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ENERGY-AWARE DEEP REINFORCEMENT LEARNING FOR ADAPTIVE TASK SCHEDULING IN INTEGRATED CLOUD–EDGE COMPUTING SYSTEMS

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ABSTRACT

The rapid growth of cloud computing, edge computing, and connected intelligent devices has created a distributed computational environment in which large numbers of tasks must be processed efficiently across resources with different processing capabilities, energy characteristics, communication conditions, and workload capacities. Conventional task scheduling approaches often depend on fixed rules or predetermined allocation policies and may struggle to respond effectively to continuously changing workloads and resource conditions. This research proposes an Energy-Aware Deep Reinforcement Learning approach for adaptive task scheduling in integrated cloud–edge computing systems, with the objective of reducing energy consumption while maintaining acceptable execution time, resource utilization, and task completion reliability. The proposed approach models task scheduling as a sequential decision-making problem in which the learning agent observes the current state of the cloud–edge environment and selects an appropriate computational resource for each incoming task. The state representation incorporates task characteristics, processor availability, queue length, computational demand, memory requirements, network conditions, estimated execution time, and energy consumption. A deep reinforcement learning model is employed to learn scheduling policies from interactions with the dynamic computing environment rather than relying exclusively on manually defined allocation rules. The reward mechanism jointly considers energy usage, task completion delay, resource imbalance, and deadline violations, encouraging the agent to identify scheduling decisions that provide an effective balance between computational efficiency and energy sustainability. The proposed framework also considers workload fluctuations and heterogeneous resource availability, enabling scheduling decisions to be continuously adjusted as system conditions change. Its performance can be evaluated against established scheduling strategies using measures such as total energy consumption, average task completion time, resource utilization, deadline violation rate, task success rate, and scheduling overhead. The expected outcome is an adaptive scheduling mechanism capable of reducing unnecessary energy consumption while maintaining responsive task execution across cloud and edge resources. The study contributes toward intelligent and sustainable distributed computing by demonstrating how deep reinforcement learning can support autonomous scheduling decisions in environments where workload intensity, resource availability, and communication conditions vary continuously.

KEYWORDS: *Deep Reinforcement Learning; Energy-Aware Scheduling; Cloud–Edge Computing; Task Scheduling; Resource Optimization*

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