A Total Energy Consumption Model

The total energy consumption of terminal devices originates mainly from two categories of tasks: external communication and local processing, expressed, respectively, as communication overhead $E_{\rm comm}$ and local overhead $E_{\rm local}$. We combine them into a unified model:

$$E_{\text{total}} = E_{\text{comm}} + E_{\text{local}}.$$
 (1)

This formulation emphasizes that communication intensity and computational load jointly determine system lifetime. For example, a heavier communication burden directly raises E_{comm} , while optimized local processing can mitigate E_{local} , indirectly extending the usable energy budget.

A.1 Communication Energy Consumption Modeling

Communication energy is usually the dominant part for battery-free nodes (BFNs). To analyze the impact of transmission, reception, and protocol design on energy efficiency, we decompose E_{comm} into four components: E_{tx} , E_{rx} , E_{ctrl} , and E_{sec} . Each part is sensitive to a different set of parameters, such as distance, rate, or packet size.

A.1.1 Transmission Energy Consumption

For BFNs, transmission cost grows rapidly with the number of packets and the size of each packet. The basic model is given by

$$E_{\rm tx} = N \times \left((P_c + \eta \cdot P_{\rm te}) \times \frac{L}{R} \right),$$
 (2)

where the trade-off is clear: a larger rate R shortens duration $\frac{L}{R}$ but increases the dynamic circuit power P_{mod} . Similarly, a longer distance d raises P_{te} due to path loss, which in turn worsens overall efficiency.

The circuit power P_c is determined as

$$P_c = P_{\text{base}} + P_{\text{mod}}, \quad P_{\text{mod}} \propto R^{\beta}, \quad (\beta \approx 1),$$
 (3)

indicating that aggressive rate scaling may backfire by significantly raising power consumption.

The effective transmit power P_{te} compensates for propagation path loss:

$$P_{\text{te}} = \frac{\text{SNR} \cdot N_0 \cdot d^{\alpha}}{\eta \cdot h},\tag{4}$$

so that a longer communication distance d or a higher path loss exponent α can exponentially increase transmission cost. Meanwhile, amplifier efficiency η follows a saturation curve:

$$\eta = \eta_{\text{max}} \cdot \left(1 - e^{-\gamma P_{\text{te}}}\right),\tag{5}$$

meaning that additional transmit power yields diminishing returns when the efficiency nears its maximum.

Finally, packet size L and transmission rate R are also critical:

$$L = \left(\left\lceil \frac{\text{size}}{\text{MTU}} \right\rceil \cdot B + \text{size} \right) \cdot 8, \tag{6}$$

$$R = B \cdot \log_2 \left(1 + \frac{S}{N + N_{\text{interf}}} \right) \cdot C, \tag{7}$$

where increasing L amplifies per-packet overhead, while R depends not only on the signal-to-noise ratio but also on hardware capability C and interference level N_{interf} .

A.1.2 Reception Energy Consumption

Reception cost is mainly proportional to packet length and inversely proportional to rate:

$$E_{\rm rx} = N \cdot \left(P_{\rm rx} \cdot \frac{L}{R} \right) + P_{\rm idle} \cdot T_{\rm idle}.$$
 (8)

However, in passive BFNs adopting low-power listening (LPL), idle listening is replaced by periodic wake/sleep cycles, which reduces unnecessary energy waste but introduces wake-up overhead:

$$E_{\rm rx}^{\rm LPL} = N \cdot \left(P_{\rm rx} \cdot \frac{L}{R} \right) + \left(P_{\rm wake} \cdot T_{\rm wake} + P_{\rm sleep} \cdot T_{\rm sleep} \right) \cdot \frac{T_{\rm idle}}{T_{\rm cycle}}. \tag{9}$$

Thus, the choice of cycle length $T_{\rm cycle}$ directly affects the balance between responsiveness and energy efficiency.

A.1.3 Protocol Control Overhead

Protocol signaling further introduces energy cost:

$$E_{\text{ctrl}} = N_{\text{ctrl}} \cdot \left(\frac{P_{\text{tx}} \cdot C}{R} + \frac{P_{\text{rx}} \cdot C}{R}\right) + E_{\text{proc}} \cdot N.$$
 (10)

For intermittent devices, a more refined model accounts for wake-up events and periodic control messages:

$$E_{\rm ctrl}^{\rm LPL} = N_{\rm wake} \cdot \left[N_{\rm ctrl}^{\rm per} \cdot \frac{(P_{\rm tx} + P_{\rm rx}) \cdot C}{R} + E_{\rm proc} \cdot N_{\rm ctrl}^{\rm per} \right]. \tag{11}$$

Here, the number of wake-ups N_{wake} becomes a key determinant: more frequent wake-ups improve latency but significantly raise control overhead.

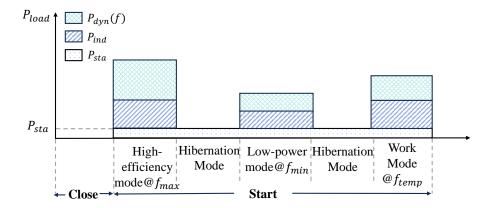


Figure 1: Power consumption in different modes of BFNs. The analytical models describe quantitative scaling, while the figure illustrates qualitative differences across system modes.

A.1.4 Secure Transmission Overhead

Security adds additional computation and message authentication cost. A simple model is

$$E_{\text{sec}} = N \cdot (E_{\text{enc}} \cdot L + E_{\text{dec}} \cdot L + E_{\text{auth}}). \tag{12}$$

To adapt to varying packet lengths and algorithmic complexity, we further generalize as

$$E_{\text{sec}} = N \cdot (E_{\text{enc}}(l) \cdot L + E_{\text{dec}}(l) \cdot L + E_{\text{auth}}(l)), \qquad (13)$$

where l denotes security level. Increasing l raises per-packet cost but strengthens protection.

A.2 Modeling of Local Processing Energy Consumption

Local energy consumption originates from processor operation, static leakage, and frequency-independent system overhead. Unlike communication cost, which is largely determined by the wireless channel, local consumption can be tuned through task scheduling, operating frequency, and voltage scaling. The system typically operates in three modes—high-efficiency, low-power, and normal operation—as illustrated in Fig. 1. The figure shows qualitatively how different operating states influence baseline consumption and transition overheads, while the following equations provide quantitative models.

A.2.1 System Load Power Consumption

The total system load is composed of three parts. First, the frequency-dependent power consumption

$$P_{\rm dyn,sys}(f) = \alpha C_{\rm eq} V_{\rm op}^2 f, \tag{14}$$

demonstrates that higher CPU frequency f improves task throughput but increases energy quadratically with voltage $V_{\rm op}$. Second, the frequency-independent component

$$P_{\text{ind}} = P_{\text{mem}} + P_{\text{IO}} + P_{\text{aux}},\tag{15}$$

forms a baseline overhead that cannot be eliminated by frequency scaling. Finally, static leakage

$$P_{\text{sta}} = V \cdot I_{\text{leak}},\tag{16}$$

becomes increasingly relevant in scaled technologies where leakage dominates standby power. $\,$

A.2.2 Task Execution Time

Execution time further modulates local energy. In parallel mode,

$$T = \max\left(\frac{C}{f_{\text{cpu}}}, \frac{D_{\text{tx}} + D_{\text{rx}}}{B}, \frac{S}{R_{\text{sto}}}\right),\tag{17}$$

the bottleneck dominates; thus, boosting CPU frequency only helps if computation is the slowest part. In serial mode,

$$T = \frac{C}{f_{\text{cpu}}} + \frac{D_{\text{tx}} + D_{\text{rx}}}{B} + \frac{S}{R_{\text{sto}}},\tag{18}$$

all terms accumulate, so improving any single factor reduces total delay. This distinction highlights the trade-off: parallelism reduces latency but increases instantaneous power, whereas serialization smooths consumption but prolongs duration.

Summary

This appendix provides supplementary details of the proposed energy-driven task scheduling mechanism, including implementation examples, data analysis, and experimental results. The additional figures and explanations are intended to complement the main body of the paper by clarifying design choices, demonstrating performance trade-offs, and validating the effectiveness of the approach under dynamic energy conditions. Together, these results further confirm the practicality and adaptability of the proposed mechanism in energy-constrained IoT environments.