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AI-Assisted Self-Powered Flexible Electronic System for Energy Management

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Abstract

Flexible electronic systems hold immense potential for applications such as wearable devices, electronic skin, and healthcare monitoring, but their advancement is significantly hindered by the bulky size and mechanical limitations of conventional rigid batteries. Furthermore, existing flexible battery technologies still face a persistent trade-off between energy density and mechanical flexibility. To address the fundamental mismatch between energy supply and demand, this review systematically examines recent progress in AI-enabled energy management strategies for self-powered flexible electronic systems. Facilitated by the development of lightweight models and Edge AI, artificial intelligence can now be deployed on resource-constrained devices to reduce reliance on cloud computing and minimize latency. This paper categorizes AI integration across three key dimensions: at the algorithmic level, predictive models and reinforcement learning enable dynamic power allocation and coordinate multi-source energy harvesting from intermittent sources like triboelectric and thermoelectric generators; at the device and circuit level, AI facilitates adaptive voltage regulation and dynamic compensation for hardware performance degradation over time; and at the system level, AI transforms traditional passive architectures into autonomous, self-optimizing platforms capable of prioritizing and scheduling tasks based on real-time energy conditions. While significant progress has been made, challenges regarding the high computational demands of AI, long-term device reliability, system integration complexity, and data privacy remain. Future advancements will rely on cross-layer co-optimization to fully realize sustainable, intelligent, and autonomous flexible electronic platforms.

Keywords

flexible electronic systems, energy management, artificial intelligence, self-powered systems, edge AI

1. Introduction

Flexible electronic systems have attracted substantial interest in recent years due to their potential applications in wearable devices [1], electronic skin [2], and implantable biomedical systems [3]. By achieving high-sensitivity sensing, their mechanical flexibility and dynamic response capabilities enable them to be highly compatible with the human body and complex environments.

With the rapid advancement of these technologies, there has been a growing demand for miniaturized, integrated, and self-powered systems, particularly in emerging fields such as portable electronics, flexible displays, healthcare, and fitness-tracking devices. Consequently, flexible energy storage and power supply technologies have attracted increasing attention as essential components for supporting the continuous operation of such systems.

However, conventional rigid batteries exhibit inherent drawbacks, including bulky size, limited mechanical compliance, and limited lifespan, which significantly impede their integration with flexible electronic devices and have gradually emerged as a major bottleneck to the advancement of flexible systems. These batteries are typically constructed from stiff and fragile components, such as electrodes, separators, and encapsulation materials, rendering them incapable of withstanding mechanical deformations, such as bending, stretching, or twisting, that are commonly encountered in wearable applications [4].

To overcome these limitations, considerable efforts have been devoted to developing flexible battery technologies. Nevertheless, most existing strategies inevitably compromise critical performance parameters, particularly energy density and cycling durability. For example, the energy density of currently reported flexible batteries generally remains below 100 Wh L^{-1}, whereas that of commercial lithium-ion batteries can readily exceed 300 Wh L^{-1} [5]. Consequently, flexible batteries have yet to demonstrate a decisive performance advantage over their rigid counterparts.

In addition, key concerns, such as operational safety under realistic conditions and long-term reliability, have not been adequately addressed. At present, flexible battery technologies are still largely confined to the proof-of-concept stage, with a persistent trade-off among energy density, mechanical flexibility, and safety that continues to hinder their practical deployment in flexible electronic systems [5].

Therefore, developing and introducing intelligent energy management technology that efficiently coordinates energy acquisition, distribution, and scheduling processes is of great importance. Against this background, this article aims to address the fundamental mismatch between energy demand and supply in self-powered, flexible electronic systems by systematically reviewing recent progress in AI-enabled energy management strategies.

This review presents an AI-enabled intelligent framework for energy management in self-powered flexible electronic systems, offering a promising pathway to enhance energy efficiency and operational stability. By leveraging artificial intelligence, the proposed paradigm enables optimized power allocation and adaptive energy scheduling, effectively addressing performance degradation induced by stochastic energy fluctuations.

The insights provided in this work are expected to facilitate the development of next-generation applications, especially for wearable devices, thereby supporting the realization of sustainable, intelligent, flexible electronic platforms.

2. Theoretical Background

The last decade has witnessed a remarkable development in artificial intelligence (AI). AI has significantly expanded its applicability across various domains, including signal and information processing applications, such as IoT and smart sensing [6]. However, this process requires substantial computational resources. That is due to its original design, which prioritizes accuracy and flexibility. Although these advantages enable AI models to capture complex phenomena and outperform conventional approaches, they also entail significantly higher computational costs [8]. And this trend will never cease—especially as AI-driven flexible electronics push toward real-time, on-device inference under stringent energy constraints. Another key limitation hindering the integration of AI with flexible electronic systems is its heavy reliance on cloud-based computing resources. Cloud computing refers to a paradigm that provides on-demand access to computational resources, including processing power, storage, and applications, through Internet-based platforms [7]. While the integration of AI with cloud computing enables efficient large-scale data processing, cost-effectiveness, scalability, and accelerated model training via GPU resources [9], cloud computing also presents several inherent limitations that, in turn, limit its compatibility with flexible electronic systems. However, cloud computing also presents several inherent limitations that, in turn, limit its compatibility with flexible electronic systems. In recent years, the limitations of cloud-based AI have become increasingly evident, particularly in addressing latency issues [10].

To address the limitations associated with high computational demands and reliance on cloud-based infrastructure, extensive research efforts have been devoted to improving the efficiency and deployment capabilities of AI models. With the rapid expansion of model scale, modern deep learning architectures often include superfluous parameters, leading to longer prediction times [12]. This has made it increasingly challenging to deploy such models in resource-constrained environments.

In response, a variety of lightweight model designs and compression techniques have been developed, including pruning, weight sharing, trained quantization, and Huffman coding. These methods effectively compress the model. Notably, lightweight neural networks have demonstrated the ability to achieve competitive accuracy with significantly fewer parameters [13]. As a result, it has significantly reduced storage requirements for network models and computational cost [12].

These advancements have facilitated the transition of AI from cloud-based systems toward embedded and on-device implementations. In recent years, the development of GPUs and TPUs has enabled efficient training and deployment of deep neural networks (DNNs) on large-scale datasets. By scaling down the DNN, it has been successfully compatible with limited-resource devices, without any obvious decrease in performance and accuracy [14]. This shift not only enhances system responsiveness but also improves energy efficiency, making AI increasingly fit the requirements of portable and flexible electronic systems.

With the continuous advancement of embedded machine learning technologies, the demand for deploying deep neural networks (DNNs) on resource-constrained devices has increased significantly [15]. However, due to the inherent complexity of deep learning models, their implementation on embedded platforms such as microcontrollers, field-programmable gate arrays (FPGAs), and system-on-chip (SoC) devices still faces substantial challenges in terms of memory capacity, computational capability, and energy consumption. To address these limitations, various optimization strategies have been proposed, including model compression, quantization, and hardware-aware design approaches, which effectively reduce model size and resource requirements while maintaining acceptable performance [17].

Furthermore, the development of hardware accelerators and customized computing architectures has significantly improved the feasibility of deploying artificial intelligence in embedded systems, enabling efficient inference under strict power and resource constraints [18]. These advances have gradually shifted artificial intelligence away from traditional cloud-centric computing paradigms toward localized, on-device intelligence.

On this basis, Edge Artificial Intelligence (Edge AI) has emerged as a promising paradigm in which data processing and decision-making are performed directly on local devices [19]. This approach effectively reduces dependence on cloud computing while significantly decreasing system latency, communication overhead, and energy consumption. Such characteristics make Edge AI particularly suitable for applications requiring real-time responsiveness under constrained energy conditions, thereby demonstrating strong compatibility with flexible electronic systems operating in dynamic environments [11].

As a result, artificial intelligence technologies have gradually become feasible for practical integration into flexible electronic systems.

3. Literature Review

3.1 AI-Driven Dynamic Power Allocation Strategies (Algorithm Level)

At the algorithmic level, AI-driven dynamic power allocation strategies provide an effective approach for addressing the mismatch between energy supply and power demand in flexible electronic systems. In particular, predictive power management methods based on machine learning can estimate future energy requirements by analyzing user behavior patterns and environmental information.

Studies have shown that wearable devices exhibit highly dynamic power consumption. Different application scenarios, such as sleep monitoring and motion tracking, may lead to frequent transitions between low-power and high-power operating states [20]. Such variability requires systems to possess real-time adaptive capabilities. In contrast, conventional rule-based or static strategies are often unable to cope with complex, continuously changing operating environments, resulting in low energy utilization efficiency and rapid power depletion.

To address these challenges, reinforcement learning (RL), particularly deep reinforcement learning (DRL) [16], has been introduced into energy management to develop adaptive power regulation models. These approaches can continuously learn user behavioral characteristics through interactions with the environment and subsequently achieve dynamic optimization of power consumption. For example, multi-agent DRL frameworks can model different functional modules within a device, including sensors, processors, and communication units, and realize fine-grained power control by adjusting parameters such as CPU frequency, sensor activation states, and display brightness.

Furthermore, by integrating user activity recognition information with multi-source sensing data, AI models can predict short-term energy demand and proactively allocate system resources. This context-aware energy management strategy enables systems to dynamically regulate power consumption based on individual usage patterns, thereby improving energy efficiency and user experience. Experimental studies have demonstrated that DRL-based adaptive power management approaches can significantly extend device lifetime while maintaining system performance.

Overall, the combination of predictive models and reinforcement learning provides an efficient and flexible solution for dynamic energy management, particularly for self-powered, flexible electronic systems with intermittent, unstable energy inputs.

Beyond power consumption optimization, recent studies have increasingly focused on integrating AI-based energy management strategies with energy harvesting technologies to enhance system sustainability further. Among these technologies, triboelectric nanogenerators (TENGs) and thermoelectric generators (TEGs), which harvest energy from mechanical motion and waste heat, respectively, have emerged as important energy sources for self-powered flexible electronic systems.

However, these energy-harvesting approaches generally exhibit significant intermittency and instability, as their outputs depend strongly on environmental conditions and user activities. For example, TENGs rely on irregular mechanical stimuli such as human motion [21], whereas TEGs depend on continuously varying temperature gradients [22]. These factors can cause substantial fluctuations in energy supply, thereby posing challenges to stable system operation.

To address these issues, AI-based predictive and adaptive algorithms can be introduced to enable coordinated management of energy harvesting and energy consumption [23]. By integrating real-time sensing data with historical information, AI models can predict variations in harvestable energy and dynamically adjust power allocation across system modules. In particular, reinforcement learning approaches can continuously interact with the environment and learn optimal control policies under varying operating conditions, thereby achieving a dynamic balance between energy input and energy consumption.

Such coordinated optimization strategies not only effectively mitigate the effects of energy fluctuations but also improve overall energy utilization efficiency, enabling the stable operation of self-powered systems. Therefore, integrating AI-driven energy management approaches with multi-source energy-harvesting technologies represents a key pathway toward autonomous, sustainable, and flexible electronic systems.

3.2 AI-Assisted Regulation of Flexible Power Devices and Circuits (Device/Circuit Level)

At the device and circuit levels, the introduction of artificial intelligence has driven the transition of flexible electronic systems from conventional fixed-parameter power management to adaptive, intelligent control. Traditional power circuits are generally designed based on predefined parameters and static control strategies, making them difficult to accommodate the complex operating environments and dynamic load variations encountered in wearable and flexible applications.

By incorporating AI-based adaptive control methods, power circuits can dynamically adjust their operating modes according to real-time system conditions. For example, intelligent control algorithms can regulate critical power converter parameters, such as switching frequency, duty cycle, and operating modes, thereby improving system efficiency and stability under varying load and environmental conditions.

Furthermore, AI-driven predictive models enable voltage regulation and power allocation to evolve from passive response mechanisms into proactive control strategies. By forecasting short-term load variations and user behavioral patterns, the system can adjust voltage regulator output levels and power distribution strategies in advance, ensuring operation within optimal efficiency regions[23]. Under low-load conditions, supply levels can be reduced to minimize energy consumption, while still providing sufficient energy during high-load conditions to maintain system performance.

In addition, flexible electronic devices inevitably experience performance degradation over long-term operation due to mechanical deformation, material fatigue, and environmental influences [24]. AI-based approaches can continuously learn from operational data, identify these non-ideal characteristics, and incorporate them into power management strategies, thereby enabling dynamic compensation for device aging and parameter drift while improving long-term reliability and overall system performance.

Overall, the integration of AI at the circuit level equips power regulation with intelligent, predictive, and adaptive capabilities, providing essential support for the efficient and stable operation of self-powered, flexible electronic systems in dynamic, complex environments.

3.3 AI-Assisted Overall Operation of Flexible Power Systems (System Level)

At the system level, integrating artificial intelligence enables holistic intelligent operation of flexible power systems, transforming them from conventional passive energy-supply architectures into adaptive, self-optimizing systems [25]. Unlike traditional designs based on fixed scheduling and predefined operating modes, AI can dynamically coordinate sensing, computation, and communication activities according to real-time energy conditions and task priorities.

Specifically, AI-based scheduling mechanisms can comprehensively evaluate current energy states and task importance to allocate system resources appropriately. Under energy-constrained conditions, critical functions can be prioritized to ensure reliable operation. At the same time, non-essential tasks may be delayed, simplified, or temporarily suspended, thereby improving system robustness under unstable energy supply conditions.

In addition to real-time scheduling, AI can further optimize long-term power management strategies. By continuously collecting historical data on user behavior, environmental conditions, and system operating states, AI models can progressively refine and optimize energy management policies, enabling systems to gradually adapt to long-term usage patterns and complex environmental changes while improving overall energy efficiency and system stability.

Moreover, the integration of AI enables flexible electronic systems to evolve from passive responses to energy input into autonomous decision-making systems. Rather than merely reacting to energy fluctuations, the system can actively plan operational strategies to balance energy harvesting, storage, and consumption dynamically. This capability is particularly important for wearable and implantable systems, which must maintain stable operation under highly dynamic and resource-constrained conditions[26].

Overall, AI-based system-level regulation achieves coordinated optimization across multiple functional layers, equipping flexible electronic systems with intelligent, adaptive, and autonomous operational capabilities.

4. Discussion

Despite the rapid development of AI-assisted, self-powered, flexible electronic systems in recent years, significant challenges remain at the algorithmic, device, system integration, and data security levels.

At the algorithmic level, a notable contradiction exists between the high computational demands of artificial intelligence models and the limited energy budgets of flexible electronic systems. Deep neural networks require substantial computational resources during both training and inference processes, which becomes particularly problematic in energy-constrained systems. Although lightweight models and model compression techniques can reduce computational overhead to some extent, these approaches often come at the expense of model accuracy, resulting in an inherent trade-off between system performance and energy efficiency.

At the device level, the long-term reliability of flexible power devices remains a critical bottleneck. For example, triboelectric nanogenerators (TENGs) are susceptible to performance degradation under repeated mechanical deformation, while thermoelectric devices are strongly influenced by fluctuating temperature gradients, leading to unstable energy output [21]. Although several studies have attempted to employ AI-based compensation strategies to mitigate these issues, most existing approaches are still limited to proof-of-concept demonstrations and have not yet achieved stable engineering implementation in practical applications.

At the system level, integrating multiple functional modules introduces substantial complexity. Differences in material properties and operating mechanisms across energy harvesting, power management, sensing, and computation modules make it highly challenging to achieve high-density, reliable integration while maintaining mechanical flexibility. Therefore, cross-layer co-optimization spanning algorithms, circuits, and system architectures is required to ensure efficient and stable system operation.

Furthermore, the incorporation of artificial intelligence introduces challenges related to data privacy and system architecture. Cloud-based processing frameworks may pose potential privacy risks due to data transmission and centralized computation. Although Edge AI can effectively reduce external data transmission by enabling on-device processing, it simultaneously imposes stricter requirements on computational capability and energy efficiency, thereby creating new trade-offs among privacy protection, performance, and power consumption.

Overall, future research should focus on advancing low-power AI algorithms, reliable, flexible power devices, and system-level optimization strategies, thereby promoting the practical deployment and long-term development of self-powered, flexible electronic systems.

5. Conclusion

In conclusion, this review systematically summarizes the integrated development of artificial intelligence and self-powered flexible electronic systems from the perspectives of algorithms, devices/circuits, and system-level operation. At the algorithmic level, dynamic power allocation strategies based on reinforcement learning and predictive models enable accurate estimation of future energy demands and adaptive regulation of power consumption. At the device and circuit level, artificial intelligence facilitates intelligent regulation of voltage output, power distribution, and impedance matching, while also enabling dynamic compensation for performance degradation in flexible devices. At the system level, AI promotes the transition of flexible electronic systems from passive energy supply to autonomous decision-making, enabling coordinated scheduling of sensing, computation, and communication tasks.

Although significant progress has been achieved in this field, challenges related to energy constraints, device reliability, system integration complexity, and data privacy remain. Future research should further focus on the development of low-power artificial intelligence models, reliable flexible devices, and cross-layer co-optimization strategies.

Looking forward, AI-enabled self-powered flexible electronic systems demonstrate broad application prospects in wearable healthcare, intelligent textiles, VR/AR technologies, bioelectronics, and brain–computer interfaces. These systems are expected to enable continuous, personalized, and intelligent monitoring and interaction, thereby advancing the evolution of electronic systems toward autonomous, sustainable development.

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The authors declare no conflict of interest.

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