Innovative Approaches using Generative Artificial Intelligence (GAI) with Diffusion Models, GANs, and Optimization of Spectrum, Power, Routing, and Network Scheduling in Wireless Networks

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Abstract

Future wireless networks such as 5G and upcoming 6G require highly efficient resource management to handle massive devices, high data rates, and low-latency applications. Traditional optimization techniques struggle due to complex traffic patterns and unpredictable wireless environments. This paper explores innovative approaches that use Generative Artificial Intelligence (GAI) — including diffusion models, GANs, and transformers — to optimise spectrum, power, routing, and network scheduling.

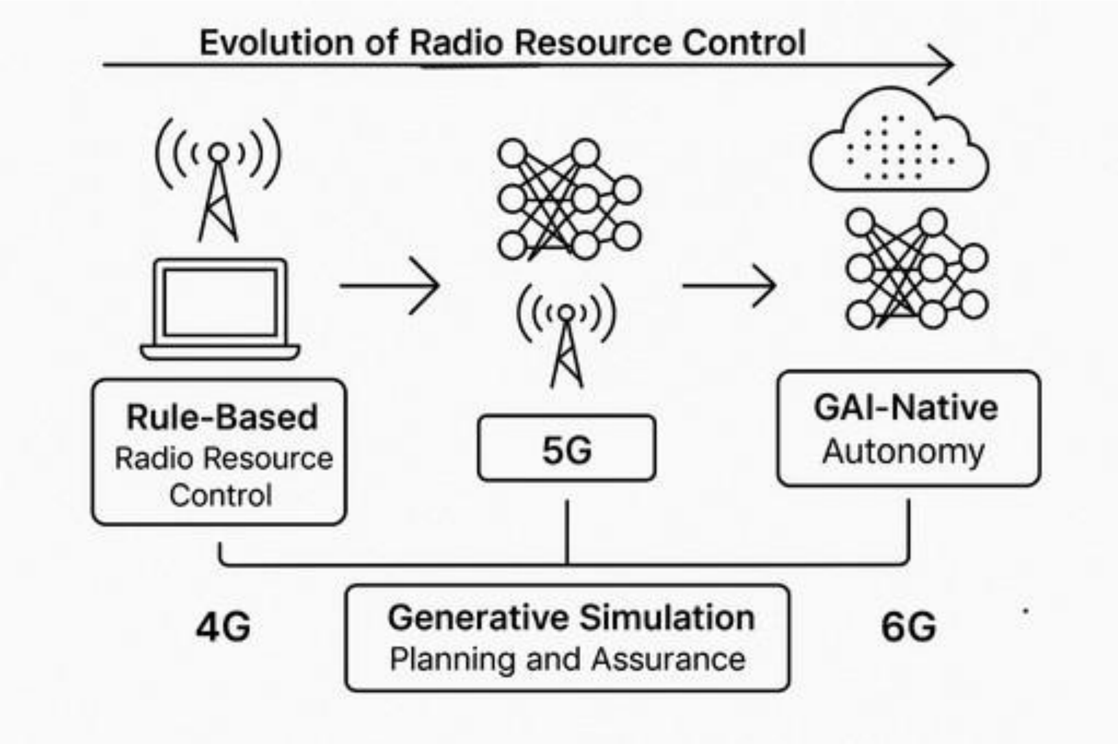
Generative AI can simulate real network scenarios, create synthetic datasets, design optimal configurations, and support autonomous decision-making. The study highlights how GAI significantly reduces optimisation time, improves network reliability, and lays the foundation for intelligent, self- adaptive wireless systems.

Keywords: 6G, generative AI, diffusion models, GANs, VAEs, digital twin, resource allocation, routing, spectrum, ISCC, edge intelligence, intent-driven networking.

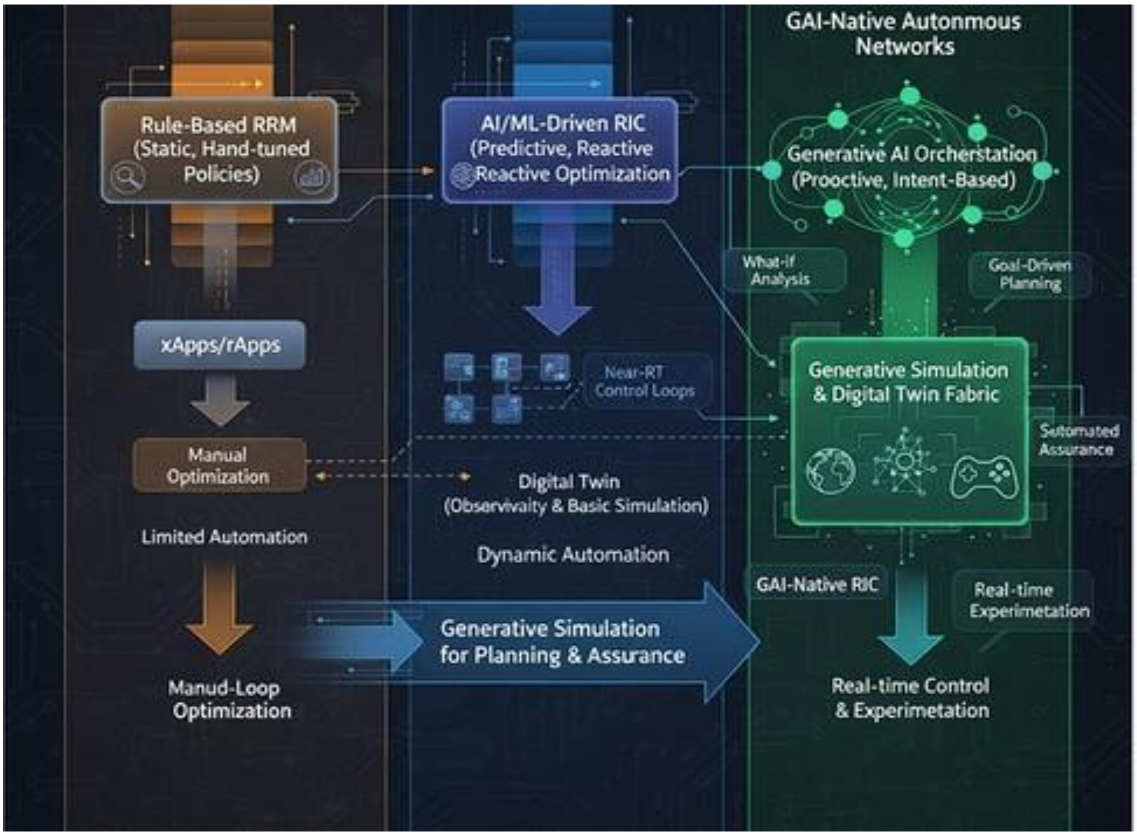
1. Introduction

Wireless networks are rapidly expanding due to high-speed communication demands, IoT devices, autonomous systems, cloud gaming, and real-time applications. Managing network resources like spectrum, power, and bandwidth has become extremely challenging. Traditional algorithms rely on fixed rules or large labelled datasets, making them inefficient during sudden changes in network behaviour.

Generative AI models are emerging as powerful tools because they can learn network patterns, generate realistic conditions, and suggest optimal resource allocations before actual deployment. These capabilities make GAI highly suitable for future networks, especially 6G, which will require autonomous, intelligent decision-making.



shows the conceptual evolution from rule-based radio resource control to GAI-native autonomy across 4G→5G→6G, highlighting the role of generative simulation for planning and assurance.



Conceptual evolution from rule-based optimization to GAI-native autonomy across generations; digital twins enable safe offline validation.

2. Role of Generative AI in Wireless Networks

Generative AI can understand the underlying distribution of wireless data and create new scenarios that help networks prepare for complex situations. Key advantages include:

•Data generation for rare network failures

•Predicting spectrum demand

•Fast optimisation without heavy online training

•Intelligent planning through virtual simulations

•Reduced operational cost and improved QoS

These features help in achieving high reliability and low latency.

3. Applications in Resource Optimization

Generative AI offers powerful capabilities for transforming how wireless networks manage limited resources such as spectrum, power, bandwidth, and routing paths. By learning the behaviour of users, channels, and interference patterns, GAI can create predictive and adaptive optimisation strategies that operate more efficiently than traditional algorithms. These applications are especially important for future 6G networks, where extremely dense device connectivity and ultra-low latency requirements will demand intelligent and autonomous resource allocation.

3.1 Spectrum Allocation

One of the most critical resources in wireless communication is the radio spectrum, which is limited and often congested. Generative AI models can analyse historical data on spectrum usage, interference levels, and user mobility to create synthetic spectrum maps that represent future network conditions.

These models can then generate optimal channel assignment strategies that reduce interference, avoid congestion, and improve overall throughput. Diffusion models and GANs are particularly effective because they can simulate complex spectrum environments that are difficult to collect in real life. With these predictions, base stations can proactively switch frequencies or reassign channels before performance degrades.

3.2 Power Optimization

Power control plays a major role in maintaining signal quality and reducing energy consumption in wireless networks. GAI models can observe network load, device positions, mobility speed, and channel quality to generate power control recommendations. These generative models can simulate multiple power adjustment scenarios and select configurations that minimize energy usage while maintaining strong connectivity. This approach benefits both network operators—through reduced energy costs—and end-users, whose device battery life is extended. In large-scale IoT environments, GAI-driven power optimisation significantly improves network lifespan and reliability.

3.3 Scheduling and Load Balancing

Efficient scheduling ensures that network resources such as time slots and bandwidth are distributed fairly and effectively among users. Generative transformers can study past traffic patterns, identify peak usage periods, and forecast future user demand. Using these predictions, the model generates optimized scheduling policies that allocate resources dynamically. This helps avoid congestion during heavy-traffic hours and ensures fairness among users. In multi-cell networks, GAI can balance the load across neighbouring base stations, preventing overload in one area while others remain underutilised. This greatly enhances Quality of Service (QoS) and reduces latency.

3.4 Routing and Topology Management

Wireless networks often face challenges such as node failures, high mobility, and unpredictable traffic surges. GAI models can simulate various network conditions—such as sudden demand spikes, broken links, or blocked paths—and generate routing strategies that adapt in real time. These models are capable of designing new topologies for advanced systems like drone-assisted networks, satellite links, and 6G non-terrestrial networks. By predicting node movements and traffic flows, GAI helps find stable, low-latency routes that improve reliability. This proactive approach ensures continuous connectivity even in dynamic or harsh environments.

Overall Impact

By applying generative learning techniques, wireless networks can operate more intelligently, avoid unnecessary delays, and use scarce resources efficiently. GAI enables networks to anticipate problems before they occur and generate solutions that optimize performance, energy usage, and user experience.

4. Working Principle of Generative AI Models

Generative AI models operate by learning the underlying patterns, distributions, and behaviours present in wireless network data. Once these patterns are learned, the models are capable of generating new, realistic samples that resemble real network conditions. This generative ability allows them to predict channel quality, estimate traffic behaviour, and propose optimized network configurations. Each category of generative model follows a different working mechanism, enabling diverse applications in resource optimization.

4.1 GANs (Generative Adversarial Networks)

GANs work through a competitive learning process between two neural networks: the Generator and the Discriminator.

- The Generator creates synthetic data such as channel maps or interference patterns.
- The Discriminator evaluates whether the generated data is real or fake.

Through continuous competition, both networks improve. The Generator becomes skilled at producing realistic wireless scenarios that can be used for training optimisation algorithms. This helps networks learn from environments that may be difficult to capture in real-world conditions, such as rare failures or extreme interference cases.

4.2 VAEs (Variational Autoencoders)

VAEs function by compressing high-dimensional wireless data into a smaller latent space.

- The Encoder extracts the important features of the input data and converts them into a compact form.
- The Decoder reconstructs data samples from this compressed representation.

This compressed structure allows the model to generate controlled, stable outputs. In wireless networks, VAEs are used to generate channel states, mobility patterns, or power control strategies that are smooth and consistent. They are especially useful for applications requiring predictable and controllable generation.

4.3 Diffusion Models

Diffusion models work by gradually adding noise to real data until it becomes fully random, and then learning how to reverse this noise step-by-step.

- During training, the model observes how clean wireless data becomes noisy.
- During generation, it learns to remove noise gradually to create high-quality synthetic data.

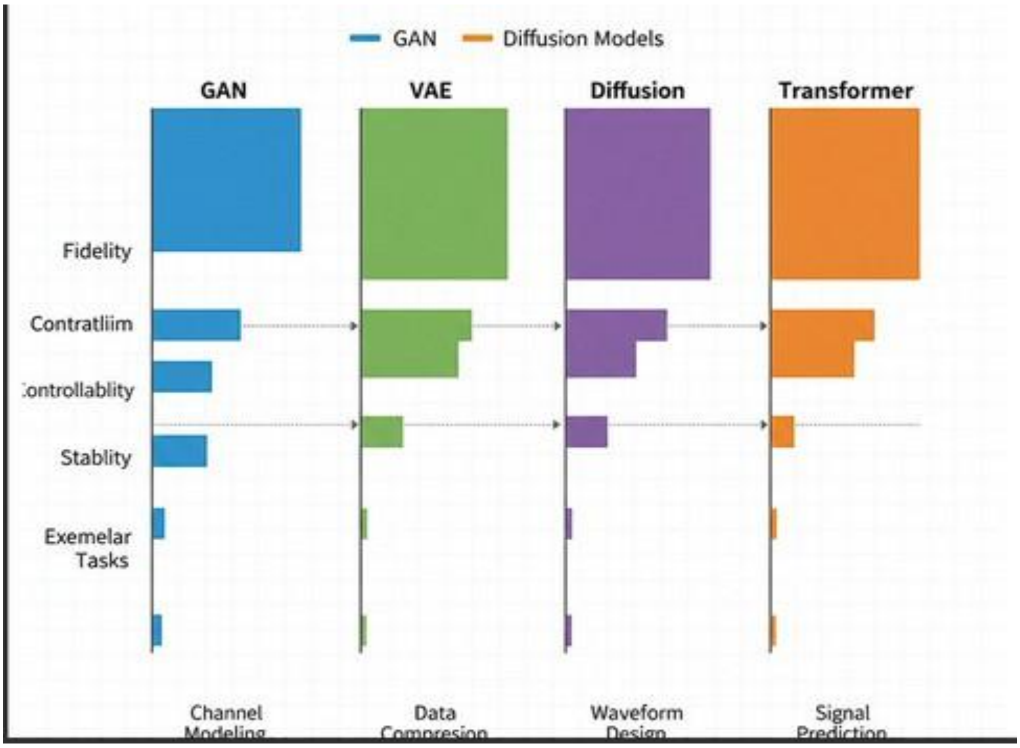
This reverse denoising process enables diffusion models to produce very accurate resource configurations. They are known for stability, high resolution, and strong performance in complex environments. In wireless networks, they are used to generate spectrum maps, predict high-density traffic situations, and simulate network loads with high realism.

4.4 Generative Transformers

Transformers rely on attention mechanisms to understand long-term dependencies in sequential data.

- They process time-series wireless data such as mobility patterns, handover events, or user traffic behaviour.
- They can generate multi-step predictions that are useful for proactive optimisation.

Transformers excel at forecasting future network states and recommending adaptive strategies. Their ability to understand and generate sequences makes them effective for routing decisions, scheduling, and real-time power adjustments.



Comparative schematic of GAN, VAE, Diffusion, Transformer along axes: fidelity, controllability, stability, likelihood, and exemplar wireless tasks.

5. Benefits of GAI-Based Optimization

•High accuracy in predicting network behaviour

•Lower interference and better coverage

•Reduced latency through intelligent scheduling

•Energy-efficient operation

•Better reliability under dynamic conditions

•Support for large-scale IoT networks

GAI allows networks to behave more like intelligent agents rather than rule-based systems.

6. Challenges

Several challenges are encountered when Generative AI is applied to future wireless networks. First, high computational demand is created by GAI models such as GANs, VAEs, diffusion models, and transformers. These models are required to be trained on large datasets, and powerful hardware is needed for both training and real-time inference. Deploying them on edge devices becomes difficult due to strict latency requirements and limited processing capacity.

Data availability and privacy concerns are also widely experienced. Large volumes of wireless data are required to be collected for effective training, but these datasets are often restricted, sensitive, or incomplete. User mobility traces and channel measurements need to be protected, and privacy- preserving techniques must be adopted to ensure secure model training.

Security risks are introduced when GAI models are used in critical network operations. These models can be influenced by adversarial attacks or synthetic data manipulation, and incorrect resource allocation may be produced if the system is compromised. Strong security frameworks are therefore required to be implemented.

Integration with existing wireless infrastructure is further complicated. Current network architectures involve multiple vendors and layered protocols, and seamless incorporation of GAI is made difficult without standardised interfaces. Real-time constraints also create challenges, as many optimisation tasks must be executed within milliseconds, while generative models often introduce computational delays.

Another major challenge is the lack of explainability. Decisions generated by GAI models cannot be easily interpreted, leading to reduced trust among operators. Additionally, high deployment and maintenance costs are incurred, as continuous updates, hardware requirements, and skilled manpower are required to support GAI-driven systems.

7. Future Scope

The future of wireless networks will heavily rely on Generative AI to achieve autonomous, intelligent, and efficient operation. The following key directions highlight the major future scope of GAI in resource optimisation:

1. Intent-Driven Networks

Users will express simple goals like "low energy" or "low latency," and GAI will automatically configure network resources to meet these intents. This will simplify management and personalise network performance.

2. Advanced Digital Twins

Generative AI will power highly realistic digital replicas of wireless networks. These twins will simulate traffic, failures, and mobility patterns, enabling safe testing and predictive optimisation before applying changes in real environments.

3. Multi-Agent Generative Optimization

Future networks will use multiple AI agents that collaborate to manage large-scale systems including satellites, drones, IoT devices, and terrestrial nodes. These agents will coordinate decisions to ensure global efficiency, fairness, and reduced interference.

4. Privacy-Preserving GAI Models

With increasing data sensitivity, future systems will use federated learning, encrypted training, and privacy-aware generative models. These models will optimise resources without exposing user information and strengthen cybersecurity.

5. Integration of Sensing, Computing, and Communication

GAI will help unify these three functions within 6G networks. This enables applications such as autonomous driving, smart factories, environmental monitoring, and disaster response through intelligent, sensing-aware resource allocation.

6. Edge-Level Autonomous Optimization

Lightweight generative models will run on edge nodes, predicting traffic, adjusting power, and reducing latency. This is essential for real-time applications like healthcare monitoring, drone communication, and industrial automation.
Overall, GAI will guide the evolution of 6G toward fully autonomous, secure, highly adaptive, and environment-aware wireless systems.

8. Conclusion

1. Generative AI (GAI) is becoming essential for future wireless networks, especially as 5G evolves toward 6G. These networks will face massive device traffic, unpredictable user movement, and rapidly changing channel conditions, which traditional optimisation methods cannot handle efficiently.

2. GAI provides a new way to optimise resources by learning patterns from large datasets and generating realistic wireless scenarios. This helps the network prepare for complex situations before they occur.

3. GANs, diffusion models, VAEs, and transformers contribute unique strengths, such as generating synthetic channel data, predicting interference, forecasting traffic load, and designing improved routing paths. Their combined power makes resource allocation faster, more accurate, and more adaptive.

4. Spectrum allocation improves significantly when generative models predict usage patterns and suggest interference-free channels. This leads to higher throughput and lower congestion.

5. Power optimisation becomes more energy-efficient, as GAI can recommend stable power levels for devices and base stations based on real-time conditions.

6. Scheduling and load balancing are enhanced, as generative transformers can forecast peak usage hours and distribute traffic intelligently across network cells.

7. Routing and topology management become more robust, especially in drone networks, satellite communication, and non-terrestrial 6G systems. GAI can simulate failures and propose reliable alternative routes.

8. Overall, Generative AI makes networks proactive instead of reactive, enabling faster decision-making, improved Quality of Service (QoS), and higher reliability under dynamic conditions.

9. As 6G develops, GAI will play a central role in building self-optimising, self-healing, and autonomous wireless systems.

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