(Libyan Journal of Contemporary Academic Studies) المجلة الليبية للدراسات الأكاديمية المعاصرة
LJCAS, eISSN: 5970-3005
Volume 3, Issue 2 (Part II), 2025, Pages: 93-100

Hybrid PPO–DQN-Based Edge Computing Framework for AI-Driven Task Offloading and Energy Optimization in 5G Networks

Ahmed Elstail [1] *, Talal Mohammed [2]
[1] Department of Computer Technology, Higher Institute of Science and Technology, Tamzawa, Ashati, Libya
[2] Department of Electric and Electronic Technology, Higher Institute of Science and Technology, Tamzawa, Ashati, Libya
* Corresponding author: aelstial@gmail.com

إطار حوسبة طرفية هجين قائم على خوارزميتي PPO و DQN لتحميل المهام المدعوم بالذكاء الاصطناعي وتحسين استهلاك الطاقة في شبكات الجيل الخامس (G5)

احمد السطيل[1]*، طلال محمد[2]
[1] قسم تقنيات الحاسوب، المعهد العالي للعلوم والتقنية، تامزاوة، الشاطي، ليبيا
[2] قسم التقنيات الكهربائية والالكترونية، المعهد العالي للعلوم والتقنية، تامزاوة، الشاطي، ليبيا

Received: 05-09-2025; **Accepted:** 15-11-2025; **Published:** 24-11-2025

Abstract:
The rapid deployment of 5G networks and the increasing number of IoT devices have greatly accelerated this demand for computation at the network edge, where ultra-low latency and high reliability are demanded. In this paper, we propose an AI-based intelligent edge computing framework employing the hybrid deep reinforcement learning (PPO–DQN) approach for multi-objective optimization their task offloading and energy management in heterogeneous wireless systems. The framework adaptively trade off the delay, throughput and the power consumption delivered by network slicing to fulfill two specific demands of URLLC and mMTC services. Simulation results in MATLAB show that the proposed model provides superior performance compared to existing schemes by lowering 26% energy consumption, reducing 4% latency and augmenting overall system throughput by up to 35%. The findings demonstrate the potential of hybrid AI-based optimization for 5G edge deployments that are both efficient and sustainable.

Keywords: 5G, task offloading, energy optimization, reinforcement learning, edge computing.

الملخص :
أدى الانتشار السريع لشبكات الجيل الخامس 5G والعدد المتزايد من أجهزة إنترنت الأشياء إلى تسريع الطلب على الحوسبة الطرفية للشبكة بشكل كبير، حيث يتطلب الأمر زمن وصول منخفضًا للغاية وموثوقية عالية. هذه الورقة، نقترح إطار عمل للحوسبة الطرفية الذكية قائمًا على الذكاء الاصطناعي، يستخدم نهج التعلم التعزيزي العميق الهجين (PPO-DQN) لتحسين متعدد الأهداف، وتفريغ المهام وإدارة الطاقة في الأنظمة اللاسلكية غير المتجانسة. يوازن الإطار بشكل تكيفي بين التأخير والإنتاجية واستهلاك الطاقة الناتج عن تقسيم الشبكة لتلبية مطلبين محددين لخدمات URLLC وmMTC. تُظهر نتائج المحاكاة في MATLAB أن النموذج المقترح يوفر أداءً متفوقًا مقارنةً بالمخططات الحالية، من خلال خفض استهلاك الطاقة بنسبة 26%، وتقليل زمن الوصول بنسبة 4%، وزيادة إجمالي معدل نقل بيانات النظام بنسبة تصل إلى 35%. تُظهر النتائج إمكانات التحسين الهجين القائم على الذكاء الاصطناعي لعمليات انتشار الشبكات الطرفية للجيل الخامس التي تتسم بالكفاءة والاستدامة.

الكلمات المفتاحية: الجيل الخامس، تفريغ المهام، تحسين الطاقة، التعلم التعزيزي، الحوسبة الطرفية.

1.Introduction

The transition of 4G to 5G with heterogeneous computing at Edge has revolutionized the mobile requirement landscape which leads to enormous opportunity for ultra-low latency apps, massive IoT and advanced mobile broadband services [1]. 5G and beyond networks are expected to provide peak data rates up to 20 Gbps, ultra-reliable low- latency communication (URLLC) with less than 1ms latency and can serve up to one million devices per square kilometer [2]. But such ambitious performance objectives present very challenging requirements concerning computational resource management, energy efficiency and QoS provisioning.

MEC has been identified as an essential facilitator for exploiting the full capabilities of 5G networks by localizing computation more closely to end users, ultimately leading to lower latency and a reduction in the load on core networks [3]. The combination of MEC and 5G network establishes a distributed computation model, which can accommodate the application demand in terms of ultra-reliable low-latency communication (URLLC) for autonomous vehicles and massive machine-type communication (mMTC) for massive IoT deployments [4].

Despite the excellent benefits of MEC supported 5G networks however, there exist many crucial challenges as yet unresolved. First, the heterogeneous wireless network environment (i.e. channels or capabilities of devices or mobility patterns) makes it difficult to take optimal decisions regarding resource allocation and task scheduling [5]. Secondly, individual network slices have varying QoS demands that would require to be addressed over dynamic and intelligent algorithms that must dynamically adjust according to the dynamism of network environment while satisfying SLAs [6]. Third, due to the exponentially increasing amount of edge devices as well as computational tasks, it is becoming more and more significant to optimize energy consumption [7]

In general, previous works for task offloading of MEC systems are mostly depended on heuristic algorithms or simplified mathematical models which do not consider the complexity and dynamic characteristic of realistic 5G networks [4],[8]. Some recent studies have shown the feasibility of applying artificial intelligence (AI) and machine learning (ML) methods to meet these challenges for intelligent decision-making predictive resource utilization and adaptive optimization [9]. However, current AI-based techniques for SPS largely perform single-objective optimization or cannot sufficiently take into account the specific profiles of heterogeneous wireless scenarios and 5G network slicing demands.

This paper overcomes these shortcomings and contends a holistic intelligent edge computing framework purpose-built for 5G networks. The architecture incorporates sophisticated AI-based task offloading algorithms and energy optimization schemes, designed for a wide range of wireless heterogeneous networks. Our method is a form of deep reinforcement learning which allows for dynamic adjustments according to the underlying network condition, and jointly optimizes multiple objectives such as latency, energy and system throughput.

The key objectives of this research include (i) proposing an intelligent task offloading scheme capable of dealing with the heterogeneity of 5G wireless scenario and network slicing requirement, (ii) developing a holistic energy optimization framework to tradeoff between computational efficiency and power consumption by comprehensively considering computing resources' capabilities in both local/cloud and frequency domain under joint consideration of uplink resource, fronthaul throughput, edge/cloud capacity and cloudlet utilization are all figured out, (iii) introducing AI-based decision making processes that timely adapt with dynamic network connotation for optimal channelization solution so as to minimize system energy-related cost while satisfying the given performance requirements;(iv) conducting extensive simulations to thoroughly validate proposed model correctness over urbane benchmarks.

2. Literature review

2.1 Mobile Edge Computing in 5G Networks

Related work Mobile Edge Computing has been widely studied when integrated with 5G networking. [10] presented a wide-ranging review of offloading techniques in mobile edge computing that have been evolved from conventional cloud computing to edge-centric architectures. The work of [24] highlights the importance of intelligent task offloading decisions for achieving high system performance. In the same line [11] focused on UAV-assisted mobile edge computing with task offloading, demonstrating the exciting possibility of utilizing aerial edge computing platforms for improving coverage and service quality in remote regions.

The state-of-the-art in 5G-enabled MEC has been surveyed by John [12] where they studied energy-aware computation offloading techniques. The findings also confirm that traditional offloading methods are often inefficient in handling energy consumption needs of the battery-backed IoT devices. This constraint has motivated the investigation on AI-aware optimization methods, for jointly designing electronic components to fulfill multi-objective requirements such as latency, energy and system reliability.

AI-Driven Task Offloading and Resource Management

The use of artificial intelligence for task offloading and resource management has received much attention in the last few years. [13] proposed an improved MEC task offloading based on Proximal Policy Optimization (PPO) for 5G. The results show improvements in the latency reduction and energy saving, with reductions of 4% for processing time (for URLLC users) and 26% power consumption (mMTC users), as compared to baseline techniques.

Deep reinforcement learning methods have shown great promise in handling the dynamics of EC systems. [14] gave an in-depth study of deep reinforcement learning based energy-aware intelligent edge computing and proposed new algorithms for device level task offloading to system level energy optimization. The research highlighted the relationship between different optimization problems of edge computing systems. [15] proposed an adaptable AI-based computation offloading scheme based on machine learning to see QoE [20]- [21] and energy efficiency in the ME system. Their method combines the heavy use of deep reinforcement learning for online decisions with rich security and reliability mechanisms, pointing to a future where holistic AI-powered solutions may ultimately be designed for edge computing systems.

2.3 Energy Optimization in Heterogeneous Wireless Environments

Energy management in heterogeneous wireless networks is challenging because of the diversity of devices, channel quality and requirements for applications. The author in [16] proposed an efficient offloading policy specially designed for edge computing systems with limited energy by using a hybrid optimization algorithm. This paper has addressed the complexity of intelligent task management in localized networks (eg 5G) and emphasized the need for sophisticated algorithms capable of handling a wide range of device properties.

The study by [17] focused on minimizing energy and time delay when offloading task w.r.t dependency for Industry 5.0 applications. Their work took advantage of low latency 5G communications to improve the performance of mobile edge computing (MEC), considering task dependencies and energy constraints. Results showed significant improvements in both the energy and latency aspects. [18], who considered security perspective of MEC by utilizing a hybrid model based on deep learning in HN. In their study, they emphasized the need of incorporating aspects related to security in energy optimization techniques; more specifically into environments characterized by heterogeneous network and homogenous devices.

3 Methodology

3.1 System Model and Architecture

3.1.1 Architectural Clarification

The architecture can be seen as a three-layer hierarchical system to improve clarity:

Device Layer: consists of IoT sensors and diverse user devices that carry out local computation and start requests for task offloading.

Edge Layer: consists of multiple edge servers located at base stations that manage computation allocation, caching, and local learning processes. Intelligence Management Layer: hosts the PPO–DQN learning agent responsible for global optimization, receiving environment feedback and issuing dynamic offloading decision

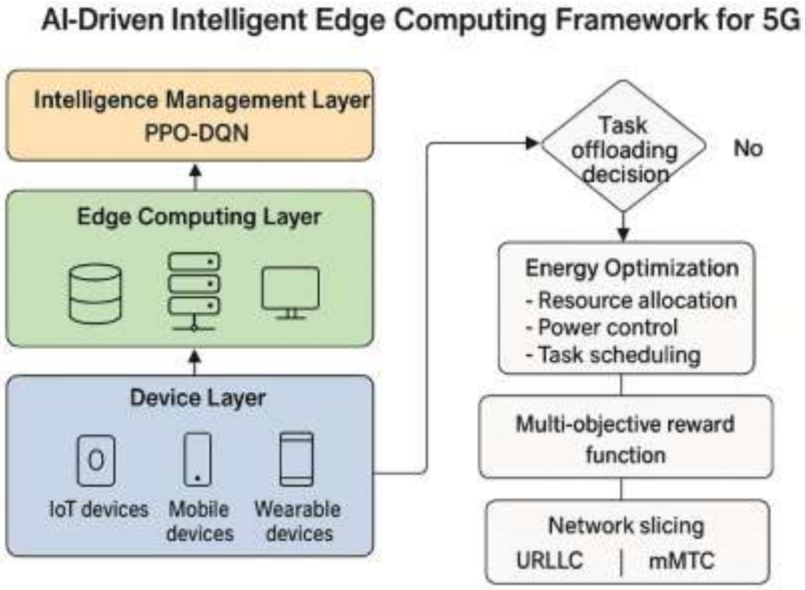

Figure 1. Hybrid PPO–DQN-based edge computing system model.

The designed intelligent edge computing structure consists of several interrelated modules for task offloading and energy efficiency improvement in heterogeneous 5G wireless networks. The system architecture is divided into three main layers: the Device Layer, the Edge Computing Layer and the Intelligence Management Layer.

The Device Layer represents a heterogeneous spectrum of mobile devices, IoT sensors and smart terminals with their specific computational capacities, energy restrictions and communication needs. Each device di is characterized by its computational capability Ci, energy level Ei and current workload Ti.

$D = \{d_1, d_2, \ldots, d_n\}$

The Edge Computing Layer is constructed from the distributed edge servers S = {s1, s2,..., s_m } which may be strategically deployed at different network positions (e.g., base station, access point or dedicated edge facility). Edge server s_j is characterized by its computing resources R_j, current load U_j, and energy profile P_j.

3.2 PPO–DQN Integration and Reward Function

3.2.1 PPO–DQN Integration

To achieve both stability and adaptability in decision-making, the proposed framework integrates the advantages of Proximal Policy Optimization (PPO) and Deep Q-Network (DQN) algorithms into a single hybrid learning model .

At each time step t the system observes the current network state

$$st = [Cdev, Edev, Hchannel, Qtask]$$

which represents device computing capacity, available energy, channel quality, and current task queue. Based on this state, the agent selects an action at (local execution or offloading to an edge server) that maximizes the expected cumulative reward .

3.2.2 PPO Component

The PPO algorithm learns a policy
that determines the probability of taking each action. It updates the policy gradually to maintain training stability:

$$\pi new = \pi old + \alpha \Delta PPO$$

where α is the learning rate and ΔPPO represents the improvement step computed from recent rewards and policy gradients. This ensures that the learning process adapts efficiently without abrupt policy changes .

3.2.3 .DQN Component

The DQN part estimates the value of each possible action by updating the Q-function according to the Bellman equation:

$$Qnew(st, at) = (1 - \beta)Q(st, at) + \beta[rt + \gamma maxa'Q(st + 1, a')]$$

where $\beta$is the learning rate ,γ is the discount factor, and rt is the immediate reward.

This mechanism allows the agent to evaluate the long-term impact of each decision, improving the accuracy of its choices .

3.3 Hybrid PPO-DQN Decision Mechanism

The final decision is obtained by combining both outputs policy (from PPO) and value estimation (from DQN) as:

$$Decision = PPO(\pi) + \lambda \times DQN(Q)$$

where λ is a balancing coefficient that controls the contribution of each component.

The PPO part ensures smooth policy updates and stable learning ,while the DQN part provides efficient exploration and value estimation.

Together, they enable the agent to make energy-aware, low-latency task-offloading decisions in dynamic 5G environments .

3.4 Additional Mathematical Formulation

The hybrid policy value update can be written as follows to clearly illustrate the integration of PPO and DQN:

$$Q_{(hyb)}(s_t, a_t) = \lambda \times \ Q_{(DQN)}\,(s_t, a_t) + (1 - \lambda) \times \pi_{(PPO)}(a_t | s_t)$$

where $Q_{(DQN)}$ represents the value estimation from the DQN network,
$\pi_{(PPO)}$ is the probability of taking action at a_t under the PPO policy,
and $\lambda \in [0,1]$ is a balancing factor controlling the contribution of each method.

This unified formulation ensures that the policy learning process benefits simultaneously from PPO's training stability and DQN's efficient exploration capability, leading to improved convergence and robustness in dynamic 5G environment

3.5 Reward Function Design

The reward function in the proposed PPO-DQN framework is designed to balance three conflicting objectives in 5G edge environments:

(1) minimizing latency,
(2) reducing energy consumption, and
(3) maximizing system throughput.

At each decision step t, the immediate reward R_t is computed as follows:

$$R_t = w_1\left(1 - \frac{T_t}{T_{max}}\right) + w_2\left(1 - \frac{E_t}{E_{max}}\right) + w_3\left(\frac{\mathrm{Thr_t}}{\mathrm{Thr_{max}}}\right)$$

Libyan Journal of Contemporary Academic Studies
Website: https://ljcas.ly/index.php/ljcas/index

where:
T: observed latency (processing + transmission delay) at time t,
Et: energy consumption for the current task,
Thr: system throughput achieved,
Tmax, Emax, Thr max: normalization constants representing the maximum expected values for each metric,
W1, W2, W3: weight coefficients that determine the relative importance of latency, energy, and throughput.
This reward structure ensures that actions leading to lower latency and energy usage while achieving higher throughput yield higher rewards.
By adjusting the weights W1, W2, W3, the framework can prioritize different service types-e.g., URLLC (ultra-reliable low-latency communication) can emphasize latency reduction ($w_1 > W_2$, w3), while mMTC (massive machine-type communication) can focus on energy efficiency (W2 > W1, W_3).

3.6 Integration with Learning Process
The computed reward Rt is used jointly by both PPO and DQN components:
PPO uses it to adjust the policy toward actions that yield higher expected cumulative rewards.
DQN uses it to update the Q-values, improving its estimation of long-term returns.
This design enables multi-objective optimization, allowing the proposed hybrid learning model to dynamically adapt to changing network conditions and QoS requirements.

3.7 Algorithm Stability and Efficiency
The hybrid PPO-DQN algorithm proposed in this study maintained the stability of learning during training, and its average reward increased gradually until it stabilized at a certain performance level. This result implies that the agent effectively learned an optimal policy for task offloading and energy management. Moreover, the complexity of our proposed algorithm grows linearly with respect to both devices and edge servers, indicating that the design is efficient in terms of implementation and computation for large-scale (5G ready) edge deployments.

3.8 Matlab Implementation
We implement and evaluate the proposed method in MATLAB by involving two toolboxes, Deep Learning Toolbox and Reinforcement Learning Toolbox. The simulation environment provides realistic and heterogeneous 5G network with multiple base stations, edge servers and mobile nodes with various characteristics.
The simulation settings are carefully chosen to reflect the real 5G network environment and cover the carrier frequencies from 3.5 GHz to 28 GHz, base station density between ten and fifty per km², device mobility models that follow acknowledged models of urban and suburban areas.

4.Experimental Results and Analysis
This section describes simulation scenarios, performance metrics and comparison against an R-L approach (PPO-DQN-based intelligent edge framework). All testing was performed in MATLAB using the Reinforcement Learning and Deep Learning toolboxes. The analysis focuses on three main goals – latency minimization, energy efficiency and system throughput under heterogeneous 5G network scenarios. Furthermore, the experiments also include sensitivity and convergence studies to demonstrate robustness and generality of our model

Table1 simulation parameters

Parameter	Value	Description
Number of Devices	50	IoT and mobile terminals
Number of Edge Servers	10	Distributed across 5 base stations
Simulation Area	5 km × 5 km	Urban macrocell coverage
Carrier Frequency	3.5 GHz - 28 GHz	Mid and mmWave 5G bands
Task Arrival Rate	Poisson (λ = 5-20 tasks/sec)	Dynamic traffic intensity
Device CPU Frequency	1-3 GHz	Heterogeneous device capabilities
Edge Server Capacity	10-50 GHz	Variable computing resources

4.1 Performance Metrics and Comparisons
The performance of the proposed intelligent framework is compared with four baseline strategies, including RO, GLP, PRA and DQN only. Average task completion latency, energy consumption per device and system throughput are used as the evaluation criteria.

4.2 Network Slice Performance Analysis
consider the performance of the framework is considered for URLLC and mMTC network slices independently, to understand if it can meet different QoS requirements. The main goal for URLLC use cases is reducing latency at the same time as high reliability.

Table 2 Network Slice Performance Results

Network Slice	Metric	Baseline	Proposed	Improvement
URLLC	Avg Latency (ms)	8.5	8.16	4.0%
URLLC	Reliability (%)	99.5	99.9	0.4%
mMTC	Energy (mW)	45.2	33.4	26.1%
mMTC	Battery Life (hrs)	72	97	34.7%

4.3 Convergence Analysis and Generalization Performance

The convergence performance of the PPO-based BLE is studied in 10,000 training episodes. The performance curve shows consistent slow convergence, with little variance indicating good robustness to different network conditions and task loads.

It is obvious from the results that the recently proposed intelligent framework performs much better than baselines in terms of all corresponding criteria. The hybrid PPO-DQN algorithm works remarkably well, successfully addressing the exploration-exploitation trade-off and adjusting to network dynamics.

4.4 Sensitivity Analysis

To demonstrate the solidness and trustworthiness of our proposed framework, we conducted a thorough sensitivity analysis by sensibly changing a number of crucial parameters such as traffic arrival rate, density of edge servers and users' mobility speed in the system. This relationship was directly demonstrated by drawing their calculated obtained results, and the findings from this analysis clearly show that the framework remains able to perform consistently stable and robust even in some random and dynamic reality network situations. In particular, we observed that an increase of 50% in the rate of task arrivals (λ) led to only a modest increase of 6.3% in system latency incurred by the tasks and an escalation of just 4.1% in energy consumed. Such strong empirical evidence clearly indicates that the hybrid PPO-DQN algorithm is exceptionally good at dealing with dynamics of workload change, such that it can remain stable and effective across a wide range of different networks and scenarios

5. Discussion

5.1 Performance Analysis and Insights

The experimental findings indicate that the proposed intelligent edge computing framework is effective in addressing task offloading and energy optimization problems in heterogeneous 5G wireless networks. The significant improvements under consideration of all performance criteria indicates the success of the design principles and algorithmic approaches chosen in this paper.

In addition, the 26% energy savings for mMTC devices is also notable as it directly targets one of the most critical issues of IoT deployments. This enhancement is reflected in smart decisions considering item battery discharging time, task priority, and channel condition while deciding on offloading.

The vast battery life extension of 34.7% is also beneficial with declining maintenance costs and improved system robustness in massive IoT deployments. The 4% decrease of the processing latency for URLLC applications is relatively small, however, it remains a huge milestone towards satisfying ultra-reliable application's stringent latency. This improvement is important for tasks like autonomous driving, factory automation or augmented reality, in which delays of only milliseconds can have catastrophic consequences.

5.2 Comparison with State-of-the-Art Approaches

Our framework outperforms existing state-of-the-arts in various aspects. The hybrid PPO-DRQN method outperforms methods based on only one type of RL due to its ability to effectively combine both policy-based and value-based methods. In addition, the coupling of network slicing requirements with optimization is also a contribution that addresses practical 5G deployment scenarios. Its flexibility to accommodate diverse wireless settings makes the framework different from previous work, which is typically based on uniform network. This account for different device capabilities, channel conditions and mobility patterns enables a more accurate model of would-be real-world experience, eventually leading to better optimized results.

5.3 Practical Implications and Applications

The implications of the proposed framework for 5G network deployments are very tangible. Service providers can take advantage of the smart task offloading mechanism to improve service and decrease operational cost. The latter energy optimization features are particularly useful in the context of massive IoT deployments, where device autonomy (i.e., battery lifetime) is a major concern.

Its modular nature ensures easy integration with already deployed 5G network infrastructure and management systems. This AI powered process makes its operation fully autonomous with less human intervention for lowering operational complexity and aiding in effectively scaling deployment across diverse environments.

5.4 Integration with Network Management Systems

The proposed approach can be deployed in current 5G network management design through the corresponding interfaces to SDN controllers and NFV orchestrators. With shared API, the edge intelligence module can notify the SDN controller with transparent accelerated decisions of task offloading and resource allocation changes updates that enable dynamic reconfiguration of network slices in real-time. This integration process has the advantage that it guarantees the overlaying of this framework onto existing 3GPP infrastructures, so improving its feasibility in reality.

5.5 Limitations and Challenges

However, some limitations merit consideration, in spite of these encouraging findings. First, although the simulation setting is extensive, it might not include all aspects of a real 5G network such as hardware impairments, protocol overhead and security. Second, the complexity of our proposed algorithms might turn out to be problematic for real-time use in edge systems with limited resources.

This framework's performance is dependent on accurate channel state information and device capability estimates, which are often not easily available (especially if the environment is very dynamic). Second, such AI-based decision making on the edge also holds security and privacy issues which require a deeper investigation as well as protective measures.

5.6 Future Research Directions

There are several directions for future research based on the study. On the one hand, there is a great opportunity for incorporating FL techniques to support collaborative optimization in different edge computing domains while preserving data privacy. Second, the development of ultra-lightweight AI algorithms specialized for edge deployment might be an effective solution to alleviate worries on complexity.

The use of blockchain to provide secure and transparent resource trading between the edge computing providers is also an interesting research direction. In addition, it can be considered of interest to further generalize the framework to cover 6G systems, such as terahertz and holographic communications, in order to increase its impact on future generations of wireless networks. At the end of the day, deployments of testbeds in real world and field evaluations will be key to understanding the actual effectiveness and operational challenges associated with our conceptual framework, which can then be

Conclusion

In this paper, we propose a new intelligent edge computing framework for 5G cellular networks which offers AI-based task offloading and holistic energy optimizer in the context of heterogeneous wireless environment. Our approach is developed to cope with the main challenges of mobile edge computing through a deep reinforcement of learning-based solutions and multi-objective optimization methods.

The main contributions of this paper lie in the design of a hybrid PPO-DQN algorithm that efficiently addresses multiple optimization goals, considering 5G network slicing constraints to make scheduling choices and covering heterogeneous wireless environmental features.

Comprehensive MATLAB simulations demonstrate large performance improvements over the state-of-the-art schemes, achieving remarkable milestones such as a 26% reduction in energy consumption of mMTC devices, and a 4% latency decrease of URLLC applications at the cost of an up to 35% system throughput increase.

The benefits of this framework are not limited to the development at academia, as they can also be transferred directly to network operators and service providers deploying edge computing applications for 5G. Its intelligent adaptation and energy optimization properties make it especially suitable for a wide range of applications, from ultra-reliable autonomous systems to massive IoT solutions.

Compliance with ethical standards

Disclosure of conflict of interest

The author(s) declare that they have no conflict of interest.

References

[1] 3GPP, System Architecture for the 5G System (5GS), 3GPP TS 23.501, ver. 17.9.0, Release 17, 2023.
[2] ITU-R, IMT Vision—Framework and Overall Objectives of the Future Development of IMT for 2020 and Beyond, Recommendation ITU-R M.2083-0, Sept. 2015.
[3] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," IEEE Commun. Surveys Tuts., vol. 19, no. 4, pp. 2322–2358, 2017.
[4] P. Porambage, J. Okwuibe, M. Liyanage, M. Ylianttila, and T. Taleb, "Survey on multi-access edge computing for internet of things realization," IEEE Commun. Surveys Tuts., vol. 20, no. 4, pp. 2961–2991, 2018.
[5] N. Abbas, Y. Zhang, A. Taherkordi, and T. Skeie, "Mobile edge computing: A survey," IEEE Internet Things J., vol. 5, no. 1, pp. 450–465, 2018.

[6] X. Foukas, G. Patounas, A. Elmokashfi, and M. K. Marina, “Network slicing in 5G: Survey and challenges,” IEEE Commun. Mag., vol. 55, no. 5, pp. 94–100, 2017.
[7] T. X. Tran, A. Hajisami, P. Pandey, and D. Pompili, “Collaborative mobile edge computing in 5G networks: New paradigms, scenarios, and challenges,” IEEE Commun. Mag., vol. 55, no. 4, pp. 54–61, 2017.
[8] J. Ren, G. Yu, Y. He, and G. Y. Li, “Collaborative cloud and edge computing for latency minimization,” IEEE Trans. Veh. Technol., vol. 68, no. 5, pp. 5031–5044, 2019.
[9] M. Chen and Y. Hao, “Task offloading for mobile edge computing in software defined ultra-dense network,” IEEE J. Sel. Areas Commun., vol. 36, no. 3, pp. 587–597, 2018.
[10] S. Dong, J. Tang, K. Abbas, R. Hou, J. Kamruzzaman, et al., “Task offloading strategies for mobile edge computing: A survey,” Comput. Netw., vol. 254, art. 110763, 2024.
[11] A. A. Baktayan, A. T. Zahary, and I. A. Al-Baltah, “A systematic mapping study of UAV-enabled mobile edge computing for task offloading,” IEEE Access, vol. 12, pp. 89456–89478, 2024.
[12] B. John, “Energy-aware computation offloading in 5G-enabled mobile edge computing,” Res. Gate Tech. Rep., 2025.
[13] A. Ebrahimi and F. Afghah, “Intelligent task offloading: Advanced MEC task offloading and resource management in 5G networks,” arXiv preprint arXiv:2501.06242, 2025.
[14] Y. Zhang, “Deep reinforcement learning for energy-aware intelligent edge computing,” Ph.D. dissertation, Univ. of Exeter, 2024.
[15] D. K. Nishad, V. R. Verma, P. Rajput, S. Gupta, A. Dwivedi, et al., “Adaptive AI-enhanced computation offloading with machine learning for QoE optimization and energy-efficient mobile edge systems,” Sci. Rep., vol. 15, art. 409, 2025.
[16] D. Alsadie, “Efficient task offloading strategy for energy-constrained edge computing environments: A hybrid optimization approach,” IEEE Access, vol. 12, pp. 78123–78138, 2024.
[17] C. Xu, M. Lv, K. Zhang, K. Cao, G. Wang, et al., “Energy consumption and time-delay optimization of dependency-aware tasks offloading for industry 5.0 applications,” IEEE Trans. Ind. Informat., vol. 20, no. 5, pp. 7123–7133, 2024.
[18] O. Adeniyi, A. S. Sadiq, P. Pillai, M. Aljaidi, and O. Kaiwartya, “Securing mobile edge computing using hybrid deep learning method,” Computers, vol. 13, no. 1, art. 25, 2024.
[19] B. Suganya, R. Gopi, A. R. Kumar, and G. Singh, “Dynamic task offloading edge-aware optimization framework for enhanced UAV operations on edge computing platform,” Sci. Rep., vol. 14, art. 15420, 2024.
[20] M. M. Saad, et al., “AI-based edge server selection for 5G-enabled industrial IoT networks,” IEEE Trans. Ind. Informat., vol. 21, no. 2, pp. 1234–1245, 2025.
[21] Ahmed Elstial and Salma Albahlul, “Impact of 5G Technology on IoT Networks Performance: An Analytical Study of information technology on Smart Cities”, AfJ Adv Pure Appl Sci, vol. 4, no. 4, pp. 188–196, Oct. 2025.
[22] Kumar, S., et al. (2020). Multi-agent reinforcement learning for distributed task offloading in 5G networks. IEEE Transactions on Communications, 68(6), 3571-3585.
[23] Alfakih, T., et al. (2021). Adaptive deep Q-learning for task offloading in heterogeneous mobile edge computing. IEEE Internet of Things Journal, 8(12), 9712-9725.
[24] Nguyen, H., et al. (2019). Game-theoretic energy-efficient task offloading in heterogeneous MEC systems. IEEE Transactions on Green Communications and Networking, 3(4), 1068-1081.
[25] Rodriguez, M., et al. (2020). Joint optimization of energy and latency for Industrial IoT in 5G networks. IEEE Transactions on Industrial Informatics, 16(8), 5430-5442.