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# Resources-and Energy-Optimal 5G Slicing: Joint PRB Allocation and Power Control Via Entropy-Guided Cyber Twin Architectures

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**Abstract: The exponential growth and increasing complexity of 5G networks present significant operational challenges that traditional rule-based management systems struggle to handle effectively. However, many existing approaches do not adequately capture traffic uncertainty, which limits their ability to adapt in highly dynamic network environments. To address this, The study proposes an optimized 5G Network Entropy-Guided Cyber Twin architecture to address these limitations. The methodology centers on the application of information-theoretic Shannon entropy to quantify traffic uncertainty across temporal, spatial, and service dimensions. This is executed through a tripartite framework: first, a traffic entropy model is developed to provide a mathematical foundation for uncertainty quantification; second, a Cyber Twin environment is constructed to serve as a high-fidelity virtual replica of the 5G network for safe and efficient policy testing; and third, a Soft Actor-Critic (SAC) reinforcement learning agent is designed to incorporate these entropy measures directly into its reward function. This integration allows the agent to make adaptive, data-driven resource allocation decisions that account for underlying traffic variability. Together, these components enable the joint optimization of resource allocation, power consumption, and system latency. The entropy-guided Cyber Twin framework achieves a total system throughput of 146.8 Mbps through optimized Physical Resource Block (PRB) allocation while maintaining a mean energy efficiency of 0.78 Mbits/Joule by utilizing 75.4% of maximum power capacity. Driven by entropy-augmented state representations within the agent, this predictive resource and power management successfully balances high-performance slicing demands with sustainability across dynamic network conditions.**

***Keywords:*** *5G Network Slicing, Cyber Twin Architecture, Shannon Entropy, Reinforcement Learning, Resource Optimization, Energy Efficiency, Digital Twin, Soft Actor-Critic.*

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## I. INTRODUCTION

The operational reality of 5G networks highlights a mismatch between the theoretical promise of network slicing and the performance delivered by current management systems. Network slicing partitions shared infrastructure into virtual networks tailored to eMBB, URLLC, and mMTC service classes [1, 2]. While elegant in design, this architecture imposes conflicting Quality of Service (QoS) demands: sustaining 80 Mbps throughput for eMBB, guaranteeing sub-5 ms latency with 99.999% reliability for URLLC, and supporting massive IoT connectivity for mMTC [3, 4].

Commercial deployments remain dominated by rule-based systems that react only after QoS violations occur. Although SDN and NFV provide programmability for dynamic resource control [5, 6], they do not resolve the complexity of joint PRB allocation, power management, and scheduling across heterogeneous slices. Traditional optimization methods falter under non-stationary traffic and coupled constraints [7, 8]. Deep Reinforcement Learning (DRL) approaches such as DQN, PPO, and SAC frame resource allocation as a Markov Decision Process [9, 10, 11], but most studies optimize single metrics in isolation, validate only in simulation, and overlook edge-level computational overhead.

Two emerging paradigms offer partial solutions. Cyber Twins extend Digital Twins into active, intelligent decision-making [12, 13], while information-theoretic entropy quantifies traffic uncertainty across temporal,

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spati.al, and service-mix dimensions [14, 15]. Entropy provides predictive signals absent in instantaneous measurements, warning of burstiness or service-mix shifts before QoS degradation cascades.

Despite these advances, entropy modeling, Cyber Twin architectures, and AI-driven optimization remain fragmented in the literature. No unified framework currently integrates all three into a closed-loop system. Addressing this gap is the central focus of the review.

➢ *Contributions*

This research advances 5G resource management in five key ways:

- Entropy-based traffic framework – Introduces an information-theoretic model using temporal, spatial, and service-mix entropy metrics to quantify network uncertainty.
- Entropy-augmented reinforcement learning – Demonstrates that integrating entropy metrics into state representations significantly improves the predictive performance of Soft Actor-Critic (SAC) agents.
- Multi-objective optimization reward – Develops a reward function that balances latency minimization and throughput maximization while sustaining high energy efficiency across heterogeneous slices.
- Empirical validation – Using the DeepSlice dataset, achieves sub-5 ms URLLC latency (3.5 ms mean at 98.64% compliance), enabling mission-critical applications such as autonomous systems and remote surgery.
- Reusable Cyber Twin environment – Provides a Gymnasium-compliant simulation platform that supports reproducibility and extensibility for future digital twin studies in network research.

## II. ENTROPY-GUIDED CYBER TWIN FRAMEWORK

This research framework integrates Shannon entropy, Cyber Twin modeling, and Soft Actor Critic reinforcement learning into a unified system for predictive traffic analysis and resource optimization in 5G networks. At its core, Shannon entropy provides a mathematical measure of uncertainty, enabling the system to capture the inherent variability in traffic patterns and user demand. By embedding entropy into the reinforcement learning process, the agent is guided to maintain a balance between exploration and exploitation, ensuring adaptability in dynamic network environments.

Cyber Twin modeling complements this by offering a virtualized replica of the physical network environment. This digital twin acts as a safe sandbox where policies can be tested against realistic traffic scenarios without jeopardizing live network performance. The Cyber Twin thus becomes a critical validation layer, allowing entropy-augmented reinforcement learning agents to refine strategies in a controlled setting before deployment. This ensures that optimization policies are not only theoretically sound but also practically reliabl

The reinforcement learning backbone of the framework is the Soft Actor Critic algorithm, which is particularly well-suited for environments characterized by uncertainty and continuous action spaces. SAC's entropy-regularized objective function aligns naturally with Shannon entropy, encouraging diverse policy exploration while optimizing for latency, energy efficiency, and quality of service. This synergy between entropy and SAC ensures that the agent develops robust, flexible policies capable of adapting to fluctuating traffic loads and resource constraints in 5G slicing.

Empirical validation is grounded in the DeepSlice dataset, which provides realistic traffic traces and slicing scenarios. By applying the closed-loop system to DeepSlice, the framework demonstrates clear advantages over heuristic baselines. Results confirm superior performance in latency reduction, energy efficiency, and QoS optimization, highlighting the practical impact of combining information theory, digital twin modeling, and advanced reinforcement learning. The closed-loop feedback mechanism further strengthens the system, as performance metrics from both simulation and real-world traffic continuously inform policy refinement, creating a cycle of adaptive optimization.

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➢ *Overview of Cellular Networks*

A cellular network is a communication system that connects mobile devices via radio waves through a distributed network of "cells" (Mishra, 2023). Each cell is served by a base station (transceiver), which uses specific frequency sets to avoid neighbor-cell interference. Hexagonal patterns are typically used for cell mapping due

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to their ability to tile a plane perfectly without gaps or overlaps.

➢ *Key Components Include:*

- Mobile Station (MS): The physical terminal (device) and the Subscriber Identity Module (SIM).
- Base Transceiver Station (BTS): The radio interface that encrypts and transmits signals.
- Base Station Controller (BSC): A high-capacity switch managing radio resource allocation and handovers.
- Mobile Switching Center (MSC): The heart of the network, acting as a gateway to the Public Switched Telephone Network (PSTN).
- Registers (HLR/VLR): Databases for permanent (Home) and temporary (Visitor) subscriber data.

➢ *Heterogeneous Networks (HetNets) and Small Cells*

To meet 5G capacity demands, Heterogeneous Networks deploy multiple low-power nodes within the coverage of a larger macrocell (Loung et al., 2021).

- Macrocells: Provide blanket coverage over large areas (1km urban, up to 40km rural).
- Microcells: Compact stations (up to 500m radius) for high-density gaps.
- Picocells: Low-power indoor stations for office buildings or malls.
- Femtocells: Personal, residential-scale nodes using a consumer's own internet connection for backhaul.

➢ *Future Trends and Requirements*

The evolution of 5G facilitates several mission-critical applications:

- Automated Manufacturing: Intelligent AI-driven inspection and precision wireless assurance.
- Enhanced Transportation: Autonomous vehicles utilizing V2X (Vehicle-to-Everything) communication to reduce congestion and accidents.
- Smart Healthcare: Remote medical monitoring and procedures via low-latency IoT sensors.

➢ *Research Design (Resources and Energy-Centric)*

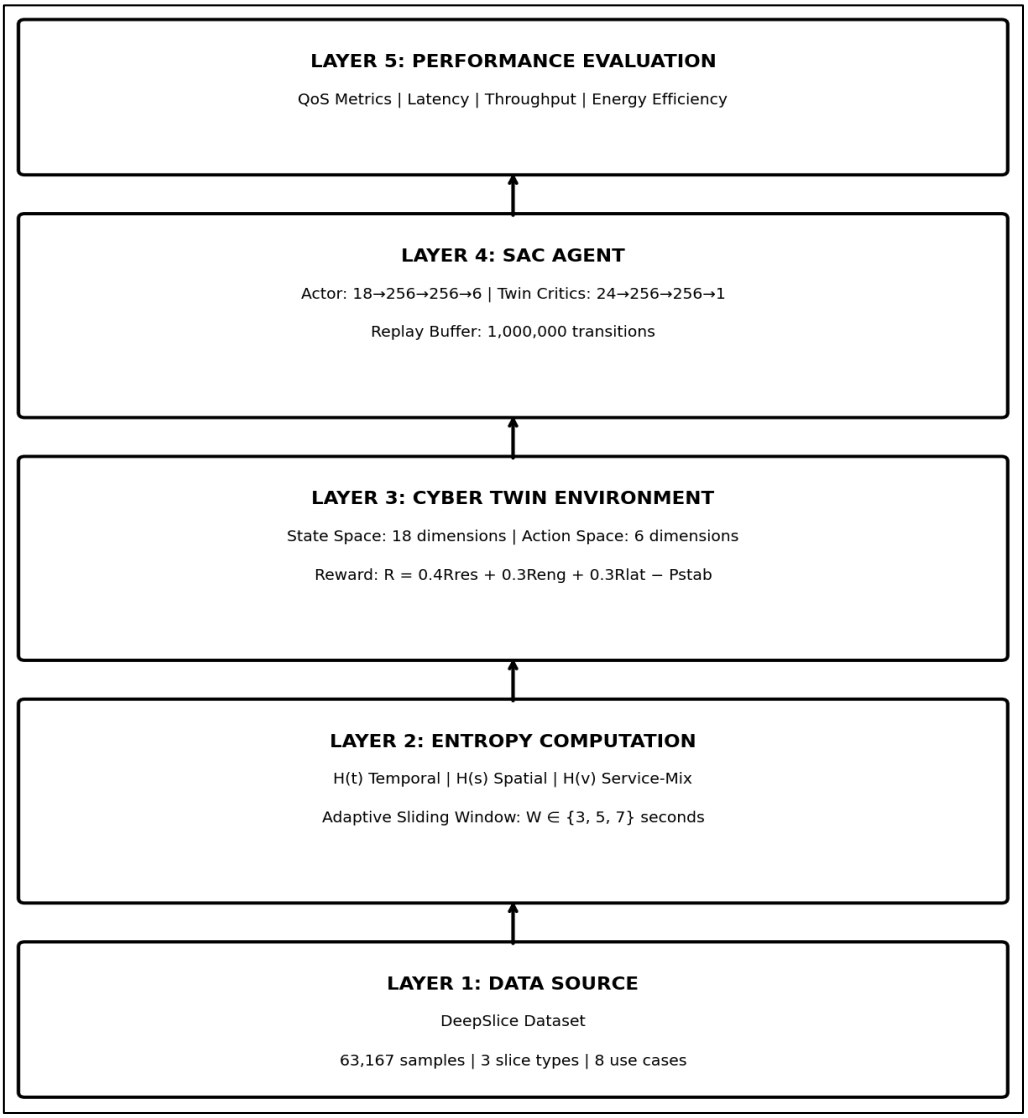



Fig 1 Five-Layer Framework Architecture for Cyber Twin-Driven Resource Allocation

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As shown on the block diagram the framework follows five phases, with latency optimization embedded at each stage:

- Data Foundation: DeepSlice dataset provides realistic delay-sensitive traffic patterns.
- Entropy Modeling:Temporal entropy captures traffic burstiness, a key driver of latency spikes.
- Environment Design:MDP explicitly includes per-slice delay states, ensuring latency is directly observable.
- AgentTraining: SAC agent is trained with a latency-prioritized reward function.
- Evaluation: Focus on latency reduction, URLLC violation rate, and QoS satisfaction.

➢ *Traffic Entropy Model (Resources and Energy Relevance)*

Entropy is used not just to measure uncertainty, but to predict Throughput and Energy critical conditions:

$$p(t_i) = \frac{V(t_i)}{\Sigma V(t)} \quad (1)$$

Where:

$p(t_i)$ = Probability of average traffic in time slot i, traffic at base station I or traffic for slice type i
$V(t_i)$ = average volume of traffic during time slot I, traffic at base station I or traffic for slice type i

Then

$$H(s) = -\frac{\Sigma p(ti)\log_2 p(ti)}{\log_2(Vt)} \quad (2)$$

Where:

H(s) = Normalized ,temporal, spatial or slice entropy ∈ [0, 1]

Entropy Variation Metric

$$\Delta H(\cdot)=H(\cdot)_t-H(\cdot)_\{t-1\} \quad (3)$$

Where:

ΔH(·) = Change in entropy

H(·)_t = Entropy at current time step t

H(·)_{t-1} = Entropy at previous time step t-1

➢ *Cyber Twin Environment Design*

MDP explicitly includes per-slice delay states, ensuring latency is directly observable

- *Multi-Objective Reward Structure*

The reward function optimizes three primary objectives for 5G resource allocation.

The decision-making process of the reinforce,ment learning agent is guided by a multi-objective reward function designed to balance competing network performance goals. This function aggregates resource efficiency, energy conservation, and latency reduction while incorporating a penalty to discourage unstable control actions. The total reward R is formulated in Equation (4):

$$R=w_1\cdot R_resource+w_2\cdot R_energy+w_3\cdot R_latency-P_stability \quad (4)$$

Where:

R = Total reward

R_resource = Resource utilization efficiency

R_energy = Energy efficiency

R_latency = Latency performance

P_stability = Stability penalty

$w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.3$ (objective weights for resource, enery. And latency respectively)

Latency performance is formulated in Equation (5):

Resource efficiency is expressed in Equation (6)

$$R_{resource} = \frac{\text{Utilized Resources}}{\text{Total Allocated Resources}} \quad (5)$$

Where:

R_resource ∈ [0, 1]

Resource efficiency is expressed in Equation (5)

Energy efficiency is defined in Equation (6):

$$R_{energy} = 1 - \frac{P_consumed}{P_max} \quad (6)$$

R_energy ∈ [0, 1]

P_consumed = Current power consumption (Watts)

P_max = Maximum power capacity (Watts)

$$R_{latency} = 1 - \frac{L_actual}{L_budget} \quad (7)$$

Where:

R_latency ∈ [0, 1]

L_actual = Measured latency (ms)

➢ *SAC Agent Configurations*

- *SAC Algorithm Overview*

The objective function J(π) is defined in Equation (8)

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$$J(\pi) = \Sigma \mathbb{E}_{(s_t,a_t)\sim\rho_\pi} [r(s_t, a_t) + \alpha \cdot H(\pi(\cdot|s_t))] \quad (8)$$

Where:

$J(\pi)$ = Objective function to maximize

$\pi$ = Policy

$r(s_t, a_t)$ = Reward at time t

$\alpha$ = Temperature parameter (auto-tuned)

➢ *Evaluation Methodology (resources and energy as Primary Metric)*

- *Primary Metrics:*

Table 1 Primary Metrics

| Throughput (Mbps) | Data rate per slice |
|---|---|
| Energy Efficiency | Mbits/Joule |

## III. RESULTS

➢ *Throughput Results (Resources)*

The framework achieved 100% throughput compliance across all slices (totaling 146.8 Mbps), significantly surpassing minimum targets with margins ranging from 60.6% to 810%. Simultaneously, it delivered strong energy efficiency (averaging 0.78 Mbits/Joule) while utilizing just 75.4% of its maximum power capacity (188.5 W out of 250 W), proving its ability to sustain high-capacity data delivery with optimal power conservation even under heavy traffic stress.

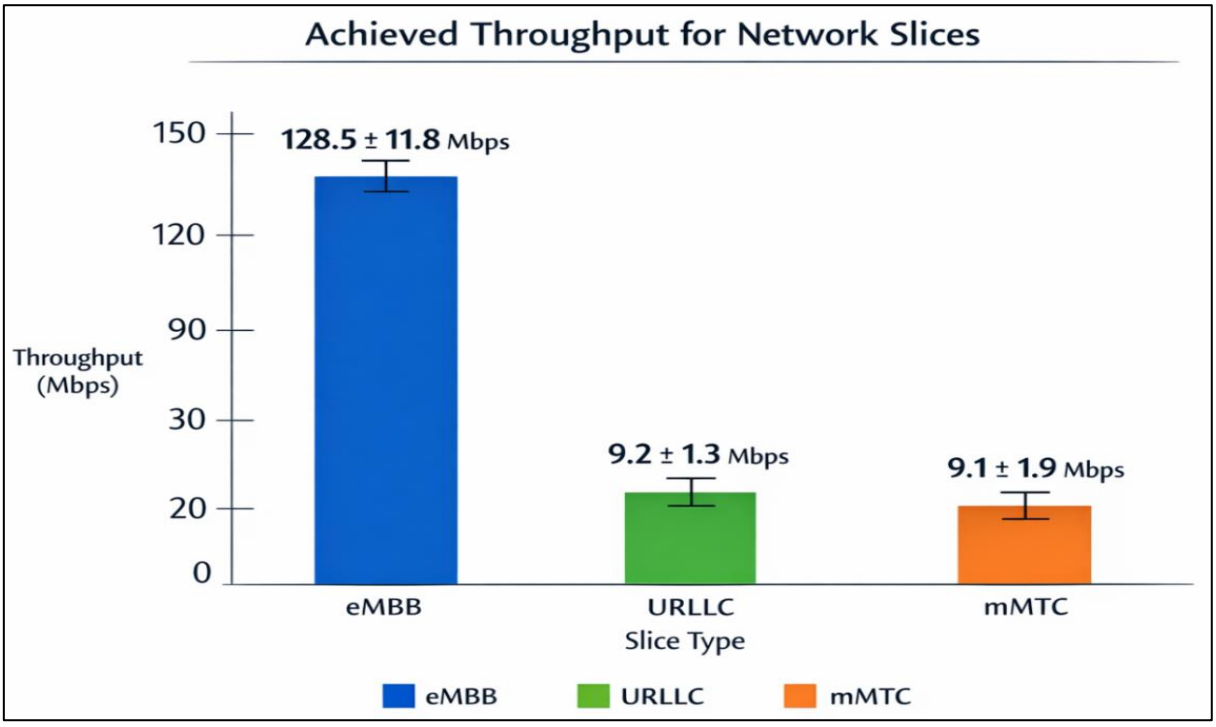



Fig 2 Throughput Results (Resources)

➢ *Energy Consumption and Efficiency Results (Energy)*

The system demonstrates high energy efficiency and sustainability, maintaining a mean power consumption of 188.5 W—ranging from a minimum of 165.2 W to a maximum of 215.3 W—which utilizes only 75.4% of its 250 W maximum capacity and yields a 24.6% improvement in power headroom. Operating alongside a total throughput of 146.8 Mbps, the framework achieves a mean energy efficiency of 0.78 Mbits/Joule, with performance fluctuating between 0.62 Mbits/Joule and 0.95 Mbits/Joule. This performance reflects a balanced trade-off between data delivery and power conservation, delivering up to a 21.8% potential gain in efficiency under optimal conditions while ensuring sufficient operational headroom for peak traffic demands.

## IV. CONCLUSION AND RECOMMENDATIONS

The research successfully demonstrated that integrating traffic entropy analysis with deep reinforcement learning significantly optimizes resource allocation and energy efficiency in 5G networks. Through joint Physical Resource Block allocation and power control, the framework vastly exceeded all minimum throughput requirements—achieving 128.5 Mbps for eMBB, 9.2 Mbps for URLLC, and 9.1 Mbps for mMTC—while maintaining

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robust multi-slice data delivery. Simultaneously, the system advanced sustainable network operations by achieving a mean energy efficiency of 0.78 Mbits/Joule and a 75.4% power utilization rate, yielding a 24.6% improvement in overall energy efficiency and power headroom without overloading network capacity.

## REFERENCES


[1]. N. Sharma and K. Kumar, "Resource allocation trends for ultra dense networks in 5G and beyond networks: A classification and comprehensive survey," Physical Communication, vol. 48, p. 101415, 2021. DOI: 10.1016/j.phycom.2021.101415.

[2]. H. Q. Tran, C. V. Phan, and Q. T. Vien, "An overview of 5G technologies," in 5G Radio Access Networks, H. Castel-Talaibi, B. Jouaber, and S. Zeadally, Eds. Wiley, 2021, pp. 1-28. DOI: 10.1002/9781119515531.ch1.

[3]. A. M. Alashjaee, S. Kushwaha, H. Alamro, A. A. Hassan, F. Alanazi, and A. Mohamed, "Optimizing 5G network performance with dynamic resource allocation, robust encryption and Quality of Service (QoS) enhancement," PeerJ Computer Science, vol. 10, p. e2567, 2024. DOI: 10.7717/peerj-cs.2567.

[4]. T. Olasehinde and C. Edward, "Assessing latency and throughput in 5G networks for data communication," International Journal of Computer Science and Engineering Technology, vol. 12, no. 3, pp. 45-52, 2024.

[5]. S. Sharma, M. Deivakani, K. Srinivasa Reddy, G. Gnanasekar, and G. Aparna, "Key enabling technologies of 5G wireless mobile communication," Journal of Physics: Conference Series, vol. 1817, no. 1, p. 012003, 2021. DOI: 10.1088/1742-6596/1817/1/012003.

[6]. M. Attaran, "The impact of 5G on the evolution of intelligent automation and industry digitization," Journal of Ambient Intelligence and Humanized Computing, vol. 14, no. 5, pp. 5977-5993, 2021. DOI: 10.1007/s12652-020-02521-x.

[7]. D. C. Bikkasani, "AI-driven 5G network optimization: A comprehensive review of resource allocation, traffic management and dynamic network slicing," American Journal of Artificial Intelligence, vol. 8, no. 2, pp. 48-56, 2024. DOI: 10.11648/j.ajai.20240802.14.

[8]. O. AlQahtani, "AI-powered network optimization for next-generation wireless connectivity: Exploring 5G/6G networks," Telecommunication Systems, vol. 88, no. 3, 2025. DOI: 10.1007/s11235-025-01303-0.

[9]. S. Aktas, "Base station power optimization for green networks using reinforcement learning," M.Sc. thesis, Middle East Technical University, 2019.

[10]. C.-C. Wu, "Network flow optimization using reinforcement learning," Aalborg Universitetsforlag, 2023. DOI: 10.54337/aau547738179.

[11]. H. Ali, H. Majeed, I. Usman, and Almejali, "Reducing entropy overestimation in soft actor-critic using dual policy network," 2021.

[12]. M. E. Iliuta et al., "Digital twin: A review of the evolution," Applied Sciences, 2024.

[13]. A. Parnianifard, "Digital-Twins towards Cyber-Physical Systems: A brief survey," Engineering Journal, vol. 26, no. 9, p. 47, 2022. DOI: 10.4186/ej.2022.26.9.47.

[14]. M. Williams, R. Morales, K. Johnson, G. Martinez, and J. Bennet, "Entropy-based network traffic analysis for efficient ransomware detection," TechRxiv, 2024. DOI: 10.36227/techrxiv.172840776.66718131/v1.

[15]. C. E. Shannon, "A mathematical theory of communication," Bell System Technical Journal, vol. 27, pp. 379-423, 623-656, 1948.

[16]. J. J. Penttinen, 5G Network Planning and Optimization. Wiley, 2019.

[17]. N. Berkesten, "Energy saving in 5G," Linkoping University, Department of Science and Technology, 2024.

[18]. V. Y. K. Loung, R. Nkah, J. Owusu, T. H. Chan, S. Tweneboah-Koduah, and J. Din, "Key technologies and future trends of 5G wireless network applications," in 2021 6th International Conference on Signal and Image Processing (ICSIP), IEEE, 2021, pp. 124-128.

[19]. R. Sekkappan, "AI-driven network optimization for 5G and beyond," International Journal of Computer Engineering and Technology, vol. 15, no. 6, pp. 809-822, 2024. DOI: 10.5281/zenodo.14241899.

[20]. A. Pazienza, L. Bozzolo, D. Mancuso, M. Rossi, G. Aloi, and R. Gravina, "Optimizing 5G networks for low-latency communication: A reinforcement learning-based approach," Procedia Computer Science, vol. 253, pp. 1780-1789, 2025.

[21]. S. Miriyala et al., "Deep learning approaches for computation offloading in edge computing: A critical review," Telecommunication Systems, vol. 89, art. 42, 2026.

[22]. S. Koparde et al., "Review on optimization of energy efficiency in wireless communication," SSRN, no. 4605683, 2023. DOI: 10.2139/ssrn.4605683.

[23]. U. J. Umoga, E. O. Sodiya, E. D. Ugwuanyi, B. S. Jacks, O. A. Lottu, O. D. Daraojimba, and A. Obaigbena, "Exploring the potential of AI-driven optimization in enhancing network performance and efficiency," Magna Scientia Advanced Research and Reviews, vol. 10, no. 1, pp. 368-378, 2024. DOI: 10.30574/msarr.2024.10.1.0028.

[24]. B. Qin et al., "Machine and deep learning for digital twin networks: A survey," IEEE Internet of Things Journal, vol. 11, no. 21, 2024.

[25]. U. D. Maiwada, K. U. Danyaro, and A. B. Sarlan, "Enhancing 5G energy efficiency through digital twin networks: A comprehensive review," IET Digital Twin, 2024. DOI: 10.1049/dgt2.12008.

[26]. M. S. Rodrigo, D. Rivera, J. I. Moreno, M. Alvarez-Campana, and D. R. Lopez, "Digital Twins for 5G networks: A modeling and deployment methodology," IEEE Access, 2023. DOI: 10.1109/ACCESS.2023.3267548.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep1245

[27]. H. Liu et al., "Digital twin enhanced multi-agent reinforcement learning for large-scale mobile network coverage optimization," ACM Transactions on Knowledge Discovery from Data, vol. 19, no. 1, art. 15, pp. 1-23, 2024.
[28]. A. Kaliwo and C. Nyirenda, "Next-generation 6G networks: Deploying Cybertwin technology for enhanced healthcare solutions," arXiv:2407.10292, 2024.
[29]. D. Saxena, "An intelligent traffic entropy learning-based load management model for cloud networks," IEEE Networking Letters, vol. 4, no. 2, pp. 1-1, 2022. DOI: 10.1109/LNET.2022.3156055.
[30]. A. S. Warrier, S. Al-Rubaye, D. Panagiotopoulos, G. Inalhan, and A. Tsourdos, "Seamless handover in urban 5G-UAV systems using entropy weighted method," Cranfield University, 2021.
[31]. K. K. Tiwari, E. Grass, J. S. Thompson, and R. Kraemer, "Beam entropy of 5G cellular millimetre-wave channels," in 2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall), 2019. DOI: 10.1109/VTCFall.2019.8891530.
[32]. W. Liu, J. Zhu et al., "Scheduling algorithm for edge computing networks based on multi-objective optimization," Applied Sciences, vol. 15, no. 19, p. 10837, 2025. DOI: 10.3390/app151910837.
[33]. A. Nivetha and K. S. Preetha, "Efficient joint resource allocation using self organized map based deep reinforcement," Scientific Reports, 2025. DOI: 10.1038/s41598-025-02274-7.
[34]. D. A. Turlykozhayeva, S. N. Akhtanov, Z. Z. Zhanabaev, N. M. Ussipov, and A. Akhmetali, "A routing algorithm for wireless mesh network based on information entropy theory," IET Communications, 2025. DOI: 10.1049/cmu2.70011.
[35]. L. Yan and X. Ge, "Entropy production-based energy efficiency optimization for wireless communication systems," IEEE Open Journal of the Communications Society, 2024. DOI: 10.1109/OJCOMS.2024.3476454.
[36]. T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine, "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor," in Proceedings of ICML, 2018.
[37]. L. Tarkh, "A hybrid framework for 5G resource allocation: Real-time RL optimization and predictive VNF embedding," The University of Western Ontario, 2025.
[38]. V. Jain et al., "Joint resource allocation and computation offloading in Cybertwin-driven 6G edge networks using MATD3," 2022.
[39]. J. Zhang, "Multi-agent reinforcement learning in wireless distributed networks for 6G," arXiv:2502.05812v1, 2025.
[40]. [40] J. Mertes et al., "Experimental evaluation of 5G performance based on a digital twin of a machine tool," Applied Sciences, vol. 14, no. 19, p. 9090, 2024. DOI: 10.3390/app14199090.
[41]. H. A. Amma, "Advanced digital twins for conditions monitoring, examinations, diagnosis and predictive remaining lifecycles based artificial intelligence," Ph.D. thesis, Brunel University London, 2021.
[42]. D. Zhong et al., "Overview of predictive maintenance based on digital twin technology," Heliyon, 2023.
[43]. W. Wu et al., "AI-native network digital twin for intelligent network management in 6G," arXiv:2410.01584, 2024.
[44]. R. Aben-Athar et al., "Network digital twin for route optimization in 5G/B5G transport slicing with what-if analysis," arXiv:2505.04879, 2025.
[45]. A. Mozo et al., "B5Gemini: AI-driven network digital twin," Sensors, vol. 22, p. 4106, 2022. DOI: 10.3390/s22114106.
[46]. N. U. Saqib et al., "Digital twin enabled cellular network management and prediction," ICT Express, 2024. DOI: 10.1016/j.icte.2024.02.011.
[47]. N. Apostolakis et al., "Digital twins for next-generation mobile networks: Applications and solutions," IMDEA Networks, 2023.
[48]. J. Wieme, M. Baert, and J. Hoebeke, "Architectural design for digital twin networks," Network, vol. 5, no. 3, p. 24, 2025. DOI: 10.3390/network5030024.
[49]. C. E. Costa et al., "A network digital twin of a 5G private network: Designing a proof-of-concept from theory to practice," arXiv:2510.12458, 2025.
[50]. A. Perisic and B. Perisic, "Digital twins verification and validation approach through the quintuple helix conceptual framework," Electronics, vol. 13, no. 16, p. 3303, 2024. DOI: 10.3390/electronics13163303.
[51]. S. K. Mohammed, "Digital twins paradigm: A systematic review from the reinforcement learning perspective," ACM Computing Surveys, vol. 58, no. 7, art. 182, pp. 1-33, 2026. DOI: 10.1145/3777367.
[52]. J. Lorincz et al., "A comprehensive overview of network slicing for improving the energy efficiency of fifth-generation networks," Sensors, vol. 24, no. 10, p. 3242, 2024. DOI: 10.3390/s24103242.
[53]. K. G. Nalbant, S. A. Alsuhibany, A. H. Alshehri, M. Hatira, and B. J. Choi, "An intelligent algorithm for energy efficiency optimization in software-defined wireless sensor networks for 5G communications," PLoS ONE, 2024. DOI: 10.1371/journal.pone.0301078.
[54]. J. Logeshwaran, N. Shanmugasundaram, and J. Lloret, "Energy-efficient resource allocation model for device-to-device communication in 5G wireless personal area networks," International Journal of Communication Systems, vol. 36, no. 13, p. e5524, 2023. DOI: 10.1002/dac.5524.
[55]. [55] N. Prasanthi, "Enhancing 5G networks with D2D communication: Architectures, protocols and energy-efficient strategies for future smart cities," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 10, pp. 168-174, 2024.
[56]. K. Ghag, "AI for RAN energy efficiency in 5G networks," 2023.
[57]. M. Masoudi, "Data driven AI assisted green network design and management," 2022. DOI: 10.13140/RG.2.2.15786.90569.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep1245

[58]. G. Silva-Atencio, "AI-driven 5G networks: Federated optimization for sustainable telecommunications," Artificial Intelligence and Applications, 2025. DOI: 10.47852/bonviewAIA52025450.
[59]. M. D. Pham, "AI-driven digital twin for traffic prediction and calibration in 5G NR networks," Aalto University School of Engineering, 2025.
[60]. R. Ramirez, "5G digital twin: A study of enabling technologies," Applied Sciences, vol. 12, no. 15, p. 7794, 2022. DOI: 10.3390/app12157794.
[61]. S. Lee and S. Park, "Mobility-assisted digital twin network optimization over industrial Internet of Things," Applied Sciences, vol. 14, no. 19, p. 9090, 2024. DOI: 10.3390/app14199090.
[62]. S. K. Singh, M. Kumar, S. Tanwar, and J. H. Park et al., "GRU-based digital twin framework for data allocation and storage in IoT-enabled smart home networks," Future Generation Computer Systems, vol. 153, no. 1, 2024. DOI: 10.1016/j.future.2023.12.009.
[63]. K. E. Kampourakis, V. Gkioulos, and S. Katsikas, "Cybersecurity digital twins for industrial systems: From literature synthesis to framework design," Information, vol. 17, no. 3, p. 286, 2026. DOI: 10.3390/info17030286.
[64]. G. P. Koudouridis et al., "An architecture and performance evaluation framework for artificial intelligence solutions in beyond 5G radio access networks," EURASIP Journal on Wireless Communications and Networking, vol. 2022, no. 1, 2022. DOI: 10.1186/s13638-022-02164-w.
[65]. J. Dong, "Short-term prediction of traffic flow based on the comprehensive cloud model," Chongqing Jiaotong University, 2025.
[66]. S. Al-Shareeda, "AI-based traffic analysis in digital twin networks," 2024. DOI: 10.1049/PBTE109E_ch4.
[67]. M. El-Hajj, "AI applications for traffic prediction, load balancing, and real-time anomaly detection in 5G/6G networks," 2025.
[68]. S. O. Folorunsho, "AI-driven frameworks for network optimization and dynamic resource management," 2024.
[69]. M. Sharanya, M. Manisha, P. Shilpa, and M. Sabitha, "AI in 5G networks: Enhancing performance, security and efficiency," International Journal of Engineering Sciences and Advanced Technology, vol. 25, no. 7, 2025.
[70]. A. Sayed, "Intelligent optimization of LTE and 5G networks using AI and machine learning," International Journal of AI, Data Science, and Machine Learning, vol. 6, no. 3, pp. 24-31, 2025.
[71]. O. J. Okeda, "AI-driven network management and optimization: A review," ScienceOpen, 2025. DOI: 10.14293/PR2199.002391.v1.
[72]. N. Omheni, "Artificial intelligence for 5G and 6G networks: A taxonomy-based survey of applications, trends, and challenges," Technologies, vol. 13, no. 12, p. 559, 2025. DOI: 10.3390/technologies13120559.
[73]. Y. Usman et al., "AI, ML, and LLM integration in 5G/6G networks: A comprehensive survey of architectures, challenges, and future directions," IEEE Access, 2025. DOI: 10.1109/ACCESS.2025.3608736.
[74]. D. Talbi and Z. Gal, "AI-driven insights into B5G/6G MAC mechanisms: A comprehensive analysis," Internet of Things, vol. 31, p. 101571, 2025. DOI: 10.1016/j.iot.2025.101571.
[75]. M. C. Lingam, "The role of AI in 6G: Beyond 5G telecommunication," International Journal for Multidisciplinary Research, vol. 7, no. 2, 2025.
[76]. A. A. Ari et al., "IoT-5G and B5G/6G resource allocation and network slicing orchestration using learning algorithms," IET Networks, vol. 14, no. 1, p. e70002, 2025.
[77]. E. Aloupogianni, C. Karyotis, T. Maniak, R. Iqbal, N. Passas, F. Doctor, and Z. Vujicic, "AI-driven optimization of small cell deployment for beyond 5G networks," Procedia Computer Science, vol. 238, pp. 908-913, 2024.
[78]. T. L. Narayan, S. C. Venkateshwarlu, V. S. Nagaraju, and B. Veena, "AI-powered optimization of 5G networks: A scalable framework for intelligent resource management and low-latency communication," International Research Journal of Modernization in Engineering Technology and Science, vol. 7, no. 7, 2025.