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Deep-Learning Assisted Finite Element Model of a Galloping Piezoelectric Energy Harvester

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ABSTRACT

One challenge in modelling a galloping piezoelectric energy harvester (GPEH) is the representation of the highly nonlinear aerodynamic force. The existing work in the literature employed various polynomial functions to fit the aerodynamic coefficient curve for simplicity, though their approximation capabilities are limited. In this paper, we propose to use the deep-learning technique to capture the aerodynamic force behaviour of a bluff body. Replacing the widely adopted third-order polynomial function by a well-trained artificial neural network (ANN) for aerodynamic force representation in modelling a GPEH, the feasibility of the proposed approach is preliminarily validated. To further improve the modelling accuracy, the electromechanical structure of the GPEH is then modelled using the finite element method. The trained ANN is integrated with the established finite element model to predict and update the aerodynamic fore applied on the bluff body in the real-time simulation. The aeroelastic motion and the electrical output of the galloping piezoelectric energy harvester are successfully predicted. Finally, based on a collection of experimental data, a well-trained artificial neural network (ANN) is proved to behave with a much better curve fitting performance than a third-order polynomial function. General procedures for using the deep learning technique to help model a general GPEH with complex geometric shapes are proposed.

Keywords: Deep learning; Artificial neural network; Finite element model; Galloping; Energy harvesting; Piezoelectric

1. INTRODUCTION

Wind energy harvesting has been increasingly attracted research interests in recent years [1, 2], as wind is a ubiquitous energy source that is renewable and has a much smaller impact on the natural environment. Unlike large-scale wind power generation using turbine plants, wind energy harvesting hereinafter refers to the technology of harnessing small-scale energy from wind-induced vibrations.

Wind-induced vibrations include galloping [3-7], wake galloping [8, 9], flutter [10], and vortex-induced vibration [11, 12]. Galloping has been extensively explored for energy harvesting since galloping-induced limit-cycle oscillation exhibits a large amplitude and takes place over a wide range of wind speeds. Most of the galloping energy harvesters proposed by researchers in the existing literature employed piezoelectric transduction to convert galloping-induced vibration into electrical energy due to the ease of implementing piezoelectric transducers [13-18]. A typical galloping piezoelectric energy harvester (GPEH) could be obtained by attaching a bluff body to the free end of a piezoelectric cantilever beam. Due to the aeroelastic coupling between the elastically mounted bluff body and the wind flow, an

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aerodynamic force is generated as the external excitation applied onto the GPEH. Therefore, once the electromechanical structure of the piezoelectric cantilever beam is determined, the aerodynamic force behaviour, which depends on the geometric profile of the bluff body, plays the dominant role in affecting the energy harvesting performance of the GPEH. According to the comparative study by Yang *et al.* [19], among various bluff bodies with different cross-sectional profiles, a square-sectioned bluff body could lead to the best energy harvesting performance. From the perspective of modifying the bluff body's aerodynamic behaviour, researchers have devoted efforts to improve the energy harvesting performance of GPEHs [20, 21].

In the studies of galloping energy harvesting, a significant challenge lies in predicting and representing the aerodynamic force [22]. An accurate representation of the aerodynamic behaviour is of great importance for predicting the energy harvesting performance of a GPEH. However, there still lacks a pure analytical method to derive the aerodynamic behaviour of a bluff body. According to the literature review, researchers usually interpreted the aerodynamic behaviour of a bluff body into various polynomial fitting functions based on the data from experiments [23] or CFD simulations [24]. Due to the concise form of third-order polynomial function, it has been widely adopted as the empirical formula for describing the aerodynamic force. Javed *et al.* [22] pointed out that choosing different polynomial expressions might lead to completely different results, in particular the bifurcation type. How to accurately represent the aerodynamic force remains a big issue in the modelling of GPEH.

Deep learning based on artificial neural networks (ANNs) has been proved to possess the ability to reproduce and model highly nonlinear processes based on a collection of discrete data without the requirement to understand the underlying physical mechanism. Hence, it has a wide application in various disciplines [25-28]. According to the study by Javed *et al.* [22], it is known that regardless of using polynomial functions of any order, there always exists a non-ignorable error in fitting the experimentally obtained aerodynamic behaviour curve. In this paper, artificial neural networks are proposed to be used to address the issue mentioned above. The rest of the paper is organized as follows. In the second section, an overview of the typical galloping piezoelectric energy harvester is provided. The third section briefly explains the working principle of artificial neural networks. The application of the artificial neural network is demonstrated in modelling a GPEH based on an SDOF representation. In the fourth section, the trained ANN is integrated with a finite element model of the GPEH to improve the prediction accuracy. In the fifth section, for a collection of experimental data from the literature, the curve fitting capabilities of the artificial neural network and a widely used third-order polynomial function are compared. Deep learning-assisted modelling procedures of a GPEH are summarized. A potential future work is proposed. Finally, remarks are concluded in the last section.

2. SYSTEM OVERVIEW

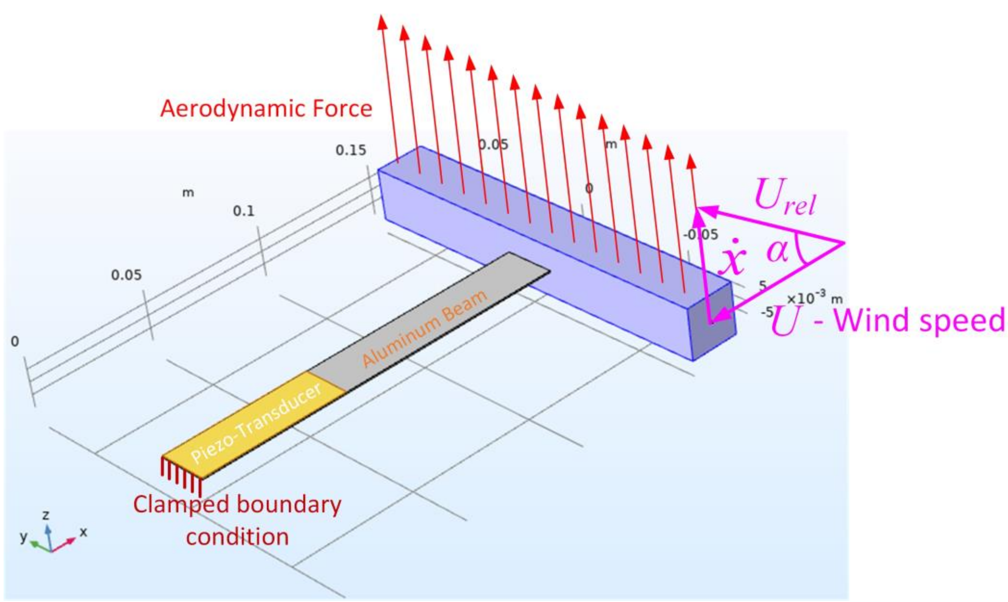


Figure 1. Schematic of the galloping piezoelectric energy harvester.

Figure 1 shows the schematic of a typical galloping piezoelectric energy harvester. It is obtained by attaching a bluff body at the free end of a piezoelectric cantilever beam. The cross-section profile of the bluff body could be square, rectangle, triangle, and D-shaped [19]. In this study, a square-sectioned bluff body is used, as its relevant information could be easily found in lots of related literature. The substrate material of the piezoelectric cantilever beam is assumed to be aluminium. The piezoelectric transducer is bonded at the clamped end of the cantilever beam, where the beam bears the largest mechanical stress during the vibration. The whole system is placed in a wind environment. The wind flow is in the negative *x*-direction, i.e., perpendicular to the beam thickness direction and parallel to the beam length direction. The bluff body subjected to the wind flow suffers an aerodynamic force due to the aeroelastic interaction. The aerodynamic force applied on the bluff body is in the *z*-direction, as sketched in Figure 1. When the wind speed exceeds a critical value, aeroelastic instability may occur, and the GPEH would conduct self-excited vibration. The parameters of the GPEH under investigation in the following case studies are listed in Table 1. The piezoelectric material parameters are from the reference [29]. The damping ratio of the GPEH around its fundamental natural frequency is assumed to be 0.008.

Table 1. System parameters of the galloping piezoelectric energy harvester.

Host Beam			
Length	150 mm	Material density	2700 kg/m^3
Width	20 mm	Young's modulus	70 GPa
Thickness	0.6 mm	Poisson's ratio	0.3
Tip Mass (Bluff Body)			
Length	150 mm	Material density	166.6 kg/m^3
Width	20 mm	Young's modulus	900 MPa
Thickness	20 mm	Poisson's ratio	0.3
Piezoelectric Transducer			
Length	60 mm	Material density	3825 kg/m^3
Width	20 mm	Young's modulus	23.3 GPa
Thickness	0.2 mm	Poisson's ratio	0.3
Piezoelectric constant d_{31}	-174 pC/N	permittivity ε_{33}^{S}	1.3281×10^{-8}F/m

For simplicity, researchers often represent a GPEH as a single-degree-of-freedom (SDOF) model. The accuracy of the SDOF representation approach has been validated in the literature. For the system parameters listed in Table 1, using the formulas derived in [30, 31], we can calculate the equivalent lumped parameters of the system as: m_1=11.08 g, k_1 = 30.96 N/m, c_1 = 0.0094 Ns/m, θ = 1.7079×10^{-4} V/N, C_p = 79.69 nF. As the third-order polynomial function is relatively concise and exhibits a sound goodness-of-fit within the range of small wind attack angles, it has been widely adopted in the literature as an empirical formula for representing the galloping aerodynamic force. Using the third-order polynomial function to describe the aerodynamic force, the governing equations of the GPEH can be written as:

$$\begin{cases} m_1\ddot{x} + c_1\dot{x} + k_1 x + \theta V = F_a = \dfrac{1}{2}\rho U^2 LDC_y = \dfrac{1}{2}\rho U^2 LD\left[a_1\alpha - a_3\alpha^3\right] \\ C_p\dot{V} + \dfrac{V}{R} = \theta\dot{x} \end{cases} \tag{1}$$

where x is the displacement of the bluff body; F_a is the aerodynamic force applied on the bluff body; ρ is the air density; L is the bluff body length; D is the side length of the bluff body's cross-section; a_1= 2.3 and a_3 =18 are the linear and the cubic coefficients of the third-order polynomial function [22], respectively; V is the voltage across the load resistor R, which is assumed to be 10^{12} Ω; α is the wind attack angle, as schematically illustrated in Figure 1. When the GPEH undergoes small amplitude vibration, the wind attack angle could be expressed as:

$$\alpha = \frac{\dot{x}}{U} \tag{2}$$

3. NEURAL NETWORK FOR PREDICTING AERODYNAMIC FORCE

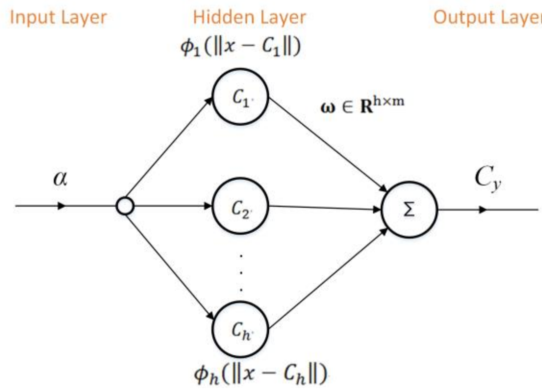


Figure 2. Architecture of a 3-layered artificial neural network with a single input and a single output.

Inspired by the neurons in a biological brain, artificial neural networks (ANNs) are computing systems that consist of a collection of connected nodes. ANNs can reproduce and model highly nonlinear processes. Thus, they have wide applications in various areas such as pattern recognition [32], system identification [33], and nonlinear function fitting [34], and intelligent control [35]. In this paper, we propose to use an artificial neural network to accurately capture the aerodynamic force behaviour, i.e., establishing an authentic nonlinear relationship between the lateral force coefficient and the wind attack angle.

Figure 2 shows the architecture of a 3-layered artificial neural network for predicting the aerodynamic force in our study. The input neuron is indirectly connected to the output neuron through the hidden neurons. A weight property depicts the connection strength between two neurons. The neurons in the hidden layers are mathematically represented by a series of activation functions, i.e., nonlinear functions ϕ_i. The signal received by the output neuron is computed by aggregating the values produced from the hidden neurons. The establishment process of an ANN model includes setting the number of the hidden neurons, selecting appropriate activation functions, and determining the weight properties of the connections between the neurons. The last step usually refers to the training of ANNs. Various algorithms have been developed to realize the training. The backpropagation (BP) algorithm is one of the most widely used ones. According to the BP algorithm, the inputs first propagate forward, and the outputs are generated. Subsequently, the generated outputs are compared with the authentic ones. The errors between them are calculated and, in turn, propagate backward. The connection strengths, i.e., weight properties, are calibrated to reduce the errors. The process of adjusting the connection weights is repeated until the resultant ANN fits the training data well, i.e., errors between the predicted and actual outputs become sufficiently smaller than the tolerance.

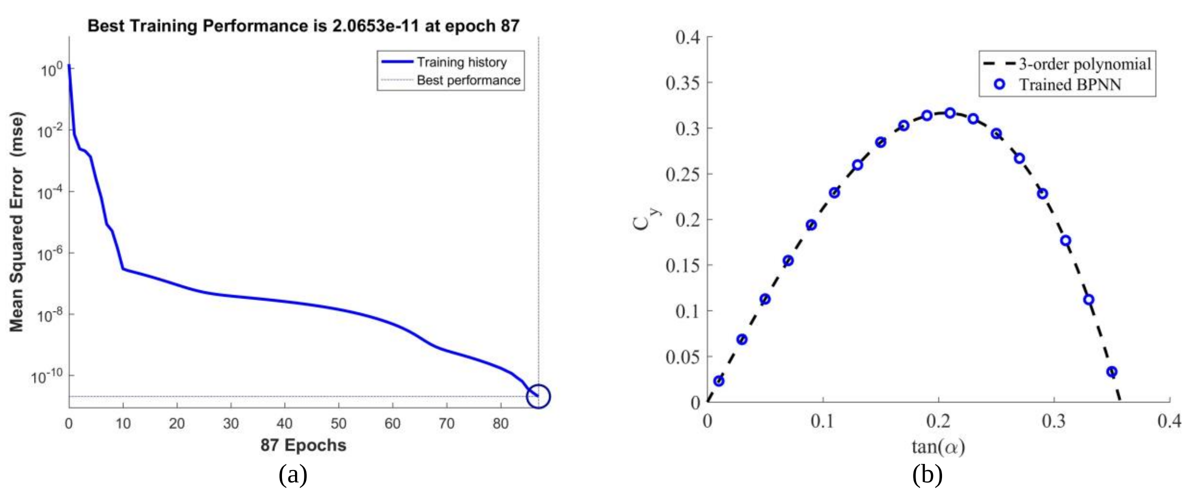


Figure 3. (a) Training performance history of the artificial neural network; (b) the prediction performance of the trained backpropagation neural network (BPNN) in terms of the aerodynamic force coefficient represented by the third-order polynomial function [22].

In our case study, the input is the wind attack angle α, and the output is the lateral force coefficient C_y. The hidden layer is designed to consist of eight neurons. The Bayesian regularization backpropagation algorithm is used for training the ANN. Figure 3 shows the prediction performance of the trained BPNN by taking the third-order polynomial function as the baseline reference. It is noted that as the nonlinearity of the third-order polynomial function is relatively 'simple', the fitting performance of the trained BPNN is extremely well: the mean squared error is only about 2.1×10^{-11}.

Subsequently, we replace the aerodynamic force term, i.e., the third-order polynomial function on the right-hand side of the first equation in Eq.(1), by the trained BPNN. In fact, the superiority and the powerful strength of using a BPNN can be demonstrated in learning a highly nonlinear aerodynamic force behaviour that any polynomial functions could not accurately capture. The following numerical example is only for validating the feasibility of the proposed methodology, mainly from the perspective of integrating the trained BPNN and the electromechanical model of a piezoelectric energy harvester.

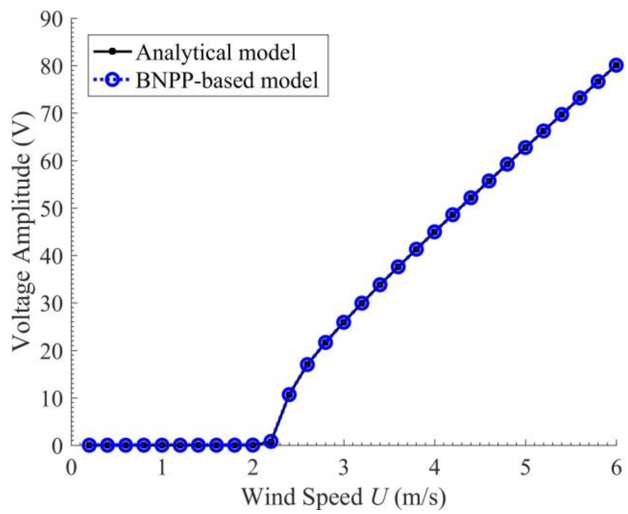


Figure 4. The relationships between the voltage amplitude and the wind speed predicted by the SDOF model using the third-order polynomial function to describe aerodynamic force (referred to as the analytical model) and the SDOF model using the trained BPNN to describe aerodynamic force (referred to as the BPNN-based model).

Figure 4 shows the relationship between the voltage amplitude produced by the GPEH and the wind speed. The solid black line with point markers denotes the result predicted by the analytical model that refers to the SDOF model using the third-order polynomial function to describe aerodynamic force. The dotted blue line with circle makers denotes the result predicted by the BPNN-based model that refers to the SDOF model using the trained BPNN to describe aerodynamic force. In Figure 4, a good agreement between both results is observed. The cut-in wind speeds predicted by both models are about 2.2 m/s.

4. DEEP LEARNING-ASSISTED FINITE ELEMENT MODEL

The electromechanical structure of the specific GPEH investigated in this study is relatively simple. However, a general GPEH might be designed based on a more practical structure with a complex geometric shape, for which the analytical model is difficult to be developed. To address this issue, the finite element method could be used as a universal approach to model the electromechanical structure of a general GPEH. COMSOL is a commercial finite element (FE) software that enables users to fast conduct multi-physics simulations. Thanks for the COMSOL LiveLink for Matlab, we can develop a BPNN using the Matlab program, then call the Matlab script of the trained BPNN in COMSOL simulation. During each simulation time step, the motion information of the bluff body is first transmitted to the BPNN. The aerodynamic force applied on the bluff body is timely predicted and updated by the trained BPNN according to the real-time motion information. By appropriately controlling the simulation time step and the computation tolerance, the simulation is supposed to converge.

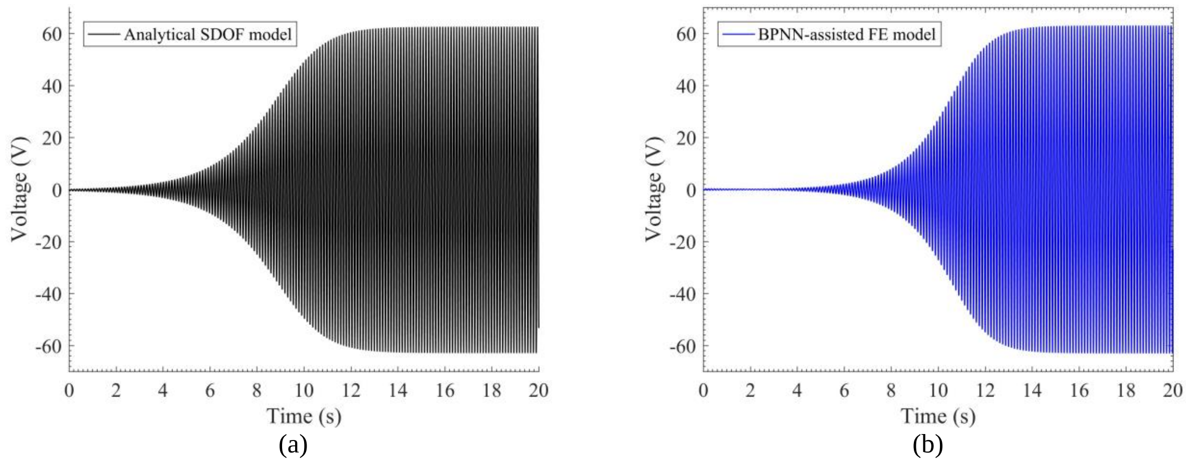


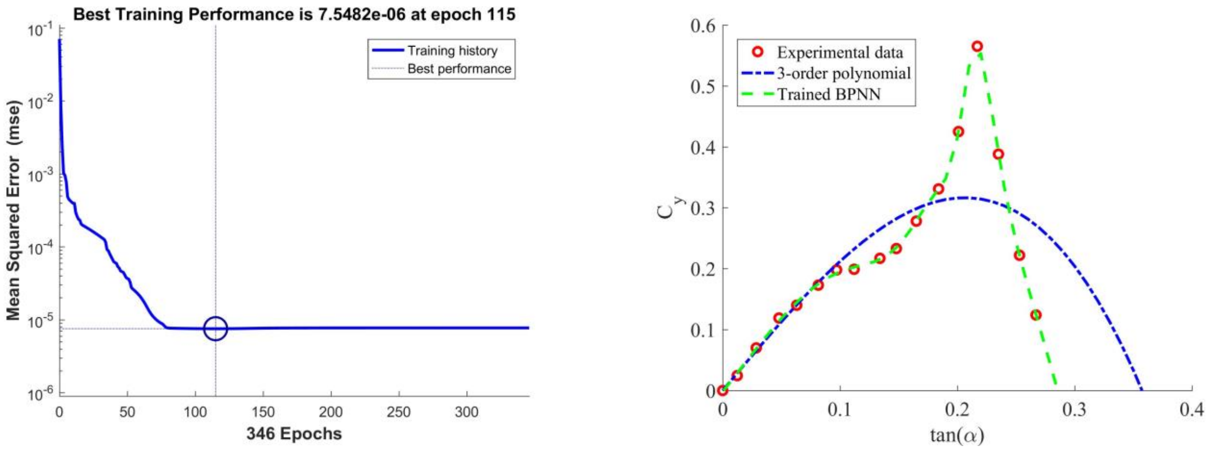
Figure 5. Under the wind speed of 5 m/s, the time-history voltage response of the GPEH modelled by (a) the SDOF model using the third-order polynomial function to predict the aerodynamic force, and (b) the FE model using the trained BPNN to predict the aerodynamic force.

For the given GPEH, a corresponding finite element model, as shown in Figure 1, is built using COMSOL. We simulate the time-history response of the GPEH under the wind speed of 5 m/s. Figure 5.(a) and (b) show the corresponding results predicted by the analytical and FE models, respectively. It is worth noting that the analytical model uses the third-order polynomial function to predict the aerodynamic force. Instead, the FE model uses the trained BPNN to predict the aerodynamic force. When the self-excitation oscillation reaches the steady state, the voltage amplitudes of the GPEH predicted by the analytical and FE models are, respectively, about 62.59 V and 63.02 V. It can be found that the predictions by both models are almost the same. In fact, the prediction of the FE model should be more accurate since there exist simplifications/assumptions in the analytical SDOF model. For example, the SDOF model assumes the bluff body as a lumped mass only and neglects the moment of inertia property of the bluff body. A more rigorous model by considering the moment of inertia of the bluff body for such kind of GPEH can be referred to [2]. Since the moment of inertia of the bluff body is neglected, the SDOF model overestimates the fundamental natural frequency of the GPEH. As we assume the damping ratio of the GPEH around the fundamental resonant frequency to be a constant of 0.008. The damping coefficient of the SDOF model is thus also slightly overestimated. This explains why the analytical SDOF model predicted voltage amplitude is slightly smaller than the FE result. Nevertheless, the feasibility of the proposed BPNN-assisted FE modelling approach is validated. Though the electromechanical structure of the GPEH investigated in the above case study is simple, the proposed approach can be universally applied to model other GPEHs with complex geometric shapes.

5. SYSTEMATIC FRAMEWORK AND PROSPECTIVE WORK

As mentioned in the introduction, the representation of the aerodynamic force is of great importance in the modelling of the GPEH. In the existing literature, researchers usually first obtain the lateral force coefficient relationship by experiments or CFD simulations. The experimental/simulation results contain only a series of discrete data. To get an explicit equation that can describe the relationship between the lateral force coefficient C_y and the wind attack angle α, high-order polynomial functions are used for curve fitting. However, the curve fitting performance is often unsatisfactory using any type of polynomial functions [22].

Take the experimental data for a square-sectioned bluff body given in [22] as an example, we demonstrate the use of an ANN for the aerodynamic force behaviour prediction. The red circles shown in Figure 6.(b) represent the experimental data, which are used as the training data. The training set contains 17 samples. Without modifying the architecture of the BPNN, Figure 6.(a) presents the training history. It can be seen that after 115 epochs, the training performance converges. The mean squared error of the trained BPNN is just about 7.5×10^{-6}. Figure 6.(b) compares the trained BPNN with the conventional third-order polynomial function (i.e., $C_y = 2.3\alpha - 18\alpha^3$ [22]) for fitting the experimental data. It can be visually observed that the trained BPNN fits the experimental data much better than the third-order polynomial function, especially when α is large.



(a) (b)

Figure 6. (a) Training performance history of the artificial neural network; (b) the prediction performance of the trained backpropagation neural network (BPNN) in terms of the aerodynamic force coefficient revealed by the experimental data [22].

As we have obtained a BPNN that can accurately capture the aerodynamic force behaviour revealed by the experimental data, we can then integrate the BPNN with traditional approaches to model the GPEH. Figure 7 illustrates the proposed BPNN-assisted modelling procedures of a GPEH. First, for the aerodynamic force behaviour, one can get the relevant data by experiments or computational fluid dynamics (CFD) simulations. The experimental/simulation data can then be fed to BPNN for training. Unlike the aerodynamic problem, there exist various rigorous modelling approaches of traditional piezoelectric energy harvesters, such as the analytical modelling approach (including single-degree-of-freedom method, distributed parameter method, etc.), the finite element modelling approach, etc. By bridging the trained BPNNs and traditional electromechanical models of the piezoelectric energy harvester, they could exchange information in real-time. According to the motion information of the electromechanical model, the BPNN could predict the aerodynamic force applied on the bluff body. The computation is supposed to converge through an iteration process and by controlling the simulation step. In this way, both the aeroelastic motion and the electrical output response are expected to be finally predicted. As currently there lacks first-hand experimental data of the energy harvesting performance of the specific GPEH, this part of validation study would constitute a potential future work.

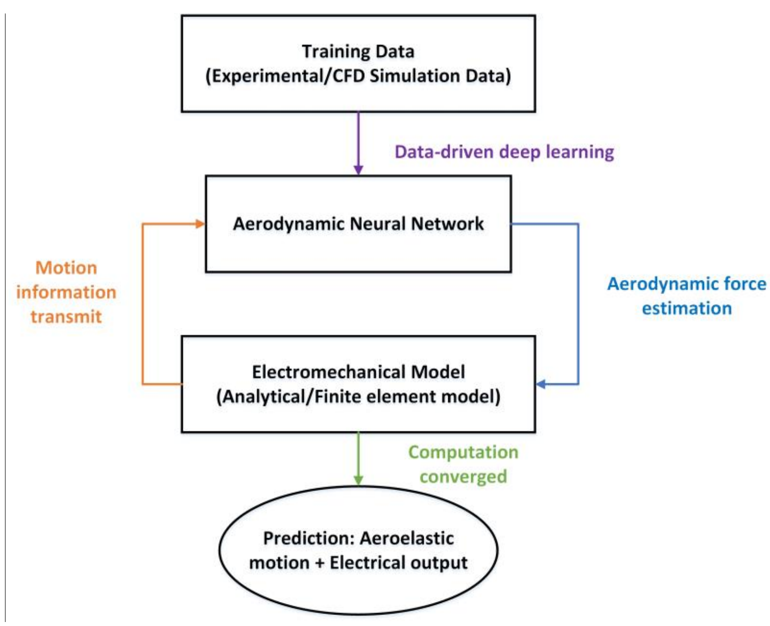


Figure 7. Deep learning-assisted modelling procedures of a galloping piezoelectric energy harvester.

6. CONCLUSIONS

This paper has proposed a deep-learning assisted approach for modelling galloping piezoelectric energy harvesters (GPEHs). By integrating a trained artificial neural network (ANN) with the electromechanical model of the GPEH, it could assist in predicting the aerodynamic force applied on the bluff body in real-time numerical simulation. A case study based on the SDOF representation of the GPEH has preliminarily validated the feasibility of the proposed method. Subsequently, the trained ANN is integrated with the finite element model of the GPEH built in COMSOL. Real-time information exchange is realized between COMSOL and Matlab. As compared to the SDOF representation-based model, the prediction by the deep-learning (i.e., ANN) assisted finite element model is expected to be more accurate and provides a universal approach for modelling GPEHs with complex geometric shapes. Finally, an ANN has been trained based on a collection of experimental data from the literature. As compared to the conventionally used third-order polynomial function, the curve fitting performance of the trained ANN has exhibited a significant improvement. General procedures of establishing deep learning-assisted models of GPEHs have been proposed.

ACKNOWLEDGEMENTS

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