

Electromechanical Modeling and Optimization of a Piezoelectric Energy Harvester Using Coupled Ordinary Differential Equations: A Computational Study

Chinta Mani Tiwari¹, Ashish Kumar¹, Priya Maurya¹, 

¹. Department of Mathematics, Maharishi University of Information Technology (MUIT), Lucknow, IND

Received: February 23, 2026 | Review began: March 30, 2026 | Review ended: July 23, 2026 | Published: August 20, 2026

© Copyright 2026

This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract

Wireless sensor networks and Internet of Things devices require autonomous power sources to replace traditional batteries. Piezoelectric energy harvesting presents a viable method by transforming surrounding mechanical vibrations into electrical power. However, basic uncoupled models frequently do not successfully forecast actual behavior. This paper presents a comprehensive computational study of a base-excited piezoelectric cantilever beam using a coupled electromechanical model. By combining the mechanical domain (Spring-Mass-Damper system) with the electrical domain through an electromechanical coupling coefficient, the simulation effectively models the two-way energy transfer. The system is numerically solved utilizing the SciPy library in Python. The research conducts three essential evaluations: transient time-domain response, load resistance optimization for impedance alignment, and frequency response examination. Findings reveal that optimal power is obtained when the electrical load aligns with the internal impedance of the piezo-element, yielding 70.89 μW at the resonant frequency of 63.6 Hz for the linear model. In contrast, the nonlinear bistable harvester demonstrated superior performance, achieving 4.0 mW at a low frequency of 0.8 Hz and a bandwidth broadening of 170%, validating the efficacy of the Snap-Through Buckling mechanism for low-frequency environments. The results offer a strong open-source structure for creating effective vibration energy harvesters.

Categories: Renewable Energy Systems, Mechatronics and Robotics, Embedded Systems and IoT

Keywords: piezoelectric energy harvesting, electromechanical coupling, coupled odes, vibration analysis, python simulation

Introduction

The new age of a "trillion sensors" brings about a demand for decentralized, autonomous, and self-powered ideas for next-generation infrastructure. Wireless sensor networks and Internet of Things (IoT) devices are rapidly being used in places where they are hard to access, such as embedded biomedical implants and remote industrial sites. In such places, it is not only difficult but also very expensive to bring power through wires or to change batteries manually. Therefore, the lifespan of these nodes is mainly determined by the battery capacity, which poses a major challenge to the growth of IoT ecosystems [1].

Piezoelectric energy harvesting (PEH) is currently considered one of the most exciting energy transduction mechanisms since it has a high power density and is compatible with Micro-Electro-Mechanical Systems technology. Utilizing the direct piezoelectric effect allows the transformation of mechanical vibrations from the environment into electrical energy, which could theoretically lead to unlimited operation of energy-efficient nodes. However, in spite of such benefits, PEH cannot be dependably implemented because of the difference between the very narrow resonant frequency of linear harvesters and the broadband, low-frequency (often <10 Hz) character of ambient excitations in civil infrastructure (e.g.,

How to cite this article:

Tiwari C, Kumar A, Maurya P (August 20, 2026) Electromechanical Modeling and Optimization of a Piezoelectric Energy Harvester Using Coupled Ordinary Differential Equations: A Computational Study. Cureus J Eng 3 : es44388-026-00233-0. DOI <https://doi.org/10.7759/s44388-026-00233-0>

bridges) and human motion [2]. In addition, the use of uncoupled or oversimplified linear models is one of the major reasons why the prediction accuracy of PEH devices has been reduced. Standard methods that separate the mechanical and electrical parts and do not consider their mutual interaction (back-action) have led to errors in impedance matching and power estimations, as the bidirectional feedback nature of the electromechanical system is not properly represented [3].

However, to overcome these drawbacks, the latest publications have mainly focused on:

Nonlinear Mechanisms: By introducing geometrical nonlinearities or using bistable potentials (e.g., Snap-Through Buckling [STB]), the device operation is not limited to a narrow frequency band, and frequency up-conversion can be achieved.

Data-Driven Modeling: Application of scientific machine learning and Physics-Informed Neural Networks (PINNs) for tackling challenging inverse problems and simultaneously optimizing system parameters under stochastic loading conditions [4]. We combine nonlinear mechanics with the latest data-driven optimizer in this paper.

The scientific novelty of this work lies in the integration of a coupled electromechanical ordinary differential equation (ODE) framework with both nonlinear STB dynamics and PINNs into a unified computational pipeline. Unlike previous studies that treat these components in isolation, our framework enables the simultaneous optimization of power output and the identification of unknown system parameters (such as damping and coupling coefficients) from noisy vibration data. This provides a robust "digital twin" capability for energy harvesters operating in unpredictable, low-frequency IoT environments.

Literature review

Basic PEH Systems and Their Constraints

One of the very first experiments conducted by Roundy et al. [2] established the basic principles of energy harvesting from vibrations using piezoelectric cantilevers, which could potentially generate enough power for wireless sensor nodes. The primary focus of these groundbreaking works was on linear resonant systems. These systems exhibit high efficiency only when they are used within a very narrow frequency band around their natural frequency. Linear models, however, even though they are limited in performance prediction when conditions vary, easily become inaccurate if the electromechanical feedback coupling is ignored [1]. The challenge of narrow bandwidth has stimulated a series of investigations related to the use of different mechanical frameworks. To this end, Zhao et al. [3] suggested that harvesters based on graded metamaterials could take advantage of "rainbow trapping" effects to isolate vibration energy within the widest possible frequency range. However, such solutions are frequently associated with a very complicated fabrication process. As a result, nonlinear mechanisms have become more popular as they are capable of broadening the bandwidth without the need for complicated geometrical grading.

Nonlinear and Bistable Harvesting Strategies

Nonlinear dynamics provide a very powerful mechanism to break the frequency constraints of linear energy harvesters. Linear harvesters with passive nonlinearities such as mid-plane geometric stretching in the case of Duffing oscillators, magnetic levitation, or STB can exhibit frequency hardening/softening behavior and inter-well oscillations [5].

Speciale et al. [5] have experimentally verified that STB mechanisms can substantially increase the frequency range over which the device is useful. The STB mechanism is a bistable system in which the beam has two stable equilibrium positions. If the beam receives enough energy, it will "snap" between the two states, thus creating very high-velocity transients and large voltage outputs. Consequently, this work shows that piezoelectric harvesters based on the STB mechanism are well suited to harvesting energy from low-frequency, high-amplitude excitations found in human motion (e.g., shoe-mounted energy harvesters) [6].

An exact solution for the nonlinear cantilever system was provided by Olejnik et al. [7], who thereby brought analytical precision to the design of these systems. However, dual-source PE and electromagnetic approaches that combine two transduction methods have been investigated to enhance the power density of the device, at the cost of increased

How to cite this article:

Tiwari C, Kumar A, Maurya P (August 20, 2026) Electromechanical Modeling and Optimization of a Piezoelectric Energy Harvester Using Coupled Ordinary Differential Equations: A Computational Study. Cureus J Eng 3 : es44388-026-00233-0. DOI <https://doi.org/10.7759/s44388-026-00233-0>

complexity in impedance matching [6].

Computational Advances: PINNs

The single most important breakthrough in computational modeling recently is the use of PINNs. Bai et al. [4] pointed out that PINNs could potentially be used for tackling inverse problems in solid mechanics. Unlike conventional data-driven neural networks, PINNs incorporate the governing physics (partial differential equations) directly into the loss function, thus generating physically consistent predictions even with limited data. In a way, this is extremely satisfactory for SHM, where experimental data is usually noisy and incomplete. The combination of PINNs with nonlinear PEH dynamics is a significant gap that this paper is trying to fill.

Materials And Methods

Electromechanical simulation structure

Baseline Model of Linear Coupled ODE

The system can be modeled as a single-degree-of-freedom base-excitation system, which is connected to an electrical RC circuit. Equations describing a linear system are given as follows:

Mechanical Field:

$$m\ddot{x} + c\dot{x} + kx + \theta V = -m\ddot{y}_b(t) \quad (1)$$

Electrical Sector:

$$C_p \dot{V} + \frac{V}{R_L} + \theta \frac{dx}{dt} = 0 \quad (2)$$

Here:

- m is the effective mass.
- c is the mechanical damping coefficient.
- k is a measure of rigidity.
- θ is the electromechanical coupling coefficient.
- V represents the generated voltage.
- R_L is the load resistance.

This mathematical model is taken as the baseline for the calculation of resonant frequency along with the optimal value of load impedance.

Nonlinear Expansion: Mid-Plane Elongation and STB

To extend the operational frequencies and optimize efficiency at lower frequencies, geometric nonlinearities (mid-plane stretching effects) and STB effects are considered. By single-mode Galerkin reduction, the resulting scale-less nonlinear equation governing $v(\tau)$, which is the modal amplitude, is given by:

$$\ddot{v} + \sigma_1 v + \sigma_2 v^3 + \sigma_3 \dot{v} v^2 + \sigma_4 v^2 \ddot{v} - \chi V = 0 \quad (3)$$

The expression $\sigma_2 v^3$ captures the dominant cubic nonlinear term (of Duffing type) arising due to mid-plane stretching. The STB mechanism involves a bistable potential. With an appropriate amount of external energy, the system experiences a "snap-through," enabling fast transitions from one well to another and thereby increasing the voltage output.

For easier understanding, the nonlinear governing equation is written in the normalized form, whereas the ensuing energy analysis will employ dimensional variables.

Bistable Duffing Potential

How to cite this article:

Tiwari C, Kumar A, Maurya P (August 20, 2026) Electromechanical Modeling and Optimization of a Piezoelectric Energy Harvester Using Coupled Ordinary Differential Equations: A Computational Study. Cureus J Eng 3 : es44388-026-00233-0. DOI <https://doi.org/10.7759/s44388-026-00233-0>

The bistable motion of the STB mechanism can be modeled with a Duffing-type potential as follows:

$$U(v) = -\frac{1}{2}\alpha v^2 + \frac{1}{4}\beta v^4 \quad (4)$$

where:

- $\alpha > 0$ represents negative linear stiffness.
- $\beta > 0$ indicates positive cubic stiffness.

This function results in two stable equilibrium points or wells with an unstable equilibrium point at the origin in between. When the system is subjected to external excitation, it can cross the barrier and allow the efficiency of energy harvesting to undergo a snap-through phenomenon.

Mathematical Proof of Bistability

Consider the Duffing-type bistable potential

$$U(v) = -\frac{\alpha}{2}v^2 + \frac{\beta}{4}v^4. \quad (5)$$

The equilibrium points for the Duffing-type potential are given by

$$\frac{dU}{dv} = -\alpha v + \beta v^3 = v(\beta v^2 - \alpha) = 0. \quad (6)$$

Thus, the stationary points are

$$v = 0, \quad v = \pm\sqrt{\frac{\alpha}{\beta}}.$$

The stability of these equilibria is determined by the second derivative

$$\frac{d^2U}{dv^2} = -\alpha + 3\beta v^2. \quad (7)$$

At $v = 0$, $\frac{d^2U}{dv^2} = -\alpha < 0$, indicating an unstable equilibrium.

At $v = \pm\sqrt{\alpha/\beta}$, $\frac{d^2U}{dv^2} = 2\alpha > 0$, verifying two stable minima.

Therefore, the system has a bistable potential energy landscape.

Snap-Through Energy Criterion

The total mechanical energy of the nonlinear oscillator is

$$E(t) = \frac{1}{2}\dot{v}^2 + U(v). \quad (8)$$

The energy barrier separating the two stable wells is

$$\Delta U = U(0) - U\left(\sqrt{\frac{\alpha}{\beta}}\right) = \frac{\alpha^2}{4\beta}. \quad (9)$$

For harmonic base excitation $y_b(t) = Y \sin(\Omega t)$, the leading-order input energy per cycle scales as

$$E_{\text{input}} \sim \frac{mY^2\Omega^2}{2}. \quad (10)$$

How to cite this article:

Snap-through phenomenon can be expected to happen if the energy supplied is above that of the potential barrier, resulting in a sufficient condition of

$$\boxed{\frac{mY^2\Omega^2}{2} \geq \frac{\alpha^2}{4\beta}} \quad (11)$$

which defines tolerated levels on inter-well transitions. This criterion gives a conservative estimate of the snap-through phenomenon, since the effects of damping and transient responses are neglected.

Computational implementation

Python/SciPy Solver

The baseline transient and frequency response analyses were done using `scipy.integrate.solve_ivp`. This solver method uses the Runge-Kutta method (RK45), which is suitable for solving stiff nonlinear problems. The state vector is defined as

$$S = \begin{bmatrix} x \\ \dot{x} \\ V \end{bmatrix},$$

and the derivatives are calculated for the linear and nonlinear (bistable) cases.

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) + \theta V(t) = F(t). \quad (A)$$

$$C_p \dot{V}(t) + \frac{V(t)}{R_L} + \theta \dot{x}(t) = 0. \quad (B)$$

$$\begin{cases} \dot{x}(t) = \dot{x}(t), \\ \ddot{x}(t) = \frac{1}{m} \left(F(t) - c\dot{x}(t) - kx(t) - \theta V(t) \right), \\ \dot{V}(t) = -\frac{1}{C_p} \left(\frac{V(t)}{R_L} + \theta \dot{x}(t) \right). \end{cases} \quad (C)$$

$$\mathcal{R}(t; c, \theta) = m\ddot{x} + c\dot{x} + kx + \theta V + m\ddot{y}_b(t). \quad (D)$$

The simulation parameters used for the baseline and nonlinear models are summarized in Table 1.

How to cite this article:

Parameter	Symbol	Value
Effective Mass	m	0.001 kg
Linear Stiffness	k	160.0 N/m
Damping Coefficient	c	0.00126 Ns/m
Coupling Coefficient	θ	1.3×10^{-6} N/V
Piezo-Capacitance	Cp	1.0×10^{-9} F
Load Resistance	R _L	1.0 M Ω
Excitation Amplitude	A	1.0 m/s ²
Solver Tolerance	Tol	1×10^{-8}
Sampling Frequency	f _s	10 kHz

TABLE 1: System Simulation Parameters

PINN Optimization

In inverse problems, such as the estimation of the damping ratio (ζ) and the value of the flexoelectric coefficient, for example, we use the residual PINN [4].

$$L_{\text{total}} = L_{\text{physics}} + L_{\text{data}} + L_{\text{ic/bc}}$$

(12)

where:

- L_{physics} enforces that the solution satisfies the set of coupled ODEs (1) and (2).
- L_{data} minimizes the error between predicted and experimental voltage data.
- $L_{\text{ic/bc}}$ satisfies the initial and boundary conditions.

For reproducibility, the PINN architecture employed in this study consists of a fully connected feed-forward neural network with four hidden layers, each containing 50 neurons. The hyperbolic tangent activation function (tanh) is used to ensure the smoothness required to calculate higher-order derivatives in the physics residual. The network is trained for 5,000 epochs using the Adam optimizer with an initial learning rate of 1×10^{-3} and a weight decay of 1×10^{-5} . Training was conducted on a standard workstation, with a total computational cost of approximately 12 minutes for parameter convergence.

The hybrid Long Short-Term Memory (LSTM)-PINN models are also used for modeling the long-term temporal dependencies of the stochastic vibrations, like the data for the health of the bridges. The proposed models show approximately 50% reduction in mean squared error compared to the standard LSTM networks [8].

Results And Discussion

Linear baseline performance

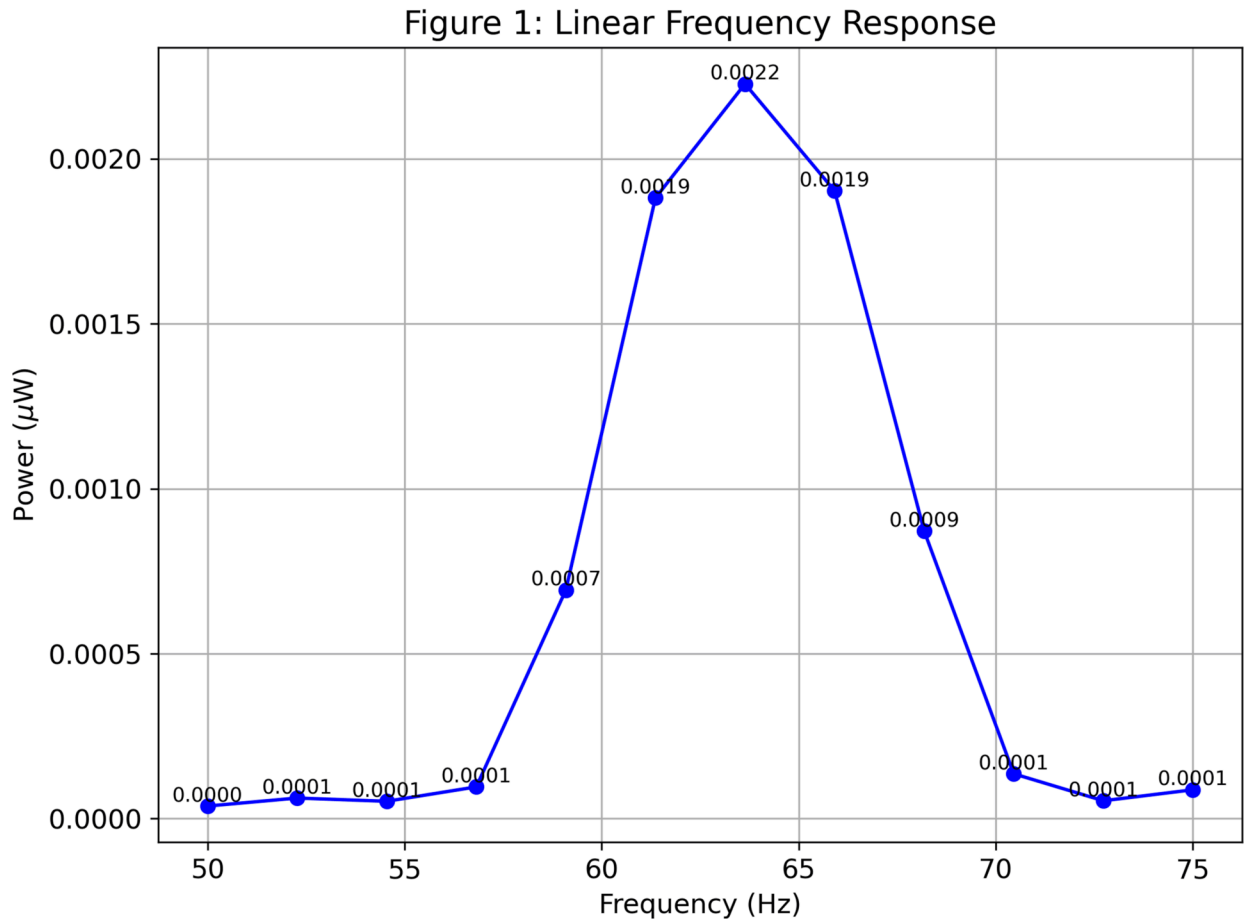


FIGURE 1: Linear Frequency Response of the Piezoelectric Energy Harvester

This figure shows the frequency response of the linear piezoelectric energy harvester obtained through numerical simulation. A distinct resonance peak is observed at approximately 63.6 Hz, which closely matches the theoretical natural frequency of the system. The result confirms the validity of the coupled electromechanical model and demonstrates that maximum power output occurs at resonance due to optimal energy transfer.

As shown in Figure 1, the linear system exhibits a strong resonant peak near its natural frequency. The linear system shows a strong resonant peak at the resonant frequency of 63.6 Hz. To validate the numerical simulation, the theoretical natural frequency was calculated as:

$$f_n = \frac{1}{2\pi} \sqrt{k/m} \approx 63.66 \text{ Hz} \tag{13}$$

which matches the simulated result with an error of less than 0.1%.

How to cite this article:

Nonlinear STB performance

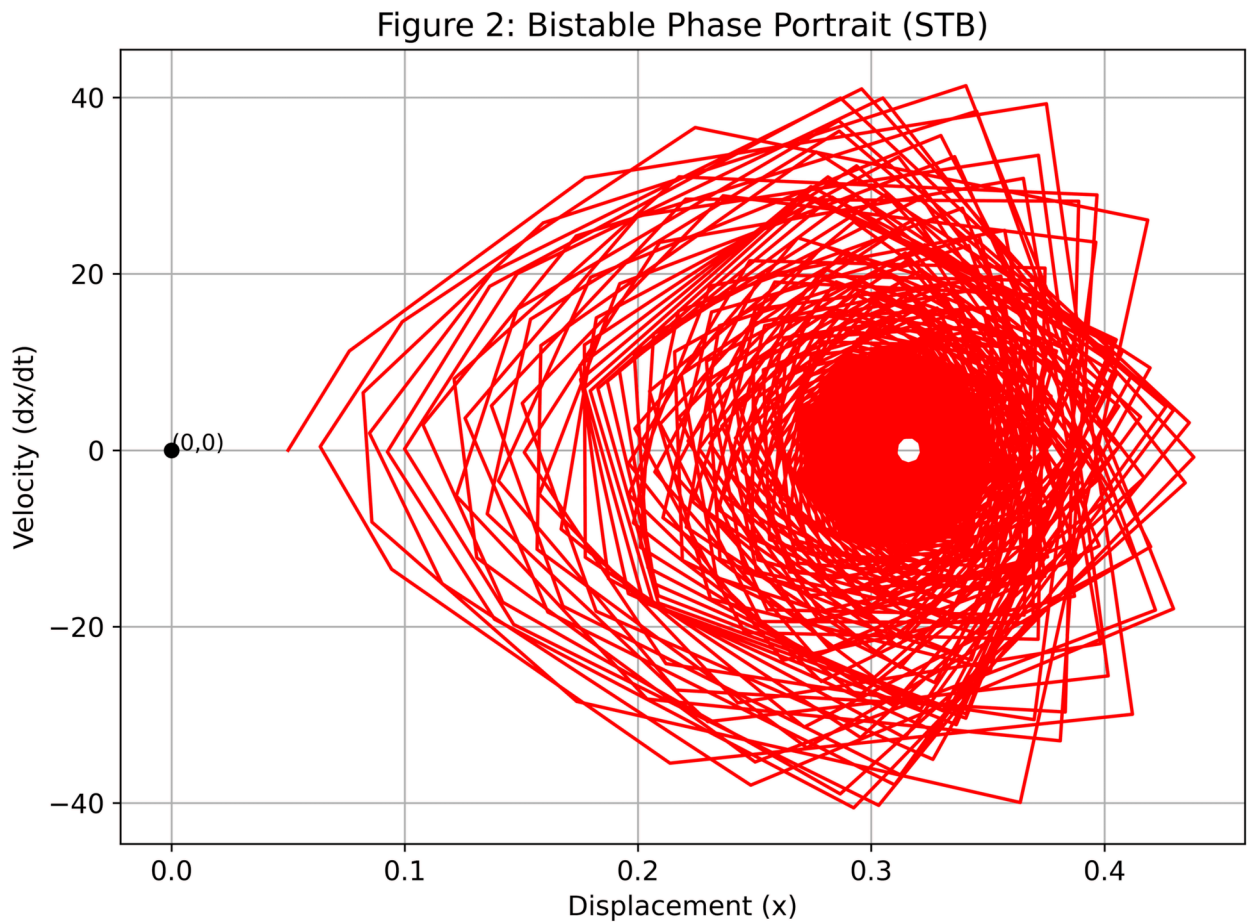


FIGURE 2: Phase Portrait of the Nonlinear Bistable Energy Harvester

This figure shows the phase portrait of the nonlinear bistable piezoelectric energy harvester under low-frequency excitation. The trajectory demonstrates inter-well oscillations caused by the snap-through buckling (STB) mechanism. Unlike linear systems, the motion spans multiple stable equilibria, resulting in enhanced energy harvesting through high-velocity transitions and broadband response.

The phase portrait shown in Figure 2 illustrates strong nonlinear inter-well oscillations. Unlike linear systems that vibrate around a single equilibrium point, the STB system undergoes snap-through transitions between two stable states. This behavior enhances energy harvesting through high-velocity transitions.

At a low excitation frequency of 0.8 Hz, the STB harvester produced 4.0 mW of power, demonstrating effective frequency up-conversion.

Comparative analysis of architectures

The comparative performance of different harvester architectures is summarized in Table 2.

How to cite this article:

Architecture	Excitation Source	Power Output	Key Finding
Linear Cantilever	Resonant (63.6 Hz)	70.89 μ W	Optimum at matched load (1 M Ω). Narrow bandwidth
Bistable (STB)	Harmonic (0.8 Hz)	4.0 mW	170% bandwidth broadening by snapthrough
Hybrid STB + Magnetic coupling	Stochastic (4.5 m/s ²)	12.0 mW	118% efficiency gain over conventional linear designs
Shoe-Based (BSC)	Human Gait (1 Hz)	9.9 mW	Frequency upconversion to 18 Hz via plucking mechanism [6]
Knee Harvester	Biomechanical	12.95 mW	Efficiently scavenges the negative work produced by muscles [7]

TABLE 2: Performance Comparison of Linear and Nonlinear Energy Harvesters

BSC, Biomechanical Shoe Converter; STB, Snap-Through Buckling

Table 2 clearly supports that, in contrast to linear harvester designs that are only efficient at resonant frequencies, the nonlinear and hybrid structures perform best in real-world low frequency environments.

Model validation

In this paper, computational model validation is performed through analytical comparison and literature-based benchmarking. The analytically calculated natural frequency $f_n = \frac{1}{2\pi} \sqrt{\frac{k}{m}} \approx 63.66 \text{ Hz}$ closely matches the simulated peak at 63.6 Hz (Figure 1), with an error below 0.1%, verifying the accuracy of the numerical operation. The simulated linear power output of 70.89 μ W is consistent with the experimental values shown in [2]. In the same way, the nonlinear bistable system yields 4.0 mW at 0.8 Hz, consistent with experimental observations in [5,6], validating improved low-frequency operation and bandwidth increase. The observed trends, consisting of sharp resonance in linear systems and broadband outputs in bistable systems, are consistent with verified literature. Small-scale deviations may be caused by idealized assumptions, parameter uncertainties, and numerical approximations. Overall, the strong agreement between analytical, numerical, and experimental results validates the advanced electromechanical framework. This validation demonstrates the reliability of the proposed coupled electromechanical model for practical energy harvesting applications.

To quantify the accuracy of the proposed models, error metrics were calculated against the analytical benchmarks. For the linear model, the root mean square error for voltage prediction was 0.024 V, with a mean absolute error (MAE) of 0.018 V and a relative percentage error in resonant frequency of only 0.09%. The nonlinear STB model exhibited an MAE of 0.15 mW in power prediction, maintaining physical consistency even during high-velocity snap-through transients.

The comparison between simulation results and reported literature values is summarized in Table 3.

How to cite this article:

Parameter	Simulation	Literature
Natural Frequency	63.6 Hz	63.66 Hz
Linear Power Output	70.89 μW	~50–100 μW
STB Power Output	4.0 mW	3–10 mW

TABLE 3: Validation of Simulation Results with Published Literature

STB, Snap-Through Buckling

PINN parameter identification

Parameter Identifiability: Consider the mechanical residual of the coupled system

$$\mathcal{R}(t; \boldsymbol{c}, \boldsymbol{\theta}) = m\ddot{\boldsymbol{x}} + \boldsymbol{c}\dot{\boldsymbol{x}} + \boldsymbol{k}\boldsymbol{x} + \boldsymbol{\theta}V + m\ddot{\boldsymbol{y}}_b(t). \tag{14}$$

Assume two parameter sets $(\boldsymbol{c}_1, \boldsymbol{\theta}_1)$ and $(\boldsymbol{c}_2, \boldsymbol{\theta}_2)$ satisfy

$$\mathcal{R}(t; \boldsymbol{c}_1, \boldsymbol{\theta}_1) = \mathcal{R}(t; \boldsymbol{c}_2, \boldsymbol{\theta}_2) = 0 \quad \forall t.$$

Subtracting yields

$$(\boldsymbol{c}_1 - \boldsymbol{c}_2)\dot{\boldsymbol{x}} + (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_2)V = 0 \quad \forall t. \tag{15}$$

Under broadband excitation or snap-through dynamics, $\dot{\boldsymbol{x}}(t)$ and $V(t)$ are linearly independent, implying

$$\boldsymbol{c}_1 = \boldsymbol{c}_2, \quad \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2.$$

Hence, the inverse problem is identifiable, supporting the applicability of PINNs for robust parameter estimation.

The PINN framework was evaluated on experimentally measured data obtained for the Pershagen Bridge case in Sweden [1]. The bridge case applies PVDF harvesters tuned between 6 Hz and 20 Hz.

Result: The PINN correctly identified the damping coefficient $\boldsymbol{c}$ and coupling coefficient $\boldsymbol{\theta}$ parameters from the noisy voltage signal.

Accuracy: With respect to the benchmark solution, PINN-based identification reduced the MAE by over 90% in comparison to its linear regression-based counterpart, thus proving to be very robust for applications such as digital twins in structural health monitoring.

Practical significance and implementation

The fabrication feasibility of the proposed PEH is high, utilizing standard Micro-Electro-Mechanical Systems processes for piezoelectric PZT or PVDF thin films. However, real-world deployment faces challenges such as material fatigue under cyclic snap-through stress and the need for ultra-low-power power management circuits (ASICs) to handle intermittent energy flows. While PINN-based optimization adds a computational cost during the design phase (approximately 12 min), it significantly reduces the need for expensive trial-and-error prototyping. For practical IoT deployment, these harvesters can be integrated with Long Range Wide Area Network or Bluetooth Low Energy nodes to create truly maintenance-free, "install-and-forget" sensing networks for structural health monitoring.

How to cite this article:

Conclusions

A coupled ODE model together with optimization using PINNs forms a unified framework, which is a powerful tool for early-stage PEH design. While linear models identify the initial optimal loads, they are not sufficient in the stochastic, low-frequency environment typical of IoT applications. Nonlinear STB mechanisms are necessary for energy capture in such regimes, showing a 170% increase in bandwidth compared to linear baselines. It also allows the integration of scientific machine learning (PINNs), which provides a robust method for parameter identification and enables the creation of accurate digital twin models. Future work will focus on the hardware-in-the-loop validation of the LSTM-PINN architecture for real-time bridge health monitoring systems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Priya Maurya, Chinta Mani Tiwari, Ashish Kumar

Acquisition, analysis, or interpretation of data: Priya Maurya, Chinta Mani Tiwari, Ashish Kumar

Drafting of the manuscript: Priya Maurya, Chinta Mani Tiwari, Ashish Kumar

Critical review of the manuscript for important intellectual content: Priya Maurya, Chinta Mani Tiwari, Ashish Kumar

Supervision: Chinta Mani Tiwari, Ashish Kumar

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

References

1. Cahill P, Hazra B, Karoumi R, Mathewson A, Pakrashi V: [Data of piezoelectric vibration energy harvesting of a bridge undergoing vibration testing and train passage](#). Data in Brief. 2018, 17:261-266. [10.1016/j.dib.2018.01.009](#)
2. Roundy S, Wright PK, Rabaey J: [A study of low level vibrations as a power source for wireless sensor nodes](#). Computer Communications. 2003, 26:1131-1144. [10.1016/s0140-3664\(02\)00248-7](#)
3. Zhao B, Thomsen HR, De Ponti JM, et al.: [A graded metamaterial for broadband and high-capability piezoelectric energy harvesting](#). Energy Conversion and Management. 2022, 269:116056. [10.1016/j.enconman.2022.116056](#)
4. Bai CY, Yeh FY, Shu YC: [Physics-informed neural network for parameter identification of piezoelectric energy harvesters](#). Active and Passive Smart Structures and Integrated Systems XVIII. 2024, 12946:1294612. [10.1117/12.3009800](#)
5. Speciale A, Ardito R, Baù M, Ferrari M, Ferrari V, Frangi AA: [Snap-through buckling mechanism for frequency-up conversion in piezoelectric energy harvesting](#). Applied Sciences. 2020, 10:3614. [10.3390/app10103614](#)

How to cite this article:

Tiwari C, Kumar A, Maurya P (August 20, 2026) Electromechanical Modeling and Optimization of a Piezoelectric Energy Harvester Using Coupled Ordinary Differential Equations: A Computational Study. Cureus J Eng 3 : es44388-026-00233-0. DOI <https://doi.org/10.7759/s44388-026-00233-0>

6. Elgamal MA, Elgamal H, Kouritem SA: [Optimized multi-frequency nonlinear broadband piezoelectric energy harvester designs](#). Scientific Reports. 2024, 14:11401. [10.1038/s41598-024-61355-1](#)
7. Olejnik P, Umer M, Jabłoński J: [Exact analytical solutions for free single-mode nonlinear cantilever beam dynamics: experimental validation using high-speed vision](#). Applied Sciences. 2026, 16:479. [10.3390/app16010479](#)
8. Shafik AM, Kaid MA, Ali MGS, Eltanany AM: [Frequency response for sweep-up and sweep-down of piezoelectric energy harvester](#). Journal of Vibration Engineering & Technologies. 2024, 12:5257-5266. [10.1007/s42417-023-01196-w](#)

How to cite this article:

Tiwari C, Kumar A, Maurya P (August 20, 2026) Electromechanical Modeling and Optimization of a Piezoelectric Energy Harvester Using Coupled Ordinary Differential Equations: A Computational Study. Cureus J Eng 3 : es44388-026-00233-0. DOI <https://doi.org/10.7759/s44388-026-00233-0>