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Modeling and Forecasting Piezoelectric Energy Harvesting Using Deep LSTM–ANN Architectures

Yurni Oktarina[1], Tresna Dewi[1], Muhammad Amri Yahya[1], Assyifa Mourlina Faraquinnsha[2]

[1]Department of Electrical Engineering
Politeknik Negeri Sriwijaya, Indonesia
[2]MAN Insan Cendekia OKI
Jl. Lintas Timur, Lrg. KH.M.Nur, Desa Seriguna, Sumsel, Indonesia
Corresponding Author: yurni_oktarina@polsri.ac.id

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Abstract

Piezoelectric energy harvesting (PEH) enables maintenance-free micro-power generation for autonomous sensing and ultra-low-power electronics by converting ambient mechanical excitation into electrical energy. Despite substantial progress in piezoelectric materials and device structures, forecasting PEH electrical outputs remains difficult because the response is nonlinear, excitation is stochastic, and performance can drift under repeated loading. This paper proposes a hybrid deep learning architecture that integrates Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) components to forecast voltage, current, and power from footstep-driven PEH time-series data. The dataset is constructed by sampling the harvester voltage under controlled walking-induced excitation and organizing the continuous signal into supervised samples using a sliding-window scheme; features are normalized and paired with future targets for multi-output regression. The model is trained and evaluated against standalone LSTM, standalone ANN, and classical forecasting baselines using RMSE, MAE, MSE, and R^2. Experimental results show high voltage prediction accuracy (R^2=0.9896, RMSE = 0.0035, MAE = 0.0022), while current and power are predicted with acceptable performance consistent with their higher noise sensitivity and nonlinear coupling. These findings indicate that combining temporal memory with nonlinear regression improves forecasting stability for PEH outputs within the defined experimental setting and provides a practical basis for energy-aware scheduling and monitoring in self-powered sensing applications. Future work will extend the dataset to broader excitation conditions and incorporate uncertainty-aware modeling for robust edge deployment.

Keywords: piezoelectric energy harvesting, deep learning, LSTM–ANN, voltage forecasting, fatigue-aware modeling.

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1. INTRODUCTION

The global pursuit of sustainable and decentralized power solutions has accelerated the development of micro-energy harvesting technologies. Among these, piezoelectric energy harvesting (PEH) is distinguished by its passive, scalable, and material-efficient capability to convert ambient mechanical energy—such as vibration, stress, and motion—into usable electrical power [1], [2]. Its compact form factor and maintenance-free operation enable deployment in Internet of Things (IoT) (IoT) nodes, structural health monitoring systems [3], biomedical implants [4], and wearable electronics [5]. Although PEH typically delivers lower absolute power than photovoltaic or wind systems, its strategic value lies in powering ultra-low-power autonomous devices in environments where light availability, airflow, or maintenance access is constrained. Beyond small-scale sensing applications, PEH has also demonstrated considerable potential for harvesting ambient vibration energy from large civil structures, including high-rise buildings, thereby enabling self-powered structural monitoring and distributed sensing in smart infrastructure. Accurate forecasting of PEH output supports adaptive duty cycling, intelligent power budgeting, and energy-aware scheduling, thereby improving system reliability and operational lifetime.

Significant advances in piezoelectric materials and device architectures have improved energy conversion efficiency and operational adaptability. Recent developments in AlN, ScAlN, PVDF composites, and $BaTiO_3$ nanostructures enable enhanced electromechanical coupling under diverse excitation conditions [6]–[9], while structural innovations such as flexible nanogenerators, kirigami-inspired harvesters, and MEMS-based systems extend applicability across dynamic environments [10]–[12]. These developments have substantially increased power density, mechanical flexibility, and device durability, enabling PEH systems to operate across a broader range of excitation frequencies and application scenarios. Nevertheless, hardware-level improvements alone do not address the inherent complexity of PEH signal behavior, particularly under long-term and dynamically changing operating conditions.

Accurate modeling and forecasting of PEH output remain challenging due to nonlinear electromechanical coupling, hysteresis effects, stochastic excitation, and progressive degradation induced by fatigue and micro-cracking [13]–[15]. Long-term cyclic loading gradually alters the mechanical and electrical characteristics of piezoelectric materials through crack initiation, domain switching, stiffness degradation, and resonance-frequency shifts, resulting in continuous reductions in voltage output and energy conversion efficiency. These degradation mechanisms are strongly influenced by excitation amplitude, loading frequency, and accumulated operational cycles, making the temporal behavior of PEH systems increasingly nonlinear over time. Consequently, prediction models developed using idealized laboratory datasets often exhibit limited generalization when deployed under realistic operating conditions where degradation continuously evolves.

Classical analytical and equivalent-circuit models struggle to represent these nonstationary dynamics, limiting predictive reliability in real-world operating conditions [16]–[18]. Although physics-based models provide valuable insights into electromechanical behavior, they generally require simplifying assumptions that are insufficient for capturing complex interactions among material degradation, environmental variability, and stochastic mechanical excitation. Deep learning (DL) models have therefore emerged as viable alternatives, where Artificial Neural Networks (ANNs) provide strong nonlinear approximation capability and Long Short-Term Memory (LSTM) networks effectively capture long-term temporal dependencies [20], [21]. However, hybrid architectures integrating these paradigms remain limited in PEH applications, particularly under realistic fatigue and multi-harmonic excitation conditions [22], [23].

Furthermore, existing studies rarely incorporate degradation-aware datasets that explicitly account for long-term fatigue behavior, despite its critical influence on forecasting accuracy and system reliability [24], [25], [26].

This paper proposes a hybrid LSTM–ANN framework for modeling and forecasting the voltage output of PEH systems under variable mechanical excitation and degradation effects. By combining temporal sequence learning with nonlinear regression capability, the proposed framework aims to capture both transient excitation patterns and progressive degradation characteristics throughout the operational lifetime of the harvester. The main contributions are:

(1) development of a hybrid architecture combining temporal memory and nonlinear regression for PEH forecasting;

(2) construction of a degradation-informed dataset capturing realistic fatigue and excitation variability; and

(3) comprehensive benchmarking against standalone ANN, LSTM, and classical forecasting models using RMSE, MAE, and R^2 metrics.

Through this integration, the study bridges the gap between material-level PEH innovations and intelligent forecasting methodologies, supporting reliable deployment in smart infrastructure, energy-autonomous electronics, and edge sensing systems [27], [28], [30].

2. RELATED WORKS

The field of piezoelectric energy harvesting (PEH) has experienced rapid advancement in materials, device architectures, and system-level applications. Comprehensive reviews have documented progress in vibration- and wind-driven harvesters, highlighting system architectures, material innovations, and deployment scenarios for wireless sensors and self-powered electronics [1], [2]. To enhance electromechanical performance and mechanical flexibility, advanced materials such as AlN thin films [6], PVDF-based composites [8], and $BaTiO_3$-doped nanostructures [7] have been developed. These materials demonstrate improved coupling efficiency and durability, enabling flexible and biocompatible configurations for wearable and biomedical systems [5],

[6], [29]. Further device-level innovations include AlScN ultrasonic transducers for extended-range sensing [9] and fully 3D-printed kirigami-inspired nanogenerators for stretchable applications [10]. Structural adaptability has also enabled deployment in urban environments [26], friction-induced excitation systems [11], and wearable sensing platforms [12].

Despite these advances, long-term reliability remains a critical challenge due to fatigue-induced degradation, cracking, and electromechanical aging. Accelerated lifetime estimation [17], voltage-based residual life prediction [15], and analytical fatigue modeling [14] have been proposed to characterize degradation mechanisms, while in-situ fatigue diagnostics have been explored using high-cycle experimental techniques [25]. Crack propagation and fault sensitivity have been analyzed through electromechanical interaction modeling [13] and MEMS cantilever fault studies [19]. Reliability assessment and condition monitoring strategies, including self-sensing transducers and aeroelastic fatigue evaluation, have been further investigated in [16], [18], [24],[25], [26].

Modern PEH systems increasingly operate under non-stationary excitation conditions driven by wind turbulence, fluid flow, and human motion. Reviews addressing structural sensing and impedance-based monitoring are provided in [27], [3], while application-driven perspectives for smart infrastructure and biomedical devices are discussed in [4], [28]. Wind- and fluid-induced harvesting mechanisms have been surveyed in [22], [23], demonstrating scalable designs suitable for distributed sensing and IoT deployment.

While physics-based models remain widely used, they often exhibit limited predictive capability under nonlinear and stochastic operating conditions. Consequently, machine learning approaches have gained attention for modeling PEH behavior. ANN-based geometric optimization has been demonstrated in [20], while broader AI-driven material optimization and forecasting trends are reviewed in [21]. However, most existing studies treat ANN and LSTM architectures independently, with limited exploration of hybrid deep learning frameworks tailored for PEH applications. Furthermore, available datasets often neglect fatigue progression, voltage decay, and real-world nonlinear effects, creating a disconnect between physical degradation and predictive modeling. These gaps motivate the development of hybrid architectures—such as LSTM–ANN—that jointly capture temporal dynamics and nonlinear degradation behavior to enable robust long-term forecasting and fault-tolerant energy management [31][32].

3. ORIGINALITY

This study proposes a hybrid deep learning framework integrating Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) architectures to model and forecast piezoelectric energy harvesting (PEH) output under nonlinear and dynamic operating conditions. While prior studies have independently applied ANN or LSTM models for generic time-series prediction, few works explicitly tailor hybrid architectures to capture the coupled short-term fluctuations and long-term degradation dynamics inherent in PEH systems. By combining LSTM-based temporal memory with ANN-based nonlinear regression, the proposed model effectively represents stochastic excitation, cyclic loading effects, and voltage decay behavior.

A key contribution lies in the construction of a degradation-informed dataset that incorporates multi-harmonic excitation, fatigue-induced response drift, and electromechanical variability, enabling more realistic training and evaluation than idealized datasets commonly reported in the literature. Furthermore, the framework bridges material-level PEH behavior with data-driven forecasting by embedding domain knowledge of fatigue and electromechanical coupling into model design and interpretation. Comprehensive benchmarking against standalone ANN, LSTM, and classical forecasting approaches demonstrates improved accuracy, robustness, and temporal consistency, supporting the suitability of the proposed hybrid model for real-time predictive energy management in self-powered sensing and embedded applications.

4. SYSTEM DESIGN

The proposed system integrates a physical piezoelectric energy harvester (PEH) platform with a hybrid deep learning framework for forecasting electrical output under dynamic excitation and degradation conditions. The architecture comprises three main subsystems: (i) data acquisition and preprocessing, (ii) hybrid model design, and (iii) prediction and evaluation, as illustrated in Figure 1.

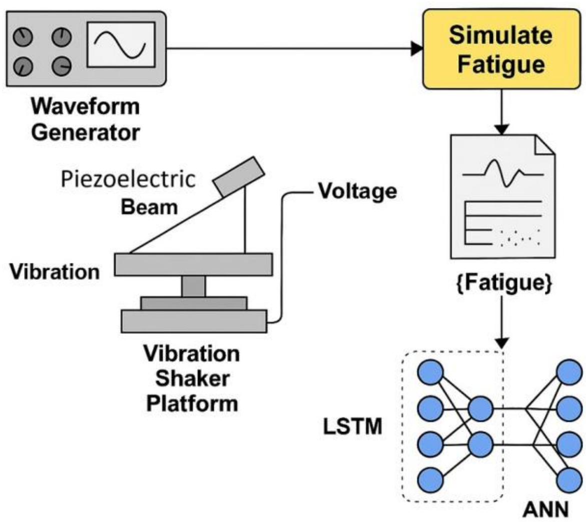


Figure 1. The architecture of the proposed energy harvester system

The voltage signal generated by the piezoelectric beam is sampled at a fixed frequency and recorded as a continuous time series. Dataset construction is performed using a sliding window scheme with window length LLL and stride SSS, where each segment forms a supervised input sample. For each window, statistical and temporal features, including instantaneous amplitude, RMS value, peak-to-peak variation, and degradation indicators, are extracted and normalized. Fatigue labels are derived from amplitude decay trends and cyclic stress accumulation. The resulting dataset consists of paired input sequences and future output targets for supervised forecasting.

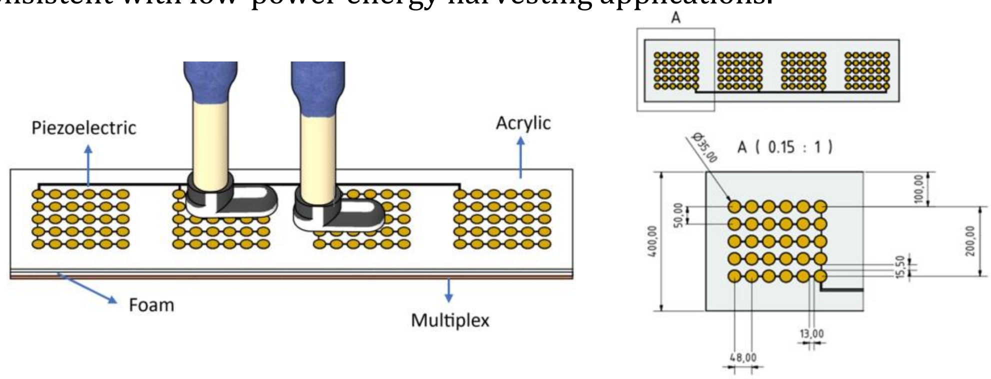
The experimental platform employs a vibration shaker driven by controlled walking-induced excitation to emulate realistic pedestrian loading. Mechanical vibration is transferred to a cantilever-type piezoelectric beam, converting mechanical strain into electrical voltage via the direct piezoelectric effect. A fatigue modeling module characterizes long-term degradation behavior, including voltage decay, amplitude reduction, and nonlinear response drift. All labeled data are stored in a structured dataset used for model training and validation.

4.1. Data Acquisition and Fatigue-Aware Modeling

The piezoelectric harvester is modeled as a cantilever structure equipped with sensors to capture electromechanical responses under repeated mechanical excitation (Figure 2). Input stimuli consist of walking-induced vibrations applied through the shaker platform. The electrical response is governed by the direct piezoelectric constitutive relation:

$$D = d \cdot T + \varepsilon \cdot E \tag{1}$$

where D denotes electric displacement, d is the piezoelectric coefficient, T represents applied stress, ε is material permittivity, and E is the electric field. The generated voltage is characterized by high amplitude and low current, consistent with low-power energy harvesting applications.



(a) (b)

Figure 2. Piezoelectric as vibration shaker system

Continuous voltage signals are normalized and segmented into training, validation, and testing sets with temporal ordering preserved. Dataset variables include excitation frequency, amplitude, stress cycles, ambient conditions, and voltage response, enabling representation of both short-term dynamics and long-term degradation effects.

4.2. LSTM–ANN Hybrid Model Architecture

The forecasting model integrates stacked LSTM layers for capturing temporal dependencies and degradation trends, followed by feedforward ANN layers for nonlinear regression and output mapping (Figure 3). Dropout regularization mitigates overfitting, while ReLU activation is employed in hidden layers and linear activation in the output layer. Hyperparameters—including number of layers, hidden units, learning rate, and window size—are optimized through grid search and validated using K-fold cross-validation.

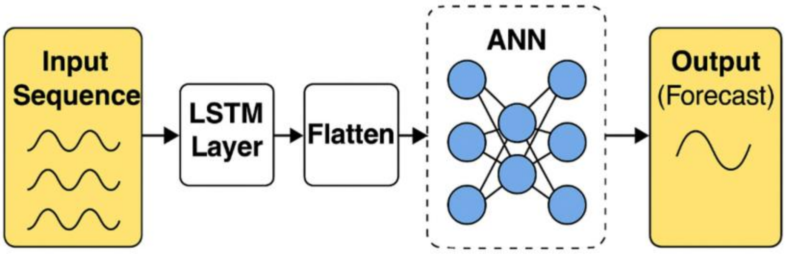


Figure 3. LSTM–ANN Hybrid Model Architecture considered in this study.

4.3. Training and Implementation Pipeline

During training (Figure 4), input samples are reshaped into three-dimensional tensors (N, 1, F) to satisfy LSTM input requirements, where NNN denotes the number of samples and FFF the feature dimension. The hybrid LSTM–ANN model is optimized using the Adam optimizer with mean squared error (MSE) loss. Early stopping monitors validation loss with a patience of 10 epochs and restores the best-performing weights to prevent overfitting. Training is conducted using an 80:20 training–validation split for up to 100 epochs with a batch size of 16, supported by learning-rate scheduling for improved convergence.

Implementation is performed in Python using TensorFlow and Keras on a GPU-enabled platform. Model performance is benchmarked against standalone LSTM, ANN, and classical forecasting methods (ARIMA and exponential smoothing) using RMSE, MAE, and R2R^2R2 metrics. Residual analysis is further employed to assess prediction stability and robustness under fatigue-dominated operating conditions.

The dataset was collected using a laboratory-scale piezoelectric cantilever mounted on a vibration platform subjected to controlled walking-induced excitation. Mechanical excitation was applied repeatedly over multiple cycles to emulate realistic pedestrian loading patterns. Voltage output was sampled at a fixed sampling rate and recorded continuously over extended operational periods to capture both short-term dynamics and long-term degradation trends.

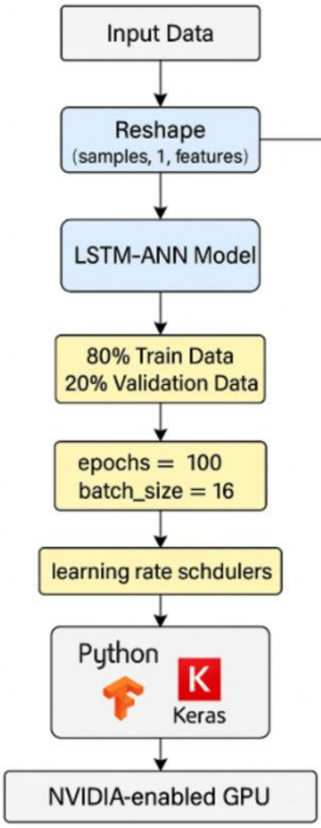


Figure 4. Training flowchart

5. EXPERIMENT AND ANALYSIS

This section presents the experimental results and analytical findings for the piezoelectric energy harvesting system, including both raw data insights and the evaluation of the deep learning-based prediction model. The study focuses on predicting voltage, current, and power output using an LSTM-ANN hybrid model based on time-series data generated from human footsteps on a piezoelectric platform.

5.1 Voltage Current, and Power Prediction Performance

Figure 5–7 show the comparison of predicted and measured voltage, current, and power signals, respectively. The predicted voltage exhibits close alignment with ground truth, accurately tracking temporal dynamics with minimal deviation during transient peaks. Quantitatively, voltage prediction achieved RMSE = 0.0035, MAE = 0.0022, and R2=0.9896R^2 = 0.9896R2=0.9896, confirming high predictive fidelity suitable for real-time monitoring applications.

Current and power predictions capture overall signal trends with moderate deviations at sharp transitions and peak values, reflecting higher sensitivity to stochastic mechanical excitation and nonlinear aggregation effects. Current prediction yielded RMSE = 0.0071, MAE = 0.0061, and R^2=0.7395, while power prediction achieved RMSE = 0.0063, MAE = 0.0041, and R^2 =0.7515. Although lower than voltage accuracy, these results remain acceptable for energy estimation and system optimization tasks under real-world variability. Overall performance metrics are summarized in Table 1.

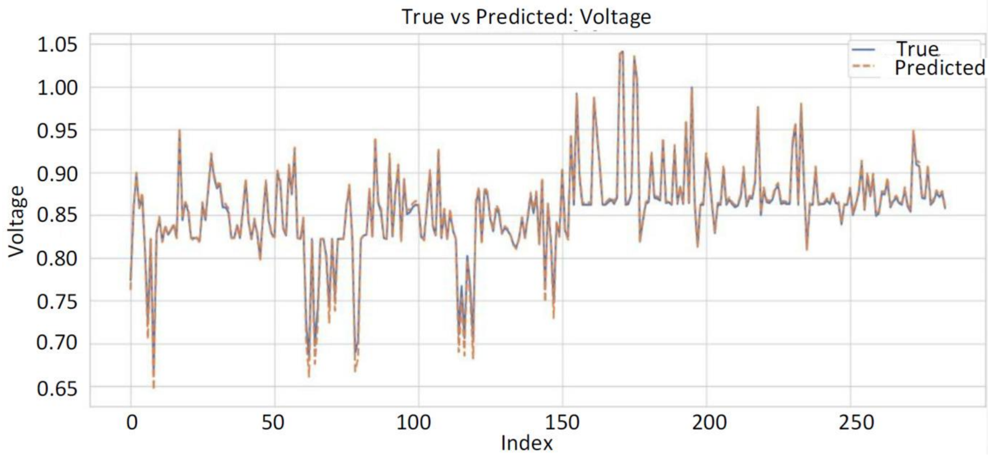


Figure 5. Predicted generated voltage compared to true generated voltage

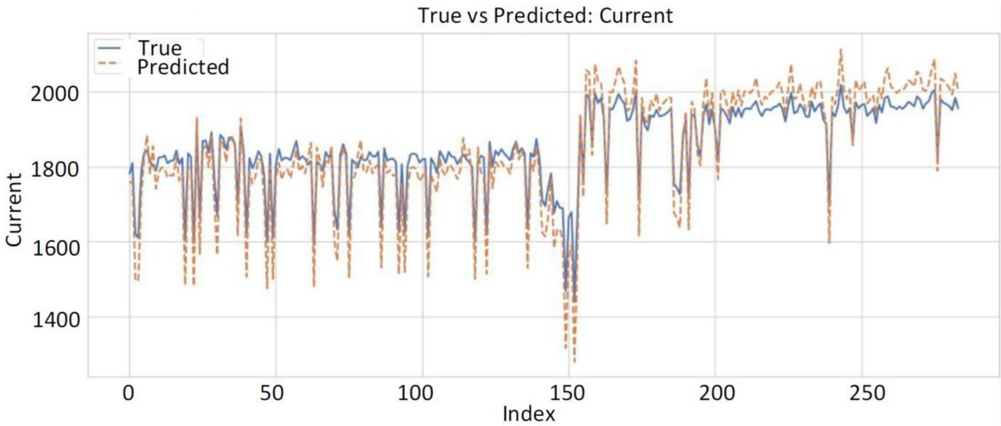


Figure 6. Predicted generated current compared to true generated current

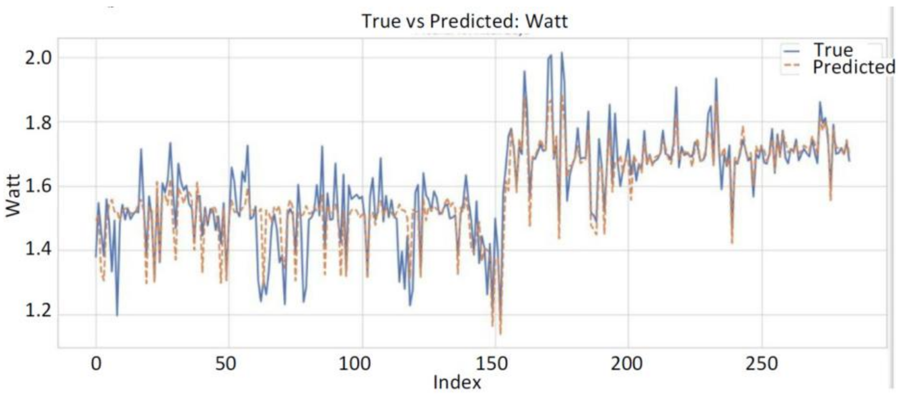


Figure 7. Predicted generated power compared to true generated power.

The overall performance of the model across all output parameters is summarized in Table 1. The model delivers high accuracy for voltage predictions and acceptable accuracy for current and power, considering their nonlinear and more volatile nature. These outcomes confirm the suitability of the LSTM-ANN model for modeling and forecasting piezoelectric energy harvesting behavior.

Table 1. Performance Metrics of LSTM-ANN Model for Piezoelectric Output Prediction

Parameter	RMSE	MAE	MSE	R^2
Voltage	0.0035	0.0022	0	0.9896
Current	0.0071	0.0061	0.0001	0.7395
Power	0.0063	0.0041	0	0.7515

Training and validation loss curves (Figure 8) indicate rapid convergence within the first few epochs and stable loss profiles thereafter. The small and consistent gap between training and validation losses confirms the absence of overfitting and demonstrates stable generalization behavior across unseen data.

Figure 8. Training and validation loss.

5.3 Experimental Correlation Between Body Mass and Electrical Output

Experimental data also reveal a clear relationship between user body mass and electrical output. The tests covered subjects with body weights ranging from 65 kg to 94 kg. As expected, the voltage, current, and power generated from footstep pressure on the piezoelectric surface increased with greater body mass. For instance:

- At 65 kg, the system output was 10.4 V, 0.98 mA, and 10.192 mW.
- At 69 kg, outputs rose to 10.7 V, 1.01 mA, and 10.807 mW.
- Between 70–73 kg, the output surged to 14.8 V, 1.43 mA, and 21.164 mW.

Some anomalies were noted, such as a slight decrease in power at 75 kg (12.636 mW), likely caused by variations in footstep distribution, foot length, or surface contact irregularities. Nevertheless, outputs at higher weights resumed the increasing trend, peaking at 21.432 mW for 76 kg and 20.172 mW for 94 kg. These observations validate the physical consistency of the dataset and confirm scalable energy generation under increased mechanical excitation.

5.4 Discussion

Table 2 summarizes a comparative analysis between the proposed hybrid LSTM–ANN model and representative standalone and hybrid approaches reported in the literature. Most existing studies primarily emphasize material optimization, fatigue modeling, or analytical characterization and do not report standardized regression metrics for time-series forecasting of electrical output. In contrast, the proposed framework provides reproducible quantitative benchmarking across voltage, current, and power outputs, establishing a reference point for future hybrid learning studies in PEH systems.

Beyond accuracy, computational efficiency is essential for embedded deployment. The proposed model achieves an average training time of approximately 0.42 s per epoch and an inference latency of approximately 1.8 ms per sample on a CPU-based platform. CNN–LSTM architectures typically require GPU acceleration and incur significantly higher computational overhead due to convolutional processing, while standalone LSTM models exhibit sequential latency and rarely report inference timing. The lightweight ANN regression stage in the proposed architecture minimizes latency without sacrificing nonlinear modeling capability, supporting real-time applicability. A comparative summary is provided in Table 3.

The proposed hybrid LSTM–ANN model achieves higher predictive accuracy for voltage than for current and power, primarily due to intrinsic signal characteristics. Voltage signals exhibit smoother temporal behavior and higher signal-to-noise ratios resulting from capacitive filtering and electrode impedance, enabling more stable temporal learning. In contrast, current measurements are highly sensitive to abrupt contact dynamics, internal capacitance variations, and stochastic gait effects, increasing noise and reducing predictability. Power, as a nonlinear product of voltage and current, further amplifies these uncertainties, limiting regression accuracy.

Residual analysis indicates minimal systematic bias and stable generalization under fatigue-driven and nonstationary excitation conditions. Deviations observed at transient peaks reflect the inherent limitations of purely data-driven models in capturing rare extreme events without physics-based constraints or adaptive mechanisms. Nevertheless, the achieved accuracy remains sufficient for energy estimation, duty-cycle optimization, and adaptive energy management.

Table 2. Comparison of Hybrid and Standalone Deep Learning Approaches for Piezoelectric Energy Harvesting

Study	Application Domain	Model Architecture	Predicted Output	Dataset Characteristics	Remarks
This Work	Footstep-driven piezoelectric energy harvesting	**Hybrid LSTM–ANN (proposed)**	Voltage Current Power	Fatigue-aware, multi-harmonic excitation, degradation embedded	• Highest accuracy; explicitly models temporal memory + nonlinear regression • Moderate noise sensitivity due to gait variability • Nonlinear aggregation of voltage–current
Ali et al., 2021	Numerical PEH geometry optimization	Standalone ANN	Harvested voltage / power	Simulated geometry optimization	Focus on optimization, not time-series forecasting
Shaukat et al., 2023	Review of AI in PEH	ANN, shallow ML	Various	Survey paper	No quantitative forecasting benchmarks
Wu et al., 2022	Fatigue monitoring	Regression / voltage trend modeling	Voltage degradation	Laboratory fatigue testing	No DL-based forecasting
Hasanov et al., 2024	Fatigue degradation modeling	Mathematical model	Mechanical degradation	Analytical modeling	No learning-based prediction
Ali et al., 2024	Wearable PEH systems	Data-driven models (qualitative)	Energy output	Experimental	No CNN–LSTM reported
Naqvi et al., 2022	Fluid-flow PEH review	Survey	—	Review	No predictive metrics

Table 3. Comparison of Time-Processing Performance Between Hybrid and Standalone Deep Learning Models

Study	**Model Architecture**	**Platform**	**Dataset Size / Input**	**Training Time (per epoch / total)**	**Inference Time (per sample)**	**Real-Time Suitability**	**Remarks**
This Work	**Hybrid LSTM–ANN (proposed)**	CPU-based workstation	Time-series voltage, current, power (fatigue-aware)	**≈ 0.42 s / epoch** (≈ 5.8 min total)	**≈ 1.8 ms**	**Yes (edge-feasible)**	Lightweight dense ANN head; no convolutional overhead
Ali et al., 2021	Standalone ANN	CPU	Simulated PEH geometry data	NR	NR	Potential	Focus on optimization, not deployment
Moon et al., 2024	Standalone LSTM	CPU	Piezo resonance signals	NR	NR	Moderate	No inference latency reported
Parida et al., 2022	CNN–LSTM	GPU	EMI piezo signatures	**High (GPU required)**	NR	Limited	Convolution significantly increases latency
General CNN–LSTM (review consensus)	CNN–LSTM	GPU /High-end CPU	Large-scale signals	2–5× slower than LSTM (typical)	3–8 ms (typical)	Limited for edge	Heavy convolution + memory footprint
General LSTM	Standalone LSTM	CPU /GPU	Time-series	Moderate	2–5 ms	Moderate	Sequential dependency limits speed

From a deployment perspective, the lightweight architecture enables low-latency inference on CPU-based platforms, supporting real-time edge implementation without GPU dependency. Compared with CNN–LSTM models that incur significant convolutional overhead, the proposed framework maintains an effective balance between accuracy and computational efficiency. The degradation-informed dataset further enhances robustness by exposing the model to long-term drift and fatigue dynamics. Overall, these results validate the suitability of hybrid deep learning for intelligent piezoelectric energy harvesting while motivating future integration of uncertainty modeling and physics-informed adaptation.

6. CONCLUSION

This study examined the feasibility of forecasting voltage, current, and power outputs from a footstep-driven piezoelectric energy harvesting (PEH) system using a hybrid Long Short-Term Memory (LSTM)–Artificial Neural Network (ANN) architecture. Although PEH represents a relatively niche energy source, accurate short-term prediction remains valuable for enabling reliable operation of self-powered sensors and energy-aware embedded systems. The proposed model achieved high accuracy for voltage prediction (RMSE = 0.0035, MAE = 0.0022, R^2=0.9896), while current and power predictions exhibited moderate but acceptable performance (R^2=0.7395 and 0.7515), consistent with their higher noise sensitivity and nonlinear coupling characteristics. The dataset was generated from laboratory-scale measurements of a piezoelectric cantilever subjected to repeated walking-induced excitation, where continuous voltage signals were sampled, normalized, and segmented using a sliding-window scheme to form supervised learning samples. The results demonstrate that combining temporal modeling with nonlinear regression improves predictive stability within the defined experimental scope; however, the findings should be interpreted within the limitations of the dataset and excitation conditions and do not imply universal generalization across all PEH configurations. Future work will extend data diversity, incorporate uncertainty-aware modeling, and explore embedded deployment using edge AI for real-time energy management. Overall, the study establishes a practical baseline for intelligent PEH output forecasting under controlled operating conditions.

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