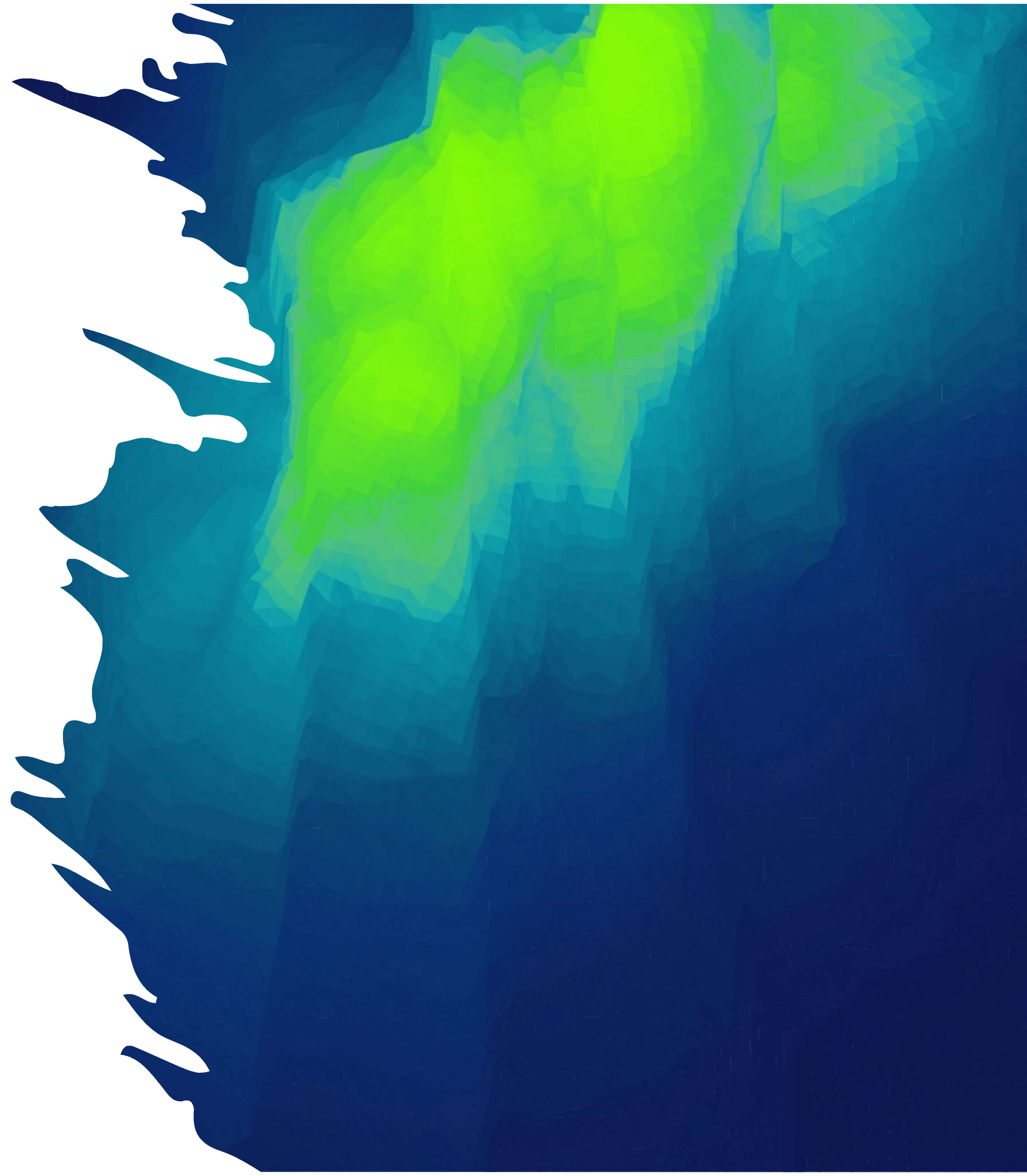
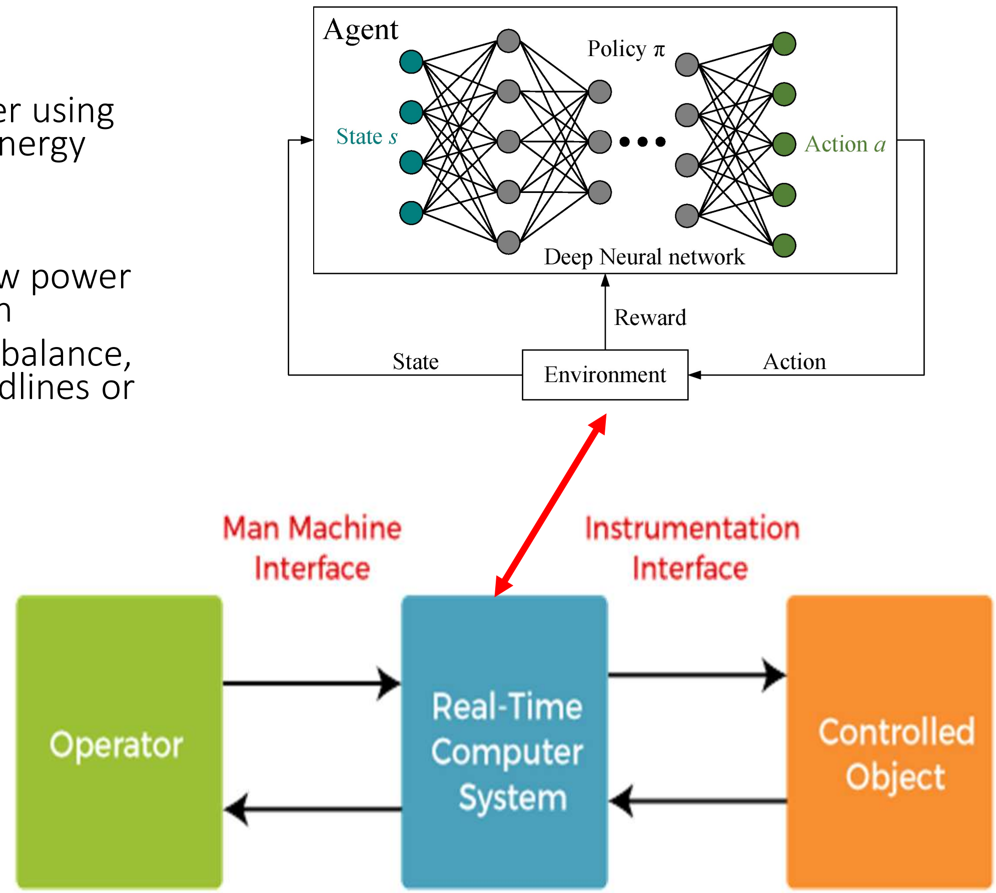
Optimizing Energy Efficiency in Real-Time Scheduling through Deep Reinforcement Learning



Research Summary

- This research aims to develop an innovative scheduler using reinforcement learning (RL) algorithms to optimize energy efficiency in Real-Time Scheduling (RTS) systems.
- Challenges
  - Balancing the trade-off between maintaining low power consumption and ensuring timely task execution
  - Traditional RTS systems often struggle with this balance, either consuming excessive energy to meet deadlines or compromising on performance to save energy.

- By utilizing state-of-the-art Python RL libraries, the project will deliver a novel solution that ensures tasks meet their deadlines efficiently while minimizing energy consumption.
- The research will include designing a reward function that penalizes deadline misses and rewards energy-efficient operation, ensuring the scheduler aligns with the dual objectives

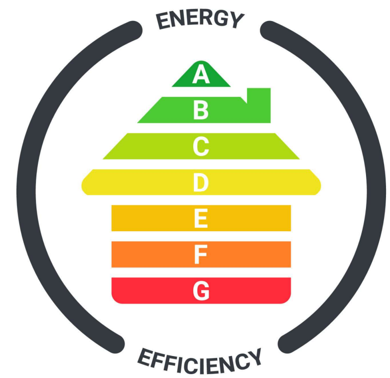


Real-Time System

Why This Research is Important

- There is an ever-growing demand for computational power in various sectors
    - Telecommunications, automotive, healthcare, etc.
- Energy efficiency in computing systems has become a critical concern.
- Improving energy efficiency not only reduces operational costs but also contributes to environmental sustainability by lowering carbon emissions.

This research will apply cutting-edge RL techniques to address these significant challenges, potentially revolutionizing how RTS systems are managed.



Limitations of Existing Approaches

- Current RTS systems predominantly use static scheduling algorithms
  - Often inefficient in dynamic environments where task demands and priorities fluctuate.
  - Cannot adapt to changes in workload or energy availability, leading to suboptimal performance and excessive energy consumption.
- While some dynamic scheduling solutions exist, they have issues that can be addressed using a DNN
  - Either unable or struggle to effectively balance the dual objectives of minimizing energy consumption and preventing deadline misses.
  - Often overlook the intricate interplay between running cores at different power levels and the resultant impact on task execution speed and energy use.
- Several existing approaches do not adequately consider the energy overhead associated with managing these systems, leading to an underestimation of actual energy usage.
  - The lack of a learning mechanism in these schedulers means they cannot improve their performance over time based on past experiences, missing out on opportunities to optimize energy use further.