

Evolutionary–Neural Hybrids for Interference-Aware Channel Assignment in Ultra-Dense 6G Networks: A Survey, Taxonomy, and Research Roadmap

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Abstract:

Ultra-dense networks (UDNs) are a defining feature of 6G: thousands of small cells and devices share a limited spectrum, so co-channel interference rather than noise limits performance. Assigning channels to cells or users in such networks is a combinatorial, NP-hard problem whose search space grows exponentially with network size. Genetic algorithms (GAs) offer powerful global search, but they repeatedly evaluate an expensive interference-based fitness function and react slowly to changing traffic. Neural networks (NNs) offer millisecond-scale inference and can learn traffic and interference patterns, but they need large training sets and give no guarantee that constraints are satisfied. Combining the two is a natural but still fast-moving research direction. This survey (i) formalises the interference-aware channel assignment problem, (ii) proposes a taxonomy of five GA–NN hybridisation patterns (surrogate-assisted, predict-then-evolve, neuroevolution, GA-labelled or seeded NN, and NN-guided operators), (iii) reviews more than 40 works spanning classical and evolutionary channel/spectrum assignment, neural and graph-based channel allocation, deep reinforcement learning, and evolutionary-computation foundations, drawing its evidence base specifically from work published between 2015 and 2025 so that the survey reflects the current, AI-native direction of 6G research, and (iv) synthesises nine research gaps, a research problem statement, and a reference framework for future work. We conclude that scalable, constraint-aware, multi-objective hybrid GA–NN methods evaluated on common benchmarks remain largely open for 6G UDNs, even as the first dedicated GA–DRL hybrids for 6G spectrum sharing and resource allocation.

Keywords — channel assignment, dynamic spectrum access, genetic algorithm, neural network, graph neural network, surrogate-assisted optimisation, interference management, ultra-dense networks, 6G.

I. INTRODUCTION

Every generation of cellular systems has promised more capacity, and every generation has met the same physical limit: spectrum is scarce. 5G raised capacity through wider bandwidth, densification, and machine-type connectivity, but heterogeneous, ultra-dense deployments remain difficult to manage efficiently [1]. 6G is expected to push these trends further, with AI-native operation,

sub-THz and shared bands, and extreme densification [2], [3]. In an ultra-dense network the inter-site distance may be tens of metres, so a user typically hears several strong neighbouring cells on the same frequency [4]. Deciding which cell or user uses which channel therefore has a first-order effect on throughput, fairness, latency, and energy, and resource-allocation strategies for such networks have been surveyed extensively over the last five years [5], [6].

Channel and spectrum assignment remains an active research area. Dynamic, learning-based spectrum management continues to outperform static allocation under bursty 6G-scale traffic [7], and multi-objective spectrum allocation in heterogeneous, cognitive deployments is now formulated explicitly as a combinatorial optimisation problem whose complexity grows sharply with network size and channel count [8], [9]. Two families of methods have grown in parallel over the last decade. Evolutionary methods, especially genetic algorithms, explore the assignment space through populations of candidate solutions, and have recently been applied to interference-graph-based device-to-device allocation [11], fairness-aware mesh-network channel assignment [12], multi-objective wireless network design [13], cognitive-radio resource allocation under primary-user protection [14], and swarm-based 5G channel allocation [15]. Neural methods, from graph-convolutional and graph-neural-network channel allocators [16]–[20] to modern deep reinforcement learning [21]–[26] and learning-to-optimize networks [27]–[29], learn assignment behaviour from data or interaction, and increasingly exploit the interference (conflict) graph directly rather than treating cells as independent.

Each family has a complementary weakness. A GA needs thousands of fitness evaluations, and in a dense network every evaluation costs a full interference computation, so a GA is too slow to re-run for every traffic change. A NN answers almost instantly but must be trained, may fail to generalise to new topologies, and can output assignments that violate interference constraints. Hybrid GA–NN designs try to obtain the global search quality of the first and the speed and adaptivity of the second. Evidence from data-driven evolutionary computation shows that approximating expensive fitness functions with learned surrogate models can sharply reduce evaluation cost [34], [35], and that gradient-free evolutionary search can design or train neural networks directly [32], [33]. Strikingly, the years immediately before this update saw the first dedicated GA–deep-reinforcement-learning hybrids built specifically for 6G: a joint NSGA-II/PPO framework for spectrum sharing in cognitive 6G radio networks [36], a DNN–GA–DRL pipeline for resource allocation and reconfigurable-intelligent-surface deployment in 6G holographic communication [37], and a hybrid

reinforcement-learning/metaheuristic scheme for frequency resource management in 6G user-centric cell-free massive MIMO [38]. These very recent, narrowly-scoped systems confirm that the hybridisation this survey formalises is now an active research front rather than a purely theoretical proposal, but none of them yet targets general interference-aware channel assignment in ultra-dense 6G networks at scale — the gap this survey positions itself against.

II. BACKGROUND

A. Ultra-dense networks and interference

Densification reuses spectrum spatially: more cells per square kilometre means more capacity per hertz, until interference between nearby cells takes over. In a UDN, overlapping coverage, irregular deployment, mobility, and bursty traffic make static frequency planning ineffective, which is why assignment must be dynamic and interference-aware [4], [5]. The same problem appears in cell-free, radio-stripe, and cognitive-radio deployments, where distributed access points or secondary users must also protect other users' quality of service [6], [8]. Fig. 2 illustrates the idea: adjacent cells that share a channel interfere, and a good assignment is a colouring of the interference (conflict) graph.

B. Problem Formulation

Consider a wireless network consisting of NN cells or access points and KK orthogonal channels. The channel assignment problem aims to allocate available channels to different cells while maximizing the overall network throughput and maintaining acceptable communication quality. A binary assignment variable is used to indicate whether a particular channel is allocated to a particular cell.

The performance of each assigned channel is primarily determined by the Signal-to-Interference-plus-Noise Ratio (SINR). The SINR depends on the received signal power, interference generated by neighboring cells using the same channel, and the background noise. Based on the obtained SINR, the achievable data rate of each cell can be calculated using the Shannon capacity relationship. The overall objective is therefore to maximize the network sum rate while ensuring adequate communication quality.

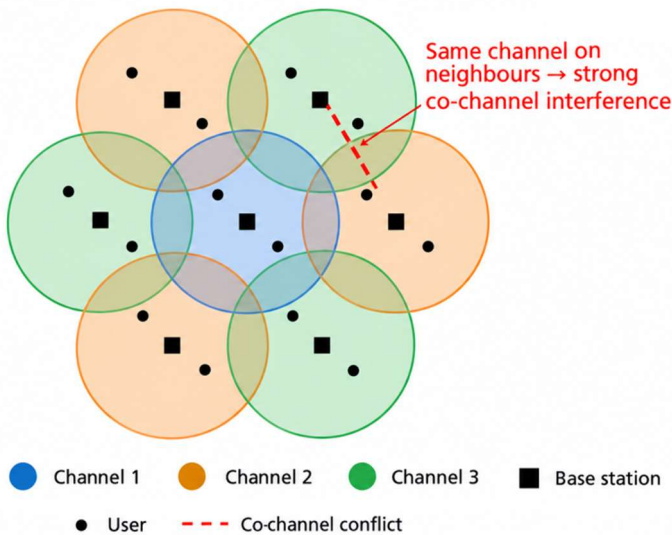
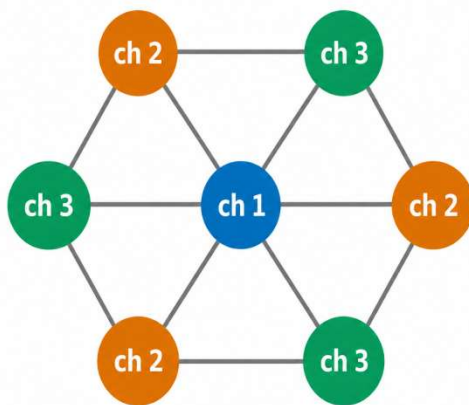
(a) Overlapping cells in a dense deployment**(b) Conflict graph with a valid 3-channel colouring**

Fig. 1. (a) Seven overlapping cells (b) The corresponding conflict graph, where each edge is a strong interference link, with a valid three-channel colouring.

The channel allocation is subject to several important constraints. First, every cell must receive its required number of channels. Second, the SINR of an active channel should remain above a predefined minimum threshold. Third, cells having a conflict relationship should not use the same channel simultaneously, as this may produce excessive co-channel interference. In cognitive-radio-based networks, an additional primary-user protection constraint is imposed to ensure that the interference generated toward licensed or primary users remains below the permissible interference threshold.

The channel assignment problem becomes computationally difficult as the number of cells and channels increases. When each cell requires one channel, the number of possible assignments grows exponentially as K^N . For example, with 100 cells

and 20 channels, the search space becomes extremely large, making exhaustive search impractical for real-time or large-scale networks.

To address this complexity, a Genetic Algorithm (GA) can be employed as a heuristic optimization technique. In the GA, each possible channel assignment is represented as a chromosome, where each chromosome contains the channel selected for every cell. An initial population of feasible or partially feasible channel assignments is generated and evaluated according to a fitness function.

The fitness function primarily considers the achievable network sum rate and incorporates penalties for violations of SINR, channel-conflict, and primary-user interference constraints. Chromosomes having higher throughput and fewer constraint violations receive better fitness values. Through the iterative processes of selection, crossover, and mutation, the GA generates new channel assignments and progressively searches for improved solutions.

In addition to throughput, fairness among cells can be considered during optimization. Jain's fairness index is commonly used to determine whether network resources are distributed uniformly among the cells. A higher fairness value indicates a more balanced distribution of achievable rates.

However, a major limitation of the conventional GA is its computational cost. For every chromosome, interference from multiple cells must be evaluated, resulting in approximately N^2 computational complexity for a single fitness evaluation.

C. Genetic Algorithm

A GA [30] maintains a population of chromosomes and improves it over generations through selection (fitter chromosomes are more likely to reproduce), crossover (recombining two parents), and mutation (random reassignment of a channel). For channel assignment, integer encodings, problem-specific crossover, and repair operators that remove conflicts are common [11], [12]. Multi-objective variants such as the genetic-algorithm-based MOONGA framework return a Pareto front of throughput, fairness, and energy trade-offs [13]. Strengths include global search, handling of discrete and non-differentiable objectives, and easy constraint penalties; other met heuristics such as particle swarm and ant-colony optimisation offer similar trade-offs and are

commonly used as GA baselines [15], [31]. Weaknesses include the number of fitness evaluations needed, sensitivity to parameters, and slow re-optimisation when conditions change.

D. Neural Networks

Neural networks used in this field fall into four groups: (i) graph-neural-network and graph-convolutional channel allocators that encode the interference (conflict) graph directly and generalise across topologies [16]–[20]; (ii) feed-forward or recurrent networks that predict traffic, occupancy, or channel quality ahead of an allocation decision; (iii) deep reinforcement learning agents that learn a channel-selection or power-control policy from interaction [21]–[26]; and (iv) networks trained to imitate or approximate an optimisation algorithm, known as learning-to-optimize [27]–[29]. Broader surveys of deep learning for wireless networks are given in [39]–[41]. This update deliberately favours these graph-based and learning-to-optimize formulations over the constraint-satisfaction neural networks of the 1990s, because they are the neural methods that dominate the 2015–2025 literature on channel and resource allocation. Strengths are fast inference and the ability to learn hidden, topology-dependent patterns; weaknesses are data and training cost, limited generalisation across unseen densities, and the absence of built-in constraint guarantees.

III. LITERATURE SURVEY

A. Stream A: evolutionary and met heuristic channel

TABLE 2. EVOLUTIONARY AND SWARM-BASED CHANNEL/SPECTRUM ASSIGNMENT,

Ref.	Year	Technique	Main contribution	Limitation
[11] Zhang et al.	2015	Interference-graph GA/heuristic (InGRA)	Interference-graph-based resource allocation for D2D communication underlying cellular networks	Heuristic repair; no learning component
[14] Robbi et al.	2019	Modified GA	GA-based resource allocation in cognitive radio networks that explicitly protects primary users	Single-cell scenarios; static primary-user traffic
[8] Dong et al.	2019	Improved NSGA-II	Multi-objective spectrum allocation for cognitive heterogeneous wireless networks	Small-scale simulated networks

[13] Bouzid et al.	2020	MOONGA (multi-objective GA)	Pareto-based multi-objective GA for wireless network resource allocation, IEEE Access	Convergence time grows with network size
[12] Ghaleb et al.	2021	Semichaotic GA	Fairness-oriented GA-based channel assignment that targets the node-starvation problem in wireless mesh networks	Mesh-network specific; interference model simplified
[15] Hussein et al.	2024	Ant colony optimisation	Swarm-based channel allocation for 5G networks as an alternative to GA	Metaheuristic only; no learned component

B. Stream B: neural and graph-based channel assignment

TABLE 3. NEURAL AND GRAPH-NEURAL-NETWORK APPROACHES TO CHANNEL AND LINK ASSIGNMENT,

Ref.	Year	Technique	Main contribution	Limitation
[43] He et al.	2021	GNN-based beam/link selection (GBLinks)	Beam selection and link activation for ultra-dense D2D mmWave networks using a graph neural network	mmWave-specific; large action space at high density
[17] Nakashima et al.	2020	DRL + graph convolutional network	Deep-RL-based channel allocation for wireless LANs that uses a GCN to represent interference	WLAN contention model; centralized training
[9] Ghaderibaneh et al.	2022	CNN-based allocator (DeepAlloc)	Convolutional-network approach to efficient spectrum allocation in shared spectrum systems	Needs simulator-generated training data
[19] Gao et al.	2022	Decentralised GNN	Decentralised channel management in WLANs using graph neural networks	Partial observability limits optimality
[10] Chen, Zhu & Evans	2024	Supervised GNN	GNN-based joint channel and power allocation in heterogeneous wireless networks	Requires retraining for large topology shifts
[18] Zhao et al.	2023	GNN link scheduling	Graph-neural-network approach to distributed link scheduling under interference constraints	Scalability to hundreds of links still being characterised
[16] Alhazmi & Arafah	2025	SDN + adaptive NN (NN-ARA)	Neural-network-based adaptive resource allocation for 5G/6G heterogeneous ultra-dense networks	Trained on simulation data; real deployment validation

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C. Stream C: deep-reinforcement-learning spectrum access and interference management

TABLE 4. DEEP-REINFORCEMENT-LEARNING DYNAMIC SPECTRUM ACCESS AND INTERFERENCE MANAGEMENT,

Ref.	Year	Technique	Main contribution	Limitation
[21] Mnih et al.	2015	Deep Q-network	Established human-level control through deep reinforcement learning, the basis for later DQN-based spectrum agents	Not wireless-specific; single-agent Atari benchmark
[22] Wang et al.	2018	DQN	Deep reinforcement learning for dynamic multichannel access with unknown channel dynamics	Single-user or small-scale setting
[27] Sun et al.	2018	Supervised deep NN (learning-to-optimize)	Trained a NN to imitate an optimisation algorithm for interference management at far lower online cost	Needs many labelled instances; fixed-size inputs
[23] Naparstek & Cohen	2019	Multi-user deep RL	Distributed dynamic spectrum access with each user acting as a learning agent	Training cost; scaling and safety in dense networks
[24] Nasir & Guo	2019	Multi-agent deep RL	Distributed dynamic power allocation in wireless networks	Power rather than channel assignment; stability
[25] Liang et al.	2019	Multi-agent RL	Spectrum sharing in vehicular networks via multi-agent reinforcement learning	Vehicular-specific; no explicit constraint guarantees
[26] Ye et al.	2019	Deep RL	Decentralised resource allocation for V2V communication	Domain-specific; training complexity
[7] Song et al.	2021	Deep RL framework	Spectrum management framework for dynamic spectrum access under IoT-scale traffic	Framework-level; large state space in dense deployments
[28] Shen et al.	2020	Learning-to-optimize (LORM)	Learned resource-management policies with few training samples	Assumes structure that may not hold for discrete channel assignment

[29] Chowdhury et al.	2021	Unfolded WMMSE + GNN	Unfolds the classical WMMSE algorithm using graph neural networks for efficient power allocation	Power allocation focus; extension to discrete assignment open
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D. Stream D: foundations for GA–NN hybridisation

TABLE 5. EVOLUTIONARY–NEURAL AND SURROGATE-ASSISTED FOUNDATIONS,

Ref.	Year	Technique	Main contribution	Relevance
[30] Alhijawi & Awajan	2024	Genetic algorithms (review)	Comprehensive review of GA theory, genetic operators, and applications	Basis of the GA engine
[31] Sadeeq & Abdulazeez	2023	Metaheuristic s (review)	Reviewed GA, PSO, and related metaheuristic algorithms	Common baselines
[32] Stanley et al.	2019	Neuroevolution	Showed how evolution can design both the topology and weights of neural networks	Pattern P3; compact policy networks
[33] Such et al.	2017	Deep neuroevolution	Showed that a simple GA can train large deep networks on RL tasks	Gradient-free training of channel-selection policies (P3)
[34] Jin et al.	2019	Data-driven evolutionary optimisation	Reviewed data-driven and surrogate-assisted evolutionary computation	Pattern P1
[35] Jin, Wang & Sun	2021	Data-driven evolutionary optimisation	Integrates evolutionary computation, machine learning, and surrogate model management	Pattern P1: when to trust the surrogate
[13] Bouzid et al.	2020	MOONGA	Multi-objective GA returning Pareto fronts for wireless network design	Throughput–fairness–energy trade-offs

E. Comparative analysis of paradigms

TABLE 7. QUALITATIVE COMPARISON OF PARADIGMS

Criterion	Classical / greedy	GA / PSO / ACO	NN (supervised / GNN)	Deep RL	Hybrid GA–NN (target)
Global search quality	Low	High	Medium	Medium	High
Online decision time	Very low	High	Very low	Very low	Low to medium

Adaptation to changing traffic	Low	Low (re-run needed)	Medium (retrain)	High	High (warm start, prediction)
Training data / time	None	None	High	Very high	Medium
Hard-constraint handling	Good	Good (penalty / repair)	Weak (improving with GNNs)	Weak	Good (GA repair)
Scalability to UDN	Good	Poor ($O(P \cdot G \cdot N^2)$)	Medium-good (graph-based)	Medium	Open question

IV. RESEARCH GAPS AND PROBLEM STATEMENT

Studies typically use 7–19 hexagonal cells or random deployments with 50–500 users and 10–30 channels, log-distance path loss with shadowing and Rayleigh or Rician fading, Poisson or bursty traffic, and Markov ON/OFF primary-user or holographic-traffic activity. Common tools are MATLAB and Python (NumPy, PyTorch, TensorFlow, with evolutionary libraries such as DEAP, PyGAD, and pymoo, and graph libraries such as PyTorch Geometric or DGL), and ns-3 for network-level realism. Ray-tracing datasets such as DeepMIMO [42] can supply more realistic channel gains than statistical models, and 3GPP-compliant channel simulators such as QuaDRiGa are increasingly used for 6G cell-free and vehicular scenarios [38].

Baselines. Random and fixed allocation, greedy and graph-colouring heuristics [11], simulated annealing, standard GA [12], [13], swarm metaheuristics such as PSO and ant-colony optimisation [15], [31], WMMSE-type and unfolded-WMMSE optimisation [29], supervised or graph-based NN [16], [17], and deep RL [23], [24].

Fig. 3 shows a reference architecture that combines patterns P1, P2, P4, and P5 in a single loop. A neural predictor turns network state into a forecast. The GA engine is warm-started with NN-seeded chromosomes, scores most candidates with a surrogate NN, applies NN-adapted operator rates, repairs constraint violations, and periodically checks elite solutions against the exact SINR evaluator, which also supplies new training data.

Measured network KPIs close the loop

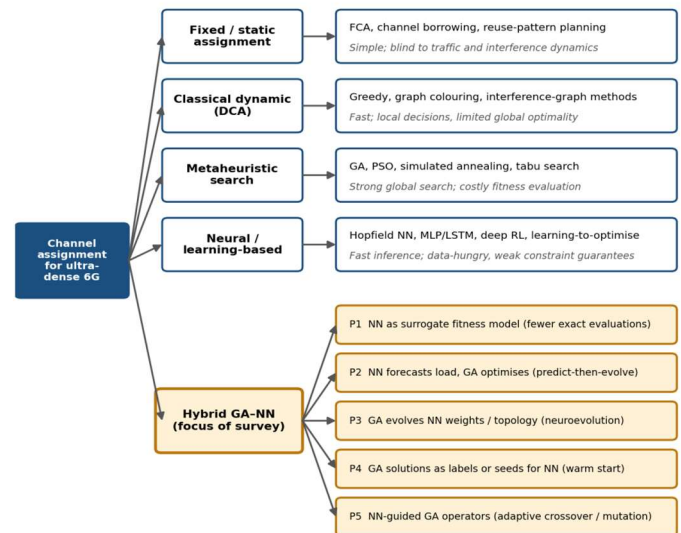


Fig. 3. Taxonomy of channel assignment approaches for ultra-dense 6G networks. The highlighted branch shows the five GA–NN hybridisation patterns (P1–P5) examined in this survey.

Given a dense network of N cells sharing K channels under time-varying traffic, mobility, and channel conditions, design a hybrid genetic-algorithm–neural-network framework that assigns channels to maximise a weighted combination of sum rate and fairness while satisfying SINR, conflict, and primary-user protection constraints, such that (i) the number of exact fitness evaluations and the decision latency are substantially lower than for a standalone GA, (ii) solution quality remains close to or better than standalone GA, swarm-metaheuristic, and deep-RL baselines, and (iii) performance is sustained as the network scales and changes.

- Graph neural networks as size-independent surrogates and predictors, matching the conflict-graph structure of UDNs [16]–[20].
- Digital twins of the radio access network to generate surrogate training data safely and cheaply.
- Federated and distributed hybrids that keep local data at the base station while sharing model updates.
- Multi-objective and green design that includes the energy cost of the learning components themselves.
- Uncertainty-aware surrogates that report confidence so the GA knows when to fall back on exact evaluation.
- Coexistence and sharing scenarios such as NR-U with Wi-Fi, mmWave/sub-THz bands, cell-free massive MIMO, and UAV or non-

terrestrial cells, extending the early 2025 hybrid systems [36]–[38] toward general, scalable channel assignment.

V. CONCLUSIONS

Interference-aware channel assignment is central to the promise of ultra-dense 6G networks, and it is hard: the search space is astronomically large, interference couples every decision to its neighbours, and conditions change constantly. Genetic algorithms give strong global search at a high evaluation cost; neural networks — increasingly graph-based — give speed and adaptivity but still-imperfect guarantees. This survey organised the many ways of combining the two into five patterns (surrogate-assisted, predict-then-evolve, neuroevolution, GA-labelled or seeded NN, and NN-guided operators), reviewed literature from 2015 to 2025 that supports each pattern, and identified nine research gaps. The literature base for this update was deliberately restricted to the last decade, which surfaced a striking trend: the first dedicated GA–deep-RL hybrids for 6G resource and spectrum problems [36]–[38], confirming that this survey's taxonomy anticipates, rather than merely follows, where the field is heading. The most promising direction remains a constraint-aware, scalable hybrid in which neural components handle the frequent, cheap work while the GA handles global search, repair, and verification, evaluated on shared benchmarks against strong baselines. We hope the taxonomy, tables, and reference framework help researchers position and evaluate future work in this area.

REFERENCES

- [1] S. K. Sharma and X. Wang, "Toward massive machine type communications in ultra-dense cellular IoT networks: Current issues and machine learning-assisted solutions," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 1, pp. 426–471, 2020.
- [2] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," *IEEE Network*, vol. 34, no. 3, pp. 134–142, 2020.
- [3] Z. Zhang et al., "6G wireless networks: Vision, requirements, architecture, and key technologies," *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 28–41, 2019.
- [4] M. Kamel, W. Hamouda, and A. Youssef, "Ultra-dense networks: A survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2522–2545, 2016.
- [5] 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, art. 101415, 2021.
- [6] F. Conceição, M. Gomes, V. Silva, and R. Dinis, "Survey on resource allocation for future 6G network architectures: Cell-free and radio stripe technologies," *Electronics*, vol. 13, no. 13, art. 2489, 2024.
- [7] H. Song, L. Liu, J. Ashdown, and Y. Yi, "A deep reinforcement learning framework for spectrum management in dynamic spectrum access," *IEEE Internet of Things Journal*, vol. 8, no. 14, pp. 11208–11218, 2021.
- [8] X. Dong, L. Cheng, G. Zheng, and T. Wang, "Multi-objective optimization method for spectrum allocation in cognitive heterogeneous wireless networks," *AIP Advances*, vol. 9, no. 4, art. 045130, 2019.
- [9] M. Ghaderibaneh, C. Zhou, P. Ranaweera, and H. Gupta, "DeepAlloc: CNN-based approach to efficient spectrum allocation in shared spectrum systems," *arXiv:2201.07762*, 2022.
- [10] L. Chen, J. Zhu, and J. Evans, "GNN-based joint channel and power allocation in heterogeneous wireless networks," in *Proc. IEEE Int. Conf. on Communications Workshops (ICC Workshops)*, 2024, pp. 233–238.
- [11] R. Zhang, X. Cheng, L. Yang, and B. Jiao, "Interference graph-based resource allocation (InGRA) for D2D communications underlying cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 8, pp. 3844–3850, 2015.
- [12] F. A. Ghaleb, B. A. S. Al-Rimy, W. Boulila, F. Saeed, M. Kamat, M. F. Rohani, and S. A. Razak, "Fairness-oriented semichaotic genetic algorithm-based channel assignment technique for node starvation problem in wireless mesh networks," *Computational Intelligence and Neuroscience*, vol. 2021, art. 2977954, 2021.
- [13] S. E. Bouzid, Y. Seresstou, K. Raoof, M. N. Omri, M. Mbarki, and C. Dridi, "MOONGA: Multi-objective optimization of wireless network approach based on genetic algorithm," *IEEE Access*, vol. 8, pp. 105793–105814, 2020.
- [14] N. M. H. Robbi, I. W. Mustika, and Widyawan, "A modified genetic algorithm for resource allocation in cognitive radio networks in the presence of primary users," in *Proc. Int. Seminar on Intelligent Technology and Its Applications (ISITIA)*, 2019, pp. 19–23.
- [15] A. Hussein, M. Anbar, M. Molhem, A. Y. Oudeh, M. Nassr, and H. Fardoun, "Channel allocation in 5G networks using ant colony optimization algorithm," in *Proc. 6th Int. Youth Conf. on Radio Electronics, Electrical and Power Engineering (REEPE)*, 2024, pp. 1–5.
- [16] A. S. Alhazmi and M. A. Arafah, "Neural network-based adaptive resource allocation for 5G heterogeneous ultra-dense networks," *Sensors*, vol. 25, no. 24, art. 7521, 2025.
- [17] K. Nakashima, S. Kamiya, K. Ohtsu, K. Yamamoto, T. Nishio, and M. Morikura, "Deep reinforcement learning-based channel allocation for wireless LANs with graph convolutional networks," *IEEE Access*, vol. 8, pp. 31823–31834, 2020.
- [18] Z. Zhao, G. Verma, C. Rao, A. Swami, and S. Segarra, "Link scheduling using graph neural networks," *IEEE Transactions on Wireless Communications*, vol. 22, no. 6, pp. 3997–4012, 2023.
- [19] Z. Gao, Y. Shao, D. Gündüz, and A. Prorok, "Decentralized channel management in WLANs with graph neural networks," *arXiv:2210.16949*, 2022.
- [20] S. He, S. Xiong, Y. Ou, J. Ren, and Y. Huang, "An overview on the application of graph neural networks in wireless networks," *IEEE Open Journal of the Communications Society*, vol. 2, pp. 2547–2565, 2021.
- [21] V. Mnih et al., "Human-level control through deep reinforcement learning," *Nature*, vol. 518, pp. 529–533, 2015.
- [22] S. Wang, H. Liu, P. H. Gomes, and B. Krishnamachari, "Deep reinforcement learning for dynamic multichannel access in wireless networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 4, no. 2, pp. 257–265, 2018.
- [23] O. Naparstek and K. Cohen, "Deep multi-user reinforcement learning for distributed dynamic spectrum access," *IEEE Transactions on Wireless Communications*, vol. 18, no. 1, pp. 310–323, 2019.
- [24] Y. S. Nasir and D. Guo, "Multi-agent deep reinforcement learning for dynamic power allocation in wireless networks," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 10, pp. 2239–2250, 2019.
- [25] L. Liang, H. Ye, and G. Y. Li, "Spectrum sharing in vehicular networks based on multi-agent reinforcement learning," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 10, pp. 2282–2292, 2019.
- [26] H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep reinforcement learning based resource allocation for V2V communications," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3163–3173, 2019.
- [27] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Transactions on Signal Processing*, vol. 66, no. 20, pp. 5438–5453, 2018.
- [28] Y. Shen, Y. Shi, J. Zhang, and K. B. Letaief, "LORM: Learning to optimize for resource management in wireless networks with few training samples," *IEEE Transactions on Wireless Communications*, vol. 19, no. 1, pp. 665–679, 2020.

- [29] A. Chowdhury, G. Verma, C. Rao, A. Swami, and S. Segarra, "Unfolding WMMSE using graph neural networks for efficient power allocation," *IEEE Transactions on Wireless Communications*, vol. 20, no. 9, pp. 6004–6017, 2021.
- [30] B. Alhijawi and A. Awajan, "Genetic algorithms: Theory, genetic operators, solutions, and applications," *Evolutionary Intelligence*, vol. 17, pp. 1245–1256, 2024.
- [31] H. T. Sadeeq and A. M. Abdulazeez, "Metaheuristics: A review of algorithms," *International Journal of Online and Biomedical Engineering*, vol. 19, no. 9, pp. 4–28, 2023.
- [32] K. O. Stanley, J. Clune, J. Lehman, and R. Miikkulainen, "Designing neural networks through neuroevolution," *Nature Machine Intelligence*, vol. 1, pp. 24–35, 2019.
- [33] F. P. Such, V. Madhavan, E. Conti, J. Lehman, K. O. Stanley, and J. Clune, "Deep neuroevolution: Genetic algorithms are a competitive alternative for training deep neural networks for reinforcement learning," *arXiv:1712.06567*, 2017.
- [34] Y. Jin, H. Wang, T. Chugh, D. Guo, and K. Miettinen, "Data-driven evolutionary optimization: An overview and case studies," *IEEE Transactions on Evolutionary Computation*, vol. 23, no. 3, pp. 442–458, 2019.
- [35] Y. Jin, H. Wang, and C. Sun, *Data-Driven Evolutionary Optimization: Integrating Evolutionary Computation, Machine Learning and Data Science*. Cham, Switzerland: Springer, 2021.
- [36] A. W. Chigaba, S. M. Nleya, M. Velepini, and S. S. Dube, "A multi-objective genetic algorithm–deep reinforcement learning framework for spectrum sharing in 6G cognitive radio networks," *Applied Sciences*, vol. 15, no. 17, art. 9758, 2025.
- [37] B. Jibia, R. Mbondjo Essomba, S. Nyatte, J. Matanga, J.-F. Essiben, and S. Nguia, "A hybrid deep reinforcement learning and genetic algorithm approach for optimized resource allocation and reconfigurable intelligent surface deployment in 6G holographic communication," *International Journal of Intelligent Networks*, vol. 6, pp. 265–282, 2025.
- [38] S. Cheggour and V. Loscri, "Frequency resource management in 6G user-centric CFmMIMO: A hybrid reinforcement learning and metaheuristic approach," *arXiv:2505.22443*, 2025.
- [39] Q. Mao, F. Hu, and Q. Hao, "Deep learning for intelligent wireless networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 4, pp. 2595–2621, 2018.
- [40] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3039–3071, 2019.
- [41] N. C. Luong et al., "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3133–3174, 2019.
- [42] A. Alkhateeb, "DeepMIMO: A generic deep learning dataset for millimeter wave and massive MIMO applications," in *Proc. Information Theory and Applications Workshop (ITA)*, 2019.
- [43] S. He, S. Xiong, W. Zhang, Y. Yang, J. Ren, and Y. Huang, "GBLinks: GNN-based beam selection and link activation for ultra-dense D2D mmWave networks," *arXiv:2107.02412*, 2021.
- [44] C. Niu, Y. Li, R. Q. Hu, and F. Ye, "Fast and efficient radio resource allocation in dynamic ultra-dense heterogeneous networks," *IEEE Access*, vol. 5, pp. 1911–1924, 2017.