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A probabilistic study of the robustness of an adaptive neural estimation method for hysteretic internal forces in nonlinear MDOF systems

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ABSTRACT

The Volterra/Wiener neural network (VWNN) has been shown to be an effective tool for on-line estimation of non-linear restoring forces and responses. However, the power of the VWNN for on-line identification has not been fully harnessed due to the high sensitivity of its parameters. This study adopts a *probabilistic* approach in examining the effects of the VWNN's parameters on the robustness and stability of its estimation capabilities. Large ensembles of simulations were conducted in which random (earthquake-like) ground motions were used to excite representative non-linear structures, and on-line estimation of their acceleration responses was performed. The nonlinearity in the system was introduced via hysteretic restoring forces, and a variety of cases were tested, including softening and hardening.

The results showed that each design parameter within the VWNN was linked to a certain type of performance sensitivity. The adaptive gain that controls the change in the weights of the VWNN was also directly linked to the stability of the estimates, as small increases in the gain led to the estimates diverging. Within the neural network, the weight within the transfer function was found to directly correlate with accuracy. The optimum set of parameters for a given excitation often produced unstable solutions for other excitations, but by understanding the relationships between the parameters and their sensitivities, a set of parameters could be carefully chosen to consistently produce accurate and stable on-line estimates for all simulations. The knowledge gained from the relationships between VWNN parameters also allowed for informed decisions on parameter sets for simulations involving different classes of nonlinearities. Offering users a starting point provides a necessary and helpful feature so often missing from other non-linear identification schemes that deal with non-parametric identification of complex nonlinear systems.

1. Introduction

Modeling and identification of non-linear phenomena is of great importance to several fields of engineering, especially structural dynamics and applied mechanics. Nonlinear hysteretic behavior is commonly encountered in buildings and other structures that are subjected to earthquake excitation, in the joints of aerospace structures, and in other vibration problems with mechanical systems. Hysteresis and nonlinear behavior have been the subject of numerous previous studies, including the development of models for bilinear hysteresis [1], yielding structures [2], degrading systems [3,4] and other hysteretic systems and structures [5–10]. Many models have been used for capturing nonlinear dynamical systems, including single-valued models [11], distributed element models [12], Masing models [13], modal models [14], Leuven models for frictional force [15] and wavelets [16]. A helpful survey of Bouc–Wen hysteretic models [17], a particular class of nonlinear models, may be found in [18]. These models have continued to advance [19–23], better capturing the complexities of different nonlinearities, such as pinching and degrading.

Several different approaches have been adopted for identification of nonlinear systems. The approaches include stochastic linearization techniques [24,25], nonparametric methods using polynomial basis functions [26–28], identification using the H_∞ filter [29], optimization algorithms [30,31] and neural networks [32,33]. The Bouc–Wen, in particular, has seen its parameters estimated via nonlinear optimization schemes [34], Bayesian state estimate with bootstrap filters [35], adaptive on-line methods [36–39], and applications of the extended Kalman filter (EKF) [40] and the unscented Kalman filter [41]. Recent developments in nonlinear identification include the use of state-space models [42,43], auto-regressive (AR) models [44], nonlinear regression models

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[45] and cellular automata nested neural networks [46]. A helpful review of nonlinear identification in structural dynamics may be found in [47].

Within the realm of nonlinear identification, on-line identification schemes are of paramount importance because they allow for the incorporation of flexible controller strategies that adapt with the structure, as structures that behave nonlinearly may only exhibit their governing response properties when excited by strong motions. While there have been several developments in on-line nonlinear identification [37,38,48,39,41,49], one of more versatile methods involves the use of adaptive neural networks. Specifically, an adaptive approach that utilizes Volterra/Wiener neural networks (VWNNs) has been shown to be a highly effective estimator of nonlinear responses [50]. Most importantly, the adaptive VWNN estimator operates without requiring measurements of the restoring forces; only measured responses are needed. These qualities have led to the incorporation of the VWNN into embedded sensor networks [51] and into other adaptive identification schemes [52].

While highly effective, the "black box" nature of neural networks, including the VWNN, often obscures the target system characteristics and leaves the user without much control. A helpful analysis of the adaptive VWNN estimator was presented in [53], but a broader study was still needed to provide unfamiliar users access to the internal workings of the VWNN. This paper presents an in-depth and probabilistic view of the VWNN in a variety of non-linear identification applications, in order to provide a greater understanding of sensitivities of the VWNN design parameters as they relate to stability and robustness.

2. Problem background

For illustration, consider the chain structure with n degrees-of-freedom (DOFs) shown in Fig. 1; for the case of a more generic structural system, readers are directed to the work in [50]. This structure may be excited by ground motions x_g, external forces f_i, and control forces u_i, where i represents the given DOF. The external forces and control forces are directly applied to DOFs at which the responses are measured. The connections between the DOFs may be generally described by the restoring forces r_j, which capture the possible nonlinear behavior.

The equation-of-motion for the ith DOF may be written as shown in Eq. (1), where m_i and $\ddot{x}_i$ are the mass and acceleration of the ith DOF, respectively, π^r_{ij} is the connectivity of the restoring forces, $\ddot{x}_g$ is the ground acceleration, and n_e describes the number of restoring force elements:

$$m_i\ddot{x}_i + \sum_{j=1}^{n_e} \pi^r_{ij} r_j = f_i + u_i - m_i\ddot{x}_g \quad i = 1, \ldots, n \tag{1}$$

The values for the connectivity in π^r_{ij} are defined in the following equation:

$$\pi^r_{ij} = \begin{cases} +1 & \text{if the } j\text{th restoring element applies a positive force to the } i \\ & \quad \text{th degree–of–freedom} \\ 0 & \text{if the } j\text{th restoring element applies no force to the } i \\ & \quad \text{th degree–of–freedom} \\ -1 & \text{if the } j\text{th restoring element applies a negative force to the } i \\ & \quad \text{th degree–of–freedom} \end{cases} \tag{2}$$

Using the form shown in Eq. (1), the equations of motion for a chain structure with three DOFs may be written as shown in the following equation:

$$m_1\ddot{x}_1 + r_1 - r_2 = f_1 + u_1 - m_1\ddot{x}_g \tag{3a}$$

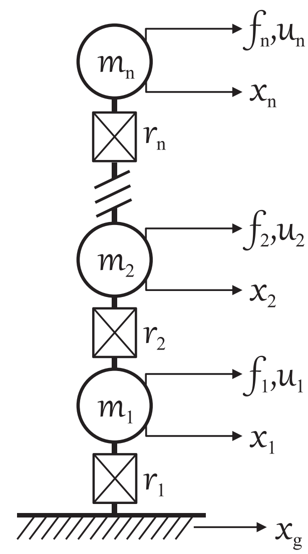

Fig. 1. Multi-Degree-of-Freedom chain structure.

$$m_2\ddot{x}_2 + r_2 - r_3 = f_2 + u_2 - m_2\ddot{x}_g \tag{3b}$$

$$m_3\ddot{x}_3 + r_3 = f_3 + u_3 - m_3\ddot{x}_g \tag{3c}$$

Displacements and velocities do not appear explicitly in the equations of motion because they are not directly available from measurements, as it is generally assumed that only the response accelerations may be measured. Additionally, it is often assumed that ground accelerations may be measured as well. The equations of motion may be re-written to reflect this, as shown in the following equation:

$$\ddot{x}_1 = \frac{1}{m_1}\left(-r_1 + r_2 + f_1 + u_1\right) - \ddot{x}_g \tag{4a}$$

$$\ddot{x}_2 = \frac{1}{m_2}\left(-r_2 + r_3 + f_2 + u_2\right) - \ddot{x}_g \tag{4b}$$

$$\ddot{x}_3 = \frac{1}{m_3}\left(-r_3 + f_3 + u_3\right) - \ddot{x}_g \tag{4c}$$

2.1. Nonlinear restoring force

The restoring forces r_j may possess nonlinear hysteretic characteristics. The general dynamics of the restoring forces may be described by the differential equation given in Eq. (5), where $\mathbf{r}$, $\mathbf{x}$, and $\dot{\mathbf{x}}$ are vectors for the restoring force, displacements, and velocities, respectively:

$$\dot{r}_j = Q_j\left(\mathbf{r}, \mathbf{x}, \dot{\mathbf{x}}\right) \quad j = 1, \ldots, n_e \tag{5}$$

The function Q_j describes a nonlinear continuous function that captures the nonlinear hysteretic effects. In this study, a Bouc–Wen model [10] was used, as shown in Eq. (6), where q_j represents the relative displacement of element j:

$$r_j = kq_j + c\dot{q}_j + dq_j^3 - \int_0^t (1/\eta)\left[\nu\left(\beta|\dot{q}_j||r_j|^{n-1}r_j - \gamma\dot{q}_j|r_j|^n\right)\right]dt \tag{6}$$

3. Identification

From the perspective of the neural network, the individual terms in Eq. (6) are ignored because no particular model is