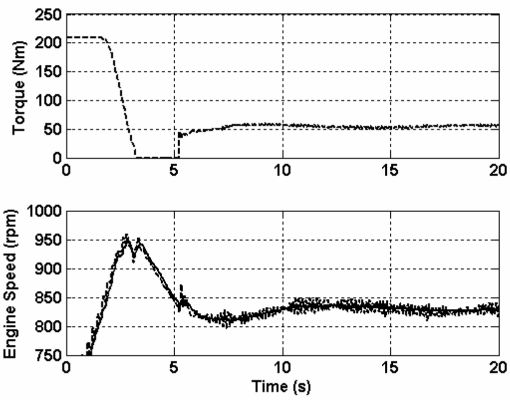

Fig. 3 Measurement (dashed line) and neuro-hybrid model simulation (solid line) results for 3rd gear shift with tuned idle speed controller

The second set of measurements considers a totally different situation. One of having a detuned idle speed controller that implements a partially on-off control behavior. In this case as documented in Fig. 4 it happens again that first the engine speed breaks at the beginning of the gear shift but after that and because of a strong controller it is not able to reach its desired steady state and enters a limit cycle that produces a permanent oscillation. In such cases the engine shows extreme nonlinear behavior but also here the identified neuro-hybrid model is able to reproduce this behavior with an acceptable error.

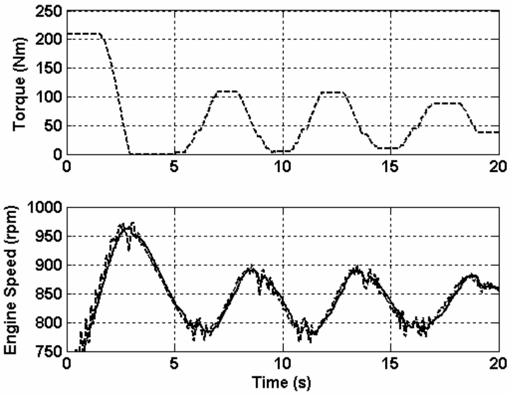

Fig. 4 Measurement (dashed line) and neuro-hybrid model simulation (solid line) results for 3rd gear shift with detuned idle speed controller

A similar analysis was performed regarding the gear shift between other gears and with other controller calibrations. In all these situations the neuro-hybrid model was able to capture the dynamics of the engine with an error that although higher when the engine showed larger nonlinear behavior was within the expected error boundaries. These boundaries are not defined by the neuro-hybrid model itself but by the set of measurements that were used for the identification.

IV. Conclusion

The concept of neuro-hybrid models provides a new tool for system modeling when it happens that the system's dynamics is only temporarily excited. In this case neuro-hybrid models are able to retain the most of the information contained among the measurements available for identification. This capability is dependent on the structure chosen for the demodulation function, e.g., type and order of the employed filters, and requires further investigation. Nevertheless it must be already stated that this type of models show great applicability potential not only in the automotive sector but overall in the industry.

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