

SELF-FORGETTING EDGE COMPUTING: ENERGY-EFFICIENT IOT WITH ADAPTIVE DATA DELETION

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Abstract: Traditional IoT systems suffer from data bloat, where redundant information is stored and transmitted, draining batteries and bandwidth. This paper presents a comprehensive framework for an energy-efficient IoT system inspired by human short-term memory. Instead of sending all sensor data to the cloud, edge nodes run lightweight algorithms to classify environmental data (temperature/humidity) as *redundant* or *critical* in real-time. The system automatically deletes redundant data locally before transmission via Delta-Encoding Data Reduction (DEDR) logic implemented at the firmware level. Experimental results from a 1,000-node, 30-day simulation demonstrate a 78% reduction in cloud storage needs, a 3.15x increase in energy efficiency, and extended field life from 142 to 455 days, making long-term wildfire or crop monitoring truly sustainable.

Keywords: IoT, Delta-Encoding Data Reduction (DEDR), short-term memory, Energy Efficient

I. INTRODUCTION

The proliferation of Internet of Things (IoT) devices in remote sensing applications—wildfire detection, precision agriculture, environmental monitoring—has created an unprecedented challenge: **data bloat**. Remote sensor networks transmit vast quantities of data to centralized cloud systems continuously, consuming:

- Significant wireless transmission power (RF transceiver activation: the dominant energy consumer)
- Cloud storage capacity for largely redundant temporal sequences
- Network bandwidth in bandwidth-constrained environments

Environmental sensor streams exhibit high temporal correlation—consecutive temperature readings typically differ by less than 0.5°C over short intervals. Current systems transmit **all** data regardless of informational content, resulting in energy-inefficient operation and shortened device lifespan in the field.

II. RELATED WORK

Edge Computing & Data Compression

Existing approaches to reduce IoT data burden include:

- **Standard compression algorithms** (gzip, LZ4): CPU-intensive, unsuitable for low-power MCUs
- **Cloud-side filtering:** Requires full transmission before reduction
- **Temporal sampling:** Risks missing critical events
- **Neuromorphic-inspired pruning:** Bio-inspired decision-making at network nodes—the approach we advance

Our framework differs by implementing decision logic **directly in SRAM buffers**, evaluating packets against entropy thresholds before RF transceiver activation, ensuring critical data always reaches the cloud.

III. METHODOLOGY

3.1 System Architecture

The IoT framework follows a three-tier architecture:

Tier	Function	Key Role
Sensor	Captures environmental variables	Data acquisition
Edge Node (MCU)	DEDR logic evaluates packets	Intelligent filtering
Cloud/Server	Stores critical data packets	Archival & analysis

3.2 Delta-Encoding Data Reduction (DEDR) Logic

At the firmware level, the DEDR algorithm evaluates each incoming sensor packet against a heuristic entropy threshold τ (tau). The core decision rule is:

Transmit packet if $|x(t) - x(t-1)| \geq \epsilon$ OR $timestamp_interval > T_max$

Where:

- **$x(t)$** = current sensor reading
- **$x(t-1)$** = previous sensor reading
- **ϵ** = magnitude threshold (e.g., 0.5°C for temperature)
- **T_max** = maximum silent interval (fail-safe, ensures periodic updates)

Packets classified as *redundant* (small delta) are deleted locally from SRAM without RF activation. This avoids the **dominant energy cost**: wireless transmission.

IV. HARDWARE IMPLEMENTATION

4.1 Microcontroller Selection

DEDR implementation targets low-power MCUs with minimal SRAM/Flash footprint:

- ARM Cortex-M0/M4 derivatives (e.g., STM32L series, nRF52840)
- Integrated RF transceiver (LoRaWAN, NB-IoT, or IEEE 802.15.4)

The DEDR algorithm requires ~200 bytes of RAM for circular buffer and threshold state. Firmware is developed in C with interrupt-driven sensor sampling at 1 Hz. The RF transceiver is enabled **only when transmission is necessary**, returning the MCU to deep sleep immediately after packet dispatch.

V. RESULTS & DISCUSSION

5.1 Simulated Experimental Setup

Simulation parameters: 1,000-node network over 30 days, simulating temperature and humidity data from wildfire-prone regions. Environmental data exhibits high temporal correlation typical of field conditions.

5.2 Key Performance Metrics

Metric	Baseline	DEDR Framework	Improvement
Data Throughput	4.2 GB	0.92 GB	78.1% ↓
Mean Active Current	120 mA	38 mA	3.15× ↓
Reconstruction RMSE	0.00%	1.24%	High Fidelity
Projected Lifespan	142 days	455 days	+313 days

5.3 Critical Findings

- **Deep Sleep Dominance:** Nodes remain in deep sleep for 92% of operational cycles, with RF transceiver active only 8% of the time
- **Temporal Correlation Exploitation:** Environmental data exhibits high temporal correlation, making delta-threshold filtering highly effective
- **Data Fidelity Maintained:** RMSE of 1.24% indicates negligible information loss while eliminating 78% of redundant transmissions
- **Field Lifespan Extension:** Projected device lifespan increases from 142 to 455 days—a 3.2× extension enabling multi-season monitoring

5.4 Analysis & Discussion

The results demonstrate that implementing *neuromorphic-inspired decision-making* at the edge is a paradigm shift from traditional cloud-centric IoT. Key insights:

- **RF Transceiver Dominates Power Budget:** A single packet transmission ($\approx 100 \mu\text{J}$) costs 2000× more energy than executing the DEDR algorithm. By avoiding unnecessary transmissions, we achieve dramatic efficiency gains.
- **Temporal Data Characteristics Matter:** Sensors with high temporal correlation (weather, environmental) see >80% reductions; high-variance streams benefit less. Threshold tuning (ϵ , T_{max}) is application-specific.
- **Fail-Safe Mechanisms:** The T_{max} timeout ensures critical-status updates even in silent intervals, preventing sensor blindness.
- **Scalability:** The 1,000-node simulation shows linear scaling; cloud load reduction is proportional to local filtering efficiency.

VI. REAL-WORLD APPLICATIONS

The DEDR framework is particularly suited for:

- **Wildfire Detection Networks:** Sensors deployed across vulnerable regions benefit from 3× lifespan extension, reducing replacement logistics costs.
- **Precision Agriculture:** Soil moisture and temperature networks spanning large fields transmit critical anomalies (drought stress, frost risk) while discarding routine readings.
- **Remote Environmental Monitoring:** Arctic/high-altitude deployments where battery replacement is logistically expensive benefit most.
- **Infrastructure Health Monitoring:** Bridge vibration, dam seepage sensors transmit when thresholds exceed safety limits, maintaining silence during normal operation.

VII. CONCLUSION

This paper presents a unified framework for energy-efficient IoT via *self-forgetting edge computing*. By implementing Delta-Encoding Data Reduction (DEDR) logic at the firmware level, we achieved:

- 78% reduction in cloud storage burden
- 3.15× energy efficiency improvement (120 mA → 38 mA mean current)
- 3.2× field lifespan extension (142 → 455 days)

The 1.24% reconstruction RMSE confirms that critical environmental data is preserved while redundancy is eliminated. Future work includes:

- Adaptive thresholding using machine learning to optimize ϵ per sensor type
- Multi-variable correlation detection (e.g., simultaneous temperature/humidity changes as anomaly signals)

- Field deployment trials in wildfire-prone regions
- Integration with advanced wireless protocols (5G NR, satellite IoT) for latency-critical applications

By bringing intelligence to the edge, we enable IoT systems that are sustainable, efficient, and capable of long-term autonomous operation in remote and resource-constrained environments.

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