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Nonlinear identification via connected neural networks for unsteady aerodynamic analysis

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A R T I C L E I N F O

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A B S T R A C T

In the present work, a nonlinear system identification strategy is proposed which is based on the series connection of a recurrent local linear neuro-fuzzy model (NFM) and a multilayer perceptron (MLP) neural network. The NFM with output feedback is initially used for multi-step ahead predictions, whereas the MLP neural network is a posteriori employed to perform a nonlinear quasi-static correction of the NFM's time-series response. The novel identification approach is utilized exemplarily as a reduced-order modeling (ROM) technique to lower the computational effort of unsteady aerodynamic simulations, although the approach is generally applicable to any nonlinear identification task. In order to demonstrate the method's fidelity for unsteady aerodynamic modeling, the NLR 7301 airfoil is investigated at transonic flow conditions, while the motion-induced aerodynamic forces are considered in particular. Therefore, the pitch and plunge degrees of freedom are simultaneously excited via forced motions to obtain the training data for model calibration, while the respective aerodynamic response is computed using a computational fluid dynamics (CFD) solver. The sequential nonlinear identification process as well as the generalization of the resulting model is presented. Besides, a Monte-Carlo-based training procedure, which is novel in the context of aerodynamic reduced-order modeling, is introduced to estimate statistical errors. It is shown that the essential linear and nonlinear system characteristics are accurately reproduced by the new approach compared to the full-order solution. Moreover, by examining the results in comparison to established ROM methods it is indicated that the connected neural network approach leads to an enhanced simulation and generalization performance.

1. Introduction

In the last decades, significant progress has been made in the research fields of system identification and model-order reduction, which is of tremendous importance for many scientific and engineering applications. In general, identification approaches are employed to obtain a mathematical model by processing known input/output data of the underlying system, whereas the objective of reduced-order models (ROMs) consists in lowering the computational effort or the memory requirements with respect to the solution of known equations. Nonetheless, black-box system identification can be also applied to realize a model-order reduction [1–3], which is the methodology followed in this work. Linear systems as well as their identification have been extensively studied and can be considered nowadays as well understood [4]. In contrast, the analysis and identification of nonlinear systems still remains a challenging task [5,6]. As the homogeneity and additivity principles can not be applied in general, the response becomes amplitude-dependent which may lead to bifurcations [7], limit-cycle oscillations (LCOs) [7–9], or even a chaotic behavior of the system [6]. Furthermore, instability of the identified nonlinear models is frequently encountered for time-marching simulations (multi-step ahead predictions) due to the output feedback and associated error accumulations [4,5]. For specific applications, the identified model may be also expected to reproduce both linear and nonlinear system characteristics depending on the operating regime, frequency bandwidth, and/or amplitude range. Hence, a variety of algorithms and approaches have been developed to cope with the difficulties of nonlinear function approximation and nonlinear identification. In the following, without any claim to comprehensiveness, some important nonlinear identification methodologies are recapitulated.

Historically, the convolution integral and impulse response approaches known from linear systems have been extended yielding for example the well-known Volterra series models [6,10]. However, the determination of the higher-order kernels becomes exhaustive which restricts the application of Volterra-series-based

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Nomenclature

ANN	Artificial neural network
APRBS	Amplitude-modulated pseudo-random binary signal
ARMA	Auto-regressive with moving average
ARX	Auto-regressive with exogenous input
CFD	Computational fluid dynamics
LA	Large-amplitude
LCO	Limit-cycle oscillation
LLM	Local linear model
LM	Levenberg–Marquardt
LOLIMOT	Local linear model tree
MC	Monte-Carlo
MISO	Multiple-input single-output
MLP	Multilayer perceptron
MUSCL	Monotonic-upstream-scheme-for-conservation-laws
NARMAX	Nonlinear auto-regressive moving-average with exogenous inputs
NARX	Nonlinear auto-regressive with exogenous input
NFM	Neuro-fuzzy model
NLR	Netherlands aerospace center
POD	Proper orthogonal decomposition
PRBS	Pseudo-random binary signal
RANS	Reynolds-averaged Navier–Stokes
RBF	Radial basis function
ROM	Reduced-order model
SA	Small-amplitude

models to weakly nonlinear problems [11]. Besides, block-oriented models such as Wiener and Hammerstein models or their respective permutations have been widely employed by numerous authors [5,6]. Thereby, a linear dynamic block is followed or preceded by a nonlinear static function approximation block. Nonetheless, block-oriented models must fit to the underlying structure of the investigated system, e.g., exhibiting linear dynamic dependencies only. Hence, they cannot be utilized for any general nonlinear identification purpose. Subsequently, approaches based on neural networks such as the multilayer perceptron (MLP) neural network [12,13,5] or the radial basis function (RBF) neural network [14,5] as well as Kriging interpolation [15] have been devised. They perform a nonlinear mapping from provided input/output data sets and can, therefore, be applied to identification tasks. Although neural networks are powerful tools for accurate, high-dimensional predictions, they are prone to simulation instabilities due to their function extrapolation characteristics [5]. The approximation of nonlinear functions by means of piecewise linear models, i.e., several blended linear models which are active in limited regimes of the model input space, is another possible approach followed by various researchers [5,6]. A popular method from this branch is the local linear model tree (LOLIMOT) algorithm that can be employed for the estimation of a local linear neuro-fuzzy model [5,16].

Focusing on aerospace applications in particular, which constitute the intrinsic motivation of the present research, computationally involved investigations such as multidisciplinary design optimizations and aeroelastic analyses must be performed. Therefore, efficient and accurate methods are required to obtain the unsteady flow-induced forces caused by gust loads or self-excited motions [17,1]. In this regard, the system embodied by the Euler or Reynolds-averaged Navier–Stokes (RANS) equations is to a large extent well-understood and a priori known. However, due to the high-dimensional parameter space spanned for instance by different freestream conditions, configuration set-ups, and excitation frequencies, the effort of comprehensive computational fluid dynamics (CFD) simulations is still not manageable using the currently available computing capacities. For this reason, CFD-based training data are exploited by means of linear or nonlinear identification techniques to obtain a reduced-order model of the aerodynamic system. Following this methodology, the unsteady aerodynamic forces can be obtained with sufficient accuracy, whereas the ROM-based simulations are carried out within a fraction of time compared to the full-order CFD solution process [16,18]. Recently, active research efforts led to several ROM concepts related to fluid–structure interaction (FSI) problems and unsteady aerodynamic applications. In the following, a brief summary of the context-related identification methodologies is given.

Various unsteady aerodynamic ROM methods originating from linear identification principles are proven to yield accurate and reliable results for small structural perturbations, i.e., for a linear relation between the flow quantities and the excitation. Examples are the eigensystem realization algorithm [19] applied by Silva and Bartels [20] as well as Fleischer and Breitsamter [21], the auto-regressive with moving average (ARMA) model utilized by Raveh [22], and the auto-regressive with exogenous input (ARX) model of Zhang and Ye [23]. Furthermore, approaches based on the proper orthogonal decomposition (POD) [24] have been proposed by Hall et al. [25], Lucia et al. [26], and Iuliano and Quagliarella [27]. The fundamental idea of the POD-based methods is a reduction of the system's degrees of freedom by extracting a comparatively small set of POD modes based on steady or unsteady flow field data. In order to capture the dynamics of large amplitude motions, varying freestream conditions, or separated flows, a nonlinear aerodynamic identification is required for accurate analyses. Even with state-of-the-art approaches, however, this is still challenging and often a non-robust task. Many nonlinear models that are based for example on MLP neural networks [28,29] or RBF neural networks [30–32] have been successfully applied to reproduce the dominant aerodynamic characteristics. Moreover, ROMs based on Kriging interpolation have shown the ability for accurate air load prediction [33]. The aforementioned nonlinear-function-approximation-based methods exhibit a high precision with respect to one-step prediction problems. However, multi-step ahead predictions often become unstable due to the feedback of the model outputs [4,31,34]. The methodologies for unsteady aerodynamic applications proposed by Winter and Breitsamter [16,35] use a neuro-fuzzy model instead, which is less prone to simulation instabilities due to the use of local linear sub-models. Moreover, the NFM based on the LOLIMOT algorithm has been successfully applied for aeroelastic predictions across a range of freestream conditions. Additionally, combinations of the POD with nonlinear identification approaches have been introduced by Lindhorst et al. [36] as well as Winter and Breitsamter [18] in order to gather information about the time-varying surface pressure distribution in contrast to solely considering integral forces and moments. Nonetheless, local linear NFMs are not very accurate if the system is governed by strong nonlinearities or if both linear and nonlinear behavior needs to be captured with a single model. Recently, Kou et al. [34] and Kou and Zhang [37] suggested the use of Wiener-type models and layered ROMs to obtain models valid for small and large amplitude motions. Considering the current diversity of approaches, a major drawback is still maintained. Either the investigations are limited to linear dynamic effects by means of a restricted model structure, or the models are likely to become unstable.

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