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A Machine Learning-Based Framework for Resource Allocation, Energy Efficiency, and Network Performance

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Abstract

With the deployment of the fifth-generation (5G) wireless communication networks, to the next-generation sixth-generation (6G) networks, the network have been presented with newer and higher demand for network capacity, spectrum efficiency, energy efficiency, latency, reliability and quality of service (QoS). Standard optimization techniques might have fixed solutions and allocation policies, which makes them less adaptable to the fast-changing traffic volumes and channel conditions. Artificial intelligence (AI) and machine learning (ML) provide the promise of helping to manage a network in an adaptive way. This paper presents a novel framework for optimization of 5G and future 6G wireless communication scenarios based on AI. The framework takes the following network parameters as the input to an intelligent optimization engine: network traffic, channel quality, user demand, bandwidth, and transmission power. Two approaches, namely, conventional resource allocation and genetic algorithm optimization, are compared against the proposed approach of deep reinforcement learning (DRL) as the main adaptive decision-making approach. Throughput, end-to-end delay, energy efficiency, PDR, packet loss, and spectral efficiency are identified as evaluation metrics. The proposed study will be correlated via simulation in varying traffic and channel conditions. At this stage no numerical improvement in performance is claimed and this needs to be confirmed by repeatable experiments, which will provide quantitative results.

Keywords

Artificial Intelligence, Machine Learning, 5G, 6G, Deep Reinforcement Learning, Resource Allocation, Energy Efficiency, Network Optimization, Quality of Service

1 Introduction

The wireless communication systems have advanced significantly, including the introduction of 5G which will provide a new generation of use cases such as mobile broadband enhancements, massive machine type communications, and ultra-reliable low latency communications. These features enable connected vehicles, industrial automation, smart healthcare, immersive media and massive Internet of Things (IoT) applications. As it is envisioned to evolve into 6G, it is likely to pose more demands such as highly reliable connections, intelligent network operation, integrated sensing and communication, support for new spectrum bands, and closer integration of communication, computing and sensing resources. The requirements impose demands for network management techniques that will be able to be adapted to varying densities, traffic patterns, interference and channel conditions.

Traditional optimization approaches tend to use analytical models, heuristics or pre-defined allocation rules. While these methods are still applicable, they may not work well when network conditions are volatile, or when multiple objectives have to be achieved at the same time. Patterns can be learned from network data using AI and ML; it can also support prediction, classification and adaptive decision-making. A specific one is reinforcement learning, which can choose an action to allocate resources within the network, according to the network state and feedback from the environment.

This paper presents a multi-objective framework for optimization of resource allocation and network performance in the context of 5G and future 6G wireless networks, which uses Artificial Intelligence (AI) as its enabling technology. The study will be centered on meeting energy, quality of service, and bandwidth requirements, and balancing throughput, latency, and energy consumption.

The main contributions of this paper are as follows. First, it presents a structured, five-stage AI-driven optimization framework that links network data collection, preprocessing, learning-based decision-making, resource control and performance evaluation in a closed feedback loop. Second, it formulates resource allocation as a weighted multi-objective problem that explicitly captures the trade-off among throughput, energy efficiency and latency under bandwidth, power and service-level constraints. Third, it defines a reproducible evaluation methodology in which a DRL agent is compared against a conventional allocation policy and a genetic algorithm benchmark under identical scenarios and metrics.

The remainder of this paper is organised as follows. Section 2 reviews related work on AI-enabled 5G and 6G networks. Section 3 states the research objectives, and Section 4 describes the proposed framework. Section 5 defines the input parameters and Section 6 discusses candidate AI and optimization techniques. Section 7 presents the mathematical formulation, including the DRL problem definition. Section 8 outlines the research methodology and Section 9 the performance evaluation metrics. Section 10 discusses expected outcomes and limitations, and Section 11 concludes the paper.

2. Literature Review

Andrews et al. [1] provided an overview of 5G network design goals such as 300x capacity, 1000x latency, and massive connectivity, and identified 3 major enablers: densification, millimetre-wave spectrum, and massive MIMO. Future visions of 6G [2], [3], [4] suggest that 6G will be significantly more complex and diverse with a requirement for embedding AI in the network, not as an extension. The works discuss one of the key open challenges of the beyond-5G systems, namely intelligent resource management.

There have been numerous studies on the use of machine learning in wireless network management. Artificial neural network-based ML for wireless networks is explained in the tutorial of Chen et al. [5], and deep learning applications are covered in the survey of mobile and wireless networking applications of Zhang et al. [6], including applications in the area of traffic prediction, resource management and network control. These surveys suggest that

supervised models do well when it comes to prediction and classification while sequential control problems like resource allocation are more naturally attacked by using reinforcement learning.

Reinforcement learning is a learning methodology where an agent learns a decision policy by interacting with an environment and getting a reward signal [7]. The ability to learn policies in high dimensional state spaces was developed by Mnih et al. [8] with the use of reinforcement learning and deep neural networks. Luong et al. [9] and Alwarafy et al. [10] review the applications of DRL in communication fields such as radio resource allocation, power control and spectrum access. Examples range from DRL based resource allocation for vehicle-to-vehicle communications [11] to multi-agent DRL for dynamic resource allocation in wireless networks [12].

Energy efficiency has become a side issue. The concepts of sustainable green 5G networks are reviewed in Wu et al. [13] and the recent trends and open issues on 5G energy efficiency are surveyed in Usama and Erol-Kantarci [14]. López-Pérez et al. [15] investigate radionetwork energy-saving approaches such as massive MIMO, lean carrier design, sleep modes and machine learning, while Fowdur and Doorgakant [16] explore ML approaches to energy-efficient 5G and 6G communications. Additionally, energy-efficient resource allocation has been explored for machine-to-machine devices [17], and recently, in the context of 5G NR, with ML-based schemes [18].

Although the number of applications of multi-objective methods has declined in recent years, some methods are still good reference points for multi-objective optimization, the genetic algorithm [19] being one of the most popular multi-objective methods for exploring trade-offs among competing objectives. While these studies show the capabilities of AI for specific goals, most of them consider throughput, power or energy efficiency separately or test performance in a few settings. This paper fills this gap by introducing a common, reproducible evaluation methodology and by proposing a unified framework that takes into account throughput, latency and energy efficiency and is evaluated against both conventional and metaheuristic baseline systems.

3. Research Objectives

1. To examine the role of AI and ML techniques in the optimization of 5G and emerging 6G wireless networks.
2. To formulate an intelligent framework for adaptive resource allocation under varying traffic and channel conditions.
3. To investigate bandwidth allocation and transmission-power control as network optimization decisions.
4. To evaluate the trade-offs among throughput, latency, energy efficiency, and reliability.
5. To compare a DRL-based approach with conventional resource allocation and a genetic algorithm-based benchmark.
6. To assess the robustness and scalability of the proposed approach across different network-load scenarios.

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4. Proposed AI-Based Optimization Framework

The proposed framework has five stages: (i) wireless network data collection, (ii) data preprocessing and feature extraction, (iii) AI/ML-based optimization, (iv) resource and power control, and (v) performance evaluation. Observations of the network are sent to the optimization engine, which determines the actions to take with regard to the allocation of resources. The network performance is then measured and given as feedback for further learning.

Data collection for wireless network: Traffic load, Channel Quality, Bandwidth available, Transmission power, Number of users, Packet delays observed.

Preprocessing and feature extraction: Identify missing or inconsistent data, standardize numerical data, and identify relevant input variables.

AI/ML optimization engine: Implement DRL for adaptive resource allocation, implement supervised learning models if traffic or performance prediction is needed.

Resource and power control: Allocate the bandwidth and transmission power feasible under the system constraints.

Performance evaluation: Compute throughput, latency, energy efficiency, reliability, spectral efficiency and resource usage.

The overall architecture of the proposed framework is shown in Fig 1, and the DRL agent–environment interaction loop that drives resource allocation is shown in Fig 2.

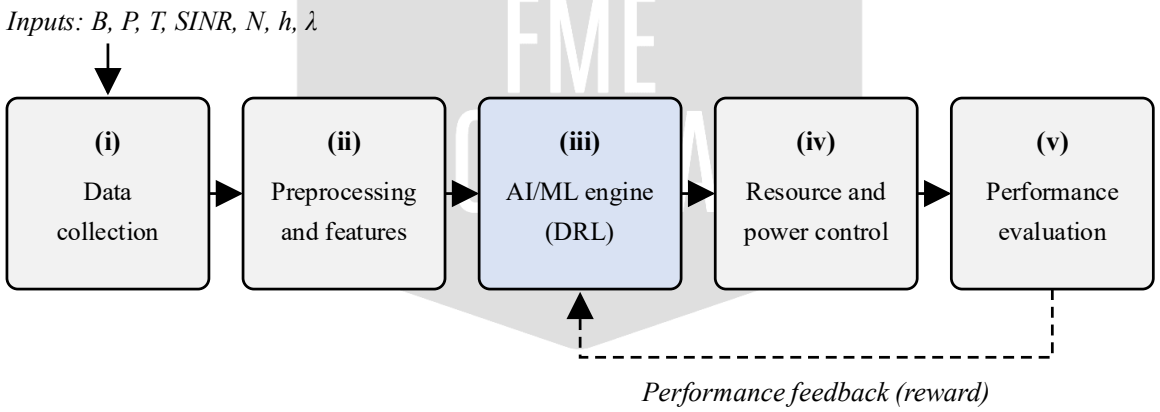


Fig 1 Overall architecture of the proposed AI-driven optimization framework.

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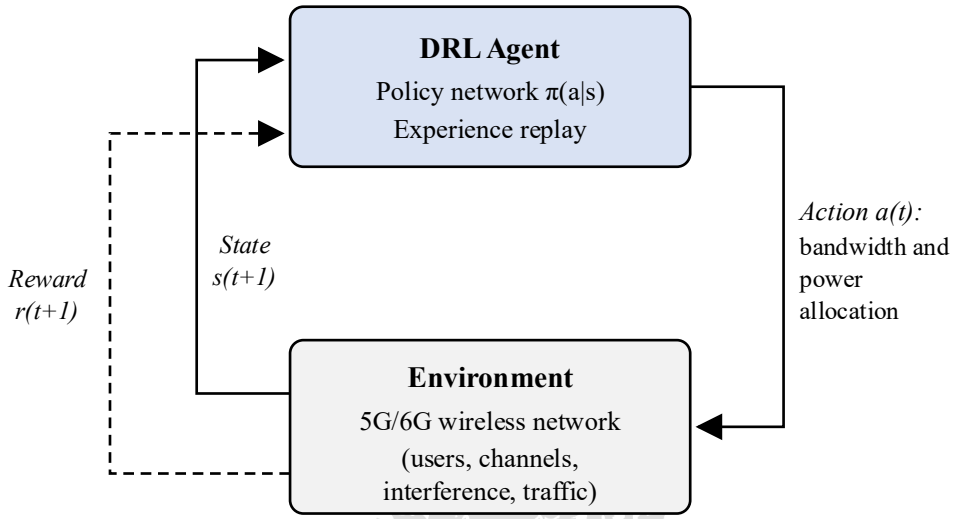


Fig 2 DRL agent–environment interaction and resource-allocation loop.

5. Input Parameters

The optimization engine observes the wireless environment through a set of measurable input parameters that together describe the state of the network at each decision interval. These parameters capture the radio resources available to the system (bandwidth and transmission power), the demand placed on it (traffic load, packet arrival rate and number of connected users), and the quality of the propagation environment (channel gain and SINR).

Each parameter is normalised during preprocessing so that variables measured on very different scales do not dominate the learning process. In the DRL formulation, a subset of these parameters forms the state vector observed by the agent, while bandwidth and transmission power also act as controllable decision variables. Table 1 summarises the input parameters, their symbols and units of measurement.

Table 1. Input parameters of the proposed framework.

Parameter	Symbol	Unit
Available bandwidth	B	Hz or MHz
Transmission power	P	W
Network traffic load	T	bps or Mbps
Signal-to-interference-plus-noise ratio	SINR	dB or linear
Number of connected users	N	Users
Channel gain	h	Linear
Packet arrival rate	λ	Packets/s

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6. Candidate AI and Optimization Techniques

A range of AI, ML and heuristic techniques can support different parts of the optimization pipeline. Supervised learning methods such as Random Forest, Support Vector Machine and Artificial Neural Networks are suited to prediction and classification tasks, for example forecasting traffic demand or identifying the current operating condition of the network. Reinforcement learning methods such as Q-Learning and DRL instead learn a control policy directly through interaction with the environment, which makes them suitable for sequential resource-allocation decisions.

Metaheuristic approaches such as the Genetic Algorithm do not learn a policy but search the solution space for near-optimal allocations, and therefore provide a useful benchmark against which learning-based methods can be compared. Table 2 lists the candidate techniques considered in this study and their potential applications within the framework.

Table 2. Candidate AI and optimization techniques and their potential applications.

Algorithm	Potential application
Random Forest	Predict network traffic or classify network conditions.
Artificial Neural Network	Predict throughput, latency, or energy consumption from network features.
Deep Reinforcement Learning	Adapt resource-allocation actions based on network state and reward feedback.
Support Vector Machine	Classify traffic or identify network operating conditions.
Genetic Algorithm	Provide a heuristic benchmark for multi-objective resource optimization.
Q-Learning	Learn discrete adaptive spectrum or resource-allocation policies.

Recommended experimental design: use DRL as the principal optimization method and compare it with a clearly defined conventional baseline and a genetic algorithm-based benchmark. Random Forest or an ANN may be added for prediction tasks, but the paper should distinguish prediction from control/optimization.

7. Mathematical Formulation

7.1 Achievable Data Rate

The Shannon capacity expression for an idealized link is:

$$R = B \log_2(1 + SINR)$$

where R is the achievable data rate in bits per second, B is the channel bandwidth in hertz, and SINR is the signal-to-interference-plus-noise ratio in linear scale. For a multi-user system, interference and resource-sharing effects must be modelled explicitly.

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7.2 Energy Efficiency

$$EE = R_total / P_total$$

where EE is energy efficiency in bits per joule, R_total is aggregate network throughput in bits per second, and P_total is the corresponding total power consumption in watts. The power model should state whether it includes only radio-frequency transmit power or also circuit, base-station, and computing power.

7.3 Average End-To-End Latency

$$L_avg = (1/N) \Sigma_{i=1}^{N} L_i$$

where L_i is the measured end-to-end delay of packet i and N is the number of packets included in the measurement window.

7.4 Multi-Objective Optimization

$$\text{Maximize } J = w_1(R/R_ref) + w_2(EE/EE_ref) - w_3(L/L_ref)$$

The weights w_1, w_2, and w_3 are non-negative and sum to one. R_ref, EE_ref, and L_ref are positive normalization constants. The weights should be selected and justified before testing, with sensitivity analysis used to examine how different priorities affect the result.

Possible constraints include:

$0 \le P_i \le P_max$, for each transmitting node i.

$\Sigma_i B_i \le B_total$, for the available system bandwidth.

$L_i \le L_max$, where a latency bound is required by the service class.

Minimum user-rate, power-budget, and fairness constraints should be included where relevant.

7.5 DRL Problem Formulation

To apply DRL, the resource-allocation problem is modelled as a Markov decision process (MDP) defined by the tuple (S, A, P, r, γ), where S is the state space, A is the action space, P describes the state-transition dynamics of the network, r is the reward function and $\gamma \in [0, 1)$ is the discount factor.

State: at each decision interval t, the agent observes a state vector $s_t = [T_t, \lambda_t, N_t, h_t, SINR_t, B_t, P_t]$, which combines the traffic load, packet arrival rate, number of connected users, channel conditions and the current bandwidth and power allocation.

Action: the action a_t specifies the bandwidth share and transmission-power level assigned to each user or node. Continuous allocations may be discretised into a finite set of levels when a value-based algorithm such as a deep Q-network is used, or treated as continuous when an actor–critic algorithm is adopted.

Reward: the reward is aligned with the multi-objective function in Section 7.4, so that $r_t = J_t - \rho \cdot C_t$, where J_t is the weighted objective at interval t, C_t measures the degree to which the power, bandwidth or latency constraints are violated, and $\rho \ge 0$ is a penalty coefficient.

The agent seeks a policy $\pi(a \mid s)$ that maximises the expected discounted return $E[\Sigma_t \gamma^t r_t]$. Training uses experience replay and a target network to stabilise learning [8], and the learned policy is evaluated on scenarios that were not used during training in order to assess generalisation.

8. Research Methodology

Topology definition, carrier frequency, bandwidth, number of users, mobility assumptions and traffic model definition. Discuss scenarios related to 5G and scenarios that are illustrative of 6G.

Generate/Acquire A Data Set: Make use of an existing simulator or available in public domain. Record the condition of the network, the steps taken and the results of the test. Recognize unambiguously manufactured data, where manufactured by simulation.

Data Preprocessing: Check and fill in missing values in data, normalize features, and split data by scenario or time (if applicable), avoiding data leakage.

Model Development: Create the DRL agent for a particular state space, action space, reward function and training algorithm. Define architecture and the hyperparameters of the neural network.

Base Implementation: Execute a standard resource allocation policy and a genetic algorithm benchmark in the same resource constraints and evaluation situations.

Testing And Validation: Test and validate the effectiveness of each of these methods over several tests, using low and medium traffic loads, as well as high traffic loads. Do not report best run, report mean values and variability.

Statistical Analysis: Analyze performance under various traffic intensities, channel conditions, number of users and reward-weight.Sensitivity analysis: Analyze performance as a function of traffic levels, channel conditions, number of users and reward-weight. Give intervals/suitable statistical comparisons.

Implementation Tools: The framework will be implemented in python, where the neural network and DRL part will be implemented using PyTorch and the environment where the agent interacts with the network will be Gymnasium compatible. Network-level behaviour will be simulated in ns-3 and physical layer and system-level modelling can be done in MATLAB with the 5G Toolbox. We will use NumPy, Pandas and Matplotlib to analyze and visualize data.

9. Performance Evaluation Metrics

A fair comparison between the proposed DRL approach and the baseline methods requires a common set of quantitative metrics, computed under identical network scenarios, traffic loads and resource constraints. The selected metrics reflect the multiple objectives of the framework: capacity is captured by throughput and spectral efficiency, responsiveness by end-to-end

latency, sustainability by energy efficiency, and reliability by the packet delivery and packet loss ratios.

Resource utilisation is also reported to indicate how effectively each method uses the available bandwidth and power budget. Each metric will be reported as a mean value together with a measure of variability across repeated simulation runs. Table 3 defines the performance evaluation metrics and the purpose of each.

Table 3. Performance evaluation metrics.

Metric	Purpose
Network throughput (Mbps or Gbps)	Measures successfully delivered data per unit time.
End-to-end latency (ms)	Measures packet delivery delay.
Energy efficiency (bits/J)	Measures delivered information per unit of energy.
Packet delivery ratio (%)	Measures the proportion of generated packets successfully received.
Packet loss ratio (%)	Measures the proportion of packets not successfully delivered.
Spectral efficiency (bits/s/Hz)	Measures throughput relative to allocated spectrum.
Resource utilization (%)	Measures the proportion of available resources being used.

10. Expected Outcomes

The framework will be expected to offer a clear approach for evaluating the impact of adaptive AI for resource allocation on balancing throughput, latency and energy efficiency. It may also be useful for ascertaining circumstances where DRL is more successful than fixed or heuristic allocation methods. These are research expectations, not findings and all numerical statements should be accompanied by numerical simulations/experiments.

Specifically, the study will assess the DRL agent's response to traffic intensity changes and channel quality changes relative to fixed allocation rules, and the influence of the choice of reward weights w_1, w_2 and w_3 on the trade-off between throughput, energy efficiency and latency. Sensitivity analysis is expected to help determine the regions where the advantages of adaptive allocation are greatest, and the regions where simpler policies yield similar results but at reduced computational cost.

There are some restrictions to be noted. The assessment is based on simulated environments and not all results can be transferred to real networks, where the measurement noise, the overhead caused by the signal and the limitation of the hardware may be more pronounced. Training DRL policies can be computationally costly and require tuning the hyperparameters and shaping the rewards a little carefully, and learned policies may break down if the network conditions vary significantly from the ones used during training. Furthermore, unlike a rule-based approach, decisions made by DRL are not as readily interpretable, which can be a challenge for network operators to adopt.

The framework will be extended to multi-agent and federated learning scenario for distributed base stations, integrate sensing and communications and frequencies relevant to 6G, and evaluate the approach with real network traces and/or testbed experiments in the future.

11. Conclusion

In this paper, the authors have presented an AI-based approach to optimize the allocation of resources and performance of 5G and future 6G wireless communication networks. The proposed solution is based on DRL to adapt the resource allocation decision based on the changing network states, and takes throughput, latency and energy efficiency as objective in the multi-objective formulation. Comparative simulation study is recommended with the conventional and heuristic baseline, where the effectiveness of the framework, robustness and computational cost are evaluated. Additional investigation has to be conducted to confirm the environment simulated, to perform as many experiments as possible and to get quantitative results to allow conclusions regarding the performance enhancement.

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