

Neural Network based Surrogate Optimization Tool for Design of Improved FIV Energy Harvester

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Abstract— Machine learning-based optimization employs model-based algorithms to find the best possible solution to engineering problems, often by iteratively improving a system or process. Neural networks are common machine learning techniques in many applications due to their several advantages, such as model-free estimation and generalization abilities. Neural networks have proven highly effective across various domains but require careful design, tuning, and training to yield optimal results for specific tasks. Recurrent Neural Networks (RNNs) are powerful tools for processing sequential data, offering flexibility and effectiveness in capturing dependencies over time. The present study uses an RNN-based optimization study to find the optimal parameters for improving the energy harvesting capability of coupled vortex-induced vibration and galloping-based laminated composite beam energy harvesting system. For this purpose, the effect of wind velocity, the coupling coefficient of vortex-induced vibration (VIV) and galloping, the cutting angle of the bluff body, the wake angle behind the bluff body, diameter to length ratio, and height to length ratio of the bluff body are considered on the output voltage. The system is composed of a laminated smart cantilever beam on which piezoelectric materials are attached for energy harvesting purposes, and at the free end of the beam, a bluff body is attached. It is found that the RNN-based particle swarm optimization method is efficient in finding the optimal parameters of the system.

Index Terms— Recurrent neural network, Flow-induced vibration-harvesting, Galloping, Optimization

I. INTRODUCTION

Recurrent Neural Network (RNN) is a type of Neural Network that uses the output from the preceding step as the input for the current step. Conventional neural networks operate on the basis of independent inputs and outputs. However, in situations when the prediction of a sentence's next word necessitates knowledge of the sentence's previous words, it is necessary to retain this prior knowledge. With the use of a Hidden Layer, RNN was able to resolve this problem and come into being. The primary and most significant characteristic of an RNN is its Hidden state, which retains some sequence-related information. Because the state retains memory of the prior input to the network, it is also known as Memory State. It uses the same parameters for every input and performs the same task on all inputs or hidden layers in order to produce the output. This reduces the parameter complexity compared to other neural networks.

Artificial intelligence (AI) refers to the ability of computers or inanimate things with computer software to think

and behave like people. AI study focuses on the decision-making, learning, reasoning, and problem-solving processes of the human brain. AI is a broad field that seeks to build machines with intelligence [1]. AI has a subfield called machine learning (ML) that identifies and learns various patterns in data sets [2]. By definition, machine learning (ML) is an AI application that does not require implicit programming and enables systems to learn on their own and get better with time [3, 4]. Neural networks, support vector machines, decision trees, random forests, logistic regression, and many other techniques are frequently used in machine learning. In addition, there are alternative subnetworks within the neural network, including the generative adversarial network (GAN) [5,6]. A hierarchy of concepts in a topic is used in the deep learning (DL) approach to help a computer learn from experience [7]. This method has been applied mostly in the fields of genetics, medicine, and voice or visual object identification [8, 9]. An artificial neural network (ANN) with multiple hidden layers is the foundation for a family of deep learning (DL) and machine learning (ML) techniques known as neural networks. A few examples of the several neural network implementations that exist with just slight structural variations include artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN) [10–11]. In certain fields, such as self-driving cars, unmanned aerial vehicles, and intricate deep learning issues, innovative neural network techniques are favoured over machine learning due to their feature engineering and decision bounds. [12]. Two algorithms are used to find the best binary schedules: the binary PSO and the binary BSA algorithm [13,14]. In addition to overcoming local minima traps, these algorithm strategies include strong optimization capabilities, a fast convergence for the solution, and a search and exploration process. Additionally, the optimal performance under various load situations is ensured by constructing an improved ANN-based BBBSA and ANN-based BPBSO schedule controller [15,16]. An ANN is a promising prediction method for determining optimal weight values for neural nets intended for high-performance system operation.

It is now more difficult for emerging nations to meet their energy needs with traditional fossil fuels due to the fast development of human society in recent decades, along with scientific and technological advancements. Additionally, the earth's ecological environment has suffered greatly as a result of an excessive reliance on fossil fuels. Due to this, researchers have shown interest in producing clean, renewable, and dependable energy sources. Hydrogen, solar, tidal, and wind energy are some of the examples of these energy sources [17,18]. In day-to-day life and industrial applications, the use of intelligent technology is very important, and nowadays, they have shown a great demand. Therefore, the use of MEMS and wireless network systems is more prominent [19, 20]. Because of its compact size and low power consumption requirements, MEMS has emerged as a critical continuous power supply issue [21]. Although energy collecting at low wind speeds is still in its early stages, numerous researchers are actively investigating methods to successfully harvest energy at low wind speeds since this is a common and endlessly renewable energy source in the environment [22]. An efficient strategy is to use FIV energy harvesting technology to continuously power MEMS and wireless sensors because it converts the kinetic energy of natural fluids into electrical energy. This generates electricity that is viable, dependable, clean, and sustainable.

The entire vibration process might be altered to get beyond the restrictions of the reducing zone to enhance energy harvesting capability if the vibration mode could switch from vortex-induced vibration (VIV) to alternate modes. The range at which galloping operates is unbounded from the perspective of vibration modes, and the range of wind speeds that can be utilized for energy harvesting is likewise greater than VIV [23]. Therefore, research work is going on to change the mode of vibration of bluff bodies. Thus, bluff bodies are attached to the VIV-based piezoelectric energy harvesting systems to change the vibration mode from VIV to galloping. When a Y-shaped bluff body is used, the mode of vibration changes from VIV to galloping, which leads to improved energy harvesting capability of the system [24]. Similarly, Hu et al. [25] also combined galloping with VIV mode and found that the efficiency of energy conversion improved significantly. In the experimental study, they attached two small rods to the bluff body of a cylindrical shape to improve the energy harvesting efficiency. Therefore, to improve the energy harvesting potential of the system, the VIV mode of vibration can be combined with galloping. However, the effect of galloping is not prominent at low wind speed compared to VIV and gradually improves when VIV reaches the lock-in region. Therefore, energy can be harvested efficiently at low and high wind speeds by combining both these modes, and the range of wind speed can be broadened for energy harvesting systems [26]. In the present study, the objective is to demonstrate the use of the neural network to find the optimal parameters of a mechanical energy harvester for improving the output harvested voltage. A coupled vortex-induced vibration and galloping-based mechanism with a laminated composite beam energy harvesting system are designed using an RNN-based particle swarm optimization technique. The energy harvesting system is composed of a laminated smart beam attached with piezoelectric patches both at the top and bottom of the beam, and a bluff body is attached at the free end of the beam. The wind is blown over the bluff body surface, and vibrations of the beam are converted

to electrical form. Various parametric studies are conducted, and training data for the neural network is prepared. Further, after the network is trained properly, an optimization problem is attempted.

II. MODELLING OF HARVESTER

The schematic diagram of the system is shown in Fig. 1. A cylindrical bluff body is attached at the end of a laminated composite cantilever beam of length L , depth h_s , and width w . Piezoelectric patches are attached on both sides of beam near to the fixed end. Fig.1 (b) shows the equivalent single degree of freedom model of the system with wind load acting at a speed U .

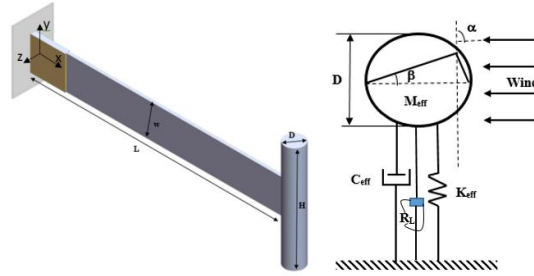


Figure 1. (a) Schematic diagram of the present system (b) equivalent single degree model

For the laminated cantilever beam under consideration, the strain-displacement relation is expressed as follows:

$$\varepsilon_x = \frac{\partial u}{\partial x} = \frac{\partial u_0}{\partial x} - z \frac{\partial^2 w}{\partial x^2} = \varepsilon_x^0 - z \vartheta_x^0 \quad (1)$$

where, ε_x^0 is mid-plane strain, $\vartheta_x^0 = \frac{\partial^2 w}{\partial x^2}$ is the curvature at the mid-plane, displacement in the thickness direction is w , and z is the vertical distance between the thicknesses of the k^{th} layer from the mid-plane. The in-plane force and bending moment for the present beam can be expressed as:

$$\begin{bmatrix} N_x \\ M_x \end{bmatrix} = \begin{bmatrix} A_{11} & B_{11} \\ B_{11} & D_{11} \end{bmatrix} \begin{bmatrix} \varepsilon_x^0 \\ \kappa_x^0 \end{bmatrix} \quad (2)$$

where, A_{11} , B_{11} , and D_{11} , the laminate parameters can be given as:

$$(A_{11}, B_{11}, D_{11}) = b \sum_{k=1}^n E_x^k \int_{h_{k-1}}^{h_k} (1, z, z^2) dz \quad (3)$$

Here, n is the number of layers. Each lamina's equivalent modulus of elasticity is denoted by E_x^k . For the simplified spring-mass system, the forced vibration equation is as follows:

$$M_{eff} \ddot{z}(t) + C_{eff} \dot{z}(t) + K_{eff} z(t) + \theta V(t) = -\frac{1}{2} \rho U^2 D H \left\{ p \left[q + \frac{\dot{z}(t)}{U} \right] - A_i \left[\frac{\dot{z}(t)}{U} \right]^i \right\} \quad (4a)$$

$$C_p \dot{V}(t) + \frac{V(t)}{R_L} - \theta \dot{z}(t) = 0 \quad (4b)$$

Where, M_{eff} , C_{eff} , and K_{eff} are the equivalent mass, damping, and stiffness, respectively. p is the coupling coefficient of galloping and VIV; $q(t)$ is the wake angle, and $f = 0$ indicates that only galloping during vibration. The aerodynamic coefficient linked to galloping is called A_i , and for a bluff body, $A_i = 0$ accurately describes VIV. $z(t)$ is displacement, $C_p = \frac{L_p w \varepsilon}{2 h_p}$ is equivalent capacitance with L_p and h_p as piezoelectric layer length and thickness, ε is the dielectric constant, R_L is load resistance, $V(t)$ is open circuit voltage. Also, D and H are the diameter and height of the cylindrical bluff body and ρ is the density of air. The electromechanical coupling coefficient can be represented as:

$$\theta = -\frac{E_p I_p d_{31} b}{2 h_p} (h_{pc}^2 - h_b^2) \approx -E_p I_p d_{31} b \quad (5)$$

where, E_p and d_{31} are represented as modulus of elasticity and piezoelectric constant, respectively. Similarly, the distance from the top of the piezo layer to the neutral axis: $h_{pc} = h_p + \frac{h_s}{2}$.

A. Recurrent Neural Networks (RNN)

In the domains of artificial intelligence, machine learning, and deep learning, neural networks replicate the operation of the human brain, enabling computer programs to identify patterns and resolve common problems. Neural networks of the RNN type can be used to model sequence data. The behaviour of RNNs, which are built from feedforward networks, is akin to that of human brains. The algorithm of the RNN model is given below.

Initialization:

- Initialize the parameters, including weights and biases, which will be learned during training.
- Set hyperparameters like the learning rate, number of hidden units, and sequence length.

Input Representation:

Encode input sequences: Convert sequential data into a format suitable for RNN input (e.g., word embeddings for text data).

Architecture:

Define the RNN architecture, specifying the number of hidden units and the type of RNN layer (e.g., vanilla RNN, LSTM, or GRU).

Forward Propagation:

- Process the input sequences through the network iteratively, step by step, for each element in the sequence.
- At each time step:
- Compute the hidden state using the current input and the previous hidden state.
- Update the hidden state using an activation function.
- Generate output based on the current hidden state.
- Store the hidden state for the next time step.

Backpropagation Through Time (BPTT):

- Calculate the loss between the predicted outputs and the actual targets.
- Use backpropagation to compute gradients with respect to the parameters.
- Update the weights and biases by applying optimization techniques (e.g., gradient descent, Adam optimizer) to minimize the loss.

Repeat Training:

Iterate through the training dataset multiple times (epochs), adjusting the network parameters to improve performance. The general architecture of RNN is shown in Fig. 2.

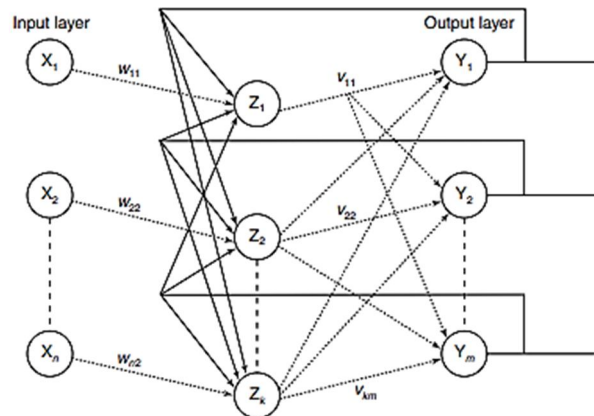


Figure 2. Multilayer recurrent network

III. RESULTS AND DISCUSSION

In the present work, a unique flow-induced vibration-based laminated smart energy harvester with several cutting angles of cylinders is analyzed. Different cutting angles of the bluff body are considered to introduce the combined

effect of VIV and galloping on the harvesting system. The purpose of this structural alteration is to improve the energy harvesting capability of the laminated smart system. The bluff body generates alternate shedding vortices when fluid flows over it. The lift force causes the bluff body to vibrate, which in turn causes the piezoelectric plate and cantilever beam to deform regularly. The system's goal is to convert the vibration energy produced by the fluid movement around the bluff body into electrical energy by using a piezoelectric patch. The CFRP cantilever beam measures 164 mm in length, 24 mm in width, and 1.2 mm in thickness. The plastic foam cylindrical bluff body measures 120 mm in height and 32 mm in diameter. Similarly, the length, width, and thickness of the piezo patches are 30mm, 24 mm, and 0.3 mm. The boundary condition and geometrical parameters of the system are shown in Fig. 1. Initially, the laminated piezoelectric beam is modelled with a cross-ply orientation scheme [0/90], and PZT-5H is used to model the piezoelectric patches. The series-configured bimorph smart beam is connected with a $R_L=10$ kohm circuit resistor. Initially, the transient response of the system is obtained for 3 secs with an initial wind velocity of 2.3 m/s. The displacement and voltage responses of the system are shown in Figs. 3 and 4 respectively.

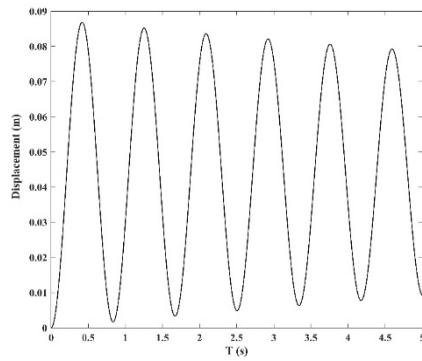


Figure 3. Displacement response of the system

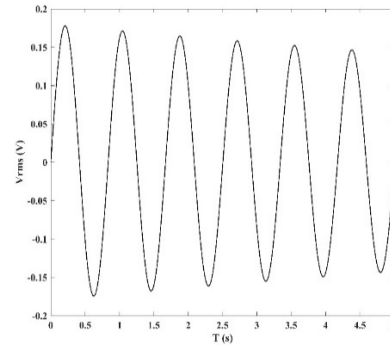


Figure 4. Voltage response of the system

The output displacement and RMS voltage response of the system is obtained at different velocities of air within the frequency range of 0-100 Hz. Initially, the effect of different cutting angles of the bluff body on the output response of the system is calculated. It is found that the effect of coupled VIV and galloping effect on the energy harvesting response of the system is more prominent at higher air velocity. Similarly, the output voltage response of the system is maximum at a cutting angle of 30 degree, as shown in Fig. 5. Further, the effect of wake angle behind the bluff body on the output voltage response is calculated. It is found that with an increase in wake angle, the energy harvesting capability of the system increases (Fig. 6).

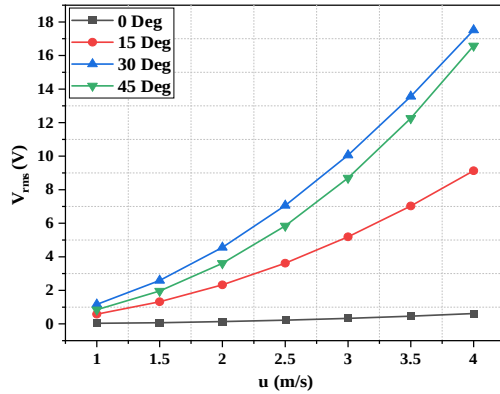


Figure 5. RMS voltage response under different cutting angles

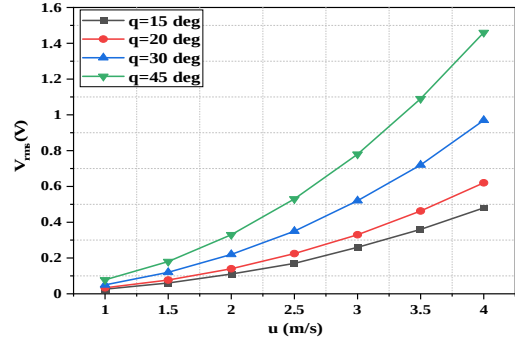


Figure 6. RMS voltage response under different wake angles

Similarly, the effect of diameter to length ratio (D/L) and height to length ratio (H/L) of the bluff and the substrate beam on the output voltage response of the beam is calculated. It is found that in both cases, as the ratio increases, the RMS voltage of the system improves. Therefore, the optimal value of all these parameters needs to be considered to maximize the energy harvesting capability of the system.

A. Neural Network Integrated Optimization study

The sequence of the 3-level design for the training and optimization of three more contributed parameters of the system is shown in Table 5. The design parameters in the present study are optimized using an L_{27} orthogonal array, which requires 27 experiments.

TABLE I. DESIGN PARAMETERS AND THEIR LEVELS

Symbol	Design Parameter	Level 1	Level 2	Level 3
A	Wake angle (α)	15°	20°	30°
B	Diameter to length ratio (D/L)	0.2	0.3	0.4
C	Height to length ratio (H/L)	0.25	0.5	1

A surrogate model is a simplified version or an approximation of a complex system or process. It's used to stand in for the original system when the latter is computationally expensive, time-consuming, or difficult to evaluate directly. Surrogate models strike a balance between accuracy and computational cost, allowing for efficient exploration, analysis, and optimization of complex systems or models. In the present study, the objective function for the optimization study is evaluated using the KNN model, which reduces the computational time of the system and improves the accuracy of the model. The representation of the architecture for the present neural network model is shown in Fig. 7. Here, the objective is to maximize the average output power.

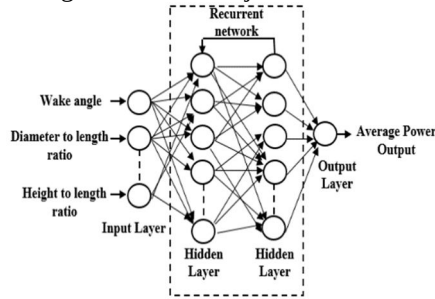


Figure 7. Architecture of the present neural network

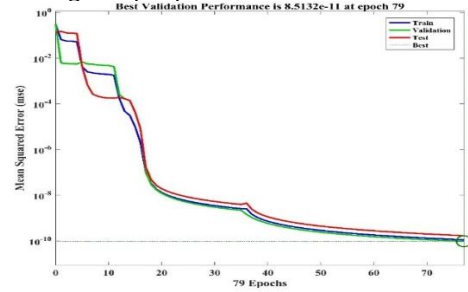


Figure 8. Performance plot of the present model.

Similarly, the performance plot of the present model is shown in Fig. 8. The maximum error target and gradient= 10^{-7} are taken into consideration as the training parameters for this architecture at a learning rate of 0.5. Moreover, the optimization is carried out by integrating the neural network model with the Particle Swarm Optimization (PSO) technique. The output of the neural network is used to formulate the objective function for this purpose. Here, weighted average method is used to obtain the objective function from the weights and biases. From optimization study, it is found that the maximum average output power is obtained at 30° wake angle, diameter to length ratio of 0.35 and height-to-length ratio of 0.9.

IV. CONCLUSION

In the present study, the energy harvesting capability of coupled VIV and galloping-based laminated piezoelectric beam systems is calculated. It is found that parameters like the cutting angle of the bluff body, wake angle of the cylinder, diameter-to-length ratio, height to height-to-diameter ratio mostly affect the output voltage response of the system. The RNN model is used for training and testing the input parameters, and the objection function for the optimization study is obtained using the RNN model. It has been found that RNN is an effective and efficient model for testing and training purposes and can be used for optimization studies based on application.

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