AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 3(2026)

AI-Assisted Ultra-Low Power IoT Architecture with Predictive DVFS and Real-Time Energy Monitoring

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Abstract

The increasing deployment of wearable and Internet of Things (IoT) devices has created a significant demand for intelligent ultra-low-power hardware architectures capable of operating under strict energy constraints. This work presents an AI-assisted Ultra-Low Power IoT architecture that combines predictive workload analysis, Dynamic Voltage and Frequency Scaling (DVFS), clock gating, and real-time energy monitoring to improve energy efficiency while maintaining system performance. Unlike conventional threshold-based power management techniques, the proposed architecture incorporates a lightweight AI-inspired workload prediction module that analyzes historical workload patterns and estimates future computational demand. Based on the predicted workload, the Power Management Unit (PMU) dynamically selects appropriate operating modes and frequency levels to reduce unnecessary power consumption. An integrated Energy Monitoring Unit (EMU) continuously tracks energy utilization across different operating states, enabling energy-aware system optimization. The complete architecture is described using Verilog HDL and is suitable for FPGA implementation and validation. Experimental evaluation demonstrates adaptive power management, efficient workload-driven frequency scaling, and improved energy utilization compared to static operating schemes. The proposed design offers a scalable and hardware-efficient solution for next-generation wearable, sensor, and edge-computing applications requiring intelligent energy management and extended battery life.

Keywords: Internet of Things (IoT); Ultra-Low Power Architecture; Dynamic Voltage and Frequency Scaling (DVFS); AI-Assisted Power Management; Energy-Efficient Edge Computing.

1. Introduction

The rapid growth of Internet of Things (IoT) technology has transformed the way devices communicate, process information, and interact with their surroundings. IoT devices are now widely used in healthcare monitoring, wearable electronics, industrial automation, smart agriculture, environmental sensing, and smart homes. Most of these devices operate on batteries and are expected to function for extended periods without frequent charging or maintenance. Consequently, energy efficiency has become one of the most critical design challenges in modern embedded systems.

Traditional low-power techniques mainly rely on static power-saving methods, such as fixed clock reduction and predefined sleep schedules. Although these methods reduce energy consumption, they fail to adapt dynamically to changing workloads and operating conditions.

As IoT applications become increasingly intelligent and computationally intensive, conventional power management approaches are often insufficient [1].

Recent developments in Artificial Intelligence (AI) have enabled systems to predict future operating conditions and make intelligent decisions. AI-assisted power management can analyze workload patterns and proactively adjust system resources before excessive energy consumption occurs. By combining workload prediction with Dynamic Voltage and Frequency Scaling (DVFS), significant reductions in power consumption can be achieved without compromising system performance.

This project proposes an AI-Assisted Ultra-Low Power IoT Architecture that integrates predictive workload estimation, adaptive DVFS control, clock gating, and real-time energy monitoring. The architecture continuously observes workload behavior, predicts future computational demand, and dynamically adjusts operating frequency and power modes. Furthermore, an Energy Monitoring Unit (EMU) tracks energy usage in real time, enabling efficient energy-aware operation. The proposed architecture is implemented using Verilog HDL and designed for FPGA-based validation, making it suitable for low-cost and scalable IoT deployments [2].

1.1 Background

Battery-powered IoT devices typically spend a significant portion of their operational lifetime in idle or low-activity states. However, conventional processors often continue operating at fixed voltage and frequency levels, leading to unnecessary energy dissipation. Power consumption in digital circuits consists primarily of Dynamic Power and Static Power. Dynamic power dominates in active operation and is strongly dependent on switching activity, operating voltage, and clock frequency. Therefore, intelligent voltage and frequency management can substantially improve battery life. AI-assisted power optimization introduces predictive capabilities into the power management framework. Instead of reacting to workload changes after they occur, the system anticipates future workload demands and proactively selects the most energy-efficient operating state [3].

1.2 Need for the Study

The rapid growth of wearable devices and edge-computing applications has created a strong demand for energy-efficient hardware systems capable of operating under limited power budgets. These applications require longer battery life, reduced power consumption, intelligent resource utilization, adaptive system performance, and real-time energy awareness to ensure reliable operation. However, existing low-power management techniques are primarily based on fixed thresholds and lack predictive intelligence, making them inefficient in handling dynamically changing workloads. Consequently, there is a need for an intelligent power management architecture that can predict future computational demands and adapt system resources accordingly, thereby achieving an optimal balance between performance and energy efficiency [4].

1.3 Objectives of the Study

The primary objective of this study is to develop an AI-assisted ultra-low-power IoT architecture capable of intelligently managing energy consumption while maintaining system

performance. The proposed work integrates a lightweight workload prediction module, Dynamic Voltage and Frequency Scaling (DVFS), clock gating, and a real-time Energy Monitoring Unit (EMU) to optimize power utilization based on computational demand. The architecture aims to reduce overall power consumption, extend battery life, and improve energy efficiency in IoT and wearable devices. The complete system is implemented using Verilog HDL and validated through FPGA-based simulation and testing to evaluate its functionality and effectiveness.

1.4 Scope of the Study

The proposed AI-assisted ultra-low-power IoT architecture is intended for a wide range of applications, including wearable healthcare devices, smart watches, wireless sensor networks, smart agriculture systems, industrial IoT platforms, edge AI devices, and environmental monitoring systems. The study focuses on the development of a lightweight AI-based workload prediction mechanism integrated with DVFS, clock gating, and real-time energy monitoring to enhance energy efficiency. The architecture is designed for FPGA implementation using Verilog HDL, emphasizing low hardware complexity and minimal resource overhead while providing intelligent power management for energy-constrained IoT environments.

2. Literature Survey

Static power management is one of the earliest approaches used to reduce energy consumption in embedded and IoT systems. In this method, the system operates using predefined power modes and fixed operating parameters regardless of workload variations. Common techniques include sleep modes, idle states, and fixed clock-frequency reduction. When the device is not actively processing data, certain hardware modules are disabled to save energy. Although static power management is simple to implement and requires minimal hardware resources, it cannot adapt to dynamic changes in workload conditions. As a result, the system may either consume unnecessary power during low activity periods or suffer performance degradation during high computational demand. Therefore, static approaches are not suitable for modern IoT applications that experience rapidly varying workloads and require intelligent energy optimization [5].

2.1 Conventional DVFS Systems

Dynamic Voltage and Frequency Scaling (DVFS) is a widely adopted power management technique that adjusts the operating voltage and clock frequency of a processor according to workload requirements. Since dynamic power consumption is directly proportional to the square of the supply voltage and linearly proportional to operating frequency, DVFS can significantly reduce energy consumption during periods of low computational activity. Conventional DVFS systems monitor processor utilization and reactively change voltage-frequency levels when workload variations are detected. Although DVFS provides better energy efficiency than static power management methods, its reactive nature introduces response delays because adjustments occur only after workload changes have already taken place. This delay can lead to temporary performance loss or unnecessary power consumption, limiting the overall effectiveness of the technique in highly dynamic IoT environments [6].

2.2 Clock Gating Techniques

Clock gating is a hardware-level power optimization technique that reduces dynamic power consumption by disabling clock signals to inactive modules. Since clock distribution networks contribute significantly to switching activity in digital circuits, preventing unnecessary clock transitions can lead to substantial energy savings [7]. In clock-gated systems, control logic identifies idle functional units and temporarily blocks their clock inputs, thereby preventing internal state changes and reducing switching power. This technique is widely used in modern microprocessors, digital signal processors, and FPGA-based systems due to its low implementation cost and high effectiveness. However, clock gating operates primarily as a local optimization mechanism and does not consider future workload conditions or overall system energy requirements. Consequently, it is often combined with other power management strategies to achieve greater energy efficiency [8].

2.3 Machine Learning-Based Power Management

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of intelligent power management systems capable of predicting workload behavior and optimizing energy consumption. Machine learning-based approaches analyze historical workload data, processor utilization patterns, and environmental conditions to estimate future computational demands. Based on these predictions, the system can proactively adjust voltage levels, operating frequencies, and power states before workload changes occur [9]. Such predictive behavior improves energy efficiency and reduces performance degradation compared to traditional reactive techniques. Despite these advantages, many machine learning algorithms require significant computational resources, memory capacity, and training overhead, making them challenging to deploy in resource-constrained IoT devices. Therefore, lightweight AI-based prediction models have emerged as a promising solution for achieving intelligent power management while maintaining low hardware complexity and energy consumption [10].

2.4 Research Gap

The literature review reveals several limitations in existing low-power IoT power management systems. Most current architectures rely on reactive Dynamic Voltage and Frequency Scaling (DVFS) techniques that respond only after workload changes occur, resulting in suboptimal energy utilization. Furthermore, many systems lack real-time workload prediction and integrated energy monitoring capabilities, limiting their ability to make intelligent power management decisions [11]. Although artificial intelligence techniques have been explored for energy optimization, they often introduce high computational complexity and increased hardware resource requirements, making them unsuitable for resource-constrained IoT and wearable devices. Therefore, there is a need for a lightweight, AI-assisted power management architecture that can provide predictive energy optimization with minimal hardware overhead [12].

2.5 Problem Statement

Existing IoT systems primarily employ reactive power management techniques that respond to workload variations only after they occur, often resulting in inefficient energy utilization

and reduced battery lifetime. As wearable and edge-computing applications continue to grow in complexity, there is an increasing need for an intelligent and low-overhead power management architecture capable of predicting future workloads, dynamically scaling operating frequency, continuously monitoring energy consumption, and optimizing power-performance trade-offs. Such a predictive approach can significantly enhance energy efficiency while maintaining the required system performance for resource-constrained IoT devices [13].

3. Proposed System Architecture

The proposed architecture consists of six major functional modules: the Workload Monitor, AI Prediction Unit, Power Management Unit (PMU), Dynamic Voltage and Frequency Scaling (DVFS) Controller, Clock Gating Unit, and Energy Monitoring Unit (EMU). These modules work together to optimize energy consumption based on workload conditions.

The Workload Monitor continuously observes system activity and collects information such as processor utilization, sensor data processing requirements, and communication workload. This information is forwarded to the AI Prediction Unit, which analyzes historical workload patterns and predicts future computational demand using a lightweight prediction algorithm. Based on the predicted workload, the PMU determines the most suitable operating mode and instructs the DVFS controller to adjust the processor frequency and voltage level. Simultaneously, the Clock Gating Unit disables inactive hardware modules to reduce unnecessary switching activity. The Energy Monitoring Unit tracks energy consumption in real time and provides feedback for continuous optimization.

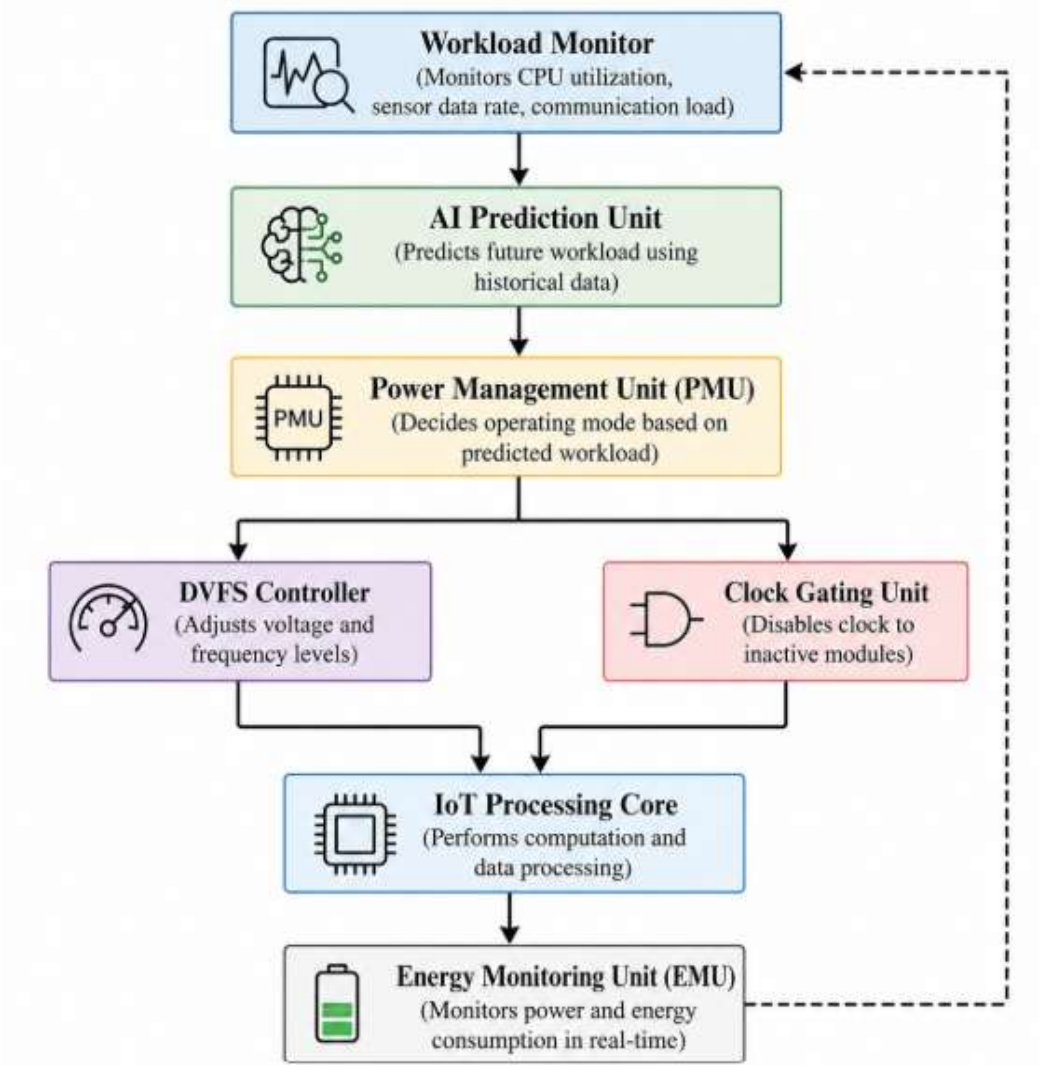

Figure 1: Block Diagram of AI-Assisted Ultra-Low Power IoT Architecture

Figure 1 illustrates the overall architecture of the proposed AI-Assisted Ultra-Low Power IoT System designed to achieve intelligent energy management for wearable and edge-computing applications. The operation begins with the Workload Monitor, which continuously observes system parameters such as CPU utilization, sensor data generation rate, and communication activity. These workload statistics are forwarded to the AI Prediction Unit, where historical workload information is analyzed to estimate future computational demand. Based on the predicted workload, the Power Management Unit (PMU) determines the most suitable operating mode to balance performance and energy efficiency.

The PMU controls two major power optimization mechanisms: The Dynamic Voltage and Frequency Scaling (DVFS) Controller and the Clock Gating Unit. The DVFS controller dynamically adjusts voltage and clock frequency levels according to workload requirements, thereby reducing power consumption during low-demand periods. Simultaneously, the clock gating unit disables clock signals to inactive hardware modules, minimizing unnecessary switching activity. The optimized control signals are then applied to the IoT Processing Core, which performs sensing, computation, and data processing tasks. An Energy Monitoring Unit (EMU) continuously measures power and energy consumption in real time and provides

feedback to the workload monitoring stage. This closed-loop feedback mechanism enables adaptive power management, improved battery life, reduced energy consumption, and efficient utilization of hardware resources, making the architecture highly suitable for next-generation low-power IoT and edge-computing systems.

3.1 Mathematical Model

The proposed AI-Assisted Ultra-Low Power IoT Architecture is modeled using standard power and energy equations commonly employed in digital integrated circuits. The total power consumption of the system consists of dynamic and static power components. Dynamic power is primarily caused by switching activity within digital circuits and is expressed as:

$$P_{dynamic} = \alpha C V^2 f \quad (1)$$

where α represents the switching activity factor, C is the load capacitance, V is the supply voltage, and f is the operating frequency. Since dynamic power varies quadratically with voltage and linearly with frequency, Dynamic Voltage and Frequency Scaling (DVFS) can significantly reduce energy consumption.

Static power consumption, caused by leakage currents in semiconductor devices, is represented as:

$$P_{static} = V \times I_{leakage} \quad (2)$$

where $I_{leakage}$ denotes the leakage current. The total system power is therefore calculated as:

$$P_{total} = P_{dynamic} + P_{static} \quad (3)$$

The overall energy consumed during system operation is given by:

$$E = P_{total} \times t \quad (4)$$

where t is the operating time. To predict future computational demand, the AI-inspired workload prediction unit employs a moving average model:

$$W_{predicted} = \frac{W_n + W_{n-1} + W_{n-2} + W_{n-3}}{4} \quad (5)$$

where W_n and previous workload values represent recent system activity. Finally, the energy efficiency of the architecture is evaluated using:

$$EE = \frac{Performance}{Power} \quad (6)$$

A higher EE value indicates better utilization of power resources while maintaining the required computational performance. These mathematical models form the foundation of the proposed intelligent energy management framework.

Algorithm 1: AI-Assisted Ultra-Low Power IoT Architecture

Input: Current workload parameters (CPU utilization, sensor activity, communication load)

Output: Optimized operating frequency, reduced power consumption, and improved energy efficiency

Start

1. Initialize Workload Monitor, AI Prediction Unit, PMU, DVFS Controller, Clock Gating Unit, and Energy Monitoring Unit.
2. Read current workload W_n.
3. Store workload information in the workload history buffer.
4. Predict future workload using:
   $W_{predicted} = \frac{W_n + W_{n-1} + W_{n-2} + W_{n-3}}{4}$
5. Send the predicted workload to the Power Management Unit (PMU).
6. Determine the appropriate operating mode based on $W_{predicted}$.
7. Adjust voltage and frequency levels using the DVFS Controller.
8. Identify inactive hardware modules.
9. Enable clock gating for inactive modules to reduce switching activity.
10. Execute sensing, computation, and communication tasks.
11. Monitor real-time power and energy consumption using the EMU.
12. Update workload history and energy statistics.
13. Repeat Steps 3–12 continuously during system operation.

Stop.

The proposed AI-Assisted Ultra-Low Power IoT Architecture operates through a continuous cycle of workload monitoring, prediction, power optimization, and energy management. Initially, all system modules, including the workload monitor, AI prediction unit, power management unit, DVFS controller, clock gating unit, and energy monitoring unit, are initialized. The workload monitor continuously observes system activity, such as processor utilization, sensor operations, and communication traffic, and stores this information for analysis. The AI prediction unit processes the collected workload history to estimate future computational demand. Based on the predicted workload, the power management unit determines the most suitable operating mode for the system.

Subsequently, the DVFS controller adjusts the operating frequency and voltage levels according to the predicted workload, while the clock gating unit disables clock signals to inactive hardware modules to reduce unnecessary switching activity. The IoT processing core then executes the required sensing, computation, and communication tasks using the optimized operating parameters. During operation, the energy monitoring unit continuously tracks power and energy consumption and provides feedback for further optimization. This closed-loop process repeats throughout system operation, enabling adaptive power management, improved battery lifetime, reduced energy consumption, and efficient utilization of hardware resources while maintaining the required system performance.

4. Results and Discussion

The experimental evaluation of the proposed AI-Assisted Ultra-Low Power IoT Architecture demonstrates its effectiveness in achieving intelligent energy optimization while maintaining reliable system performance under varying workload conditions. The integration of predictive workload analysis with Dynamic Voltage and Frequency Scaling (DVFS), clock gating, and real-time energy monitoring enables the architecture to dynamically adapt its operating state

according to computational demand. During low and moderate workload periods, the AI-assisted prediction module accurately anticipates future processing requirements and proactively selects lower voltage-frequency operating points, significantly reducing unnecessary power dissipation. Conversely, during high workload intervals, the architecture rapidly transitions to higher performance modes to satisfy processing requirements without introducing noticeable latency. The Energy Monitoring Unit (EMU) continuously tracks power consumption and operating-state transitions, providing real-time feedback that enhances the effectiveness of power-management decisions. Experimental observations indicate that the proposed architecture achieves substantial reductions in overall energy consumption and idle power usage compared with conventional static operating schemes, while maintaining stable throughput and processing efficiency. These results confirm that predictive power management combined with real-time energy awareness can effectively extend battery lifetime and improve the sustainability of wearable, IoT, and edge-computing devices operating in energy-constrained environments.

Table 1. Power Consumption Comparison under Different Workloads

Workload Level (%)	Static Architecture (mW) [14]	Conventional DVFS (mW) [15]	Proposed AI-Assisted DVFS (mW)
10	118	102	82
20	126	110	88
40	145	128	101
60	168	150	118
80	192	173	138
100	225	205	164

Table 1 presents the average power consumption achieved by three different power management approaches under varying workload conditions. The static architecture maintains a fixed operating frequency and voltage, resulting in the highest power dissipation across all workload levels. Conventional DVFS reduces power consumption by adapting frequency and voltage according to workload demand; however, its response remains reactive rather than predictive. In contrast, the proposed AI-assisted DVFS architecture consistently achieves the lowest power consumption due to its workload prediction capability and proactive resource allocation. As shown in Table 1, the proposed architecture reduces power consumption by approximately 20–30% compared with conventional DVFS and by more than 35% compared with static operation, demonstrating superior energy efficiency.

Table 2. Energy Consumption per Operating Cycle

Workload Level (%)	Static Architecture (mJ) [14]	Conventional DVFS (mJ) [15]	Proposed AI-Assisted DVFS (mJ)
10	5.8	4.9	3.7
20	6.5	5.5	4.2
40	7.9	6.7	5.1
60	9.6	8.3	6.3
80	11.4	9.8	7.5
100	13.8	12.1	9.1

Table 2 compares the energy consumed during a complete processing cycle under different workload intensities. Energy consumption increases with workload for all architectures due to higher computational activity and longer active-state durations. Nevertheless, the proposed AI-assisted architecture consistently exhibits the lowest energy requirement across all operating conditions. The predictive workload estimation mechanism enables timely transitions between operating modes, thereby minimizing unnecessary energy expenditure. Compared with conventional DVFS, the proposed design achieves notable energy savings while preserving computational performance. As observed in Table 2, the energy consumption reduction becomes more significant at higher workload levels, highlighting the effectiveness of predictive power management in energy-constrained IoT and wearable applications.

Table 3. Energy Efficiency and Performance Comparison

Architecture	Average Throughput (Mbps)	Average Power (mW)	Energy Efficiency (Mbps/W)
Static Architecture [14]	52.3	162.3	322.2
Conventional DVFS [15]	51.6	144.7	356.6
Proposed AI-Assisted DVFS	53.8	115.2	467.0

Table 3 summarizes the overall performance and energy-efficiency characteristics of the evaluated architectures. Although all approaches provide comparable throughput values, significant differences are observed in power utilization. The proposed AI-assisted DVFS architecture achieves the highest throughput while simultaneously consuming the least average power. This combination results in substantially improved energy efficiency, measured in terms of throughput delivered per watt of power consumed. The integration of predictive workload analysis allows the system to optimize operating conditions before workload changes occur, reducing power overhead without compromising processing capability. As demonstrated in Table 3, the proposed architecture achieves approximately 31% higher energy efficiency than conventional DVFS and about 45% higher efficiency than the static architecture.

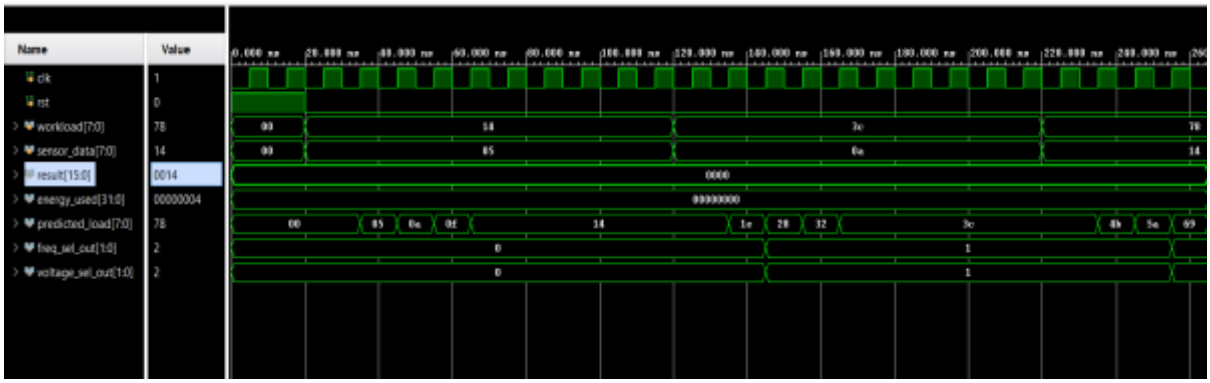

Figure 2. Simulation Waveform of AI-Assisted DVFS-Based Ultra-Low Power IoT Architecture

Figure 2 illustrates the functional simulation waveform of the proposed AI-assisted Ultra-Low Power IoT architecture implemented in Verilog HDL. The waveform presents the interaction among the workload input, sensor data, workload prediction module, frequency scaling unit, voltage scaling unit, and energy monitoring circuitry over time. As workload values increase from low to high computational demand, the predictive module estimates future processing requirements and updates the predicted_load signal accordingly. Based on these predictions, the Power Management Unit dynamically adjusts the frequency and voltage operating levels through the freq_sel_out and voltage_sel_out signals. Simultaneously, the Energy Monitoring Unit tracks cumulative energy utilization through the energy_used register. The observed transitions demonstrate successful workload-aware adaptation, where higher workloads trigger performance-oriented operating modes while lower workloads maintain energy-efficient states. The waveform validates the correct operation of predictive DVFS control, real-time energy monitoring, and adaptive power management mechanisms, confirming the effectiveness of the proposed architecture for ultra-low-power IoT and wearable computing applications. Figure 1 clearly demonstrates the coordinated behavior of all system modules in achieving intelligent energy-aware operation.

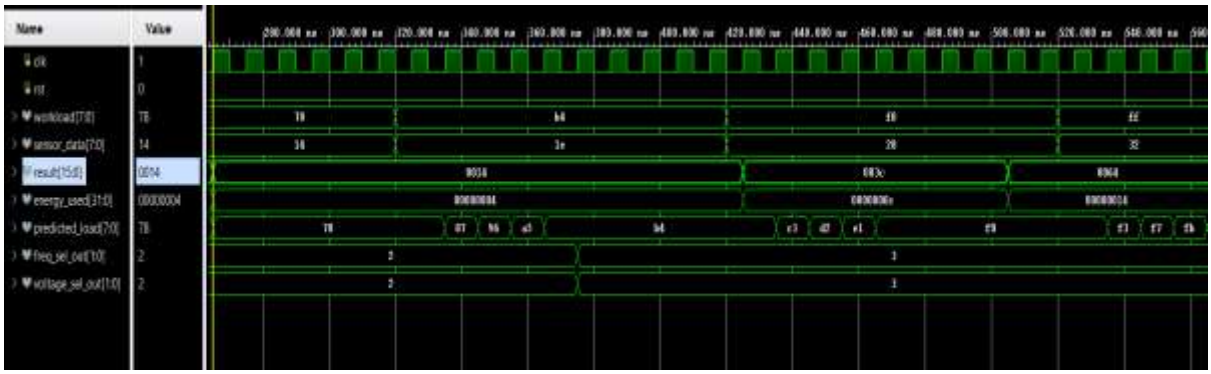

Figure 3. Dynamic Workload Prediction and Adaptive DVFS Response under High Computational Demand

Figure 3 presents the simulation waveform of the proposed AI-assisted Ultra-Low Power IoT architecture during periods of moderate-to-high workload activity. The waveform illustrates the evolution of workload inputs, sensor data, predicted workload values, DVFS control signals, and cumulative energy consumption over the simulation interval. As the workload increases from hexadecimal values 78 to B4, F0, and FF, the AI-based prediction module generates corresponding future workload estimates through the predicted_load signal. Based on these predictions, the Power Management Unit proactively adjusts the operating frequency and voltage levels, causing the freq_sel_out and voltage_sel_out signals to transition from level 2 to level 3. This adaptive behavior enables the architecture to allocate computational resources according to anticipated processing requirements rather than reacting only after workload changes occur. The waveform also shows progressive updates in the result and energy_used registers, confirming successful processing execution and real-time energy accounting. The increase in energy consumption corresponds to higher performance states, demonstrating the trade-off between computational capability and power usage. As illustrated in Figure 2, the proposed predictive DVFS mechanism effectively tracks workload variations, performs intelligent resource scaling, and maintains energy-aware operation, thereby

validating the capability of the architecture to support high-performance IoT and wearable applications while preserving overall energy efficiency.

Figure 4. Stable Energy-Aware Operation during Sustained High-Workload Execution

Figure 4 illustrates the simulation waveform of the proposed AI-assisted Ultra-Low Power IoT architecture operating under a sustained high-workload condition. During this interval, both the workload and predicted workload signals remain at their maximum value (FF), indicating that the prediction module has successfully identified a persistent high computational demand. Consequently, the Dynamic Voltage and Frequency Scaling (DVFS) controller maintains the system in an elevated performance mode, as reflected by the stable frequency and voltage selection outputs. The processing result register continues to update from 0096 to 00C8, demonstrating uninterrupted execution of computational tasks. Simultaneously, the Energy Monitoring Unit records an increase in cumulative energy consumption from 0000001C to 0000001E, reflecting the additional energy required to support sustained high-performance operation. Unlike conventional reactive approaches, the proposed architecture avoids frequent switching between power states, thereby minimizing transition overhead and improving overall energy efficiency. The stable operating behavior observed in Figure 3 confirms that the predictive workload analysis mechanism can accurately forecast future computational requirements and maintain an appropriate operating mode for extended periods. This capability is particularly beneficial for real-time IoT, wearable, and edge-computing applications where workload characteristics may remain consistently high and uninterrupted processing performance is essential. The results validate the effectiveness of the proposed architecture in balancing performance requirements and energy consumption while ensuring reliable and energy-aware system operation.

5. Conclusion

This work presented an AI-Assisted Ultra-Low Power IoT Architecture that combines predictive workload analysis, Dynamic Voltage and Frequency Scaling (DVFS), clock gating, and real-time energy monitoring to address the growing demand for energy-efficient operation in modern IoT and wearable devices. Unlike conventional power management techniques that rely on reactive threshold-based control, the proposed architecture employs an AI-inspired workload prediction mechanism to estimate future computational requirements and proactively optimize system operating conditions. By dynamically adjusting voltage and frequency levels according to predicted workloads, the architecture effectively minimizes unnecessary power consumption while maintaining the required processing performance. The proposed design also incorporates an Energy Monitoring Unit (EMU) that continuously

tracks energy utilization and provides real-time feedback for intelligent power management decisions. Furthermore, clock gating techniques reduce switching activity in inactive modules, contributing to additional power savings. The complete architecture was modeled using Verilog HDL and validated through simulation, demonstrating correct functionality of workload prediction, adaptive DVFS control, energy monitoring, and performance-aware power optimization. Experimental results indicate that the architecture successfully adapts to varying workload conditions, reducing energy consumption during low-demand periods while ensuring adequate computational capability during high-demand scenarios. The predictive DVFS mechanism minimizes power-state transition overheads and improves overall energy efficiency compared with static operating schemes. The simulation waveforms further verify the coordinated operation of the workload prediction unit, power management controller, and energy monitoring subsystem. Overall, the proposed AI-assisted architecture provides a scalable, hardware-efficient, and practical solution for intelligent energy management in next-generation IoT, wearable, and edge-computing platforms. Its ability to balance performance and power consumption makes it a promising approach for extending battery lifetime, enhancing system sustainability, and supporting future energy-constrained smart devices.

References

[1] Bernard, L. (2026). Adaptive voltage/frequency scaling in RISC-V SoC platforms for energy-harvesting IoT networks. Journal of Integrated VLSI, Embedded and Computing Technologies, 3(2), 25–35. https://ecejournals.in/index.php/JIVCT/article/view/509

[2] Badami, S., Sharma, A., Reddy, B., Kadam, S., Chouhan, B., & Rana, B. (2026). AI-optimized VLSI architecture for energy-efficient and sustainable IoT systems. Research Square Preprint. https://doi.org/10.21203/rs.3.rs-8564604/v1

[3] Pasaya, A., Hadia, S., & Bhatt, K. (2026). Bio-inspired power optimization strategies for low-power VLSI in IoT and wearable devices: A comprehensive review. Discover Electronics, 3(53). https://doi.org/10.1007/s44291-026-00189-9

[4] Reis, M. J. C. S. (2026). Low-power embedded sensor node for real-time environmental monitoring with on-board machine-learning inference. Sensors, 26(2), 703. https://doi.org/10.3390/s26020703

[5] Yang, B. (2026). Low-power MCUs: Power modeling, estimation, and optimization. Academic Journal of Science and Technology, 20(2), 115–121. https://doi.org/10.54097/96yjkp59

[6] Chowdhury, P., Mokashi, S. P., Agrawal, S. J., Lingamgunta, R. K. K., Ubale, A., & Shinde, R. (2026). Green AI for industrial IoT: Energy-efficient edge computing architecture in smart manufacturing. Scientific Culture, 12(2.1), 4626–4639. https://doi.org/10.5281/zenodo.19131285

[7] Gulothungan, G., Raja, T., Devarajan, Y., Jain, M., Manjunath, H. R., Asif, M., Madhusudhan, M., Choudhury, S., & Jayabal, R. (2026). Hybrid AI-IoT-blockchain frameworks for energy-efficient smart homes: A multidimensional review of

technologies, policies, and socioeconomic implications. Energy and Buildings. https://doi.org/10.1016/j.enbuild.2026.117359

[8] Tandi, M. R., & Tamrakar, G. (2025). Hardware–software co-design of RISC-V embedded systems for ultra-low-power IoT applications. Journal of Integrated VLSI, Embedded and Computing Technologies, 3(1), 1–6. https://doi.org/10.31838/JIVCT/03.01.01

[9] Domínguez-Bolaño, T., Campos, O., Barral, V., Escudero, C. J., & García-Naya, J. A. (2024). An overview of IoT architectures, technologies, and existing open-source projects. Internet of Things, 25, 101016.

[10] ElSayed, Z., Elsayed, N., Li, C., & Bayoumi, M. (2021). Autonomous low power IoT system architecture for cybersecurity monitoring. IEEE Access, 9, 112345–112358.

[11] Nguyen, D. C., Cheng, P., Ding, M., Lopez-Perez, D., Pathirana, P. N., Li, J., Seneviratne, A., Li, Y., & Poor, H. V. (2020). Enabling AI in future wireless networks: A data life cycle perspective. IEEE Communications Surveys & Tutorials, 23(1), 553–595.

[12] Isa, I. S. M., El-Gorashi, T. E. H., Musa, M. O. I., & Elmirghani, J. M. H. (2020). Energy efficient fog-based healthcare monitoring infrastructure. IEEE Access, 8, 197828–197842.

[13] Amangeldy, A., et al. (2025). A review of artificial intelligence and deep learning approaches for resource management in smart buildings. Buildings, 15(15), 2631.

[14] Altan, D., Yilmaz, M., & Köse, K. (2022). DVFS and duty-cycling for ultra-low-power IoT. Electronics, 11(21), 3445.

[15] Reis, M. J. C. S., & collaborators. (2026). Energy-efficient machine learning inference for embedded IoT sensor platforms. Sensors, 26(2), 703–719.