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Wavenet using artificial bee colony applied to modeling of truck engine powertrain components

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ABSTRACT

The purpose of this paper is to validate an artificial wavelet neural network, or wavenet model, combined with artificial bee colony optimization, a swarm intelligence paradigm, to model powertrain components of a truck engine. The arrangement of artificial neural networks with wavelet based functions, called artificial wavelet neural network or wavenet (AWNN), creates a valuable tool to represent the nonlinear multivariable systems. AWNN can be considered a particular case of the feed-forward basis function neural network model. To illustrate the use of the proposed AWNN based on ABC optimization for the black-box modeling, we apply it to model a truck engine with a cubic displacement greater than seven liters. Identification results were carried out using AWNN implemented in Matlab computational environment and the model accuracy is evaluated based on performance indices. Final results were compared with Elman network, Jordan network and kernel adaptive filtering in order to check the AWNN performance. The comparison methods were tuned with the same optimization algorithm in order to find their best tuning parameters. The simulation results show that the artificial wavelet neural network approach can be useful and a promising technique in powertrain components modeling. This proposed AWNN combined with artificial bee colony approach allows modeling the dynamical behavior of powertrain components of a truck engine.

1. Introduction

Simulation techniques are becoming more present in automotive development process each day. They are not covering only single components, but frequently the system approach is observed. The automotive system complexity and the aim on high model accuracy lead to a nonlinear multivariable basis. White-box modeling is being one of the main tools used by the development engineers to represent the system interactions and laws however; the level of detail and the knowledge needed to build up models are still issues (Yu and Cheng, 2011; Cieslar et al., 2014; Maghbouli et al., 2013; Pariotisa et al., 2012). On the other hand, system identification or black-box modeling is being proved to be reliable and powerful on system representations for different classical problems.

System identification is basically the process of developing or improving a mathematical representation of a system/process on forecasting the behavior of the real system under different operating conditions. Appropriate mathematical modeling through systems identification plays a significant role in natural sciences and engineering fields including simulation, automatic control, fault tolerant analysis, forecasting, filtering, among others.

Many linear system identification methods have been developed in the past decades (Ljung, 1999; Söderström and Stoica, 1989; Wang et al., 2012) and attained a state of maturity. On the other hand, identification of nonlinear systems is a relatively new topic of interest (Haber and Unbehauen, 1990; Leontaritis and Billings, 1985; Juditsky et al., 1995; Billings, 2013). Recently, efforts have been made to solve the nonlinear identification problems and several efficient identification methods and algorithms (Gregorčič and Lightbody, 2008; Su et al., 2013; Kou et al., 2011; Tijani et al., 2014; Ko, 2012) have been proposed.

System identification approaches that range from a simple linear model to a more complicated nonlinear one are not easy to handle. In this context, the black-box modeling techniques to nonlinear identification can be useful in the automotive models on and off-board when experimental data is available. Some attempts have been made to develop nonlinear identification approaches to automotive applications. In this context, see examples in (Keen and Cole, 2012; Ye, 2007; Liu and Bewley, 2003; Zito and Landau, 2005; Wu and Liu,

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2009; Worden et al., 2001; Tan and Saif, 2000; Togun et al., 2012; Antory, 2007; Coelho et al., 2014).

Recently, natural computing techniques, such as artificial neural networks (ANNs) (Kilic et al., 2014; Gil et al., 2013), fuzzy systems (Babuška and Verbruggen, 1996; Dovžan and Škrjanc, 2010) and combined neuro-fuzzy systems (Salahshoor et al., 2012) have become effective tools of identification of nonlinear processes, especially to those systems whose mathematical models are difficult to obtain. In this context, ANNs are good on tasks such as pattern matching and classification, function approximation, optimization and data clustering. The feed-forward ANNs can approximate the behavior of an arbitrary continuous or "otherwise reasonable" function within arbitrary accuracy on a compact domain (this result is called universal approximation theorem, see details in (Tikk et al., 2003; Scarselli and Tsoi, 1998)).

Since the emergence of ANN, this field gains a great interest by the researchers and new structures of ANNs have been proposed. The artificial wavelet neural network or wavenet (AWNN), which logically connects an ANN with wavelet decomposition, is based on an ANN structure and involves the wavelet transform. The main merit of wavelet transform over Fourier transform is the ability of specifying the time–frequency position. In other words, AWNNs combine the capability of artificial neural networks in learning from processes and the capability of wavelet decomposition.

On the other hand, swarm intelligence (Eberhart et al., 2001) is a category of stochastic search optimization algorithms of natural computing field based on procedures inspired by collective behavior and emergent intelligence in natural environment. The intelligence emerges from a chaotic balance between sociality and individuality. The artificial bee colony (ABC) algorithm is one of these swarm intelligence algorithms that has shown potential and good performance for solving various optimization problems (Karaboga and Basturk, 2008). ABC algorithm, described in Karaboga (2005), is inspired from the foraging behavior of honey bee colonies include three groups of bees: employed bees, onlookers and scout bees. Recently, several ABC approaches have been proposed in optimization applications (see Zhang et al., 2012; Li et al., 2014b; Tasgetiren et al., 2013).

This paper proposed an AWNN approach combined with an artificial bee colony approach to tune the spread of wavelet functions and the maximum number of neurons of the hidden layer in the network. This work attempts to demonstrate the feasibility of adapting the proposed AWNN to model the behavior of a real truck engine in an unloaded operation. The engine is modeled in the torque and crankshaft speed generation perspectives, meaning that the multivariable system representation shall deal with at least 15 input variables and nine modeled outputs. The technique shall use as input an experimental database with around 18,000 samples. The model quality will be evaluated by using control parameters like the multiple correlation coefficient, the mean squared error, the mean absolute percentage error and the time to training of AWNN model. The final usage for this crank-resolution engine is intended to hardware-in-the-loop simulations and embedded systems where actually the CFD, white and gray models are the most common alternatives. The wavenets' outcome is also compared to three classic algorithms: Elman neural network, Jordan network and kernel adaptive filtering, KAF, in order to check their performance. Elman and Jordan networks are well-known recurrent neural networks that have been applied to dynamic modeling (Pham et al., 1999; Muldera et al., 2015; Moghaddamniaa et al., 2009). The kernel based methods are also very powerful with applications from the support vector machines up to the filtering (Constantina and Lengelléb, 2013).

Finally, the black-box model generated can be applied to engine calibration purposes, fuel consumption analysis or even for component behavior study.

The remainder of this paper is organized as follows. In Section 2, the fundamentals of system identification are described. The background of the AWNN and the proposed AWNN based on ABC tuning are summarized in Section 3. Description of case study of a real truck engine and the identification results are reported in Sections 4 and 5, respectively. Benchmarks are presented in Sections 6–8. Finally, the conclusion and further research are reported in Section 9.

2. Brief fundamentals of system identification

The input–output model is a mean of describing the dynamics of a system. System identification is the process of creating models of dynamic process from input–output signals. Nonlinear system identification, which is to estimate models of nonlinear dynamic systems from observed input–output data, is still a difficult task in practice.

In general, a good model of the system dynamics can facilitate model-based design, allowing applications of control design and analysis tools. In many practical situations, designing an appropriate model of a system/process is a challenging task due to: (i) the structural complexity and nonlinearity of the plant, (ii) the degree of unknown dynamics, typically noise and outliers associated with the system/process, and (iii) the requirement for selection of proper model structure along with the accuracy and efficiency of the learning algorithm to be used for tuning/training (Baghel et al., 2011).

In general, the procedure of identification adopted is summarized by the following steps:

Step (i) Design an experiment to obtain the process input/output data sets pertinent to the model application.
Step (ii) Examine the quality of measured data, removing trends and outliers.
Step (iii) Determine a class of models and construct a set of candidate models based on information from the experimental data sets (or simulation data sets). This step is the model structure identification.
Step (iv) Select a particular model from the set of candidate models and estimate the model parameter values using the experimental data sets (or simulation data sets).
Step (v) Evaluate how good the model is using a performance criterion. This step is the validation of the modeled system.
Step (vi) If a satisfactory model is still not obtained in Step v then repeat the procedure either from Step (i) or Step (iii), depending on the problem.

3. Artificial wavelet neural networks

This section presents an overview of the wavelet transform and its features. After, we present in details the AWNN design and the proposed AWNN model based ABC tuning

3.1. Wavelet transform

Among almost all the functions used for approximating arbitrary signals or functions, none has had such an impact and spurred so much interest as wavelets. Multiresolution wavelet expansions outperform many other approximation schemes and offer a flexible capability for approximating arbitrary functions. Wavelet basis functions have the property of localization in both time and frequency. Due to this inherent property, wavelet approximations provide the foundation for representing arbitrary functions economically, using just a small number of basis functions. Wavelet algorithms process data at different scales or resolutions. Wavelet analysis is based on a wavelet prototype function, called the analyzing wavelet, mother