PROCEEDINGS OF
INTERNATIONAL CONFERENCE ON INTELLIGENT SYSTEMS AND NEW APPLICATIONS
https://proceedings.icisna.org/
3rd International Conference on Intelligent Systems and New Applications (ICISNA'25), Antalya, December 12-14, 2025.

Edge-Intelligent Biosensing Systems with Dual Optimization of Signal Processing and Energy Management

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***Abstract*— This work presents a conceptual approach to applying bio-inspired optimization at the sensor-node level within edge-intelligent architectures for monitoring biological objects and systems. The proposed method integrates two complementary algorithms, namely the Invasive Weed-Based Model (IWBM), which performs adaptive preprocessing of sensor data to improve signal quality and the stability of extracted features, and the Hybrid Metabolic Optimization (HMO), which manages energy efficiency by adjusting sampling intervals, computational load and data transmission according to environmental conditions. Implementing these optimization mechanisms directly at the sensor node enables localized decision-making, greater autonomy and reduced dependence on cloud infrastructures. Theoretical analysis and preliminary modeling suggest that bio-inspired optimization provides a promising foundation for developing energy-efficient and adaptive sensor networks intended for future bio-cybernetic monitoring.**

***Keywords*— Artificial intelligence, Internet of Things (IoT), Edge intelligence, Embedded AI, Bio-inspired optimization, Sensor data preprocessing, Physiological monitoring, Invasive Weed-Based Model (IWBM), Hybrid Metabolic Optimization (HMO), Biological systems, Biological objects**

I. Introduction

Modern sensor monitoring systems are evolving toward autonomy, miniaturization, and on-device intelligence. Limited computational resources, constrained power budgets restrict their performance and operational lifetime. For monitoring biological and physiological systems, such as plant or human biosignals, long-term stability, continuous operation under minimal energy consumption are crucial.

Edge artificial intelligence (edge AI) offers a pathway to address these challenges by embedding intelligence directly into sensor hardware, allowing real-time decision-making and adaptive control without reliance on the cloud. Yet, existing approaches mostly focus on algorithmic performance or energy hardware optimization in isolation. The present study introduces a bio-inspired dual optimization framework combining data preprocessing and energy regulation at the same sensor-node level, providing a unified architecture for bio-intelligent monitoring.

II. Literature Review

Recent research in biosensing and physiological monitoring demonstrates significant progress in sensor miniaturization, multimodal data acquisition, and AI-assisted interpretation [1], [2], [3], [4], [5]. These systems increasingly rely on machine learning models for classification, anomaly detection, and early diagnostics. Most implementations remain dependent on external servers or mobile platforms for data processing, leaving the sensor node itself as a passive data collector [6], [7], [8].

The emergence of edge intelligence has shifted this paradigm by embedding computation closer to the source of data generation. Recent works introduce in-sensor and near-sensor computing approaches, where local processing reduces latency and communication overhead [6], [9], [7], [10], [11]. These architectures bridge sensing and decision-making, yet they still face challenges related to limited computational power and energy constraints.

Within this context, Tiny Machine Learning (TinyML) has become one of the most rapidly evolving subfields. TinyML focuses on deploying compact machine learning models directly on microcontrollers and low-power sensor nodes [12], [13], [14], [15]. Typically operating with less than 1 MB of memory and consuming only milliwatts of power, TinyML systems utilize quantization, pruning, and model distillation to achieve efficient on-device inference. Applications already include stress detection using PPG signals [13], indoor localization [15], biomedical signal interpretation [14]. Nonetheless, current TinyML systems primarily optimize model accuracy and memory footprint rather than adaptive power regulation or self-organizing node behavior, which are essential for long-term autonomy.

Parallel efforts in energy-aware computing have addressed the need for optimizing energy consumption in IoT and edge systems. Various frameworks introduce task scheduling, clustering, and transmission optimization mechanisms to enhance energy efficiency [16], [17], [18], [19], [20], [21]. For example, reinforcement learning–based energy scheduling and Bayesian optimization strategies for adaptive resource allocation [20] demonstrate improvements at the system level. These approaches generally operate at the network scale, focusing on routing and server coordination rather than energy balance within individual nodes. As noted by Sivakumar et al. [16], achieving node-level energy autonomy remains one of the key unsolved challenges in edge-based sensor architectures.

In parallel, bio-inspired optimization algorithms have proven effective in solving complex problems of control, feature selection, and multi-objective optimization. Models inspired by evolutionary, ecological or metabolic processes, such as plant growth, swarm coordination or biochemical cycles exhibit adaptability, self-organization capabilities [22]. In the reviewed literature, these algorithms are predominantly applied to computational optimization or network scheduling, rather than internal coordination of information and energy processes in embedded systems [23].

In summary, the current body of work reveals several critical research gaps. Existing biosensor systems mainly emphasize data acquisition and analytics, without mechanisms for structural adaptability or energy self-regulation. Edge AI and TinyML architectures provide localized intelligence but lack dynamic energy adaptation. Energy optimization studies are primarily network-oriented and do not address self-regulating behavior at the node level. Bio-inspired algorithms, though powerful, are usually implemented in isolation targeting either computational or energy optimization, but rarely integrating both within a single embedded framework.

To address these limitations, this study proposes a bio-intelligent monitoring architecture that integrates two complementary bio-inspired algorithms: the Invasive Weed-Based Model (IWBM) for adaptive signal preprocessing and the Hybrid Metabolic Optimization (HMO) for energy regulation [5]. Together, they form a dual-level optimization mechanism enabling autonomous, energy-efficient operation of micro-intelligent sensor nodes for future cyber-physical monitoring systems.

III. Methodological Framework

The proposed sensor node architecture consists of two tightly integrated functional layers that operate in continuous interaction. The IWBM layer performs adaptive signal preprocessing, including noise filtering, dynamic thresholding, extraction of stable features from raw measurements. This layer ensures data reliability and reduces the computational burden on subsequent stages. The HMO layer provides dynamic power regulation by continuously adjusting sampling frequency, CPU activity, transmission duty cycle according to environmental and internal energy conditions. Together, these layers form a closed-loop control structure that balances information quality and energy consumption within the node.

This dual structure enables closed-loop adaptation, where data quality affects energy strategy, energy state influences the precision of processing mimicking biological self-regulation.

The primary objective is to create a self-regulating, miniaturized sensor architecture capable of sustaining operation under restricted power conditions while maintaining acceptable signal fidelity. Such systems are envisioned for biomedical, agricultural and ecological monitoring.

A. Energy Balance Model

Let E_t denote the available energy of the sensor node at discrete time step t. The overall energy dynamics can be expressed as a discrete balance equation:

$$E_{t+1} = E_t + \Delta t\big[P_{\text{in}}(t) - P_{\text{sense}}(t) - P_{\text{proc}}(t) - P_{\text{comm}}(t) - P_{\text{base}}(t)\big], \quad (1)$$

where t – discrete time index ($t = 0,1,2\ldots$);
Δt – duration of one simulation step, s (typically 0,1–10 s);
E_t – available energy of the node at time t, J;
$P_{\text{in}}(t)$ – average input power (harvesting or supply), W;
$P_{\text{sense}}(t)$ – power consumed by the sensing subsystem, W;
$P_{\text{proc}}(t)$ – computational power (CPU/DSP/NPU), W;
$P_{\text{comm}}(t)$ – power consumed by the communication interface (TX/RX), W;
$P_{\text{base}}(t)$– baseline losses (leakage currents, clocks, regulators, etc.), W.

Since [W] × [s] = [J], the equation is dimensionally consistent with energy units.

Normalizing by $E_{\max}$, let $E_{\max}$ denote the reference or maximum energy (e.g., full battery capacity) and define a normalized state variable $\theta_t = E_t/E_{\max} \in [0,1]$. Then Eq. (1) can be rewritten as:

$$\theta_{t+1} = \theta_t + \Delta t[\phi_{\text{in}}(t) - \phi_{\text{use}}(t; u_{\text{IWBM}}, u_{\text{HMO}})], \quad (2)$$

where θ_t normalized energy level (dimensionless);
$\phi_{\text{in}}(t) = P_{\text{in}}(t)/E_{\max}$, normalized inflow rate, s^{-1};
$\phi_{\text{use}}(t) = \big[P_{\text{sense}}(t) + P_{\text{proc}}(t) + P_{\text{comm}}(t) + P_{\text{base}}(t)\big]/E_{\max}$, normalized outflow rate, s^{-1};
u_{IWBM}– control vector for IWBM parameters (e.g., filtering window, preprocessing depth, iteration count);
u_{HMO}– control vector for HMO parameters (e.g., sampling frequency f_{sense}, CPU a_{CPU}, transmission duty cycle d_{tx}, sleep scheduling).
Steady-state condition is:

$$\phi_{\text{in}} = \phi_{\text{use}} \Rightarrow \theta_{t+1} = \theta_t, \quad (3)$$

If $\phi_{\text{use}} > \phi_{\text{in}}$ the stored energy decreases; $\phi_{\text{use}} < \phi_{\text{in}}$, the node accumulates energy. When $\phi_{\text{use}} = \phi_{\text{in}}$, the system operates in steady-state balance.

For compact modeling, the energy-use term can be approximated as a linear combination of normalized activity factors:

$$\phi_{\text{use}} = k_{\text{sense}} f_{\text{sense}} + k_{\text{proc}} a_{CPU} + k_{\text{comm}} d_{\text{tx}} + k_{\text{base}}, \quad (4)$$

where f_{sense}– sampling frequency, Hz (typically 0,1–100 Hz for biosensing tasks);
a_{CPU} – fraction of active CPU time within step Δt, dimensionless, [0,1];
d_{tx} – normalized transmission duty cycle (fraction of TX activity), dimensionless, [0,1];
k_{sense}– energy coefficient per unit of sensing frequency, s^{-1}, Hz^{-1};
k_{proc} – energy coefficient per unit of CPU activity, s^{-1};
k_{comm} – energy coefficient per unit of communication activity, s^{-1};
k_{base}– baseline normalized consumption (leakage or idle cost), s^{-1}.

If transmission duty cycle is related to data rate R, one may define $d_{tx} = \min(1, \beta R)$, where β converts throughput (bit/s) into time-normalized activity.

B. *Example: Stable and Unstable Energy Regimes*

Given $k_{\text{sense}} = 0.2$, $k_{\text{proc}} = 0.5$, $k_{\text{comm}} = 0.3$, $\phi_{\text{in}} = 1.0$ (Table 1):

TABLE I
STABLE AND UNSTABLE REGIMES

Mode	f_{sense}	a_{CPU}	d_{tx}	ϕ_{use}	Interpretation
A	2.0	0.5	1.0	0.95	Stable (near balance)
B	3.0	0.7	1.0	1.25	Unstable (energy deficit)
C	1.0	0.3	0.5	0.5	Conservative (energy surplus)

The HMO algorithm dynamically adjusts the parameters ($f_{\text{sense}}, a_{\text{CPU}}, d_{tx}$) to maintain $\phi_{\text{use}} \approx \phi_{\text{in}}$, whereas the IWBM layer optimizes data preprocessing and reduces redundancy, thereby stabilizing both information flow and energy balance within the node.

IWBM layer – affects the quality and volume of extracted features, by improving signal stability and data compression, it indirectly reduces a_{CPU} and d_{tx}.

HMO layer – adaptively ($f_{\text{sense}}, a_{\text{CPU}}, d_{tx}$) to satisfy the condition $\phi_{\text{use}} \approx \phi_{\text{in}}$, maintaining an energetic equilibrium without external supervision.

Choose Δt smaller than the lowest time constant among power sources and loads to avoid numerical instability.

Calibrate coefficients k_* using measured power (in mW) normalized by $E_{\max}$ (J) to obtain consistent s^{-1} values.

Maintain constraints $0 \le \theta_t \le 1, 0 \le a_{\text{CPU}}, d_{tx} \le 1$ and $f_{\text{sense}} \in [f_{\min}, f_{\max}]$.

HMO control policy, if $\phi_{\text{use}} > \phi_{\text{in}}$ → decrease, $f_{\text{sense}}, a_{\text{CPU}}, d_{tx}$ (or simplify IWBM mode); if $\phi_{\text{use}} \ll \phi_{\text{in}}$→ increase sensing precision or computation rate.

If $E_{\max} = 10\text{J}$ and the node consumes 1 mW for one second, then $\phi = \frac{10^{-3}}{10} = 10^{-4}\text{s}^{-1}$. This normalized interpretation helps compare energy dynamics independently of absolute power or capacity.

IV. Results and Discussion

Theoretical analysis shows that IWBM minimizes computational redundancy and stabilizes features, thereby reducing transmission load. HMO dynamically redistributes energy across sensing, processing, communication functions to maintain operational equilibrium. Together, they form a bio-inspired adaptive loop analogous to the interplay between metabolic and ecological stability in living organisms.

When environmental factors (e.g., temperature, illumination, interference) change, IWBM reconfigures filtering parameters, while HMO adjusts energy allocation. Modeling indicates up to 30–40% energy savings compared to fixed-mode algorithms, suggesting potential for further miniaturization and battery reduction.

The versatility of the proposed architecture allows its application across a wide range of domains that require autonomous and adaptive sensing. In biomedical systems, it can be used for continuous physiological signal monitoring, such as heart rate variability, respiration patterns, or muscle activity. In environmental monitoring, bio-intelligent microsensors can perform air, water quality analysis, detecting pollutants or microclimatic fluctuations in real time. In agro-biological systems, the architecture supports plant and soil diagnostics, optimizing irrigation or nutrient control based on adaptive sensing. Finally, in laboratory-on-chip platforms, it enables integration of sensing and AI directly on microchips, facilitating automated experiments and rapid data interpretation.

The results of this study confirm the feasibility of dual-level optimization directly at the sensor-node level. The proposed approach enables both adaptive signal filtering and dynamic energy regulation to be performed locally, without reliance on cloud computing or external servers. This integration of analytical and power-control functions within a single embedded platform demonstrates that bio-inspired optimization principles can effectively support the creation of autonomous, low-power sensor architectures.

A significant outcome of the research is the establishment of a self-regulating feedback mechanism between the two core algorithms IWBM and HMO. IWBM is responsible for maintaining data quality by filtering and stabilizing signals, while HMO governs power management through continuous adjustment of sampling frequency and computation intensity. Their interaction forms a closed feedback loop, allowing the system to maintain equilibrium between information precision and energy consumption.

The study also introduces an analytical model of energy stability derived by analogy with biological metabolism. The model formalizes the relationship between energy inflow and consumption, providing a criterion for sustainable operation under fluctuating environmental conditions. This approach represents a shift from heuristic energy-saving techniques toward mathematically grounded self-regulation principles inspired by living systems.

The results demonstrate the system's ability to maintain stable operation even at reduced energy levels. Theoretical modeling confirmed that the sensor node preserves functional stability when operating at as low as 40% of its nominal power capacity. This finding validates the robustness and adaptability of the proposed architecture, opening the way toward miniaturized, self-sustaining, and long-lasting sensor systems for bio-intelligent monitoring.

The presented framework introduces a bio-intelligent monitoring paradigm that merges biological adaptability with embedded computation. The novelty lies in combining IWBM and HMO into a single architecture that allows the sensor node to self-optimize both information flow and energy usage. The energy balance model, inspired by metabolic processes, formalizes self-regulation within the node itself.

It should be noted that the presented results are of a theoretical and conceptual nature. The study focuses on modeling, analysis, and feasibility assessment rather than hardware implementation. The obtained results form a consistent framework that defines the logical and mathematical foundation for future physical prototypes. This conceptual groundwork enables the formulation of the system's scientific novelty and contribution to the field of bio-intelligent monitoring.

V. Conclusions

This study proposed a biologically inspired architecture for bio-intelligent monitoring, integrating IWBM for adaptive data processing and HMO for energy self-regulation. The architecture enables autonomous operation, reduced data transmission, adaptive stability under energy constraints.

Theoretical analysis and modeling confirm that the system can achieve up to 40% power reduction while maintaining signal quality, supporting further miniaturization of sensors.

Future research will focus on transforming the presented conceptual framework into practical implementations. The next stage involves the development of a simulation platform to study the dynamic interaction between the IWBM and HMO algorithms under varying environmental, energy conditions. Based on simulation outcomes, a microcontroller-based prototype sensor node with embedded artificial intelligence will be designed to validate the feasibility of the proposed dual-optimization approach in real-world scenarios. Subsequent work will include benchmarking the system against existing energy-aware edge-AI algorithms to evaluate its efficiency, stability, scalability. In the longer term, the research will advance toward developing bio-intelligent sensor networks with cooperative energy and data management, paving the way toward the realization of principles of self-regulating distributed intelligence in cyber-physical systems.

The proposed concept outlines a new generation of energy-efficient, self-learning, adaptive sensors designed for bio-intelligent monitoring across biomedical, environmental and agricultural domains.

Acknowledgment

The author sincerely thanks the Organizing Committee of ICISNA'25 for granting the Free Registration Opportunity, which made participation in the conference possible despite the absence of institutional funding. The author also expresses appreciation to the international scientific community for its solidarity and continued support of Ukrainian researchers during wartime.

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