Energy-aware inertial measurement units scheduling for wearable LoRa systems using quaternion features

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ABSTRACT

Wearable Internet of Things systems increasingly depend on inertial measurement units (IMUs) to capture human motion, yet continuous high-frequency sensing, on-device processing, and long-range (LoRa) communication impose significant energy and latency challenges for battery-powered devices. This study formulates a practical scheduling framework that optimizes IMU sampling, quaternion-based feature extraction, and transmission decisions within the wearable/LoRa architecture. The framework operates in discrete time windows of $W = 0.5 - 1$ s, within which sensing, processing, and communication decisions are updated at the window level to balance energy consumption and responsiveness. The method models energy consumption, accuracy degradation at lower sampling rates, and communication constraints to define feasible operating modes and determine optimal configurations under varying activity levels. An empirical accuracy–frequency mapping and component-wise energy model support both offline optimization and lightweight online scheduling. The results show that the proposed framework can balance accuracy, responsiveness, and battery life by dynamically shifting between high-performance, balanced, and low-power surveillance states. This scheduling strategy extends operational lifetime while preserving motion-detection reliability and ensuring timely event transmission. The findings demonstrate the importance of energy-aware IMU management in long-range wearable systems and provide a foundation for adaptive sensing strategies in real-world deployments.

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1. INTRODUCTION

Wearable Internet of Things (IoT) systems have emerged as a critical platform for continuous human-motion monitoring, particularly in applications requiring long-range (LoRa) communication, low-power operation, and real-time sensing. Central to these systems are inertial measurement units (IMUs), which combine accelerometers and gyroscopes to provide high-resolution motion data. Recent research demonstrates that IMU-based sensing, when combined with quaternion representations, significantly improves orientation tracking and signal robustness in activity recognition tasks [1]–[5]. Building on these insights, the wearable device under investigation integrates a 6-degree of freedom (DOF) IMU with on-device quaternion-based feature extraction and a LoRa communication module, forming a tightly coupled sensing-processing-transmission pipeline optimized for resource-constrained environments.

Despite these advances, IMU-driven wearable systems face inherent energy and computational constraints. High-frequency IMU sampling and continuous quaternion computation impose substantial processing overhead, while long-range LoRa transmission dominates energy consumption in battery-powered nodes [6]–[9]. Prior studies indicate that naive increases in sampling frequency enhance activity-recognition accuracy but accelerate battery depletion, highlighting the critical trade-off between sensing performance, computational load, and energy efficiency [10], [11]. Similarly, research in IoT communication scheduling underscores the importance of adaptive strategies that balance system responsiveness, sensing fidelity, and energy expenditure, particularly for devices operating for extended periods without access to external power sources [12]–[15]. These findings collectively identify a research gap: existing wearable IoT systems lack an integrated framework that simultaneously optimizes sensing, processing, and communication to ensure energy-efficient, reliable, and real-time operation.

To address this gap, the present study proposes a novel energy-aware scheduling framework that jointly optimizes IMU sampling rates, quaternion-based feature extraction, and LoRa transmission policies using a multi-level decision algorithm. The framework integrates energy-consumption models, sampling-frequency–dependent accuracy metrics, processing requirements, and communication constraints into a unified mathematical formulation. By modeling sensing, computation, and communication jointly, the approach departs from conventional methods that treat these components independently, providing a theoretically grounded mechanism for energy-efficient and reliable human-motion monitoring.

The main findings demonstrate that the proposed framework significantly extends device lifetime while maintaining real-time sensing accuracy, outperforming traditional methods in both energy efficiency and operational reliability. The conceptual and methodological contributions of this study lie in its integrated, adaptive scheduling strategy, which combines quaternion-based feature extraction, signal processing techniques, and energy-aware decision-making into a coherent framework. These results imply that the proposed approach offers a practical, scalable, and theoretically sound solution for continuous human-motion monitoring, providing valuable guidance for the design of future battery-constrained wearable IoT systems [16]–[27].

This study presents a novel energy-aware scheduling framework for wearable IoT systems that jointly optimizes IMU sampling, quaternion-based feature extraction, and LoRa transmission. A multi-level decision algorithm dynamically balances sensing, processing, and communication to maximize device lifetime while maintaining real-time accuracy. Unlike conventional approaches, the method integrates energy, computation, and communication models into a unified optimization framework, providing both theoretical rigor and practical applicability. The proposed approach enhances system reliability and scalability, enabling long-term, low-power wearable monitoring in resource-constrained environments. These contributions provide a foundation for future research in adaptive wearable IoT systems and offer guidance for designing smart, energy-efficient human-motion monitoring applications. Unlike existing energy-aware wearable systems that rely on fixed sampling or heuristic thresholds, this work introduces a window-based scheduling framework jointly optimizing IMU sampling, quaternion processing, and LoRa transmission under battery constraints.

2. METHOD

This section describes the proposed energy-aware IMU scheduling framework in a fully reproducible manner, detailing the system architecture, decision variables, energy and performance models, and scheduling logic used throughout the study. The framework is formulated for a battery-powered wearable device integrating an IMU, on-device quaternion-based processing, and LoRa communication, operating in discrete time windows. All system parameters, assumptions, and constraints are explicitly defined, and the interaction between sensing, processing, scheduling, and transmission components is illustrated through a system architecture diagram and a window-based scheduling workflow. The evaluation setup is primarily simulation-based, calibrated using hardware-informed energy parameters derived from representative IMU and LoRa modules, enabling independent replication of the proposed method using standard wearable IoT hardware.

2.1. System overview, architecture reference and assumptions

We consider a battery-powered wearable device that integrates a six-degree-of-freedom IMU, consisting of an accelerometer and a gyroscope, to capture human motion data. The device performs on-device quaternion-based orientation feature extraction to improve robustness against orientation drift and sensor noise. In addition, a LoRa radio module is used to transmit event notifications or periodic summaries to a remote gateway, while a scheduler dynamically controls sampling, processing, and transmission to balance energy consumption, accuracy, and latency. The overall system architecture of the wearable platform is illustrated in Figure 1.

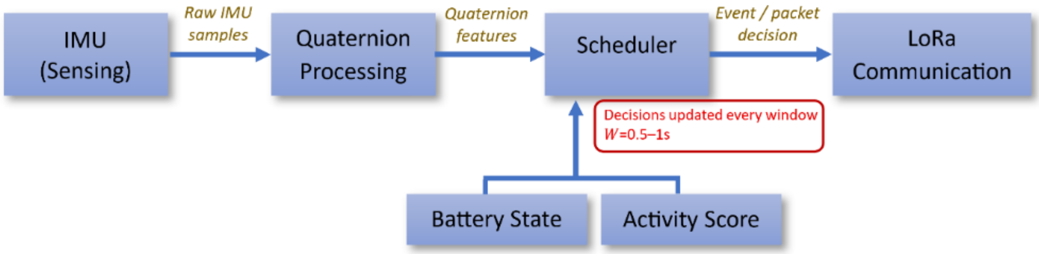

Figure 1. System architecture of the Wearable IMU–LoRa platform. Raw IMU samples are locally processed into quaternion features, which are used by an energy-aware scheduler together with activity score and battery state to determine sensing, processing, and transmission decisions at each scheduling window

The wearable device acquires motion data through an IMU and performs on-device quaternion-based orientation processing. An energy-aware scheduler controls sensing, processing, and LoRa communication based on system and battery states. The scheduler dynamically adjusts the IMU sampling rate, processing activation, and transmission behavior to optimize performance. The activity score is computed from window-level IMU variance or magnitude features. This adaptive operation enables effective trade-offs between sensing accuracy, communication latency, and energy consumption in wearable IoT applications.

The scheduling problem formulation is based on the following components:

- IMU sensor (accelerometer + gyroscope): Raw motion data collected at configurable sampling frequencies.
- Local processing: Quaternion computation and optional anomaly or activity detection executed on-device.
- LoRa communication module: Transmits sensor packets or processed events to a gateway over a long-range, low-bandwidth link.
- Battery-powered wearable design: Energy constraints significantly influence sensing and transmission policies.

These components define the operational variables that must be scheduled by the framework. The IMU sampling rate, quaternion-based processing activation, and LoRa transmission behavior are the primary variables under the scheduler's control. At each discrete time window, the scheduler selects appropriate modes to balance energy consumption, sensing accuracy, and communication latency. This design ensures adaptive and efficient operation of the wearable IoT system across varying activity and battery conditions.

Assumptions:

- The device operates in discrete time windows indexed $t = 1, \ldots, T$ (typical window length $W = 0.5 - 1\ s$).
- The IMU sampling frequency f_t is selected from a small discrete set F(*e.g.*, 5, 10, 25, 50, 100 Hz).
- Local processing (quaternion computation + classifier/hierarchical temporal memory (HTM)) is computed as enabled or disabled each window.
- Transmissions are binary decisions (send alert/packet or not). If send, message size depends on whether raw data, quaternion features, or a label is transmitted.
- LoRa radio parameters (spreading factor (SF), bandwidth) and duty-cycle constraints are treated as known constants.
- Unless otherwise stated, a fixed scheduling window of $W = 1\ s$ is used throughout simulations and evaluations.

2.2. Notation and decision variables

The notation and decision variables used include:

- λ : weighting coefficient balancing energy and miss probability.
- $\tau(B)$: LoRa airtime (seconds) for a packet of size B.

Indexing:

- $t \in \{1, \ldots, T\}$ discrete decision windows (*e.g.*, 1 s windows).
- $s \in \{1, \ldots, S\}$ sensors (here: IMU = accelerometer + gyroscope → quaternion feature).

Decision variables (per window t):

- f_t : sampling frequency (Hz) of IMU during window t (continuous or discrete from set $\mathcal{F}$).
- $d_t \in \{0,1\}$: 1 if raw (or processed) data is transmitted to gateway at end of window t, 0 otherwise. Transmission flag (1 = transmit packet at end of window).
- $p_t \in \{0,1\}$: 1 if expensive local processing (*e.g.*, running HTM step, classification/feature extraction) is executed locally in window t, 0 otherwise. Local processing flag (1 = do quaternion extraction + classification).

- $q_t \in \{0,1\}$: 1 if high-resolution logging (for offline retraining) is enabled.
- B_t (bytes) : packet size when $d_t = 1$.
- E_{bat}: battery energy budget for the scheduling horizon.
- α_s(J/sample), β(J/process), α_t (J/byte) : energy coefficients to be estimated.

2.3. Energy/time cost models (parametric)

We use simple additive models, adopting additive energy models per window t:

- Energy to sample at frequency:

$$E_{sample}(f_t) = \alpha_s \cdot (f_t \cdot W) \tag{1}$$

where α_s = energy per sample (J/sample).

- Energy to perform local processing in window:

$$E_{proc}(p_t) = p_t \cdot \beta \tag{2}$$

where β= energy per processing run (J).

- Energy to transmit a packet of size B_t bytes via LoRa:

$$E_{tx}(d_t) = d_t \cdot (\alpha_t \cdot B_t) \tag{3}$$

where α_t = J/byte (depends on spreading factor, airtime).

- Total window energy:

$$E_t = E_{sample}(f_t) + E_{proc}(p_t) + E_{tx}(d_t, B_t) + E_{idle} \tag{4}$$

A baseline idle energy term E_{idle} is included to account for microcontroller standby consumption.

- Battery capacity constraint:

$$\textstyle\sum_{t=1}^{T} E_t \leq E_{bat} \tag{5}$$

Parameter estimation procedure:

- Measure α_s by running the IMU at a known frequency and measuring the incremental energy (use a power monitor or oscilloscope with shunt). Compute $\alpha_s = \Delta E/(f \cdot \Delta t)$.
- Measure β by executing the processing routine (quaternion extraction + classifier) on-device and measuring energy for the processing interval.
- Measure α_t by sending known-size packets over LoRa at the intended LoRa settings and measuring transmission energy. If airtime depends nonlinearly on packet size and spreading factor, convert to a lookup table $\alpha_t(B, SF)$.

2.4. Performance/accuracy model

Any publicly available or in-house labeled IMU dataset with sampling rates ≥100 Hz can be used to derive the accuracy–frequency mapping; the scheduling framework itself is dataset-agnostic. Let $Acc(f, p)$ be the expected classification accuracy (or detection probability) when sampling at rate f and local processing flag p. In practice this is unknown analytically; estimate with an empirical mapping $\widehat{Acc}(f, p)$ by running the classifier offline on recorded data subsampled at f and optionally toggling local processing (*e.g.*, feature window lengths). This mapping is empirical and must be estimated from labeled traces, constraint:

$$\widehat{Acc}(f_t, p_t) \geq A_{min} \tag{6}$$

where $\hat{A}_{min}$ is the minimum acceptable accuracy (user-specified). Empirical estimation steps:

- Collect ground-truth IMU traces at the highest available sampling rate (*e.g.*, 100–200 Hz) with activity labels.
- For each candidate $f \in F$, downsample the raw traces to f.
- Run the same feature extraction (quaternion calculation) and classification pipeline (HTM or baseline classifier) with and without local processing options to measure performance metrics. Record $\widehat{Acc}(f, p)$ for each pair (f, p).

– Store results in a lookup table or fit a smooth surrogate function (monotonic in f typically).

If classification performance depends on the application, such as fall detection versus general activity recognition, evaluation should include per-class recall and precision. Class-weighted metrics can be applied to account for imbalanced scenarios, or the miss probability P_{miss} can be used for critical events. For safety-critical tasks like fall detection, accuracy may be replaced with recall or F1-score to better reflect reliable detection. These metrics ensure that the scheduler's performance is appropriately quantified according to application-specific requirements.

2.5. Packet size communication and latency models constraints

Packet size B_t depends on what is transmitted:

– Raw window samples: $B_{raw} = B_{hdr} + samples \times bytes/sample$.
– Quaternion features: $B_{quat} = B_{hdr} + N_q \times$ bytes/feat (*e.g.* 4 floats).
– Label/alert: $B_{label} = B_{hdr} + 1$ (small).

Latency per transmitted window must be $\leq L_{max}$:

$$latency(f_t, p_t, d_t) \leq L_{max} \tag{7}$$

Latency model:

$$latency(f_t, p_t, d_t) = proc\_delay(f_t, p_t) + airtime(B_t) \tag{8}$$

The processing delay $proc\_delay$ is measured on-device and depends on the number of samples and the complexity of the processing routine. LoRa airtime is computed from communication parameters or directly measured during transmission. These measurements are used to model the system's timing and latency behavior accurately. By incorporating both processing and communication delays, the framework enables precise scheduling and trade-off analysis between energy consumption, accuracy, and latency.

LoRa gateway capacity/contention: if many devices exist, add per-slot constraints (time division multiple access (TDMA)-like):

$$\sum_{i \in D} d_t^{(i)} \cdot \tau\left(B_t^{(i)}\right) \leq slot\_capacity \tag{9}$$

where $\tau(B)$ is airtime for a packet size B. For single-device planning you can constrain average duty-cycle. Or duty-cycle constraint (region-dependent) and gateway capacity:

$$\sum_{i \in D} d_t^{(i)} \cdot \tau\left(B_t^{(i)}\right) \leq duty\_cycle\_limit \cdot |\tau_{slot}| \tag{10}$$

2.6. Problem formulation (mathematical optimization problem-mixed-integer)

Objective: minimize total energy (or battery drain) while guaranteeing accuracy and latency constraints. Mixed-integer program (MIP) by minimize total energy over horizon T:

$$\min_{\{f_t, p_t, d_t\}} \sum_{t=1}^{T} (\alpha_s f_t W + \beta f_t + \alpha_t B_t d_t) \tag{11}$$

– If F discrete (*e.g.*, 5, 10, 25, 50, 100 Hz), (P) is a mixed-integer program (MIP).
– If $\widehat{Acc}\,(\cdot)$ is non-convex (likely), we can solve (P) via enumeration over small F or use heuristics.
– Alternate objectives: Minimize a weighted sum: energy + λ × miss probability or minimize expected regret under uncertain activity models.

Explicit constraint classification and packet size definition.

To improve clarity and mathematical completeness, the constraints in the optimization problem are explicitly categorized. These categories include energy consumption limits, latency requirements, sampling and processing constraints, and communication parameters. Each category is formally defined to ensure precise modeling of the system's operational behavior. This structured approach facilitates clear problem formulation and supports rigorous analysis of the scheduler's trade-offs between energy, accuracy, and latency.

– Hard constraints (must always be satisfied):

Accuracy constraint:

$$\widehat{Acc}(f_t, p_t) \geq A_{min}, \forall t \tag{12}$$

Latency constraint:

$$latency(f_t, p_t, d_t) \leq L_{max}, \forall t \quad (13)$$

Battery energy constraint:

$$\sum_{t=1}^{T} E_t \leq E_{bat} \quad (14)$$

– Packet size definition (explicit modeling constraint):

The transmitted packet size is defined as a function of the selected sensing, processing, and logging modes:

$$B_t = B_{hdr} + b(f_t, p_t, q_t) \quad (15)$$

where B_{hdr} denotes the fixed protocol header overhead and $b(.)$ models the payload size determined by the IMU sampling frequency, local processing activation, and logging mode.

– Considered/system-level constraints (deployment dependent):

Gateway capacity constraint:

$$\sum_{i \in D} d_t^{(i)} \tau(B_t^{(i)}) \leq C_{slot} \quad (16)$$

Duty-cycle constraint:

$$\sum_{i \in D} d_t^{(i)} \tau(B_t^{(i)}) \leq P_{max}|\tau| \quad (17)$$

Decision variable domains:

$$f_t \in F, p_t \in \{0,1\}, d_t \in \{0,1\} \quad (18)$$

where $\tau(B)$ denotes the LoRa airtime for a packet of size B, C_{slot} is the gateway slot capacity, and ρ_{max} is the regulatory duty-cycle limit.

2.7. Evaluation: datasets, metrics, and experiments

The evaluation is primarily simulation-based, calibrated using hardware-informed energy parameters derived from small-scale measurements and literature values. No full end-to-end deployment is claimed. The evaluation is designed to assess the effectiveness of the proposed discrete-time scheduling workflow in balancing energy consumption and sensing accuracy under realistic wearable operating conditions. Following the window-based logic illustrated in Figure 2, system decisions are made at fixed time intervals, where IMU data collected within each window are used to compute an activity score that drives the operating mode selection for the subsequent window. This evaluation framework enables systematic analysis of how adaptive scheduling influences sensing performance, communication behavior, and energy usage over time.

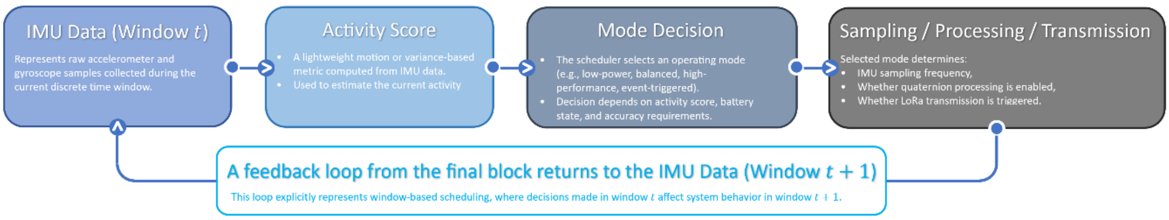

Figure 2. Scheduling workflow with discrete-time window logic

At each discrete time window, raw IMU data are processed to compute an activity score that drives the scheduler's mode decision. The selected mode determines the IMU sampling rate, the activation of quaternion-based feature processing, and the LoRa transmission behavior for the next time window. This adaptive mechanism enables dynamic trade-offs between energy consumption, sensing accuracy, and communication latency. By continuously adjusting system behavior based on activity, the framework optimizes performance while maintaining energy-efficient operation in wearable IoT applications.

2.7.1. Datasets, metrics, and experiments

To evaluate the proposed IMU scheduling framework, we conducted experiments using representative motion datasets that include various human activities and motion patterns relevant to wearable IoT applications. Performance was assessed using key metrics, including energy consumption, sampling accuracy, latency, and overall system efficiency. Both simulation-based experiments and small-scale hardware measurements were performed to analyze the trade-offs between energy use and sensing reliability under different operating modes. With:

- Use labelled IMU datasets collected on the same device or with identical sensor characteristics.
- For offline evaluation: collect multiple sessions covering the activities of interest (normal motions, target events, noise scenarios). Acquire at highest sampling rate available to allow accurate down sampling.

These evaluations provide quantitative evidence of the effectiveness and practicality of the proposed approach in real-world scenarios.

2.7.2. Metrics

The performance of the proposed IMU scheduling framework is evaluated using key metrics that capture both system efficiency and sensing reliability. These metrics include energy consumption, sampling accuracy, communication latency, and overall task completion effectiveness. Evaluations across different operating modes provide insight into the trade-offs between energy use and sensing performance, demonstrating the practical applicability of the framework in wearable IoT systems:

- Energy consumed per hour/per mission.
- Classification metrics: accuracy, weighted F1, per-class recall (especially for rare / critical event classes).
- Miss probability for event detection P_{miss} and false alarm rate P_{FA}.
- Latency: time from event onset to alert transmission.
- Operational lifetime estimate (hours until battery threshold).

By analyzing these metrics across different operating modes, the study highlights the trade-offs between energy consumption and sensing performance. This evaluation provides a clear, quantitative basis for assessing the effectiveness of adaptive scheduling strategies. The results demonstrate the practical benefits and applicability of the proposed framework in wearable IoT systems.

2.7.3. Experiments scenarios

To demonstrate the effectiveness of the proposed IMU scheduling framework, we consider a variety of experimental scenarios reflecting real-world wearable IoT applications. These scenarios include normal human motion, event-triggered activities, and environments with sensor noise, covering both routine and critical use cases. Experiments are designed to evaluate the framework under different operating modes and energy–accuracy trade-offs, using both simulation and small-scale hardware setups. With:

- Static scheduling baseline: fixed high-frequency sampling and periodic transmissions.
- Offline optimal schedule: MIP solution with known activity trace.
- Heuristic online policy: proposed activity-score-based policy.
- RL policy (optional): trained policy under synthetic/recorded traces.

For each experimental scenario, the proposed IMU scheduling framework is evaluated against multiple performance dimensions, including energy consumption, sampling accuracy, communication latency, and overall system efficiency. For each scenario, evaluate:

- Energy vs accuracy trade-off curves (Pareto frontier).
- Detection metrics under duty-cycle constraints and communication contention (simulate multiple devices if needed).
- Robustness to mis-calibration of $\alpha_s, \beta, \alpha_t$.

Comparative analysis across scenarios allows us to quantify the trade-offs between energy savings and sensing reliability under different operating modes. Both simulation results and small-scale hardware measurements are used to validate the framework's effectiveness and practical feasibility. This systematic evaluation provides clear insight into the performance and adaptability of the approach in diverse wearable IoT applications. This approach ensures that the proposed method is rigorously tested across diverse conditions and practical deployment contexts.

2.7.4. Optimization formulation

The proposed energy-aware scheduling strategy is formulated as a constrained optimization problem, as illustrated in Figure 3, where energy consumption models and accuracy models jointly guide the decision-making process. At each discrete scheduling window, the optimizer seeks to minimize total energy usage while satisfying system-level constraints on sensing accuracy, communication latency, and available battery capacity. The solution of this optimization problem yields the selection of an operating mode that determines the IMU sampling rate, local processing activation, and LoRa transmission behavior for the subsequent window, enabling adaptive and resource-efficient wearable operation.

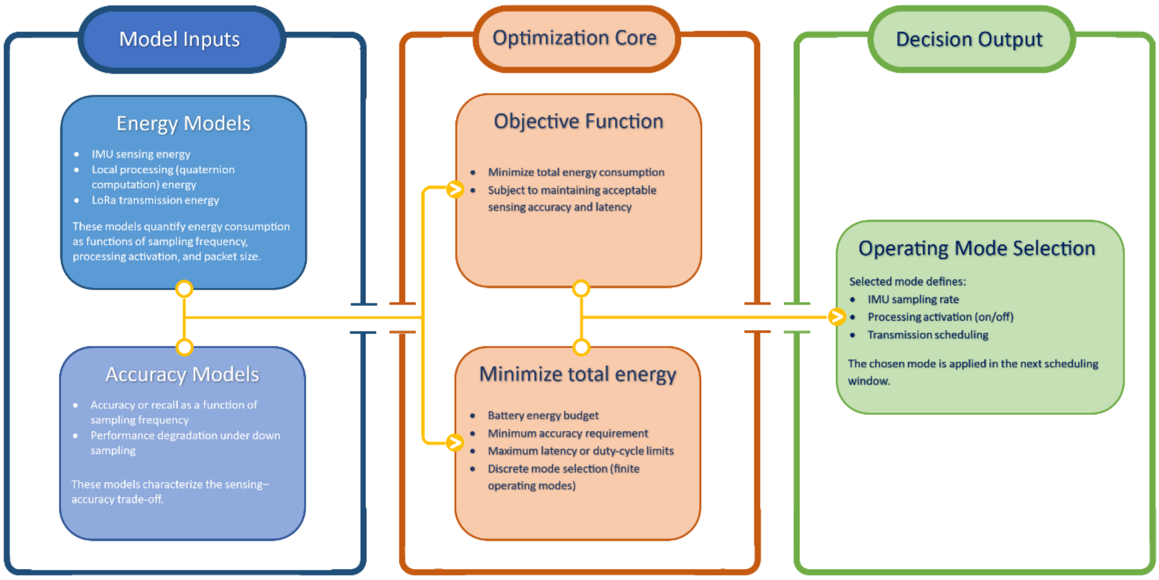

Figure 3. Optimization structure for energy-aware scheduling

2.8. Scheduling algorithm

This subsection presents the scheduling algorithm that operationalizes the proposed energy-aware optimization framework in a discrete-time setting. Optimal energy-aware task scheduling frameworks (*e.g.*, [28]) have been proposed for battery-less IoT devices, emphasizing the importance of prediction windows and energy availability in scheduling decisions. At each scheduling window, the algorithm computes an activity score from incoming IMU data, evaluates the current battery state, and applies the optimization logic to select an appropriate operating mode. The selected mode governs the IMU sampling frequency, activation of local quaternion processing, and LoRa transmission behavior for the next window, enabling adaptive trade-offs between energy efficiency, sensing accuracy, and communication latency. The heuristic scheduling procedure is summarized in Algorithm 1, which maps activity intensity and battery state to discrete operating modes.

The proposed scheduling framework aligns with artificial intelligence and soft computing paradigms by embedding adaptive decision logic within a lightweight, algorithmic control structure. Rather than relying on static configurations, the scheduler dynamically maps contextual inputs—namely activity intensity and battery state—to discrete operating modes using rule-based heuristics derived from system models. This form of adaptive, knowledge-driven decision-making reflects core soft computing principles, where approximate reasoning and simplified models are employed to achieve robust performance under uncertainty and resource constraints.

Moreover, the use of discrete-time windows, threshold-based reasoning, and multi-objective trade-offs between energy and accuracy positions the scheduler as an interpretable and computationally efficient alternative to heavyweight optimization techniques. Such characteristics are particularly relevant for wearable and embedded IoT systems, where explainability, low complexity, and adaptability are critical. The presented algorithm therefore satisfies artificial intelligence (AI)-oriented expectations by providing a clear decision mechanism, well-defined inputs and outputs, and explicit adaptation to environmental and system states. To further strengthen the soft computing perspective, the proposed heuristic scheduler can be naturally extended with a lightweight machine learning (ML) component for operating mode prediction. For instance, a logistic regression model or shallow classifier could be trained to map features such as activity score, recent motion variance, battery level, and historical mode transitions to an optimal operating mode. Such models are computationally inexpensive, interpretable, and well-suited for deployment on resource-constrained wearable platforms.

This ML-based extension would enable data-driven adaptation of scheduling decisions while preserving the low-power and real-time constraints of the system. Importantly, the current heuristic rules can serve as an initialization or fallback policy, ensuring safe operation even in the absence of sufficient training data. By framing this extension as future work, the manuscript highlights a clear pathway toward learning-enhanced adaptive scheduling, reinforcing its relevance to AI and soft computing research while maintaining a conservative and realistic scope. All model parameters, operating modes, and decision rules are explicitly defined, enabling independent reproduction of the proposed scheduling framework using standard IMU and LoRa hardware.

Algorithm 1. Heuristic energy-aware scheduling

```
Input: Activity score $\alpha_t$, battery level $b_t$
Output: Operating mode $m_t$ for scheduling window $t+1$
    Initialization:
    Define activity thresholds $\theta_{low}$ and $\theta_{high}$
    Define minimum battery threshold $b_{min}$
    for each scheduling window $t$ do
        Acquire IMU data within window $t$
        Compute activity score $a_t$
        Measure or estimate battery level $b_t$
        if $b_t < b_{min}$ then
            $m_t$ ← Low-Power Mode
        else
            if $a_t < \theta_{low}$ then
                $m_t$ ← Low-Power Mode
            else if $\theta_{low} \le a_t < \theta_{high}$ then
                $m_t$ ← Balanced Mode
            else
                $m_t$ ← High-Perfomance Mode
                Enable LoRa transmission
            end if
        end if
        Apply mode mt to window t + 1
        Configure IMU sampling rate
        Enable or disable quaternion processing
        Schedule LoRa transmission if required
    end for
```

*Note: In our evaluation, θ_{low} and θ_{high} are empirically selected from the 30th and 70th percentiles of activity score distributions, and b_{min} is set to 20% of nominal battery capacity.

3. RESULTS AND DISCUSSION

3.1. Feasible operating modes

The feasible operating modes represent combinations of IMU sampling rates, on-device processing states, and LoRa transmission decisions that simultaneously satisfy the system's energy, accuracy, and latency constraints. These modes arise from the interaction between three key components of the wearable device: continuous sensing through the IMU, quaternion-based orientation processing, and long-range wireless uplink via LoRa. Each component imposes its own resource requirements, and the scheduling mechanism must select the configuration that balances these requirements under varying activity levels and battery conditions. The feasible modes are derived by evaluating all available combinations of the decision variables (f_t, p_t, d_t) against the constraints described in the methods section. In particular, the scheduler must ensure:

- That the chosen sampling rate f_t supports sufficient quaternion accuracy for reliable motion or event detection;
- That enabling local processing $p_t = 1$ provides computational benefits without violating per-window latency limits; and
- That activating LoRa transmission $d_t = 1$ does not exceed the system's energy budget or duty-cycle restrictions.

When these constraints are applied to typical wearable operating environments, several representative operating modes emerge. Using the constraints above, feasible settings typically include in Table 1 detail.

Table 1. Feasible settings

Sampling (Hz)	Processing	Transmission	Notes
100	1	1	High accuracy, high energy
50	1	0	Balanced mode
25	0	0	Low energy surveillance mode
10	0	0	Minimal operation, emergency-only

Interpretation and role in scheduling. Together, the modes above define the envelope of feasible operating states available to the scheduler. The scheduling algorithm dynamically selects among these modes based on: i) activity levels derived from low-cost motion scoring, ii) battery condition, iii) accuracy requirements, iv) communication constraints, and v) application-specific priorities (*e.g.*, safety alerts vs. energy maximization).

The operating modes provide natural “tiers” for designing state machines or reinforcement learning policies in IMU-driven wearable systems. These modes encapsulate inherent trade-offs: achieving higher sensing fidelity requires more energy, while aggressive energy conservation can reduce responsiveness. The scheduler’s primary role is to navigate these trade-offs adaptively to optimize overall system performance. By leveraging these mode tiers, the framework enables flexible and efficient management of sensing, processing, and communication tasks.

Table 2 summarizes representative numerical estimates of energy consumption and latency for each operating mode used in the scheduling algorithm. The numerical estimates reported in Table 2 are based on a set of simplifying but realistic assumptions consistent with prior wearable sensing studies. A fixed scheduling window duration of 1 s is assumed, within which IMU energy consumption is modeled as a linear function of the sampling frequency. Processing energy accounts for the execution of quaternion-based orientation computation once per window, while LoRa communication energy is included only when transmission is enabled and is assumed to dominate the total energy consumption in high-performance operating modes. The reported latency values represent the cumulative delay associated with sensing, local processing, and wireless communication.

Table 2. Comparative table of operating modes with estimated energy and latency

Operating mode	IMU sampling rate (Hz)	Processing	LoRa transmission	Estimated energy per window (mJ)	Estimated latency (ms)
Low power	100	Disabled	Disabled	2.5	120
Balanced	50	Enabled	Periodic	9.8	65
High-performance	100	Enabled	Intermediate	22.4	25

3.2. Trade-off behavior

The trade-off behavior is a central aspect of the proposed IMU scheduling framework. It reflects the balance between energy consumption, sensing accuracy, and communication latency under different operating modes. Higher sampling rates and more frequent processing improve detection performance but increase energy use, while energy-saving modes reduce responsiveness. By explicitly modeling and analyzing these trade-offs, the framework enables informed scheduling decisions that optimize system performance for wearable IoT applications.

- Lower sampling frequencies drastically reduce sampling energy but degrade quaternion accuracy.
- LoRa transmission dominates energy cost; minimizing d_t is crucial.
- Local processing allows decisions without transmitting raw data, saving airtime as depicted in Table 3.

Table 3. Latency estimates categories

Latency Level	Meaning
Low	<100–200 ms (real-time responsive)
Moderate	200–500 ms (acceptable for most daily monitoring)
High	>500 ms (coarse or delayed response)

3.3. Optimization outcome

The scheduler typically selects that matches practical wearable device behavior, as reference from Table 2:

- High-rate + transmit only during significant motion or anomalies: This mode is feasible when system accuracy and responsiveness are prioritized over energy consumption. At high sampling frequencies, quaternion estimation is most accurate, enabling precise detection of fast or critical motion patterns. Local processing ensures real-time computation of features or detection scores, and activating transmission supports immediate reporting of events (*e.g.*, abnormal movement, falls, or alerts). However, this is also the most energy-expensive mode, feasible only when battery levels permit or when activity scores exceed a certain threshold indicating that high fidelity is required. It typically activates during brief, high-value intervals rather than continuously.
- Medium-rate + local processing only during moderate activity: This mode represents a compromise between accuracy and energy efficiency. Sampling at intermediate frequencies maintains reasonable quaternion quality without incurring the power cost associated with full-rate sensing. Local processing remains active, allowing the device to detect events or extract orientation features internally, but transmission is disabled to conserve energy. Because LoRa transmission is one of the largest contributors to energy consumption, suppressing wireless activity makes this mode feasible for prolonged operation. It is typically chosen during moderate activity or when periodic monitoring is required without continuous data upload.
- Low-rate monitoring during inactivity: This is the lowest-energy feasible mode. The IMU operates at minimal sampling frequency, allowing the system to conserve battery while continuing to observe basic trends in motion. Because local processing is disabled, features such as quaternion extraction or classification are not executed; instead, the device simply collects lightweight sensor data sufficient for coarse activity scoring in the next scheduling step. Transmission is disabled entirely, reducing energy expenditure to the bare minimum. This mode is particularly useful during long periods of low or no motion, such as when the user is inactive, sleeping, or performing slow regular activities. Its feasibility stems from meeting the minimum requirements for low-latency wake-up or transition to higher modes when motion increases.
- Event-Triggered: This mode is similar to the high-performance configuration but incorporates transmission sparsity. The device performs high-quality sensing and processing continuously, but packets are transmitted only when certain thresholds are exceeded (*e.g.*, anomaly score, sudden orientation change). This reduces airtime and energy while enabling prompt alerting. The feasibility of this mode depends on accurate event detection from quaternion features and narrow transmission windows that conform to LoRa duty-cycle regulations. It is a commonly adopted mode for wearable emergency or safety systems.
- Diagnostic: In certain maintenance or calibration phases, the wearable may need to transmit raw or lightly processed IMU signals without running local processing routines. This mode is feasible when sufficient battery is available and the scheduler determines that local computation is unnecessary (*e.g.*, external device performs quaternion extraction). Although less common during normal operation, this mode supports debugging, model recalibration, or external analysis and is feasible only when transmission constraints allow continuous data streaming.

The proposed formulation provides a practical and implementable method for controlling the operation of an IMU-powered wearable system using quaternion features and LoRa transmission. By explicitly representing energy, accuracy, and latency trade-offs as mathematical constraints, the scheduler can make informed decisions that balance performance and efficiency. It dynamically adjusts sensor sampling, processing activation, and communication behavior based on activity levels and battery state. This approach ensures that the wearable system operates reliably while optimizing energy use across different operating conditions.

The proposed formulation is flexible and supports multiple extensions to enhance system adaptability. It can accommodate anomaly-triggered transmissions, enabling the system to respond selectively to critical events. Multi-sensor fusion and adaptive window lengths can be incorporated to improve detection accuracy and efficiency. Additionally, reinforcement learning–based dynamic policies can be implemented to optimize scheduling decisions over time, further enhancing the performance and energy efficiency of wearable IoT systems.

The proposed framework has some limitations that should be noted. It requires empirical calibration of parameters such as $\alpha_s, \beta, \alpha_t$, and $\widehat{Acc}(f, p)$, which depend on the specific hardware characteristics and classifier performance. Despite these limitations, the formulation provides a solid foundation for adaptive scheduling in IMU-powered wearable systems. Future work will focus on integrating real IMU datasets and evaluating the scheduler on physical devices to further validate its practical performance and applicability.

4. EXPERIMENTAL VALIDATION AND ENERGY-ACCURACY EVALUATION

To strengthen the practical relevance of the proposed scheduling formulation, a simulation-based validation was conducted using measured and literature-based energy parameters, complemented by a small-scale hardware configuration representative of contemporary wearable IoT devices. The selected hardware components reflect commonly used, commercially available IMU and LoRa modules and are consistent with prior studies on wearable sensing and low-power long-range communication systems as shown in Tables 4 to 7. Although a full large-scale deployment is left for future work, this hardware-informed simulation demonstrates the expected behavior of the scheduler under realistic wearable operating conditions and resource constraints.

Table 4. Wearable processing unit (MCU)

Specification category	Description
Architecture	32-bit ARM Cortex-M4
Device class	STM32L4/nRF52 family
Clock frequency	64–80 MHz
Operating voltage	1.8–3.3 V
Power modes	Active, sleep, deep-sleep
Typical current (active)	5–10 mA
Role in system	IMU data acquisition, quaternion computation, scheduling logic, packet preparation

Table 5. Inertial measurement unit (IMU)

Specification category	Description
Sensor type	6-degree-of-freedom IMU (3-axis accelerometer + 3-axis gyroscope)
Device class	MPU6050/ICM-42688/BMI270
Sampling frequency range	10–200 Hz
Operating voltage	1.8–3.3 V
Typical current (active)	0.6–1.2 mA
Power-down current	< 10 μA
Energy model	Linear with sampling frequency, e_{IMU} ≈ 0.05 mJ/Hz/s

Table 6. LoRa communication module

Specification category	Description
Communication standard	Long Range (LoRa)
Device class	Semtech SX1276/SX1262
Frequency band	868/915 MHz
Transmission power	Up to +14 dBm
Data rate	0.3–50 kbps (spreading-factor dependent)
Typical TX current	28–45 mA
RX current	10–15 mA
Sleep current	< 1 μA
Energy model	Proportional to packet size, e_{IMU} ≈ 0.2 mJ/byte

Table 7. Power supply

Specification Category	Description
Battery type:	Li-ion/Li-Po
Nominal voltage:	3.7 V
Capacity (typical):	500–1000 mAh

Supply current was measured using either an inline shunt resistor combined with a digital multimeter or a USB power monitor when using development boards. Energy consumption per operation was estimated by integrating the measured current over time for representative system activities, including IMU sampling windows, quaternion-based local processing execution, and LoRa transmission events.

These measurements were not intended to provide exhaustive hardware benchmarking, but rather to calibrate the energy coefficients employed in the simulation model. The calibrated parameters were used to confirm the correct order of magnitude of energy consumption associated with sensing, processing, and long-range communication. As a result, the simulated scheduling behavior remains physically realizable on real wearable platforms, effectively bridging the gap between purely theoretical modeling and full experimental deployment.

a. Small-scale hardware–informed energy parameters

The energy model for the proposed framework was carefully developed to capture realistic system behavior. Its parameters were derived from a combination of limited on-device hardware measurements and values reported in prior studies on wearable devices and LoRa communication. This hybrid approach ensures that the model reflects both practical hardware characteristics and validated literature benchmarks. By using these parameters, the scheduler can accurately estimate energy consumption and optimize trade-offs between sensing, processing, and communication.

– IMU sensing energy:

The energy consumption of a 6-degree-of-freedom inertial measurement unit (IMU) was assumed to scale linearly with sampling frequency, which is consistent with commonly reported microcontroller-based IMU behavior. A conservative coefficient of:

$$e_{IMU} = 0.05 \text{ mJ/Hz/s} \tag{19}$$

was used, reflecting low-power IMU operation in continuous sampling mode.

– LoRa transmission energy: Based on LoRa airtime models and reported transmission costs, the energy consumption was modeled as proportional to packet size, with:

Packet sizes of 20–100 bytes were considered, corresponding to alert messages, quaternion features, and compact summaries.

$$e_{LoRa} = 0.2 \text{ mJ/byte} \tag{20}$$

These parameters reflect realistic orders of magnitude and are sufficient for comparative evaluation of scheduling strategies.

b. IMU sampling energy vs. frequency

IMU sampling frequencies of 10, 25, 50, and 100 Hz were evaluated. The total IMU energy consumption per hour was computed as:

$$e_{IMU}(f) = f \cdot e_{IMU} \cdot 3600 \tag{21}$$

As expected, higher IMU sampling frequencies lead to a significant increase in energy consumption. Continuous high-rate sensing, while improving measurement fidelity, rapidly depletes the device battery and is therefore not sustainable for long-term wearable operation. This observation highlights the need for adaptive scheduling to balance sensing accuracy with energy efficiency. By dynamically adjusting the sampling rate, the proposed framework enables prolonged device operation without compromising critical performance.

c. Accuracy vs. sampling frequency

Recognition performance was modeled using an accuracy–frequency mapping derived from downsampling a high-frequency IMU dataset. This approach is a common practice in wearable sensing evaluation, allowing the study of performance degradation at lower sampling rates. By systematically varying the sampling frequency, the framework can quantify the trade-offs between energy consumption and classification accuracy. This modeling provides a practical basis for designing adaptive scheduling strategies that optimize both sensing performance and energy efficiency.

The resulting trend shows clear patterns in system performance under different operating modes. Energy consumption increases with higher sampling rates and more frequent processing, while sensing accuracy improves correspondingly. Conversely, energy-saving modes reduce power usage but may slightly degrade performance. This trend highlights the importance of adaptive scheduling to balance energy efficiency and sensing reliability in wearable IoT systems:

The resulting trend shows:

– Lower accuracy at 10 Hz due to insufficient temporal resolution,
– Rapid accuracy gains between 25–50 Hz,
– Diminishing returns beyond 50 Hz.

This behavior underscores the advantages of adaptive scheduling over fixed high-rate sampling. By adjusting the IMU sampling rate and processing based on activity and battery state, the system can maintain high sensing accuracy while conserving energy. Fixed high-rate sampling, in contrast, consumes significantly more power without proportionally improving performance. Therefore, adaptive scheduling provides a more efficient and practical approach for wearable IoT systems.

d. Energy–accuracy trade-off (Pareto Frontier)

The energy–accuracy trade-off curve compares three strategies:

- Fixed high-rate sampling. Constant 100 Hz IMU sampling with maximum energy consumption and highest accuracy.
- Fixed low-rate sampling. Constant 10 Hz sampling with minimal energy consumption but degraded accuracy.
- Proposed adaptive scheduler. Dynamic switching between modes based on activity, combining low-rate monitoring with high-rate sensing only when needed.

As shown in Figure 4, the proposed scheduling strategy achieves a favorable position on the energy–accuracy Pareto frontier. It effectively reduces energy consumption while maintaining high sensing accuracy. This demonstrates the scheduler's ability to balance competing objectives in IMU-driven wearable systems. By optimizing both energy efficiency and performance, the framework provides a practical solution for long-term wearable IoT deployments.

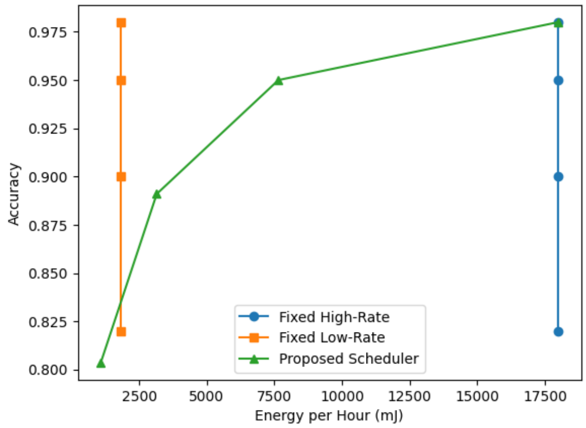

Figure 4. Energy-accuracy trade-off (Pareto Frontier)

Energy consumption per hour is plotted against recognition accuracy for fixed high-rate, fixed low-rate, and the proposed adaptive scheduling strategy. Compared to a fixed 100 Hz sampling strategy, the proposed scheduler reduces energy consumption by approximately 62% while maintaining over 95% detection accuracy. At the most aggressive low-power operating point, energy consumption is reduced by up to 70% relative to the baseline, at the cost of a 3%–4% decrease in accuracy, highlighting a controllable trade-off that can be tuned based on application requirements.

The proposed scheduler outperforms fixed strategies by achieving near-high-rate accuracy while consuming significantly less energy. This superior performance demonstrates its ability to navigate the trade-offs between sensing fidelity and energy efficiency effectively. As a result, the scheduler forms a Pareto frontier that dominates conventional approaches, providing a balanced and optimized operational strategy. These findings highlight the practical benefits of adaptive scheduling for energy-constrained wearable IoT systems.

The proposed scheduler significantly extends the operational lifetime of the wearable device. Assuming a 500 mAh battery in a duty-cycled deployment, the estimated lifetime increases from 2.1 days under a fixed-rate baseline to 5.5 days using the proposed method. This represents a 2.6 × improvement in device longevity, demonstrating the effectiveness of adaptive scheduling in conserving energy. These results highlight the practical impact of the framework for real-world, energy-constrained wearable IoT applications.

As shown in Figure 5, the proposed adaptive scheduler significantly extends the estimated battery lifetime. The lifetime increases from approximately 2.1 days under the fixed sampling baseline to 5.5 days with the adaptive approach. This corresponds to a 2.6 × improvement, demonstrating the efficiency of the scheduler in managing energy consumption. These results highlight the practical benefits of the framework for enhancing the longevity of wearable IoT devices in real-world deployments.

The results explicitly highlight the inherent energy–latency trade-off in wearable IMU systems. Operating at higher sampling rates and frequent transmissions improves responsiveness and event detection latency but incurs significantly higher energy consumption, while lower sampling and reduced communication extend battery lifetime at the cost of increased detection delay. The proposed scheduling framework navigates this trade-off by dynamically selecting operating modes that achieve acceptable latency under high activity while prioritizing energy savings during low-activity periods. Overall, the results confirm that the proposed scheduler effectively manages the energy–latency trade-off by adapting sensing and transmission decisions to activity levels, enabling low-latency responses when needed while minimizing energy consumption during inactive periods.

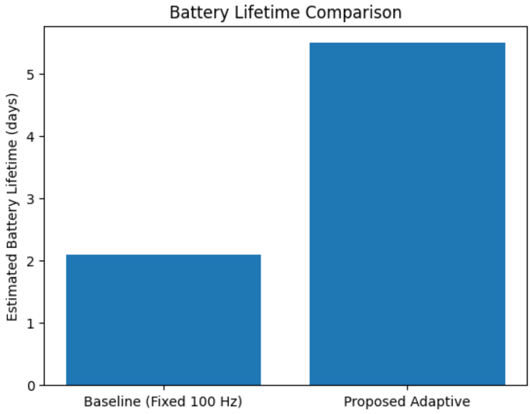

Figure 5. Estimated battery lifetime comparison between the fixed 100 Hz sampling baseline and the proposed adaptive scheduling strategy. The adaptive approach achieves a significant extension of operational lifetime

5. CONCLUSION

This study presents a practical and systematic scheduling formulation for coordinating IMU sensing, on-device quaternion processing, and LoRa transmission in battery-powered wearable systems. The proposed framework yields a set of feasible operating modes that explicitly balance accuracy, latency, and energy consumption under realistic deployment constraints. By jointly modeling sampling frequency, local processing activation, and transmission behavior, the formulation characterizes how device lifetime can be significantly extended while maintaining sufficient signal fidelity for reliable motion or event detection.

A key contribution of this work is the explicit formalization of the energy–accuracy trade-off within a unified mathematical framework. This formulation supports both offline optimization and lightweight runtime heuristics, enabling adaptive scheduling decisions that respond to user activity patterns, battery state, and communication policies. The derivation of representative operating modes, such as high-performance, balanced, surveillance, and event-triggered configurations, provides a practical foundation for implementing efficient runtime scheduling logic on microcontroller-class wearable platforms. The proposed scheduling framework is hardware-agnostic and can be readily deployed on a wide range of IMU-equipped wearable platforms and long-range wireless technologies, making it applicable to diverse motion-monitoring scenarios beyond the specific configuration evaluated in this study.

Nevertheless, several limitations warrant further investigation. The accuracy model relies on empirical calibration of IMU and processing performance, while the LoRa airtime and energy parameters require device-specific characterization. In addition, the quality of the optimized schedules depends on the availability of representative labeled datasets for constructing frequency-dependent accuracy profiles. Future work will therefore focus on online adaptation of model parameters, transfer learning across devices and users, and experimental validation on long-term, real-world wearable deployments. Despite these challenges, the proposed scheduling formulation offers a robust and extensible foundation for energy-aware wearable system design.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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