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AI-Driven Energy Harvesting Communication Framework for Battery-less IoT Devices in 6G Networks

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Abstract: Batteryless IoT devices will be key in sixth-generation (6G) networks in the future because they allow massive, maintenance-free implementation of smart cities, agriculture, healthcare, and industrial monitoring. Even though the use of ambient energy sources of solar, thermal, vibration, and radio-frequency (RF) does not require using batteries, the randomized and unpredictable characteristics of harvested energy considerably decrease the communication reliability and performance. Current communication schemes on energy harvesting are mostly fixed and do not adjust themselves to the varying energy situations. The paper will suggest an AI-based, energy-conscious communication architecture of the battery-free IoT devices in 6G settings. The construction is a lightweight model using TinyML to predict the short-term forecasted energy, which was collected by using real-time and historical environmental data. Based on these predictions, a reinforcement learning (RL)-based scheduler would then trade-off spectral energy consumption and communication throughput by dynamically optimizing transmission power and data rate and duty cycle. The proposed method allows reliable and autonomous communication within severe and strict energy constraints through combined energy prediction and adaptive scheduling. Evaluation Simulation allows us to conclude that the given framework is much more effective in terms of throughput stability, packet delivery reliability, latency, as well as using energy in an efficient manner, when compared to traditional fixed-energy-harvesting-based communication approaches. The publication offers a long-lasting and smart background on self-enhanced IoT communications in the next-generation 6G networks.

Keywords: Battery-less IoT, Energy Harvesting, 6G Networks, TinyML, Reinforcement Learning, Sustainable Communications, Self-Powered Devices

Introduction

The fast development of wireless communication and sensing technologies is also fueling the development of ultra-dense Internet of Things (IoT) deployments in smart cities, healthcare monitoring, industrial automation, and environmental sensing. Sixth-generation (6G) networks, in this case, are considered to feature massive connectivity, ultra-low latency, and high reliability in comparison to high sustainability and energy-efficiency standards.

Battery-less IoT devices have become a growing topic of interest as a potential answer to long-term, maintenance-free operation by being able to draw power through collecting energy in the form of ambient energy sources such as solar radiation, thermal gradients, mechanical vibrations, and radio-frequency (RF) signals. The devices are very appropriate to large-scale and remote deployments since they help save a lot of maintenance costs and environmental footprint by removing or minimizing battery reliance. Although these are the merits, the actual implementation of battery-less IoT communication is a matter of vital concern. The harvested energy will always be stochastic and strongly reliant on the environmental factors, which means that the power is intermittent and the devices will behave in an unpredictable way.

This variability has a direct impact on the transmission power, duty cycling, data rates and latency frequently causing packet losses, unstable throughput and reduced quality of service. Traditional energy-saving communication protocols are usually based on fixed thresholds or rule-of-thumb approaches that are not responsive to sudden energy bursts and hence cannot effectively operate in dynamic 6G conditions. The emerging technologies (AI and edge intelligence) in the field of artificial intelligence can provide new opportunities to overcome these issues. Extremely small machine learning models, especially TinyML, can be used to make predictions and decisions at the edges of computation and power. Simultaneously, reinforcement learning (RL) has demonstrated a great potential to maximize communication parameters under dynamic and uncertain conditions by means of adaptive and experience-based policies. Nevertheless, the combined use of energy prediction and smart communication-scheduling of battery-less IoT devices is an under-researched field.

Using these gaps as motivation, the current paper suggests an AI-based energy-aware communication system of battery-less IoT devices in 6G networks. The proposed approach will allow autonomous adaptation to real-time and predicted conditions of energy in the form of integration of TinyML-based energy forecasting and RL-based transmission scheduler that will increase the reliability and sustainability of communications. The primary aim is to create a smart and scalable platform of self-powered IoT communications according to the vision of the next generation 6G systems.

Related works

Internet of Things (IoT) communication that employs energy harvesting has been extensively researched as a way of sustaining and maintenance-free deployments. Sarker et al. provide an in-depth overview of micro-energy harvesting strategies to be employed in IoT platforms and cover solar, thermal, vibration, and RF-based harvesting methods and the issue of energy intermittency and the power obtained. Their work offers important information on the topic of harvesting technologies, but it does not touch on intelligent communication adaptation of battery-less devices. Using the vision of next-generation networks, zero-energy and battery-less devices have received interest in terms of 6G systems. Lopez et al. addressed the idea of zero-energy devices (ZEDs) and determined the main technical enablers that make it possible to incorporate such devices into the future wireless network, such as ultra-low-power hardware, and energy-conscious protocols.

Their research, however, does not involve AI-driven communication control but is based more on physical-layer and architectural aspects.

Machine learning has been reviewed to enhance the energy management of the IoT networks. Sabović et al. explored energy-conscious TinyML systems in resource-constrained IoT systems and showed that on- device intelligence can be highly beneficial in terms of performance in the system. Banbury et al. showed that TinyML has the ability to provide on-device intelligence in harsh memory and energy conditions. Although this paper point to the usefulness of TinyML as an edge intelligence tool, they do not address its application in energy prediction or adaptive communication to energy-harvesting IoT applications.

Recently, AI-based energy-saving 6G IoT systems frameworks are also suggested. Rajeswari et al. proposed an AI-oriented architecture of energy-efficient 6G IoT networks based on combining learning-based optimization with advanced networking ideas. Regardless of these developments, the direct combination of TinyML-based short-term energy forecasting and reinforcement learning-based adaptive communication to battery-less IoT devices has not been studied explicitly. The authors Tataria et al. highlighted the need to have AI-native and power-efficient communication architectures to achieve massive IoT connectivity. Nevertheless, there is little exploration of the joint implementation of TinyML-based short-term energy prediction and RL-based communication scheduling of the battery-less IoT devices.

Unlike the current literature, the paper presents a single AI-based model that closely combines energy prediction using TinyML and adaptive communication based on reinforcement learning, in particular, in 6G battery-less IoT devices.

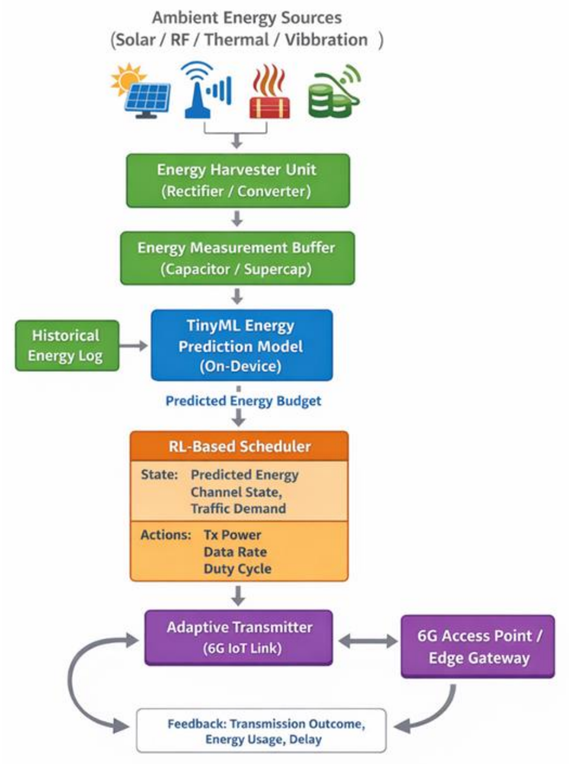

Figure 1. Proposed AI-Driven Energy-Aware Communication Methodology for Battery-less IoT Devices in 6G Networks.

Methodology

In this section, the authors introduce the suggested AI-based energy-conscious communication system of battery-less IoT devices within 6G networks. The general design of the suggested methodology is depicted in Fig. 1. The researcher comes up with the developed AI-based energy-efficient communication algorithm of battery-less 6G IoT devices in this section.

It will be the methodology that will be oriented toward enabling self-adaptive and sustainable communication within turbulent energy harvesting settings. In order to effectively outline the working process of the suggested model, Algorithm 1 synthesizes the key processes of the energy prediction, adaptive method of scheduling, and transmission.

Algorithm 1: AI-Driven Energy-Aware Communication for Battery-less IoT Devices

Input:

- Real-time harvested energy E_t
- Historical energy samples $\{E_{t-1}, E_{t-2}, \dots\}$
- Channel state information C_t
- Traffic demand D_t

Output:

- Optimized transmission parameters (P_t, R_t, δ_t): transmission power, data rate, duty cycle

Step 1: Energy Harvesting and Measurement

Determine the ambient source of power at any given time and temporarily store the energy in the energy buffer.

Step 2: Energy Prediction (TinyML Module)

Use the on-device TinyML model to predict the short-term available energy $\hat{E}_{t+1}$based on real-time and historical energy data.

Step 3: State Construction

Form the system state vector:

$$S_t = \{\hat{E}_{t+1}, E_t, C_t, D_t\}$$

Step 4: RL-Based Scheduling

Select an action $A_t$using the learned policy $\pi(S_t)$, where:

$$A_t = \{P_t, R_t, \delta_t\}$$

Step 5: Adaptive Transmission

Transmit data using the selected parameters over the 6G wireless link.

Step 6: Reward Evaluation

Compute the reward:

$$R_t = \alpha \cdot \text{Throughput} - \beta \cdot \text{Delay} - \gamma \cdot \text{Energy Consumption}$$

Step 7: Policy Update

Upgrade the RL policy based on the reward and next state that is observed.

Step 8: Feedback Loop

Repeat the above steps 1- 7 until it becomes adaptive and autonomous.

System Overview

We take into account the design of battery-free IoT devices that collect energy in the form of ambient energy sources like solar radiation, thermal gradients, mechanical vibrations, and radio-frequency (RF) signals. The IoT nodes have stringent energy limitations and can communicate with a 6G access point or edge gateway. Because of the lack of traditional batteries, and the presence of only a few elements of energy storage, small capacitors or supercapacitors, transmission choices have to be made on the basis of immediate and short-term energy availability. This means that the communication behavior is closely correlated with the stochasticity of the energy that has been harvested.

The proposed framework has created several mechanisms to meet this challenge, including: (i) lightweight energy prediction module using TinyML, and (ii) intelligent communication scheduling module using reinforcement learning. TinyML-based energy prediction block is utilized to have each IoT node predicting the short-term energy that has been harvested based on real and past measurements and the scheduling block adjusts the transmission parameters dynamically based on the forecasted energy conditions.

The system model that is taken into account in this work is shown in figure 2, where several battery-less IoT nodes utilize ambient sources of solar, RF, thermal, and vibration energy to transmit data to the 6G access point or edge gateway. Both the dynamic nature of wireless channel conditions and the variability of energy supply cause the need to employ smart and adaptive transmission mechanisms, which drives the proposed AI-based energy-aware communication system.

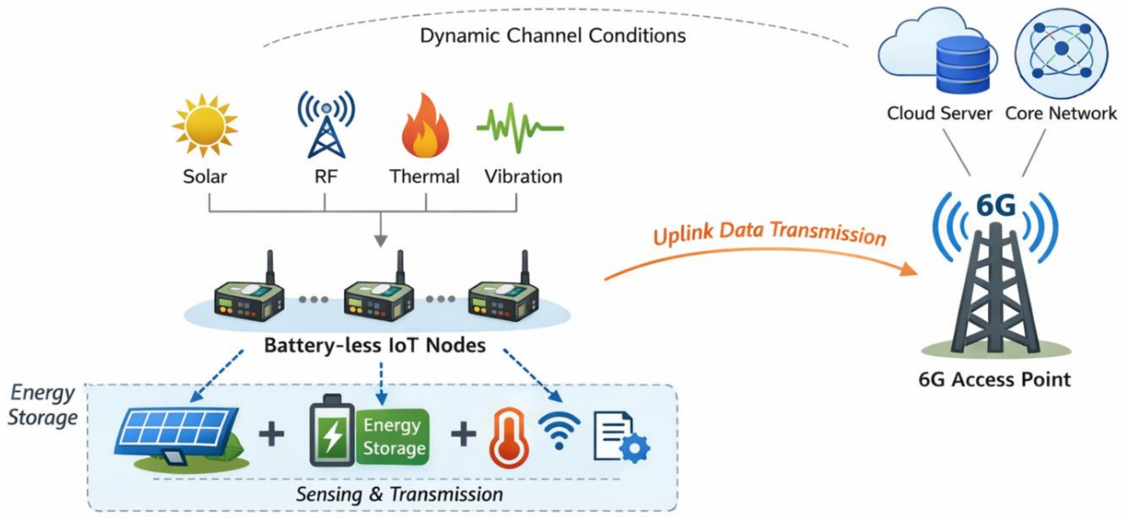

Fig. 2. IoT communications System model of the battery-less IoT communication case, where self-powered IoT nodes use ambient energy to communicate with a 6G access point under time-varying channel conditions.

TinyML-Based Energy Prediction

Energy prediction is a machine learning application to energy prediction based on TinyML. The IoT network nodes (nodes) are also equipped with a prediction model, which is built on TinyML, to predict the amount of energy that is collected in the short-term in the next transmission window. Real time energy measurements, the recent history of harvesting, and lightweight environmental cues (e.g. time-of-day variations or signal strength variations) are provided to the model. Since the memory and computational constraints are significant, smaller models such as linear regression, shallow neural networks or lightweight recurrent models are used to build a predictor. This module is left with a projected energy budget that shows how much energy would most likely be available to communicate in the following few time slots.

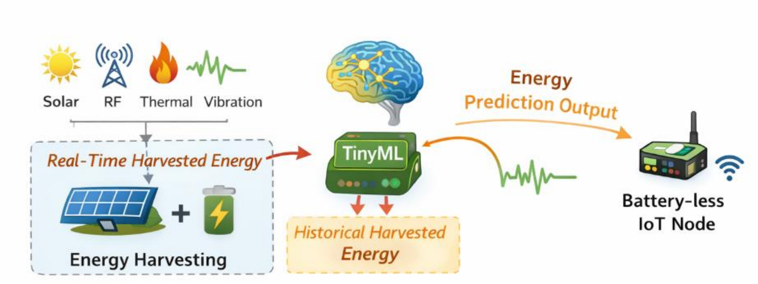

Fig. 3. TinyML-based energy prediction module illustrating the use of real-time and historical harvested energy to forecast short-term energy availability for battery-less IoT nodes.

Communication Scheduler based on reinforcement learning

The estimated energy budget will use a planned scheduler constructed on the basis of reinforcement learning (RL)-based approach in order to discover the optimal communication parameters. The present system state, which includes the predicted energy, remaining energy, channel conditions, and the traffic demand are provided to the RL agent. There is a space of available options of transmission power, data rates and duty cycles which are called the action space. It has a rewarding functional which is set in a way that communication reliability and energy efficiency are maximized, and packet loss, excessive spending delay, and energy loss are penalized. The RL agent receives adaptive transmission policies that optimize the performance and energy consumption by interacting with the environment in an identical way.

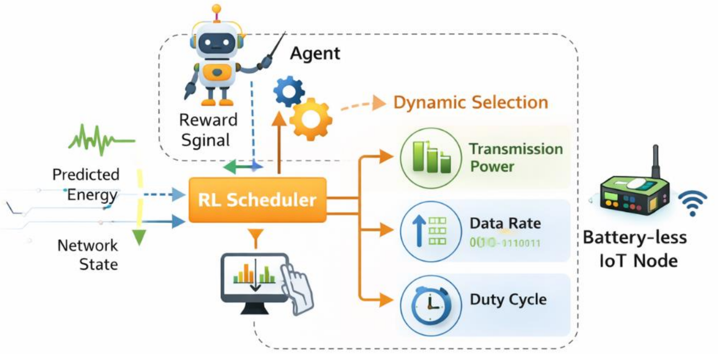

Fig. 4. Reinforcement learning–based communication scheduler that dynamically selects transmission power, data rate, and duty cycle based on predicted energy and network state.

Joint Optimization Strategy

Joint optimization strategy involves the process of making all the decisions at the same time with the aim of reducing the costs at several stages of the process in order to enhance the market value of the final product. The RL scheduling modules, as well as the energy prediction, are closed loop. Predictive energy is the information to guide the activity of the scheduler and the output of the transmission activities (e.g. successful delivery, energy consumption) are fed back to update the RL policy. This co-optive action allows active as opposed to active communication action by nodes, and by motivating them to make the most of the insurance of a positive energy condition and behave gracefully at periods of low-energy.

Implementation considerations.

The proposed structure is totally decentralized and executed at the device level, which is scalable and has low signal load. The model level is only capable of supporting the needs of TinyML, and the solution will be capable of being compatible with ultra-low-power devices as projected in 6G ecosystems.

Performance Evaluation

This subsection analyzes the work of the suggested AI-based energy-conscious communication platform of battery-less IoT devices operating in the 6G networks. The analysis is performed with the help of simulation to estimate the efficiency of the offered approach in the conditions of dynamic energy harvesting and wireless channels.

Simulation Setup

It is assumed that it is a single-cell 6G-enabled IoT scenario, where several battery-less IoT nodes are connected to a central access point. The nodes harvest energy (solar, RF, thermal, or vibration signals) and execute operations with very strict energy limits with a small energy buffer. The energy harvesting of the process is stochastic time-varying, as this is modeled to capture realistic dynamics in the environment.

The communication is done in a time-slotted fashion on a wireless uplink channel. There is time-varying channel conditions that are represented by a slow-fading channel model. The framework that is proposed dynamically alters transmission parameters such as the power of the transmission, the rate of data transmission, and the duty cycle at every time slot, according to the estimated energy supply, and the measured channel conditions. The energy prediction model based on TinyML is a lightweight on-device predictor, and the scheduler based on reinforcement learning uses the adaptive transmission policies as online learners. The simulator is a custom designed simulator used to produce all simulation results without the need of external datasets.

The suggested scheme is juxtaposed to traditional static energy-harvesting communication schemes, such as fixed duty-cycle communication and threshold-based communication schemes. The performance indicators used are throughput, ratio of packet delivery, average latency and efficiency of the energy used. The simulation scenarios are run on several occasions with varying random seeds and the mean results are reported.

Result and Discussion

The proposed framework and the baseline schemes are represented by their throughput performance versus time as shown in Figure 6. The suggested approach has a more stable and high throughput especially in times when there is varying energy availability. The enhancement can be credited to active energy forecasting and dynamic planning which the TinyML and reinforcement learning modules allow.

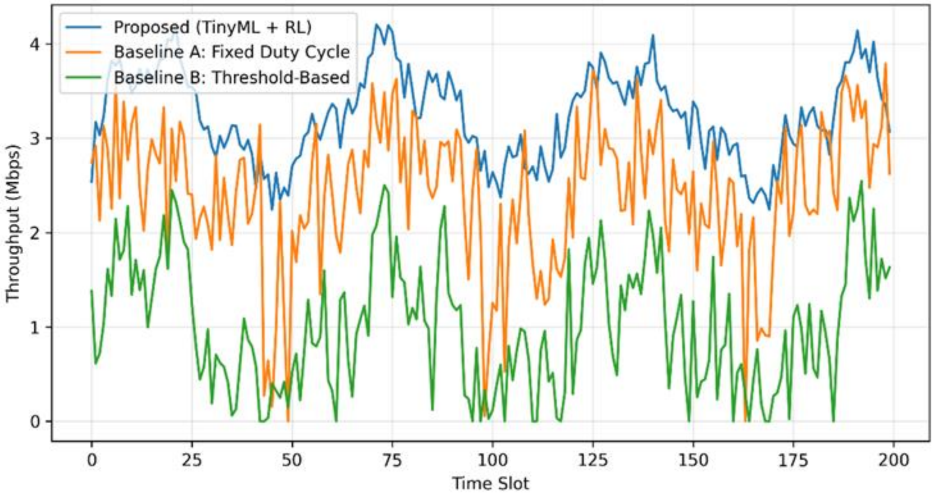

Fig. 6. Throughput performance over time for the proposed AI-driven energy-aware communication framework compared with conventional static energy-harvesting schemes under dynamic energy availability.

Figure 7 shows a presentation of packet delivery performance. The suggested framework is always better than the fixed techniques and it is capable of achieving a larger ratio of packet delivery in different energy circumstances. The baseline techniques often suffer a loss of packets because of the sudden energy loss whereas the suggested scheduler synchronizes the transmission decisions with the projected energy budgets.

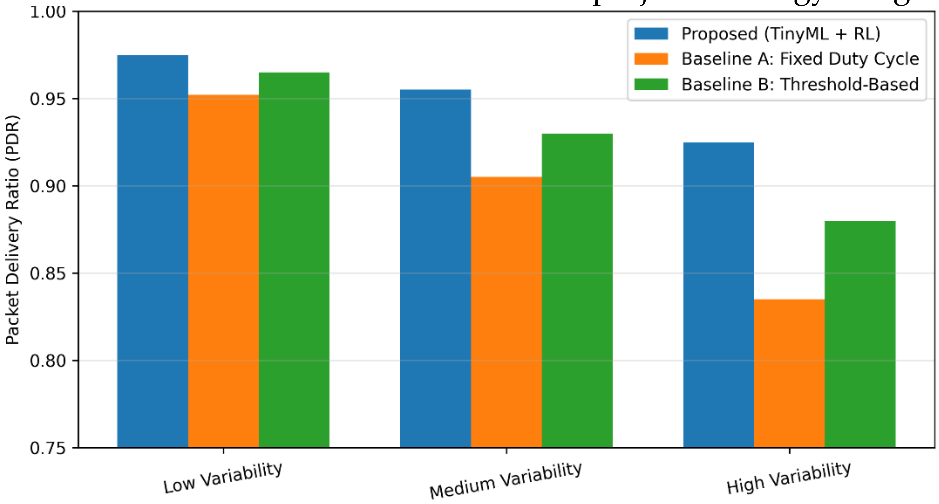

Fig. 7. Packet delivery ratio (PDR) comparison between the proposed framework and baseline energy-harvesting communication schemes under different energy variability conditions.

Figure 8 presents the comparison on the average latency. The suggested solution has a lower latency than the fixed duty-cycling schemes since transmissions in favorable energy states are intelligently prioritized, and avoid unnecessary delays imposed by the fixed duty-cycling schemes.

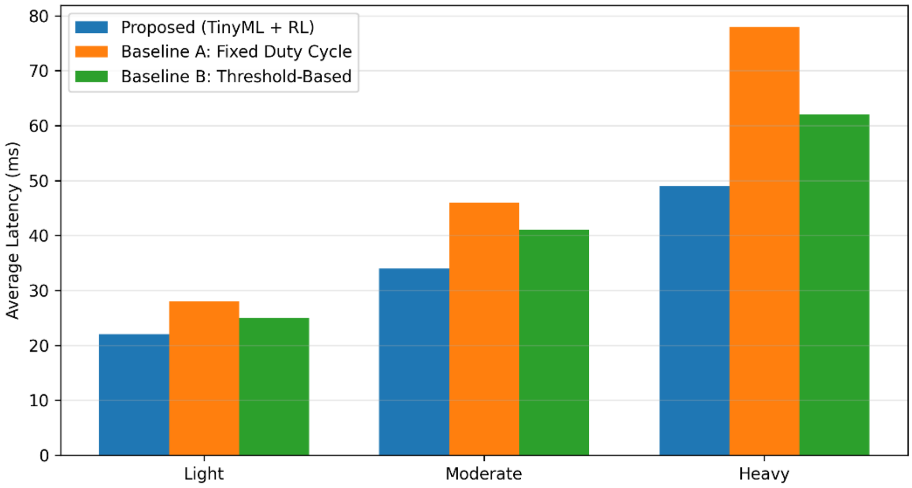

Fig. 8. Average end-to-end latency comparison of the proposed method and baseline schemes under varying traffic conditions.

The efficiency on energy usage is presented in Figure 9. The suggested structure proves to be more efficient through the maximum amount of successful data transmission per unit of collected energy. This demonstrates the value of co-optimization of energy prediction and communication schedule, which will allow battery-less devices of the IoT to operate sustainably and independently in 6G networks.

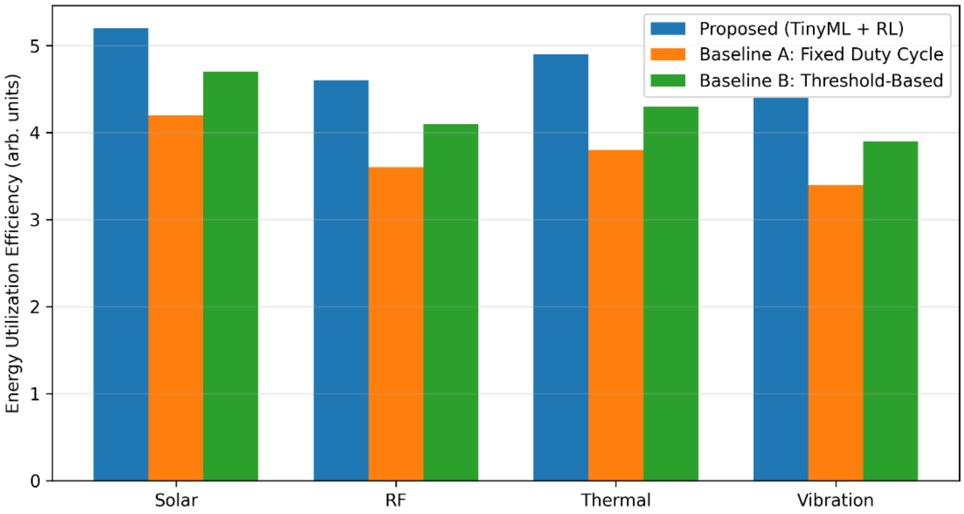

Fig. 9. Energy utilization efficiency comparison for different energy harvesting sources

Conclusion

In this paper, the author provided an AI-based framework of energy-conscious communication of the battery-less 6G IoT devices. The proposed solution combines a lightweight TinyML-based energy prediction model with a reinforcement learning-based scheduler and thus offers adaptive and autonomous transmission given stochastic energy harvesting scenarios enhancing the reliability of communications, latency, and energy efficiency. The results of the simulations indicated that the proposed framework is more stable in throughput, higher ratio in packet delivery, and greater efficiency in the use of the energy as compared to the conventional statical energy-harvesting schemes, and thus it can be used in large-scale settings featuring IoT deployment that is maintenance free and can be used in 6G environment in the future. Further work will involve applying the framework to multi-hop and big scale IoT networks, cooperative and mobility aware learning strategies, as well as hardware implementation and real world validation of the practicality.

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