August 27-31, 2023
FLORENCE - ITALY
16th International Conference on Wind Engineering
ICWE 16

Enhancing the analysis of galloping instability by Artificial Neural Networks

Fabio Rizzo [1], Luca Caracoglia [2], Giuseppe Piccardo [3]

[1]*Polythecnic University of Bari, Bari, Italy, fabio.rizzo@poliba.it*
[2]*Northeastern University, Boston, Massachusetts 02115, USA, lucac@coe.neu.edu*
[3]*University of Genoa, Genoa, Italy, giuseppe.piccardo@unige.it*

SUMMARY:
Although the evaluation of the critical galloping conditions is apparently very simple for 1 degree-of-freedom systems (whose expression is reported by many codes and guidelines), it actually hides pitfalls due to the uncertainty inherent in practically all the parameters involved, in particular in the static aerodynamic coefficients (besides the structural damping ratio). Furthermore, if one intends to evaluate the possible non-linear behaviour of the system, as occurs in energy harvesting problems, the uncertainties explode since high-order derivatives are needed to adequately describe the aerodynamic force coefficient. An Artificial Neural Network algorithm, suitably trained on simulated experimental data, appears to be a possible tool for providing more reliable evaluations of critical conditions and non-linear responses. The authors intend to investigate the benchmark case of the square section with sharp and rounded corners, on which many experimental, wind tunnel data are available. A preliminary example of numerical simulation results concerning galloping critical velocity is presented and compared against the theoretical solution.

Keywords: galloping analysis, aerodynamic load variability, Artificial Neural Networks

1. INTRODUCTION AND AIM

Galloping is an important aeroelastic phenomenon that can be either detrimental to a low-damped, slender structure or possibly exploited for energy harvesting purposes (e.g., Hémon et al., 2017). Even though the classical galloping theory is based on the quasi-steady approach (e.g., Païdoussis et al., 2011), the application of which may be questionable in many real cases, it remains a widely used analysis approach by engineers and it is present in all design standards (e.g., CNR, 2019; EN 1991-1-4, 2010). Moreover, the quasi-steady aerodynamic theory has been usually considered acceptable to study this phenomenon for a variety of structures, since the earliest studies (e.g., Parkinson and Smith, 1964; Novak, 1972) until the latest applications as a wind-based harvester (e.g., Zhang et al., 2021). Galloping usually manifests itself as a strong transverse self-excited oscillation triggered above a critical wind velocity threshold, and results from the detrimental effects of the transverse (*often* vertical) components of the lift and drag forces acting on the body. Aerodynamic forces produce a negative aerodynamic damping effect that can nullify the total damping available. Therefore, galloping is a (wind) velocity-dependent, damping-controlled instability problem (Païdoussis et al., 2011).

The propensity to galloping instability is governed by the static aerodynamic coefficients and their derivatives with respect to an initial angle of attack, which coincides with the mean-wind incoming flow direction in the classic Den Hartog criterion. Reliable estimate of the force coefficients, only possible by wind tunnel tests for most body shapes, is essential for a correct assessment of the galloping conditions. Unfortunately, several uncertainties exist. They arise either from simplified external flow conditions, experimental estimation errors or structural damping predictions (Pagnini et al., 2017), besides modelling approximations of the static coefficients (e.g., Ng et al., 2005). For example, flow conditions affect the galloping onset through turbulence intensity (and scale), and air density. Structural properties can be either accurately determined, such as the fundamental frequency of the transverse mode, or poorly assigned, such as the structural damping (inherently random). Aerodynamic parameters can be either inferred by extrapolation using measures carried out on similar body shapes or found by specific wind tunnel tests. In all cases, uncertainty analysis is necessary to characterize the sensitivity to the galloping onset, especially those variables resulting from the selection of the aerodynamic coefficients, either associated with experimental wind tunnel errors, or extrapolation of their values from design standards, which often recommend very scattered values even for a cross section as simple as a square. Uncertainty analysis also needs the use of stochastic (or perturbation) methods or Monte Carlo sampling, both of which are not ideal for preliminary design since they require computationally expensive dynamic analysis, either at incipient instability or to predict the post-critical vibration ranges.

The purpose of this study is to explore the use of Artificial Neural Networks (ANNs) to enhance galloping analysis by simplifying and replacing closed-form solution to the incipient galloping critical velocity. Various polynomial approximations of the transverse static force coefficient can be considered to describe the aerodynamic force. The case of the square section prism is examined since a comprehensive collection of experimental data is available and may be used to derive suitable polynomial approximations along with their variability. This study is the first step towards future implementation of post-critical, nonlinear dynamic analysis using ANN-based approaches.

2. BACKGROUND ON GALLOPING INSTABILITY

The classical solution to galloping instability can be recast into a reduced-order model describing the transverse motion (with respect to mean wind direction) through an *equivalent* one degree-of-freedom system. The model can be interpreted as a generic structural mode of a more complex structural system. The critical galloping instability can be conveniently expressed in terms of dimensionless quantities through dynamic similarity; the dimensionless equation of the galloping critical velocity U_{cr} [m/s] is:

$$U_{cr}/(n_0 B) = 2\,\mathrm{Sc}\Big/\left\{-\left(\frac{dC_L}{d\alpha} + C_D\right)_{\alpha=\alpha_0}\right\} \quad (1)$$

where the reduced critical velocity $U_R = U_{cr}/n_0 B$ is proportional to the Scruton number $\mathrm{Sc} = 4\pi m\,\zeta_0/\rho B^2$. In the previous equation ρ is the air density, B is a reference width of the cross section, m is an equivalent mass per unit length, n_0 is the fundamental frequency of the transverse mode involved, ζ_0 is the modal structural damping ratio; $C_D(\alpha)$ and $C_L(\alpha)$ are the drag and lift static aerodynamic coefficients at mean angle of attack $\alpha = \alpha_0$, or mean flow direction referred to incipient instability. The necessary condition for galloping to occur is that $\{(\mathrm{d}C_L/\mathrm{d}\alpha + C_D)_{\alpha=0}\} < 0$ (Den Hartog's criterion). The quantity $[(dC_L/d\alpha) + C_D]_{\alpha=\alpha_0}$ is the first-order Taylor expansion of the quasi-static transverse force coefficient $C_{F_y}(\alpha) \approx -[(dC_L/d\alpha) + C_D]_{\alpha=\alpha_0}(\alpha - \alpha_0)$ about an initial angle α_0, which may not be exactly zero but still close to it. This condition is possible at full scale because of the inherent variability in the wind direction compared to a hypothetical initial angle $\alpha_0 \approx 0$. A polynomial expression has been proposed to represent the force coefficient C_{F_y} at various mean-wind incidence angles α since the pioneering works on galloping (e.g., Parkinson and Smith, 1964):

$$C_{F_y} = A\left(\frac{\dot{y}}{U}\right) + B\left(\frac{\dot{y}}{U}\right)^3 + C\left(\frac{\dot{y}}{U}\right)^5 + D\left(\frac{\dot{y}}{U}\right)^7 + E\left(\frac{\dot{y}}{U}\right)^9 + F\left(\frac{\dot{y}}{U}\right)^{11} \tag{2}$$

Eq. (2) can be applied to galloping since the velocity of the transverse vibration $\dot{y}$ is related, through dimensionless velocity quantity $\dot{y}/U$, to instantaneous dynamic angles of attack α. If the initial condition $\alpha_0 = 0$ is exact, A is only necessary for critical condition assessment, unless a flatter C_{F_y} curve is found experimentally, with $A \approx 0$ and B being the first significant term. This remark is clearly connected to the avenues of uncertainty, previously described. The galloping condition in Eq. (1) is even more uncertain if $\alpha_0 \neq 0$ (slightly) and the previous expression is used to predict the first derivative of C_{F_y}. Furthermore, Eq. (1) is only approximate if $\alpha_0 \neq 0$ (Nikita and Macdonald, 2014); this can lead to additional errors in the estimation of galloping threshold if A in Eq. (2) is used to express the C_{F_y} term.

3. PROPOSED METODOLOGY

The ANN (e.g., Rumelhart and McClelland, 1987; Hornik at al., 1989) is a computer algorithm that imitates the behavior of brain synapses through interconnected "neurons" to reconstruct the nonlinear relationship between a set of independent input variables x_k and output variables y_i. ANN neurons are organized in an input layer, hidden layer(s), and an output layer. Each neuron in each layer is connected to each node of an adjacent layer. Hidden layers result from calculations using the input layer and outcomes are propagated to the next layer. The output layer is the final calculation result. The generic input-output calculation makes use of a transfer or "activation" function $\mathrm{g}(.)$ between adjacent layers. If a three-layer ANN is used (Fig. 1) the following equation can be used to predict the generic output y_i (with $i = 1,2,\ldots,N_o$), accounting for all synapses originating from all the inputs x_k (with N_i number of inputs):

$$y_i = \mathrm{g}\left[\sum_{j=1}^{N_h}\left(w_{ij}\mathrm{g}\left(\sum_{k=1}^{N_i} v_{jk}x_k + \theta_{vj}\right) + \theta_{wi}\right)\right] \tag{3}$$

In the previous equation w_{ij} are "connective weights" between any two nodes in the hidden and output layers; v_{jk} are "connective weights" between any two nodes in the input and hidden layer; θ_{vj} and θ_{wi} are bias terms; the symbols, N_i, N_h, and N_o represent the numbers of nodes in the input, hidden and output layers, respectively; g is a transfer (or activation) function. An ANN model can be employed for predictions only after calibration of the hyperparameters, which is carried out using an existing set of input-output data. The calibration is usually carried out in three steps: training, validation and testing. In this study, the training of the ANN is performed through a standard back-propagation algorithm that involves error minimization. More specifically, the variables x_k with $N_i > 1$ are the Scruton number Sc, an estimation of the initial, mean-wind incidence angle α_0 (equal or close to 0), the order of the polynomial used to approximate C_{F_y} by Eq. (2) and the coefficients A through F of the polynomial approximation. The output variable y_i with $N_o = 1$ is the reduced critical velocity $U_{cr}/(n_0B)$.

4. DISCUSSION AND OUTLOOK

The study will examine several ANN architectures (i.e., number of hidden layers and their neurons) for the prediction of $U_{cr}/(n_0B)$ by varying the order of the polynomial used to describe Eq. (2). Two section geometries will be investigated: a theoretical shape of a square cylinder with sharp edges, and a more realistic body shape with rounded edges. Experimental data on square cylinders and the approach proposed by Pagnini et al. (2017) will be used to derive the coefficients A to F that describe the static coefficients in Eq. (2) along with their uncertainty. Information from a previous investigation on ANN methods applied to aeroelastic instability will be considered (Rizzo and Caracoglia, 2020). Fig. 1a illustrates a typical ANN architecture with one hidden layer. Fig. 1b presents a preliminary example of numerical simulation results; $U_{cr}/(n_0 B)$ is predicted by an ANN model "1-30-1" ($N_i = 1, N_h = 30, N_o = 1$) and is compared against the theoretical solution in Eq. (1) by suitable variation of Sc (i.e., from 30 to 40, to keep the quasi-steady theory valid) and A within a typical range (i.e., from 3 to 4; e.g., Ng et al., 2005). ANN prediction gives a relative error of less than 1%.

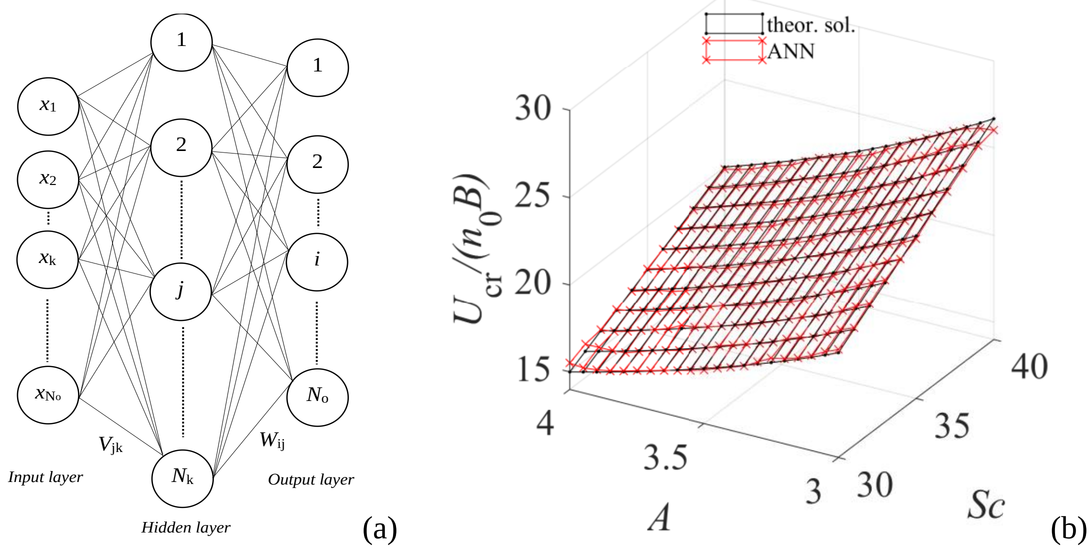

Figure 1. (a) Typical ANN architecture with one hidden layer, (b) square-prism galloping analysis with ANN-based model: Sc and A coefficient *vs.* galloping critical reduced velocity $U_{cr}/(n_0 B)$.

REFERENCES

CNR, 2019. Guide for the assessment of wind actions and effects on structures – CNR-DT 207 R1/2018, National Research Council of Italy, Rome (in Italian).

EN 1991-1-4, 2010. Eurocode 1: Actions on Structures – Part 1.4: General Actions – Wind Actions. CEN, European Committee for Standardization, Brussels.

Hémon P., Amandolese X., Andrianne T., 2017. Energy harvesting from galloping of prisms: A wind tunnel experiment. Journal of Fluid and Structures, 70, 390-402.

Hornik K., Stinchcombe M., White H., 1989. Multilayer feedforward networks are universal approximators. Neural Networks, 2, 359-366.

Nikitas N., MacDonald J.H.G., 2014. Misconceptions and generalizations of the Den Hartog galloping criterion. J. Eng. Mech.-ASCE, 140(4), 04013005.

Novak M., 1972. Galloping oscillations of prismatic structures. Journal of Engineering Mechanics Division, 8692, 27-46.

Ng Y.T., Luo S.C., Chew Y.T., 2005. On using high-order polynomial curve fits in the quasi-steady theory for square-cylinder galloping. Journal of Fluid and Structures, 20, 141-146.

Pagnini L.C., Freda A., Piccardo G., 2017. Uncertainties in the evaluation of one degree-of-freedom galloping onset, European Journal of Environmental and Civil Engineering, 21:7-8, 1043-1063.

Païdoussis M. P., Price S. J., De Langre E., 2011. Fluid-Structure Interactions, Cambridge University Press, New York, NY, USA, ISBN 978-0-521-11942-9.

Parkinson, G.V., Smith, J.D., 1964. The square prism as an aeroelastic non-linear oscillator. Quarterly Journal of Mechanics and Applied Mathematics 17, 225–239

Rizzo F., Caracoglia L., 2020. Artificial Neural Network model to predict the flutter velocity of suspension bridges. Computers and Structures, 233 (2020) 106236.

Rumelhart D. E., McClelland J. L., 1987. Parallel distribution processing: explorations in the microstructure of cognition: foundations. MIT Press.

Zhang M., Abdelkefi A., Yu H., Ying X., Gaidai O., Wang J., 2021. Predefined angle of attack and corner shape effects on the effectiveness of square-shaped galloping energy harvesters. Applied Energy, 302, 117522.