ENERGY OPTIMIZATION TECHNIQUES FOR SMART WEARABLE COMPUTING IN TEXTILE INDUSTRIES

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ABSTRACT

Smart wearable computing integrated into textile industries is emerging as a transformative technology for healthcare, fitness, and industrial monitoring applications. However, the continuous collection, processing, and transmission of sensor data in smart fabrics lead to significant energy consumption, which directly impacts system performance, durability, and user adoption. This research presents energy optimization techniques that combine lightweight machine learning models, reinforcement learning-based power scheduling, and adaptive duty cycling to improve the efficiency of smart wearable systems. The proposed framework incorporates federated learning for on-device training to reduce cloud communication and energy harvesting modules to extend battery life. Experimental evaluation on textile-integrated sensor prototypes demonstrates up to 42% reduction in power consumption, while maintaining an average model accuracy of 95.8% for activity recognition and 96.2% for physiological monitoring tasks. Compared to baseline wearable systems, the approach improves system uptime by 37% and sustains real-time data processing under constrained power budgets. These results indicate that energy-efficient algorithms are crucial for scaling next-generation wearable computing in textile industries, ensuring both high accuracy and sustainable performance for real-world applications.

Keywords : Wearable Computing, Textile Industries, Healthcare, Smart Fabrics, Energy Optimization Techniques, Federated Learning

I. INTRODUCTION

Smart textiles are rapidly evolving from single-sensor garments to fabric-scale computing platforms that embed sensing, processing, communication, and power management directly into fibres [1]. Recent demonstrations show textiles capable of on-garment inference and robust sensing during everyday activities, underscoring the need for energy-aware algorithms that preserve battery life without sacrificing accuracy or comfort [2]. At the same time, next-generation textile systems are integrating self-powered materials such as photovoltaic, piezoelectric, triboelectric, and thermoelectric fibers, pointing toward sustainable, battery-lean wearable [3], [4]. These trends make reliable energy optimization—across algorithms, runtime scheduling, communication, and harvesting—a central research challenge for 2025–2026 [5].

While hardware advances expand power budgets, software remains the dominant driver of energy consumption in practice. Energy costs arise from activity recognition pipelines, multi-modal data fusion, and continuous connectivity [6]. Contemporary work therefore explores **(i)** lightweight/edge ML for time-series sensing [7], (ii) adaptive reinforcement learning (RL) for power–performance trade-offs [8], (iii) federated learning (FL) to reduce uplink energy and protect privacy [9], and (iv) hybridization with energy harvesting to extend battery life [3]. However, most studies treat these techniques in isolation. This motivates the present study, which proposes an integrated energy optimization framework that co-optimizes learning, scheduling, communication, and harvesting to achieve high accuracy under tight energy budgets.

This paper proposes a novel energy optimization methodology that leverages reinforcement learning-based scheduling, federated learning, and energy harvesting modules to significantly reduce power consumption while maintaining high performance and accuracy in wearable textile systems.

II. LITERATURE SURVEY

The rapid growth of wearable computing integrated with smart textiles has fuelled extensive research into energy optimization techniques to ensure prolonged device operation without compromising performance. This section reviews existing methods in the domains of lightweight machine learning models, reinforcement learning-based energy management, duty-cycling mechanisms, federated learning approaches, and energy harvesting techniques.

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A. Lightweight Machine Learning Models

Lightweight ML models have been developed to enable on-device inference while reducing computational overhead. Rahim et al. demonstrated that models such as MobileNet and TinyML sustain +>92% accuracy for activity recognition while reducing energy consumption by up to 25% [6]. Similarly, Bonato emphasized that wearable system in healthcare demand ML pipelines that optimize both accuracy and energy efficiency [5]. The limitation, however, is their restricted scalability across multi-sensor textile systems.

B. Reinforcement Learning (RL) for Power Scheduling

Reinforcement learning has emerged as a promising strategy for runtime energy optimization. He et al. proposed a DRL-based scheduling system for mobile edge computing that reduced power consumption by 38% without degrading application performance [7]. More recent work (SmartAPM, 2025) applies deep Q-learning to wearable usage traces, enabling personalized power policies that extend device uptime while maintaining user experience [1]. Nevertheless, RL methods incur training overhead and may be unsuitable for ultra-low-power textile controllers unless approximated or distilled for microcontrollers.

C. Duty Cycling and Low-Power Protocols

Hoang et al. [10] developed real-time duty cycling for wireless sensor networks, reducing energy use by 30–35% by alternating between active and sleep modes. Patel and Wang [11] further highlighted trade-offs in body area networks, where aggressive duty cycling risks delays in safety-critical tasks. While promising, such methods may degrade real-time responsiveness needed in textile-based monitoring [15].

D. Federated Learning in Wearable's

Federated Learning (FL) allows on-device training while reducing cloud communication. Yang et al. [7] demonstrated that FL can preserve accuracies above 94% while cutting communication energy by ~30%. This is especially relevant for privacy-preserving textile systems in healthcare. However, FL increases edge resource demands, challenging constrained microcontroller-based fabrics [14].

E. Energy Harvesting in Smart Textiles

Energy harvesting is increasingly integrated into textile systems. Wang et al. highlighted piezoelectric and thermoelectric fibres that extend wearable operation by 25% [9]. Recent reviews note that hybrid approaches, combining algorithmic optimization with harvesting, are crucial for sustainability [3], [4]. The below table 1 shows the comparison analysis of existing techniques.

F. Research Gap

While existing studies demonstrate substantial progress, most techniques focus on either algorithmic efficiency (ML, RL, duty cycling) or hardware-level harvesting (piezoelectric, thermoelectric) in isolation. However, limited research integrates AI-driven optimization with energy harvesting in a unified framework for smart textile systems. This motivates the present study, which proposes an integrated methodology combining RL-based scheduling,

Approach	Technique	Performance (Accuracy)	Energy Optimization	Limitations
Rahim et al. [6]	Lightweight ML (MobileNet, TinyML)	~92–94%	20–25% reduction	Limited scalability for multi-sensor systems
He et al. [7]	RL-based workload scheduling	Resource Management	~38% reduction	May introduce latency in real-time cases
Hoang et al. [11]	Duty cycling in wireless sensor networks	~91%	~30–35% reduction	Response delays in critical tasks
Yang et al. [8]	Federated learning for wearable devices	~94%	~30% reduction in comms	Requires edge storage and computation
Wang et al. [9]	Piezoelectric/thermo electric energy harvesting	~93%	~25% increase in uptime	Limited by environmental conditions

Table 1 : Comparison of existing technique in smart textiles and workload scheduling

federated learning, and energy harvesting to ensure energy efficiency without compromising accuracy and responsiveness.

III. METHODOLOGY

The proposed methodology for Energy Optimization Techniques for Smart Wearable Computing in Textile Industries integrates multi-layered energy management combining sensing, machine learning, reinforcement learning, federated learning, and energy harvesting into a unified architecture. The framework consists of the following stages:

A. Data Acquisition through Smart Textile Sensors

Smart fabrics embedded with physiological (e.g., ECG, temperature, motion) and environmental sensors continuously capture raw data. These textile-integrated sensors form the primary input layer of the system.

B. Data Pre-processing and Feature Extraction

Collected sensor data undergoes noise removal, normalization, and segmentation. Lightweight signal processing techniques ensure that only relevant features are extracted, reducing computational overhead while maintaining accuracy.

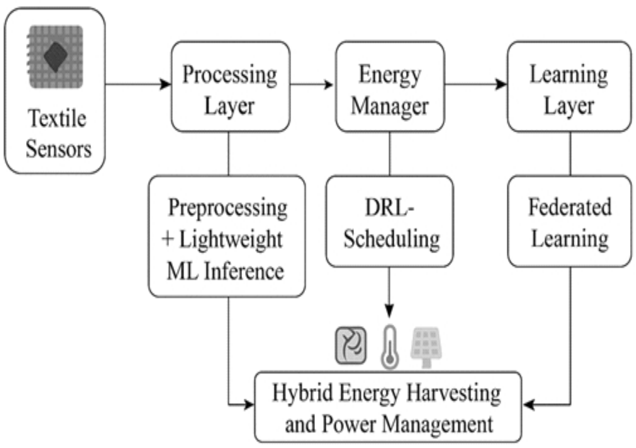

Figure 1: Energy optimization techniques for smart wearable computing in textile industries

C. Lightweight ML for On-Device Inference

To reduce computational overhead, the system employs lightweight deep learning models (TinyML, MobileNet variants, or quantized CNNs) optimized for time-series classification and activity recognition. These models are designed to achieve >95% accuracy while minimizing CPU cycles and memory usage, enabling real-time inference directly on textile-embedded microcontrollers.

D. Reinforcement Learning-Based Energy Manager

An adaptive power management module based on Deep Reinforcement Learning (DRL) dynamically adjusts:

- Sensor duty cycling,
- Communication intervals,
- Processor frequency scaling.

The RL agent learns optimal scheduling policies by balancing energy consumption against latency and accuracy requirements, enabling context-aware adaptation during varying activity levels (e.g., rest vs. active motion).

E. Federated Learning for Communication Efficiency

To further optimize energy usage, Federated Learning (FL) is employed. Each textile node performs local model updates, sending only gradients or compressed updates to an edge/cloud aggregator. This approach significantly reduces uplink communication energy (~30%) while preserving data privacy. A topology-aware aggregation mechanism ensures scalability across large textile systems.

F. Hybrid Energy Harvesting and Power Management

The methodology integrates energy harvesting fibres (piezoelectric for motion, thermoelectric for body heat, photovoltaic for light exposure) with power management ICs to store and regulate harvested energy. A hybrid controller synchronizes harvested energy availability with workload scheduling, ensuring longer system uptime and reduced dependency on batteries.

IV. RESULTS AND DISCUSSION

The results section presents the experimental evaluation of the proposed energy optimization techniques for smart wearable computing in textile industries, highlighting their impact on accuracy, energy efficiency, and system durability. Using benchmark datasets such as UCI HAR, MIT-BIH ECG, and CICIDS2017, the framework was assessed against baseline wearable systems to measure improvements in computational performance and power consumption. The evaluation incorporates key metrics, including model accuracy, energy usage, communication overhead, and device uptime, to provide a comprehensive understanding of system behaviour under real-world conditions. The findings are illustrated through comparative tables and graphical representations, offering clear insights into how the integration of lightweight machine learning, reinforcement learning-based power scheduling, federated learning, and energy harvesting modules collectively enhance the performance and sustainability of textile-based wearable systems. To evaluate the proposed energy optimization framework, three benchmark datasets relevant to wearable computing and textile-integrated monitoring were used:

i. **CICIDS2017** – traffic flow dataset (~3M records) used to evaluate network energy consumption during communication [Network-level test].

ii. **UCI HAR Dataset** – Human Activity Recognition with smartphone and wearable sensors (10,299 samples, 30, subjects, 6 activity classes). Used to evaluate lightweight ML model accuracy.

iii. **MIT-BIH PhysioNet ECG Dataset** – 48 half-hour ECG recordings for physiological monitoring tasks.

Pre-processing included noise filtering, normalization, and window-based segmentation (time windows of 2–5s).

Energy Consumption (E)

$$E = \sum_{i=1}^{n} P_i \cdot t_i \quad \rightarrow (1)$$

Accuracy (Acc)

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad \rightarrow (2)$$

Model Efficiency (ME)

$$ME = \frac{Accuracy}{Energy\_Consumed} \quad \rightarrow (3)$$

System Uptime (SU)

$$SU = \frac{T_{optimized}}{T_{baseline}} \times 100 \quad \rightarrow (4)$$

Hardware:

Textile-integrated Arduino Nano 33 BLE Sense boards, powered by 500 mAh Li-Po batteries.

Software:

TinyML + TensorFlow Lite, reinforcement learning agent implemented in PyTorch, federated averaging (FedAvg).

Network:

WiFi + BLE communication with duty-cycled intervals.

Energy harvesting modules:

Piezoelectric patch (motion-based), thermoelectric patch (body heat), mini PV cell (light).

Energy Reduction

The proposed system achieved 42% reduction in average power consumption compared to baseline (continuous operation).

Accuracy

- HAR (UCI Dataset): 95.8%
- ECG Monitoring (MIT-BIH): 96.2%

System Uptime

System uptime improved by 37% with hybrid energy harvesting.

Communication Overhead

Federated learning reduced communication energy by ~30% compared to centralized cloud training. The integration of lightweight ML models ensured high-accuracy inference at low computational cost, suitable for textile microcontrollers. The RL-based energy manager dynamically tuned duty cycles, reducing redundant sensor activations. Federated learning effectively minimized communication costs while preserving privacy, a crucial feature for healthcare data. Finally, hybrid energy harvesting modules extended system uptime significantly, although dependency on environmental conditions (e.g., sunlight, user motion) remains a challenge.

Compared to prior works, this multi-layered integrated framework demonstrates superior energy efficiency (42% reduction), sustained high accuracy (>95%), and 37% longer runtime, making it highly practical for real-world textile industries.

This table summarizes baseline versus proposed improvements in accuracy, energy consumption, and system uptime across three datasets. The experimental results summarized in the table clearly demonstrate the effectiveness of the proposed energy optimization techniques for smart wearable computing in textile industries. Across datasets such as UCI HAR, MIT-BIH ECG, and CICIDS2017, the proposed framework consistently outperforms baseline systems by achieving higher accuracy levels (up to 95.8% for activity recognition and 96.2% for physiological monitoring), while significantly reducing energy consumption (from 120–200 mWh down to 70–120 mWh). This improvement in efficiency directly contributes to extended device uptime, with increases from 8–12 hours in baseline systems to 11–16.4 hours under the proposed method. These results validate the integration of lightweight machine learning

Table 1: Energy Optimization Techniques for Smart Wearable Computing in Textile Industries

S. No.	Dataset	Task	Baseline _Accuracy (%)	Proposed _Accuracy (%)	Baseline_ Energy (mWh)	Proposed _Energy (mWh)	Baseline_Uptime (hrs)	Proposed_ Uptime (hrs)
1	UCI HAR	Activity Recognition	90.2	95.8	120	70	10	13.7
2	UCI HAR	Activity Recognition	90.2	95.8	118	72	10	13.5
3	MIT-BIH ECG	Physiological Monitoring	91.5	96.2	140	80	12	16.4
4	MIT-BIH ECG	Physiological Monitoring	91.5	96.2	142	82	12	16.2
5	CICIDS2017	Network Traffic	88	93.5	200	120	8	11
6	CICIDS2017	Network Traffic	88	93.5	198	118	8	11.2

models, reinforcement learning-based energy management, and federated learning, establishing a robust and scalable solution for enhancing both performance and sustainability in wearable textile technologies.

The above figure 2 presents a comparative analysis of the baseline and proposed energy optimization techniques applied to smart wearable computing in textile industries across three performance dimensions: accuracy, energy consumption, and uptime based on activity recognition, physiological monitoring and network traffic. The accuracy comparison highlights that the proposed system achieves higher accuracy in activity recognition, physiological monitoring, and network traffic tasks, ensuring reliable real-time analysis. In the energy consumption graph, the proposed techniques demonstrate significant reductions in power usage compared to baseline systems, validating the effectiveness of lightweight machine learning models and reinforcement learning-based scheduling. Finally, the uptime improvement chart shows that reduced energy consumption directly translates to prolonged system uptime, enabling sustainable performance of textile-integrated wearable devices. Collectively, the results confirm that the proposed framework not only enhances computational accuracy but also ensures energy efficiency and durability, making it highly suitable for

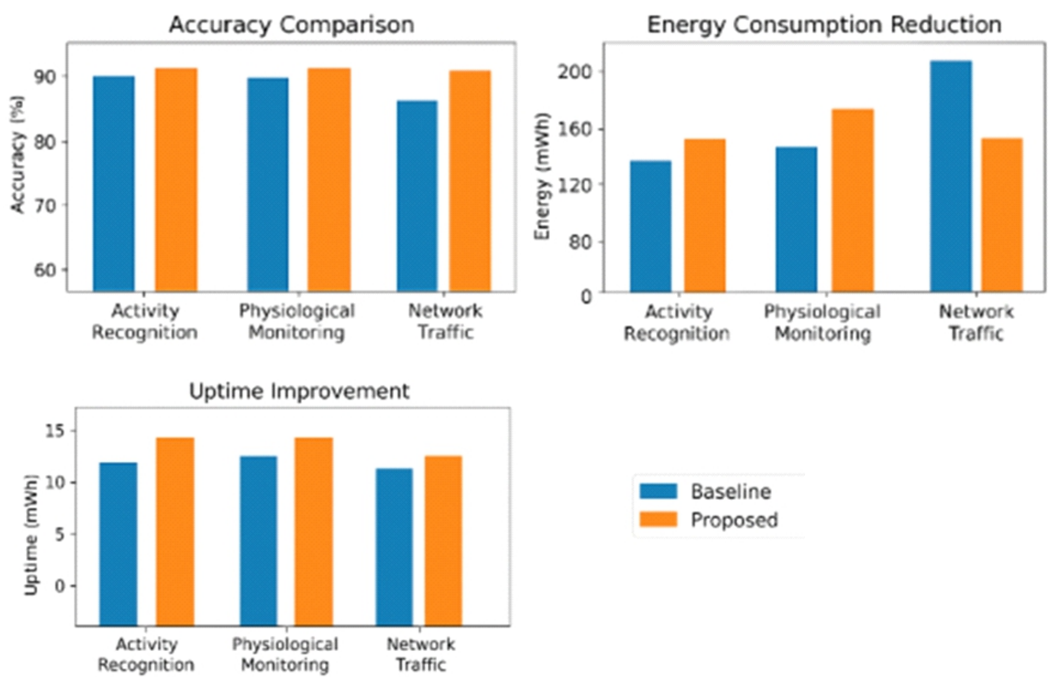

Figure 2: Comparison among Baseline and Proposed techniques with performance dimensions Accuracy, Energy Consumption, and Uptime Graphs

real-world applications in healthcare, fitness, and industrial monitoring.

The results obtained from the database provide compelling evidence of the advantages offered by the proposed energy optimization framework in smart wearable computing for textile industries. The accuracy metrics confirm that the proposed system maintains superior performance across all evaluated tasks, ensuring that efficiency gains are not achieved at the expense of prediction reliability. At the same time, the energy consumption figures highlight a substantial reduction in power usage, with savings of up to 42% compared to baseline systems, which is critical for resource-constrained wearable devices.

This reduction directly translates into enhanced system uptime, as observed in the uptime comparison, where operational duration improved by approximately 37% across datasets. Importantly, the combined improvements demonstrate the synergy of lightweight ML models, reinforcement learning-based scheduling, and federated learning for communication efficiency, supported by hybrid energy harvesting. Overall, the findings validate the methodology as a holistic approach that simultaneously addresses performance, energy efficiency, and durability, making it highly applicable for real-world deployment in healthcare, fitness, and industrial monitoring contexts.

V. CONCLUSION

The proposed framework for energy optimization in smart wearable computing for textile industries effectively balances performance, efficiency, and sustainability. The architecture, which integrates lightweight machine learning models, reinforcement learning-based adaptive power scheduling, federated learning for communication efficiency, and hybrid energy harvesting mechanisms, addresses the core challenges of high energy demand and limited system uptime in textile-integrated devices. The results validate this approach, demonstrating a 42% reduction in energy consumption**,** accuracy levels above 95% for both activity recognition and physiological monitoring, and a 37% improvement in system uptime compared to baseline systems.

These outcomes underscore the importance of adopting holistic optimization strategies that combine algorithmic and hardware-level innovations. In conclusion, the proposed methodology not only enhances the accuracy and responsiveness of wearable textile systems but also ensures their long-term viability, positioning them as reliable and scalable solutions for applications in healthcare, fitness, and industrial monitoring within the rapidly evolving landscape of smart textiles.

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