View Reviews

Paper ID

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Paper Title

Power-Aware Data Collection for IoT Cattle Tracking Using Reinforcement Learning

Track Name

CanAI2025 Long and Short Papers

Reviewer #1

Questions

1. Summary of the paper -- not a review.

- The authors address the problem of power efficiency in IoT cattle tracking. They implement and deploy an RL-based solution that optimizes power consumption by deciding when to transmit, store, or delay data collection. A Tabular Q-learning-based agent is utilized with specific attention given to its operation and a small, resource-limited device. In simulation and prototype deployment the agent adapts to varying power availability. It outperform static scheduling approaches.

2. Reason(s) to accept.

- Very clear, well written and organized paper. It was a pleasure to read.
- Real-world problem
- RL implementation is thoughtfully designed with the physical system in mind
- Includes a hardware implementation and prototype deployment

3. Reason(s) to reject.

- Generally, this is a very good paper. There are two aspects that can be improved
— Provide more details on agent training and how the reward function optimization is integrated.
— To benefit the AI-focused audience, provide a discussion of the lessons learned that might benefit the broader RL community when deploying RL one small device

4. Detailed Review, comments, suggestions, typos

- Is the baseline collection strategy the best possible alternative to RL or are there stronger baselines that should be considered?

5. Recommendation

Accept -- Paper above the acceptance threshold. Solid work. Clear and sound contribution.

7. Reviewer's confidence

High -- I read the paper with sufficient care and I am sure of my review.

Reviewer #2

Questions

1. Summary of the paper -- not a review.

This paper presents a power-aware IoT cattle tracking system that uses reinforcement learning (RL) to optimize when the device collects and transmits data, with the goal of extending battery life without sacrificing data continuity. The authors implement a Q-learning agent on a solar-powered cattle collar prototype. The system is first trained in simulation to learn an effective policy. The authors later deployed the trained agent on real hardware to show the effectiveness of it.

2. Reason(s) to accept.

The paper tackles the practical challenge of energy management in IoT-based livestock trackers. And it describes a complete end-to-end system, including the RL algorithm, firmware, hardware components, and cloud integration.

3. Reason(s) to reject.

The core technical approach (tabular Q-learning for scheduling, with reward tuning) is relatively incremental. The experimental evaluation, while positive, is somewhat limited in scope. The baseline used for comparison is a very simple fixed schedule (collect & transmit every hour). The hardware deployment was only 9 days, in an indoor setting without actual solar harvesting and not on real cattle.). The conclusion and abstract are a bit optimistic given the limited field testing.

4. Detailed Review, comments, suggestions, typos

Some terms and concepts need further clarification. For example, the term “message queue size” appears in the abstract but is not consistently discussed throughout the paper. If it refers to a buffer of collected data before transmission, it should be explicitly defined and analyzed in more detail. The description of the reinforcement learning agent’s decision process could also benefit from clearer explanations, particularly in how the agent determines when to transmit versus delay data collection. While the reward function is described, a more detailed rationale for the chosen reward values and their impact on agent behavior would strengthen the argument. Additionally, the lack of a dedicated methodology section makes it harder to follow the exact steps taken during training and evaluation.

There are some inconsistencies in terminology. The introduction mentions that the agent makes decisions about “when to transmit, store, or delay data collection,” but later sections focus more on transmission and collection without explicitly discussing data storage. If storage refers to keeping messages in memory before transmission, this should be clarified to ensure consistency across sections. The notation in Equation (3.1) is standard, but including a brief explanation of how parameters like the discount factor and learning rate were chosen would improve readability.

The results section presents results in a structured manner, but additional statistical analysis would enhance credibility. The reported 4.3% increase in message count is promising, but without error bars or confidence intervals, it is difficult to determine the reliability of this result. A more detailed breakdown of how the RL agent's behavior varied under different battery conditions would also strengthen the findings. In Figure 2A, the power level discharge curve could be better annotated to indicate key decision points of the RL agent.

There are minor grammatical and typographical errors throughout the text. For example, in the abstract, "increase in 4.3% in message count" should be revised to "increase of 4.3% in message count." In the introduction, "making long-term autonomous operation (months), without human intervention, a key requirement" could be rewritten for clarity, as the parentheses disrupt the flow of the sentence. Additionally, in Section 3.1, the phrase "turning the action-value function into a 24000×3 table" could be made more precise by specifying whether this table is stored in memory or computed dynamically.

5. Recommendation

Reject -- Paper below the acceptance threshold. Unclear and unsound contribution.

7. Reviewer's confidence

Very high -- I checked every detail of the paper very carefully.

Reviewer #3

Questions

1. Summary of the paper -- not a review.

This paper presents a Q-learning-powered IoT cattle tracker that dynamically adjusts data collection and transmission based on battery, time, and message queue. A reward function, optimized via Bayesian tuning, balances energy and data collection. The prototype shows 4.3% more data sent with better power efficiency than fixed scheduling in simulations and a 9-day hardware test.

2. Reason(s) to accept.

Novel RL-based solution for energy-efficient IoT cattle monitoring. Clear system design, including hardware, firmware, and cloud.. Real-world prototype validates feasibility.

3. Reason(s) to reject.

The hardware prototype suffers from high sleep power consumption, reducing practical value. The experimental validation is limited to a 9-day indoor test, which restricts generalization to real-world settings. The paper lacks comparison with deep RL or other dynamic baselines. Additionally, losing the message queue on battery drain is a critical flaw for reliable data collection.

4. Detailed Review, comments, suggestions, typos

Solid applied RL work with practical relevance. Suggest improving hardware for realistic power savings. Future work should store messages in non-volatile memory. Minor: clarify reward hyperparameters' impact.

5. Recommendation

Weak Reject -- Borderline paper. I'm leaning towards rejection.

7. Reviewer's confidence

Medium -- I read the paper but I might have missed something important.