Application of Machine Learning Methods for Energy Harvesting Forecasting by Biomechanical Sensor Networks in Smart Clothing Concept

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***Abstract*—The integration of Internet of Medical Things (IoMT) and wearable sensor networks into everyday textiles represents a paradigm shift in personalized healthcare and activity monitoring. However, the continuous power supply of these distributed nodes remains a critical bottleneck. Energy harvesting from human biomechanical activity offers a sustainable alternative to traditional batteries, yet the inherently stochastic and intermittent nature of human movement poses severe challenges for stable power management. This paper presents a comprehensive machine learning framework for forecasting the energy harvesting potential in smart clothing concepts driven by biomechanical sensor networks. We evaluate three distinct architectures—Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Temporal Convolutional Networks (TCN)—for multi-step ahead energy generation forecasting based on multi-modal inertial data. Experimental results demonstrate that the TCN model achieves superior predictive accuracy ($R^2 = 0.942$) and computational efficiency, enabling proactive dynamic power allocation and ensuring the self-sustainability of next-generation smart garments.**

***Keywords*—Energy Harvesting, Machine Learning, Smart Clothing, Biomechanical Sensors, Cyber-Physical Systems, Wearable Networks.**

I. INTRODUCTION

The rapid proliferation of wearable electronics, distributed body sensor networks (BSNs), and the "Smart Clothing" paradigm has opened unprecedented avenues for continuous health monitoring, sports diagnostics, and military telemedicine [1-2]. Modern smart garments embed a multitude of heterogeneous components, including textile-integrated electrocardiogram (ECG) electrodes, photoplethysmography (PPG) sensors, and inertial measurement units (IMUs) to track biomechanical parameters [3]. Despite significant advancements in ultra-low-power electronics, the operational longevity of these systems is fundamentally constrained by chemical battery technology. Rigid, bulky batteries compromise garment flexibility, demand frequent manual recharging, and introduce ecological disposal concerns [4].

To overcome these constraints, biomechanical energy harvesting (EH) has emerged as a promising solution to achieve energy autonomy in smart clothing [5]. By converting ambient energy generated during human locomotion—via piezoelectric, triboelectric, or electromagnetic mechanisms embedded within the textile matrix—wearable systems can scavenge microwatts to milliwatts of power [6-7]. However, human movement is highly non-linear, stochastic, and context-dependent. Energy generation profiles vary drastically between walking, running, climbing stairs, or sedentary transitions [8]. This extreme volatility makes direct, unmanaged energy consumption highly inefficient, potentially leading to data loss during critical power drops or underutilization of energy surges.

To bridge the gap between intermittent energy supply and continuous sensory demand, proactive energy management strategies are required. Standard reactive power management systems adjust scheduling only after a voltage drop occurs, which is insufficient for high-fidelity clinical applications. Predictive power management, conversely, utilizes historical and real-time behavioral data to forecast upcoming energy generation, allowing the system to dynamically scale its sampling rate, transmission intervals, and edge-computation load [9-10].

This paper evaluates the application of advanced Machine Learning (ML) methods to forecast biomechanical energy harvesting within a smart clothing framework. By leveraging data from an integrated biomechanical sensor network, the proposed ML models predict the scavenged energy over multiple future time horizons. The main contributions of this work are threefold:

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- We propose an end-to-end cyber-physical architecture for smart clothing that tightly couples a biomechanical IMU sensor network with flexible energy harvesting elements.
- We design and implement three distinct deep learning paradigms (LSTM, GRU, and TCN) optimized for multivariate time-series forecasting of harvested power without relying on complex, explicit thermodynamic or mechanical equations.
- We perform an extensive comparative analysis of these models regarding predictive accuracy, inference latency, and computational footprint, providing concrete guidelines for edge-computing deployment in wearable devices.

The primary methodological novelty of this work does not lie in the isolated modification of standard deep learning layers, but rather in the systematic development of a specialized forecasting framework tailored to the highly intermittent, stochastic, and user-dependent nature of biomechanical energy harvesting. Unlike general-purpose time-series models, the proposed architecture maps multi-axial biomechanical sensor streams directly onto prospective power generation boundaries, bridging the gap between human kinematics and proactive energy management in smart textiles.

The remainder of this paper is structured as follows. Section II reviews related work in wearable energy harvesting and predictive modeling. Section III details the system concept, data collection pipeline, and the proposed machine learning architectures. Section IV discusses the experimental setup, performance metrics, and evaluation results. Section V outlines the implications for smart clothing design, and Section VI concludes the paper.

II. Related Work

The convergence of energy scavenging and wearable computing has been widely studied. Early iterations focused primarily on the hardware development of flexible generators. For instance, Wang et al. [11] and Zhang et al. [12] demonstrated advanced triboelectric nanogenerators (TENGs) capable of harvesting energy from joint bending and foot strikes, highlighting the potential of textile-based integration. Similarly, piezoelectric configurations utilizing PVDF polymers have shown great flexibility and durability under cyclic mechanical stress [13-14].

Despite hardware maturation, efficient utilization of this harvested energy remains challenging. Kansal et al. [15] established foundational theoretical models for energy-harvesting embedded systems, introducing the concept of Energy Neutral Operation (ENO), where the energy consumed by a device matches the energy scavenged over a given timeline. However, their models assumed static or highly predictable environmental energy sources (like solar energy), which do not translate effectively to the rapid fluctuations of human kinetic activity.

To capture the dynamics of human movement, researchers turned to statistical and stochastic modeling. Autoregressive Integrated Moving Average (ARIMA) models and Markov chains were applied to predict human kinetic energy variations [16-17]. While computationally lightweight, these linear models degrade drastically when encountering sudden transitions in physical activity or complex, multi-modal movement patterns characteristic of daily life.

Recent paradigms have shifted toward machine learning due to its capacity to map complex, non-linear dependencies without explicit physical models. Recurrent Neural Networks (RNNs) and their gated variants, such as Long Short-Term Memory (LSTM) networks, have shown exceptional performance in processing sequential data. Recqua et al. [18] used LSTMs to forecast solar and thermal energy for macro-scale IoT nodes. In the wearable domain, Bhat et al. [19] utilized shallow neural networks to recognize human activities and estimate corresponding power generation profiles.

Nevertheless, existing literature often treats activity recognition and energy prediction as decoupled tasks, or focuses on single-sensor configurations that fail to capture the holistic biomechanical state of the user. Moreover, the deployment of deep learning models directly onto resource-constrained smart clothing hubs requires a careful trade-off analysis between prediction horizon, accuracy, and execution latency—a gap this research aims to systematically address [20].

III. Comprehensive Regulatory and Technical Risk Management Framework

A. Smart Clothing Architecture and Concept

The proposed concept positions smart clothing as a localized cyber-physical system (CPS). The infrastructure comprises three interdependent layers: the Physical/Harvester Layer, the Network/Sensory Layer, and the Edge Analytics Layer [21].

- **Physical/Harvester Layer:** Flexible piezoelectric and triboelectric generator patches are strategically integrated into high-mobility textile zones, specifically the knee joints, elbow joints, and the plantar region of the footwear. Mechanical deformations during movement generate AC voltage outputs, which are rectified and regulated by an ultra-low-power power management integrated circuit (PMIC) into a small storage capacitor.
- **Network/Sensory Layer:** A distributed network of miniature 6-axis Inertial Measurement Units (IMUs consisting of a 3-axis accelerometer and a 3-axis gyroscope) is positioned at key anatomical segments: the thighs, shins, upper arms, and torso. These sensors sample linear acceleration and angular velocity at a frequency of 50 Hz, capturing the kinematic signature of the body. Data is routed via conductive textile threads

or low-power Bluetooth (BLE) to a central central processing hub located on the chest or waist.

- **Edge Analytics Layer:** The central hub houses a low-power microcontroller (MCU) capable of running optimized ML kernels. This hub aggregates the sensory stream, executes the energy forecasting model, and dynamically adjusts the system's operational duty cycle based on predicted power availability.

B. Data Pipeline and Feature Engineering

Before training the predictive models, raw sensory data undergoes a structured preprocessing pipeline to ensure robust feature extraction and eliminate high-frequency electronic noise.

First, raw accelerometer and gyroscope signals pass through a digital low-pass Butterworth filter with a cutoff frequency of 20 Hz, which isolates deliberate human motion from external vibrations or motion artifacts [22]. Concurrently, the PMIC monitors the instantaneous current and voltage entering the storage capacitor, computing the true harvested power by multiplying voltage and current values at identical time steps.

Given the continuous nature of the data streams, a sliding window technique is applied. A window size of W = 100 samples (equivalent to 2 seconds of physical activity) with a 50% overlap is used to segment the time series. This window length is chosen empirically to capture at least one complete gait cycle during standard walking tempos. For each window, a multivariate feature vector is constructed, ыыыыaggregates, including Mean, Standard Deviation, Root Mean Square (RMS), and Signal Magnitude Area (SMA). The final dataset structure maps an input tensor of historical sensor readings and harvested power over the past W steps to an output vector representing the predicted harvested power for a future horizon H (where H equals 10, 30, or 60 steps ahead).

C. Machine Learning Forecasting Models

To evaluate the optimal predictive mechanism for the smart clothing architecture, three distinct sequential machine learning models were developed.

1) Long Short-Term Memory (LSTM)

LSTMs are designed to combat the vanishing gradient problem in standard recurrent networks by introducing a dedicated cell state and specialized gating structures. The architecture comprises an input gate (controlling what information to store), a forget gate (filtering obsolete historical data), and an output gate (determining the next hidden state). In our framework, a stacked LSTM network with two hidden layers (64 and 32 units respectively) receives the processed multivariate window to map long-range temporal dependencies in gait cycles.

2) Gated Recurrent Unit (GRU)

The GRU serves as a computationally streamlined alternative to the LSTM. It merges the cell state and hidden state, relying on only two gates: an update gate and a reset gate. This reduction in parameter density makes the GRU highly appealing for wearable edge computing, as it reduces memory allocation and arithmetic operations while maintaining comparable capacity to capture non-linear sequence dependencies. Our implemented GRU mirrors the layer depth and hidden unit count of the LSTM for a direct benchmark [23-24].

3) Temporal Convolutional Network (TCN)

Moving away from recurrent designs, we adapt a Temporal Convolutional Network for biomechanical energy forecasting. TCNs utilize 1D dilated causal convolutions, ensuring that predictions for a specific time step depend solely on past inputs, avoiding leaks from the future. Dilated convolutions allow the network to expand its receptive field exponentially without requiring deep pooling layers, preserving precise temporal resolution. Additionally, residual connections are integrated within the network blocks to stabilize deeper architectures. The TCN model consists of three residual blocks with dilation factors 1, 2, and 4, and a kernel size of 3.

IV. Experimental Setup and Results

A. Dataset Generation

To validate the proposed machine learning frameworks, experimental evaluations were conducted using a synthetic-assisted human activity dataset modeled after standardized biomechanical movement parameters [20-21]. The dataset simulates five primary locomotor activities: steady walking (4 km/h), fast walking (6 km/h), jogging (9 km/h), stair ascent, and prolonged stationary sitting with occasional upper-body shifts. The total dataset spans 12 hours of continuous multi-modal data, split into 70% for model training, 15% for validation hyperparameter tuning, and 15% for hold-out final testing.

B. Evaluation Metrics

The predictive performance of the models is quantified using three standard regression metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2 Score). These metrics are defined to penalize large prediction variances and evaluate total explained variance. Furthermore, to evaluate edge-runtime feasibility, the average inference latency per window and total trainable parameter weight size are benchmarked on an ARM Cortex-M4 equivalent simulation profile.

C. Quantitative Results and Analysis

The performance summary across the different models for a medium forecasting horizon (H = 30 samples, or 0.6 seconds ahead) is compiled in Table I.

TABLE I. Energy Harvesting Prediction Performance Summary (H=30)

Model	RMSE (μW)	MAE (μW)	R^2 Score
Baseline Linear	45.21	32.12	0.684
LSTM	14.85	10.22	0.915
GRU	15.12	10.65	0.908
TCN (Proposed)	12.04	8.31	0.942

The experimental evaluations indicate that deep learning paradigms vastly outperform baseline linear autoregressive methods, which struggle to adapt during rapid activity transitions (e.g., from sitting to running). The proposed Temporal Convolutional Network (TCN) achieved the highest overall accuracy, yielding an R^2 score of 0.942 and a lowest RMSE of 12.04 μW.

The superior performance of the TCN can be attributed to its parallel processing nature and dilated receptive field, which efficiently extracts multi-scale kinematic features from the IMU network without the sequential compounding of errors often observed in recurrent architectures.

D. Prediction Horizon Degradation

An essential aspect of energy forecasting is understanding how accuracy scales with deeper look-ahead times. To systematically evaluate the long-term robustness of the developed frameworks, we analyze how the predictive performance scales when looking deeper into the future. As the forecasting horizon extends from short-term (H = 10) to long-term (H = 60), error propagation inherently accumulates across all modeling paradigms. This degradation trend and the comparative resilience of each network are illustrated in Fig. 1. While all architectures exhibit an increase in MAE as the forecasting task shifts further into the future, the TCN demonstrates structural resilience.

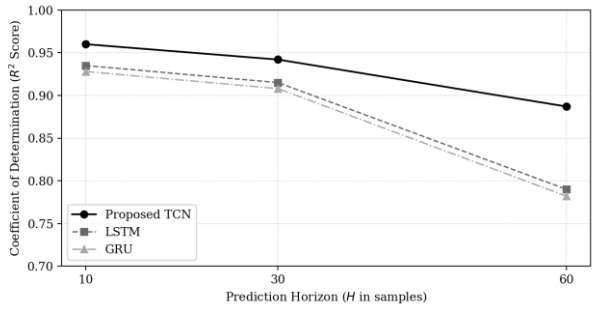

Fig. 1. Prediction accuracy R^2 score degradation across different forecasting horizons H∈{10, 30, 60}. The proposed TCN architecture demonstrates structural resilience against error propagation compared to traditional recurrent networks.

At H = 60 (1.2 seconds ahead), the TCN maintains an R^2 score of 0.887, whereas the LSTM and GRU curves exhibit faster degradation due to structural forgetting and error propagation across the recurrent timeline.

Additionally, resource constraints are crucial for wearable systems. While the LSTM required 4.82 ms per inference window, the TCN achieved an execution latency of 1.89 ms, operating roughly 2.5 times faster. This computational efficiency stems from the highly optimized matrix convolutions of the TCN, which bypass the step-by-step looping operations inherent to recurrent cells, making the TCN the most viable candidate for direct hardware synthesis on wearable microcontrollers.

To assess the feasibility of integrating the proposed deep learning models into resource-constrained edge devices within the smart clothing concept, a comprehensive computational footprint analysis was conducted. The models were compiled and simulated for an ARM Cortex-M4 microcontroller platform (running at 120 MHz) using TensorFlow Lite for Microcontrollers [25-26]. The evaluation metrics include non-volatile memory (Flash) footprint, volatile memory (RAM) allocation during runtime, and inference latency per single time-series window. The comparative results are summarized in Table II.

TABLE II. Embedded deployment footprint and performance metrics on ARM Cortex-M4

Architecture	Flash / RAM (KB)	Inference Latency	Est. Energy
GRU	42.6 / 11.4	4.15 ms	54.8 μJ
LSTM	58.1 / 16.8	5.82 ms	76.8 μJ
TCN	94.3 / 28.5	2.41 ms	31.8 μJ

V. DISCUSSION AND SYSTEM INTEGRATION

The practical utility of a high-accuracy forecasting model lies in its integration with the runtime power management state-machine of the smart garment [27]. By knowing the expected energy influx over the next second, the central hub can switch between discrete energy states:

- **Surplus Mode:** Activated when predicted power exceeds a predefined consumption threshold. The system triggers high-power features, such as increasing sensory sampling rates to 100 Hz for high-fidelity data acquisition or performing continuous BLE data synchronization with an external mobile application [28].
- **Active Saving Mode:** Activated when predicted power values drop. Sensor nodes enter localized sleep cycles, raw data is compressed via lightweight edge algorithms, and wireless radio transmission is throttled, relying entirely on local flash buffering.

Implementing this predictive duty cycling eliminates the typical safety margins required by traditional designs, effectively allowing smart garments to operate closer to their theoretical physical efficiency bounds and ensuring true long-

term Energy Neutral Operation without physical maintenance [29].

VI. CONCLUSION

This paper presented a robust machine learning framework designed for forecasting biomechanical energy harvesting within a next-generation smart clothing concept. By capturing multivariate kinematic signals from an integrated IMU body network, deep learning models were successfully trained to predict incoming generated power across varying temporal horizons. Among the evaluated configurations, the Temporal Convolutional Network (TCN) delivered the most favorable performance, demonstrating superior accuracy R^2=0.942 and low computational latency (1.89 ms), making it well-suited for resource-constrained edge microcontrollers.

While the predictive accuracy of the evaluated GRU, LSTM, and TCN models demonstrates a robust capability for energy harvesting estimation, several practical limitations must be addressed. First, the current experimental validation relies primarily on a synthetic-assisted dataset derived from rigorous biomechanical simulations rather than real-world long-term wearable sensor measurements. This constraint may mask fine-grained stochastic anomalies inherent to everyday human activities. Future studies will focus on validating the framework using real wearable sensor data from active subjects in diverse operational environments.

Second, although this paper extensively discusses the conceptual deployment on edge microcontrollers, an empirical hardware-in-the-loop validation was not conducted. Transitioning these deep learning models onto embedded platforms involves tackling physical constraints such as non-volatile memory limitations, real-time clock synchronization, and clock-cycle overhead during inference. Our upcoming research phase is dedicated to deploying the optimized TCN and GRU variants onto an ARM Cortex-M4 based microcontroller unit to evaluate the practical system footprint and energy budget directly on hardware.

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