Improving the Energy Performance of Battery-Powered Mobile Networks via Reinforcement Learning

Wei Shi*†, Hossein S. Ghadikolaei† , Gabor Fodor*†, Lackis Eleftheriadis† , and Mikael Skoglund*
*KTH Royal Institute of Technology, Stockholm, Sweden,
†Ericsson Research, Sweden

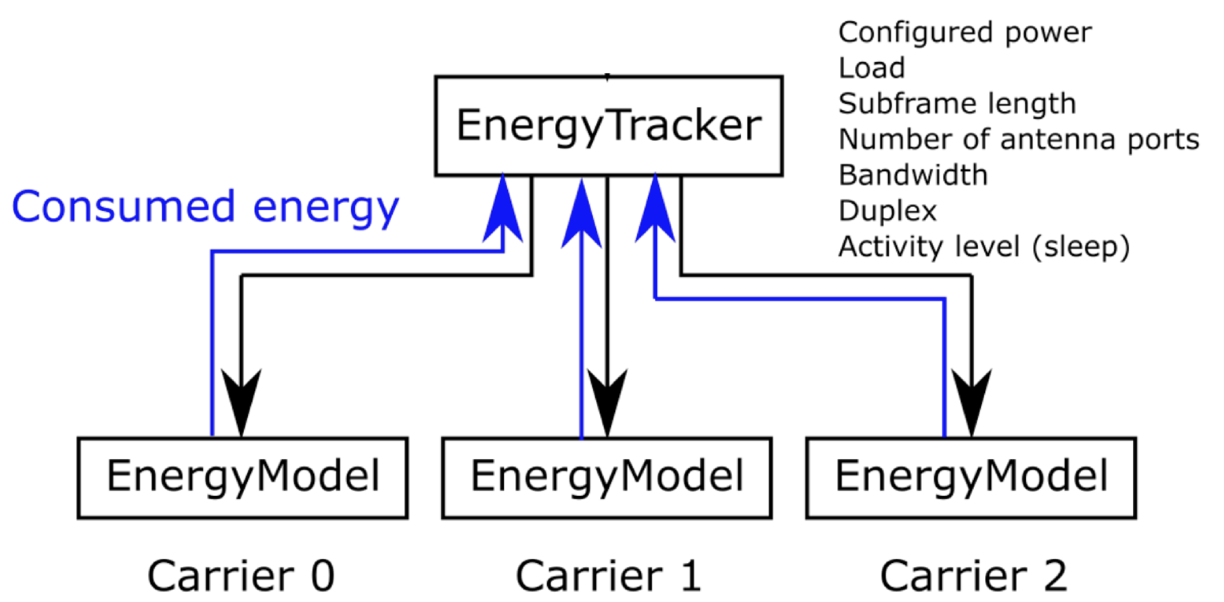
Abstract

Energy performance refers to reducing energy consumption without compromising service quality. While base station (BS) sleeping is a common practice to enhance energy performance, it is rarely implemented in practice due to its negative impact on service quality. This paper addresses this challenge by **integrating the local battery of the BS into the BS sleeping design**. By synchronizing battery operations with real-time energy prices and network traffic loads, our solution **dynamically adjusts BS sleeping parameters to consistently maintain service performance while minimizing operational costs**. This study highlights the considerable potential of battery-powered BSs to improve existing trade-offs in energy performance.

Methods

Sleep mode design:

Energy model will monitor the duration of the transmission delay and simulate the energy consumption at different sleep modes.

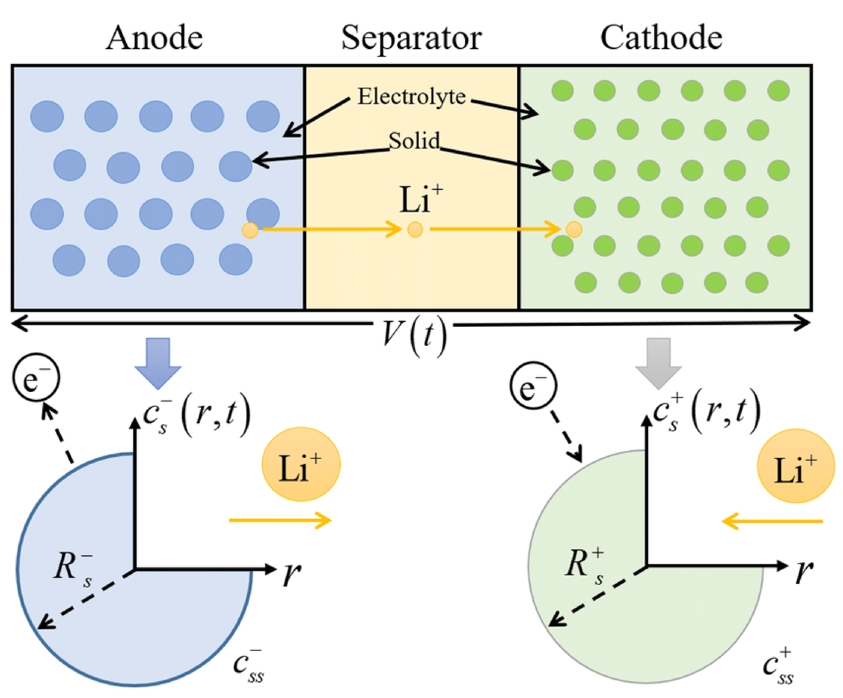


Mode	Active	MicroSleep	LightSleep	DeepSleep
Power (relative)	200	60	25	1
Duration [ms]	symbol time: 0.5		5-25	25-50

Lithium-ion battery model:

Single particle model (SPM)

SPM uses the current I divided by the electrode thickness L_k to represent the flux on the particle surface, characterized by

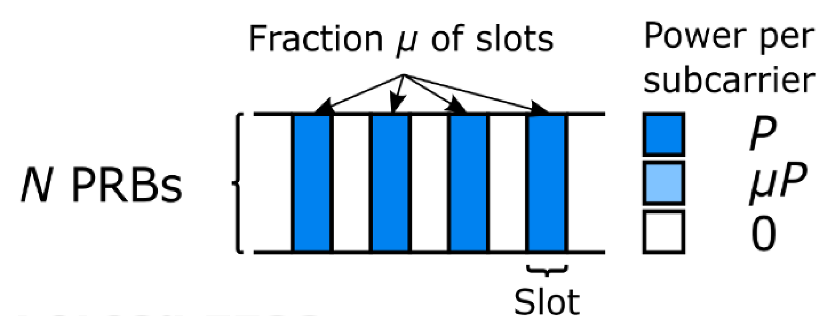


$$\frac{\partial c_k}{\partial t} = -\frac{1}{\phi_k^2}\frac{\partial}{\partial \phi_k}\left(\phi_k^2 N_k\right), N_k = -\theta_k(c_k)\frac{\partial c_k}{\partial \phi_k}, \qquad (1)$$

$$N_k\big|_{\phi_k=0} = 0, \quad -N_k\big|_{\phi_k=1} = \begin{cases} \frac{I}{F a_n L_n}, & k = n, \\ -\frac{I}{F a_p L_p}, & k = p, \end{cases} \qquad (2)$$
$$c_k(\phi_k, 0) = c_{k,0}, \quad k \in \{n, p\}$$

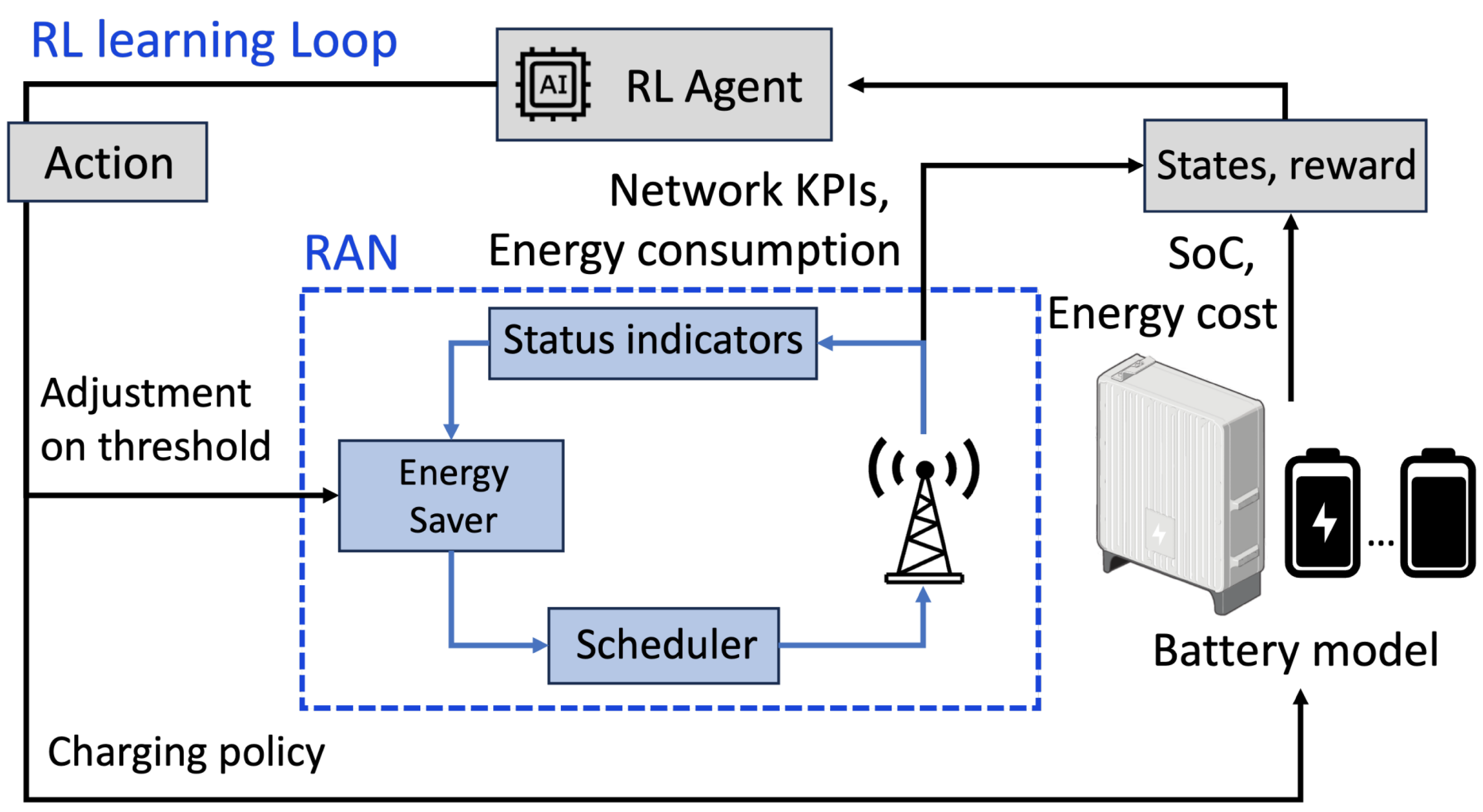
Energy Saving Algorithm:

Sits on the top of the existing scheduler, Constantly monitors the delay status of the packets in the downlink buffer and stops the scheduler from allocating PDCCH resource to the cell when the delay is lower than the threshold.

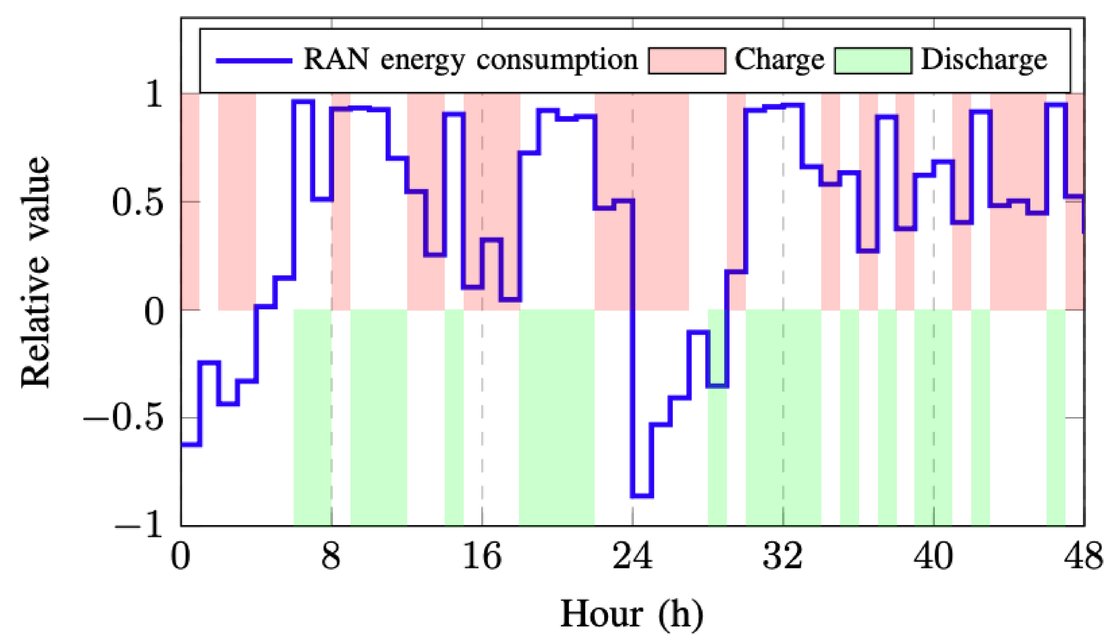


Optimization via RL:

A single RL agent interacts with the BS energy saver, downlink scheduler, and battery model, generating two concurrent actions: adjusting the sleep mode and managing the battery charging policy.

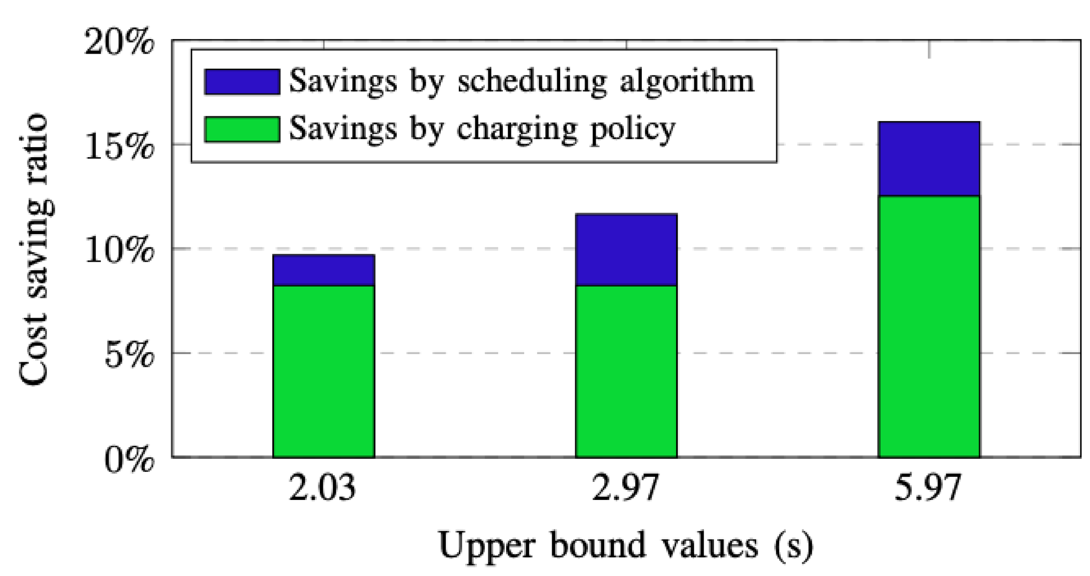


Selected Results



Examples of optimal battery operations and corresponding energy consumption.

Our experiments demonstrate significant energy savings with minimal impact on service delays, and the strategic charging policy further reduces energy costs by utilizing low-price electricity periods.



Ratio of energy cost savings by the RL-based scheduling algorithm and charging policy under different upper bounds for object delay, compared to the baseline cost.

Loosening delay constraints provides the RL agent with more flexibility to prioritize energy savings.

The battery strategically charges during low-price periods, incentivizing the BS to select lower during peak traffic hours.