6G Wireless Networks in the Generative AI Age: Overview, Techniques, and Future Trends

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***Abstract*—As the world move beyond the 5G era, the emergence of 6G promises a significant integration with innovative communication paradigms and burgeoning technology trends, actualizing previously utopian concepts alongside increased technical complexities. Analytical models offer basic frameworks, but ML and AI now outperform them in solving complex problems, either by augmenting or supplanting model-based methodologies. The predominant focus of data-driven wireless research is on discriminative AI (DAI), which necessitates extensive real-world datasets. In contrast to DAI, Generative AI (GenAI) refers to generative models (GMs) that can identify the fundamental data circulation, patterns, and characteristics of the incoming data. Given these attractive characteristics, GenAI can either substitute or augment DAI methodologies in multiple contexts. This comprehensive tutorial-survey article begins with an overview of 6G and wireless intellectual ability by delineating potential 6G applications and services. The aspects presented in this paper support the internet of things integration with 6G networks with the support of the AI as intelligent systems. This review paper concentrates on fundamental wireless research domains, encompassing network optimization, organization, and management. It examines the foundational learning principles of DAI and its methodologies, the application of DAI in wireless networks, and the utilization of GMs in 6G networks. Due to its comprehensive nature, this paper will act as a crucial reference for researchers and professionals exploring this dynamic and promising field.**

Keywords*—GenAI; 6G; generative models; intelligent systems; wireless communication

I. Introduction

The evolution of wireless networks has been characterized by significant innovations, with each generation introducing dramatic changes that redefine our interaction with digital environments. As we move beyond the 5G era, defined by remarkable data speeds and strong connectivity [1], a new vista emerges with the introduction of 6G. Although 5G was lauded for its massive machine-type communications (mMTC), ultra-reliable low-latency communications (URLLC), and enhanced mobile broadband (eMBB), 6G transcends being a mere enhancement of its predecessor; it signifies a fundamental transformation aimed at redefining the principles of wireless connectivity. The anticipated 6G aspires not only to enhance key performance indicators (KPIs) but also to integrate with innovative communication paradigms and future technical pathways, actualizing previously utopian concepts [2].

6G represents a major step toward a more connected and intelligent future, not just an incremental upgrade. We highlight innovative technologies that pave the way for an era when communication transcends mere connectivity, enabling deeper, more meaningful, and intelligent interactions in an increasingly digital landscape. Exploring the potential technological advancements of 6G, semantic communications stand out as a fundamental element, striving to surpass traditional data transfer models by facilitating networks that understand and interpret content semantics, thereby ensuring communication that is not only ultra-fast but also contextually astute [3]. In the past decade, articles have highlighted the possibility of data-driven methodologies to supplement or replace model-based approaches. Analytical models provide foundational insights, while AI models use real-life datasets for exact adaptation to complicated situations.

Most modern wireless data research relies on DAI models, which prioritize identifying distinctions between data types. Three fundamental learning paradigms are commonly used in DAI models, as shown in Fig. 1. These principles will be discussed in Section II.

While these learning paradigms are versatile, obtaining large real-world training datasets can be costly in terms of money, effort, and computer resources. In addition to performing ML tasks (e.g., classification, regression, clustering, pattern search, dimensionality reduction). DAI models may struggle to interpret data and miss subtle patterns/states, presenting challenges in complex real-world scenarios. Unlike DAI, GenAI refers to GMs that can identify the distribution, patterns, and properties of incoming data [4].

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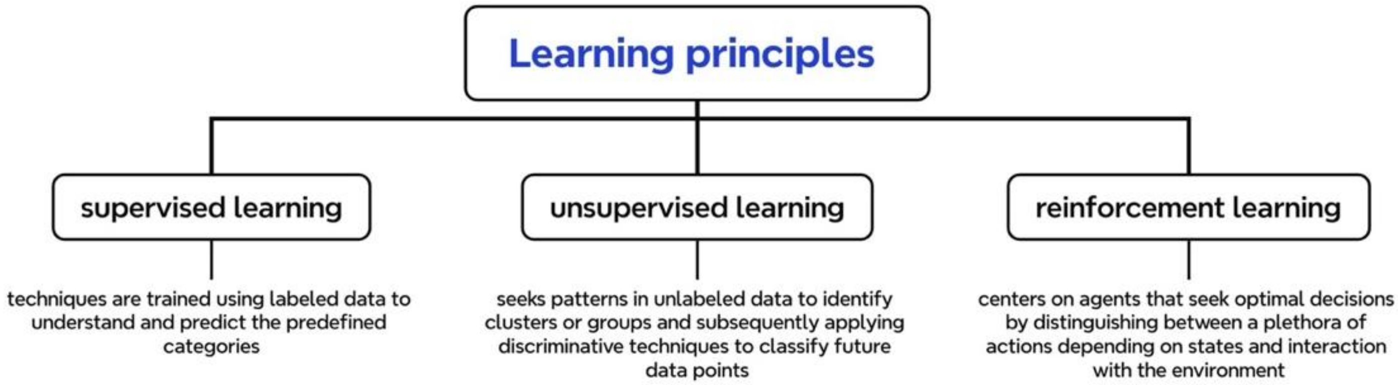

Fig. 1. Fundamental learning principles used in DAI.

After modelling the data distribution, GMs can produce new instances that are similar to the training data and examples. This is crucial in wireless domains where real-world data is limited, fragmentary, costly, and difficult to understand or grasp. It is essential for data augmentation, imputation, disentanglement, anomaly detection, and more. Despite the idea that GenAI is a new trend, our study of 120 technical articles highlights the extensive research across key wireless research pathways. GenAI gained attention after the release of big language model-based chatbots by tech heavyweights such as OpenAI's ChatGPT in Nov. 2022, Google's BARD in Mar. 2023, and Microsoft's Bing Chat in Feb. 2023. These developments sparked attention in both the industrial and intellectual sectors. With renewed attention, GenAI-driven wireless communication and networking research is poised for growth. Our study is comprehensive and rich in material, making it a valuable reference for scholars and professionals in this important and growing field.

GMs are gaining popularity in wireless telecommunication and networking. The research in [5] explores the benefits and drawbacks of using GMs for wireless channel modelling. Traditional channel modelling requires special skill and is technically demanding. To solve this problem, they developed a Generative Adversarial Network (GAN) technique to model wireless channels autonomously from raw data. GenAI for wireless networks is covered in [6], with an emphasis on three sample GMs: GANs, variational autoencoders (VAEs), and diffusion-based generative models (DGMs). A GenAI-based paradigm for wireless network management is developed, challenging established approaches, and promoting GM solutions. This case study optimizes contracts in mobile AI-Generated Content (AIGC) services using DGMs. A recent assessment highlights the growth of mobile AIGC networks, emphasizing real-time, tailored services that prioritize user privacy.

In response to DAI model issues in industrial IoT, [7] recommends GM adoption and examines current GMs for IIoT-related tasks such as anomaly detection, trust-boundary protection, network traffic prediction, and platform monitoring. According to [8], GANs have great potential for privacy and security due to their ability to produce realistic data. The authors analyze the merits, weaknesses, and future trajectories of GANs, addressing the lack of thorough surveys in this area. According to [9], GANs can be used for tasks such as spectrum sharing, anomaly detection, and security threat mitigation. The study highlights the benefits of GANs, including synthesising field data and recovering corrupted spectrum bits. GANs are rapidly being used in cybersecurity, particularly for jobs involving imbalanced datasets. The IoT applications hold potential for commercialization through the deployment of 6G communication networks.

The lack of studies on reviewing the wireless communications, especially the 6G networks, in the Generative AI era is the main motivation for this study. For autonomy and context, we begin with 6G network and wireless intelligence foundations in Section I. Section II provides a brief introduction of 6G communications and networking trends, including their numerous uses and offerings. Considering that we established the context with the requisite background knowledge, GenAI for wireless networks' optimization, organization, and administration is presented in Section III. Section IV outlines the strategic significance of GMs for emerging domains of 6G network research. Finally, the conclusion is shown in Section V.

II. The Role of Discriminative AI in 6G Networks

This section highlights developing trends in 6G communications and networking technology, followed by problems faced in achieving 6G implementation. Key concepts of DAI approaches are also covered. Here, we simply discuss how DAI approaches have been used to address key wireless network issues. This article explains use cases of DAI in wireless networks. The parts that are included in this section are illustrated in Fig. 2.

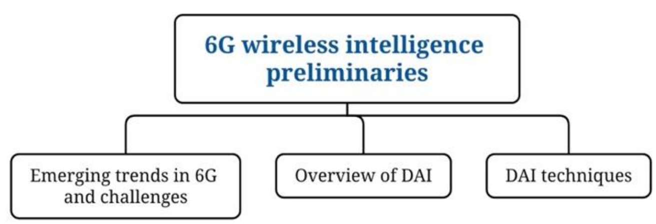

Fig. 2. 6G wireless intelligence preliminaries.

The emergence of 6G networks will revolutionize technology, introducing new applications and offerings beyond 5G capabilities.

TABLE I. COMPARISON OF SL, USL, AND RL

	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Pros	1. Effective for well-defined tasks with labelled data 2. Good performance in classification and regression tasks	1. Does not require labelled data - Can discover hidden patterns and structures in data 2. Useful for data pre-processing, dimensionality reduction, and clustering	1. Suitable for sequential decision-making problems 2. Can learn from delayed feedback. 3. Capable of dealing with dynamic environments
Cons	1. Requires labelled data - Prone to overfitting if not properly regularized 2. May not generalize well to new tasks or domains	1. No explicit target labels, making evaluation challenging 2. May require more complex models and training techniques	1. Can be computationally expensive 2. Requires exploration 3. exploitation trade-off - Sensitive to reward function design
Preferred	1. When labelled data is available 2. For tasks with clear input output relationships 3. When the goal is prediction or classification	1. When labelled data is scarce or unavailable. 2. For tasks focused on discovering hidden patterns or relationships. 3. When the goal is data analysis or pre-processing	1. When the problem involves sequential decision-making. 2. In dynamic environments with delayed feedback. 3. When the goal is to learn an optimal policy or strategy

These innovations aim to establish an increasingly connected and productive world by integrating growing technologies. Terahertz (THz) communications, a fundamental element of 6G, offer ultra-high-speed data transfer and sophisticated sensing uses with better bandwidth and spatial accuracy than existing technologies. Ultra-Large Antenna Arrays (ULAA) and Near-Field Communications (NFC) offer more spatial multiplexing and reduced interference, but architecture and operational issues remain [10].

6G networks require semantic interaction, which shifts from data transfer to valuable knowledge sharing. Consider context, receiver knowledge, and data intent to improve network efficiency and intelligence. Optical Wireless Communications (OWC) [11], [12], [13] provides a spectrum-rich replacement to RF communications, resistant to electromagnetic noise but affected by meteorological conditions and line-of-sight restrictions [14], [15], [16]. Parallel to this, 6G will apply AI to improve user experiences [17] in material recommendation, smart infrastructure [18], and wellness.

Large-scale IoT installations and digital twins will benefit from 6G, enabling real-time synchronization and better decision-making across industries. 6G will enhance the metaverse by enabling adaptive and reactive engagements via digital twins, edge AI (EAI), and holographic telecommunications [19]. Even with technological breakthroughs, 6G networks confront considerable obstacles. Spectrum management is vital as the radio spectrum grows scarce and new frequency bands like THz require research. Meeting varied QoS needs requires advanced resource management and traffic methods. Flexible network architectures and protocols are necessary for 6G networks due to the diversity of devices, technology, and services. Scalability is crucial for managing the expanding number of connected devices and services. Energy efficiency is crucial for IoT deployments using battery-powered devices. Finally, comprehensive security and privacy protection are crucial as networks become more complicated and large. Successfully implementing and operating 6G networks requires addressing these problems, where AI/ML can play a crucial role.

DAI techniques have improved significantly in complicated network settings by filling gaps in analytical methodologies. While their deployment relies on real-life data, it might be challenging in terms of time and expense. There are basic kinds of ML techniques: supervised learning, unsupervised learning, and reinforcement Learning, which includes generative models. Each ML class has unique techniques and strategies for various tasks. We analyze the pros and cons of different ML types in Table I and explain their suitable use based on situations and goals. The specific characteristics of each ML class offer advantageous solutions for various wireless network difficulties. Summarised as follows:

1) Supervised Learning (SL): A dataset of input-output pairings, marked output, is used for training models. To generalize and predict unknown data, the model must learn a mapping from inputs to outputs. The SL is commonly used for classification and regression applications, including Support Vector Machine (SVM), decision trees, naive Bayes, k-Nearest Neighbors (K-NN), and linear/ridge/lasso analysis.

2) Unsupervised Learning (USL): Models learn from unlabelled datasets. The aim is to discover hidden patterns, structures, or correlations in the data. Some unsupervised learning tasks are:

a) Clustering and pattern search: Use K-means and fuzzy C-means clustering.

b) Dimensionality reduction: Analyses include Principal Component Analysis (PCA), t-stochastic neighbour embedding, and linear discriminant evaluation.

3) Reinforcement Learning (RL): Using environmental interactions, agents learn to make decisions. While receiving rewards or penalties, the agent aims to learn a policy that maximizes cumulative return over time. RL functions differently from SL and USL by addressing sequential decision-making challenges and operating in delayed feedback environments.

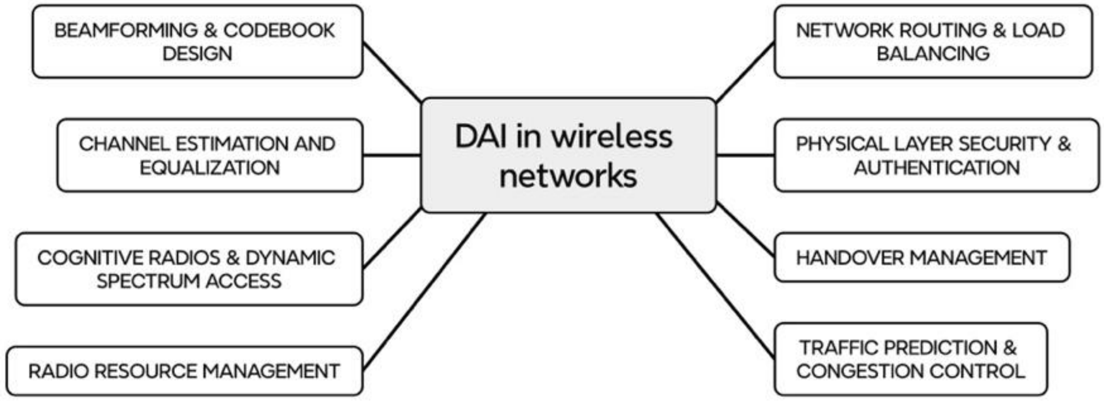

Fig. 3. The use of DAI in wireless networks.

RL algorithms include Q-learning, state-action-reward-state-action, Deep Q-Learning (DQN), Deep Deterministic Policy Gradient (DDPG), and Twin Delayed DDPG (TD3), arranged by development time.

Deep neural networks (DNNs) [20] provide superior performance in generalization, prediction, and classification compared to classic ML techniques due to their capacity to learn complicated and hierarchical data representations. A DNN architecture typically includes an input layer, hidden layers, and an output layer. The input layer accepts raw data, whereas the output layer produces the final prediction or representation. Hidden layers change data, acquiring complex features and high abstraction levels as it flows through the network. include Feedforward Neural Networks (FNNs), Multilayer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Autoencoders (AEs). GMs and transformers are classified as DNNs/DL and will be elaborated in later parts.

The intrinsic DL features eliminate manual feature engineering and enhance model performance across many tasks. DL models are made to scale with huge datasets and utilize modern hardware processing capability. DL models can learn end-to-end mappings from input data to desired output, simplifying the learning process and enabling smooth integration into multiple applications. Due to their fundamental properties, DL models are becoming a popular research tool for solving complex wireless communication and networking issues. Recently, wireless network performance has been improved using DAI models. Fig. 3 shows the usage of DAI in wireless networks that are explained in this section.

The two SL and USL algorithms, especially DL, are capable of learning to estimate channel state information (CSI) and executing equalization. Precise Channel State Information estimation is essential for numerous activities, including beamforming, resource allocation, and link adaption. Conventional pilot-based methods may prove inefficient for intricate and non-linear channels in dynamic environments, whereas deep neural networks can be trained on previous data to properly forecast channel state information.

DL algorithms can adjust beamforming parameters accordingly to CSI and other external parameters using archived and real-time data. To address CSI acquisition issues, pre-defined beamforming codebooks are used for initial access and data transfer [21]. Instead of relying on conventional codebooks, DL models could analyze huge quantities of data from an operational site to create adapted codebooks that accurately reflect the site's distinctive characteristics. Hybrid architectures manage hardware complexity with MIMO gain, allowing DL algorithms to optimize analog and digital beamforming weights, resulting in enhanced system performance and energy economy.

RL agents can optimize spectrum assignments in unpredictable contexts, determining optimal communication bands with little interference and maximum use. RL enables smart radios to adjust parameters like transmit power, modulation initiatives, and coding rates to enhance communication performance and coexist with other radio systems in a joint spectrum.

In wireless networks, ML may optimize resource allocation, power control, and network setup, enhancing radio asset administration and energy conservation [22]. DL models anticipate user behaviour and traffic sequences, while deep RL (DRL) methods aid in resource allocation decisions. In dynamic network systems, SL techniques can simulate power levels and performance measures, while RL methods can identify ideal power control rules. Fig. 4 shows a DRL hosted in a cloud where a DRL optimization procedure (DRL-OP) will be started on the cloud, requiring negotiation where the elements and the flow of the process are illustrated.

SL helps detect and prevent eavesdropping and jamming attacks by recognizing and classifying hostile network events [23]. SL may enable RF signal fingerprinting for user authentication or geolocation by identifying unique properties. USL detects network breaches and abnormalities by identifying unexpected traffic patterns at an early stage, preventing cyber risks, network outages, and performance deterioration. Integrating SL and USL techniques improves wireless communication security, confidentiality, integrity, and overall security.

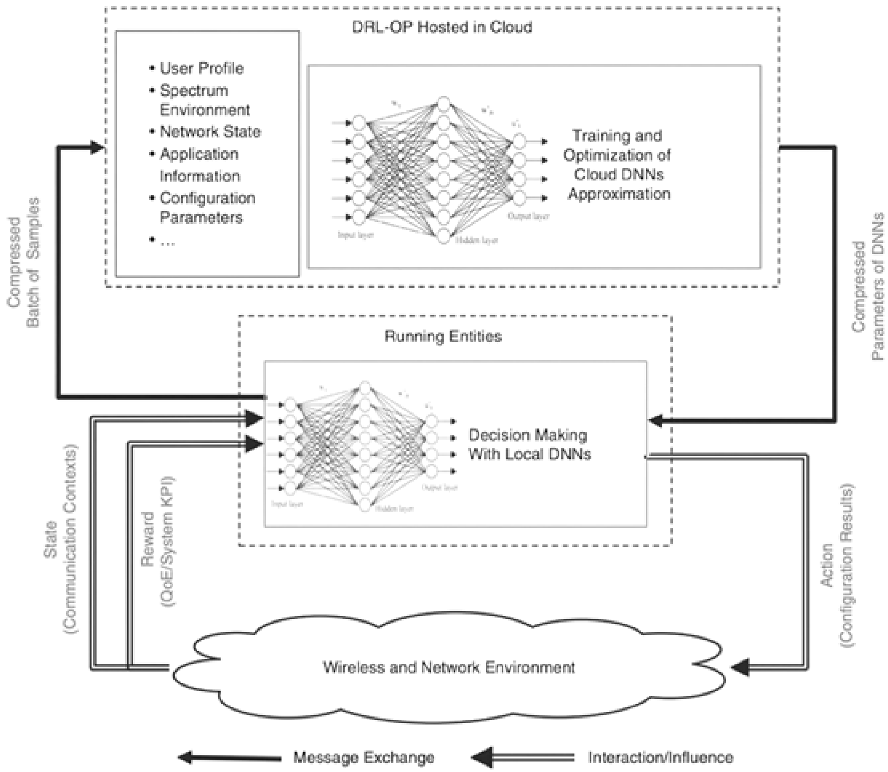

Fig. 4. The interactive DRL loops.

ML enhances handover handling by optimizing decision-making and ensuring smooth connectivity and QoS for mobile users across different cells or access points [24]. Handover control can benefit from ML techniques for projection, decision-making, and optimization. Digital neural networks can forecast handovers by examining historical data, user movement patterns, and network conditions, enabling proactive handovers, lowering delays and increasing user experience. In contrast, DRL agents can improve handover decisions by considering user movement, signal strength, network load, and QoS needs, determining the optimal target cell or access point for every user.

SL algorithms anticipate future traffic trends using marked training data, while USL algorithms detect underlying patterns and structures in network traffic data for prediction [25]. Network traffic forecasting can benefit from time series prediction methods developed for temporal data. By training on historical data with labeled congestion conditions, SL algorithms can forecast levels and take necessary actions to address the issue. USL methods, including clustering and dimensionality reduction, can uncover patterns, analyze congestion reasons, and develop mitigation strategies.

USL approaches like clustering and anomaly detection can organize network elements with similar properties and find novel traffic trends or activities. This information aids in establishing effective routing tactics, optimizing load circulation, and preserving network performance under dynamic situations. However, RL enables network agents to learn from their surroundings and adjust routing and load balancing techniques gradually. RL algorithms enable network agents to maximize load distribution, identify optimal pathways, and make better judgments in dynamic settings like shifting traffic loads and connection capacity. Fig. 5 depicts a centralized DL-based load balancing model [26] for heterogeneous networks. Data from the network is sent into the DL model, which processes information and applies it to the network.

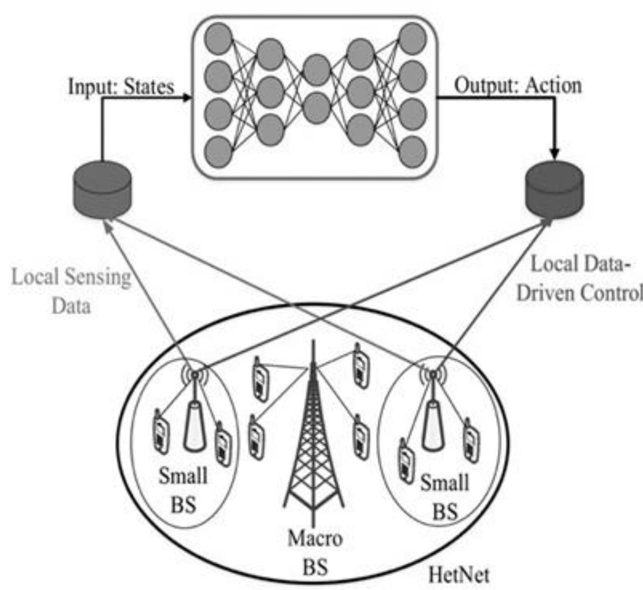

Fig. 5. A DL-based centralized load balancing mechanism in a heterogeneous network. After feeding cell data into the DL model, the HO variables are determined based on its result.

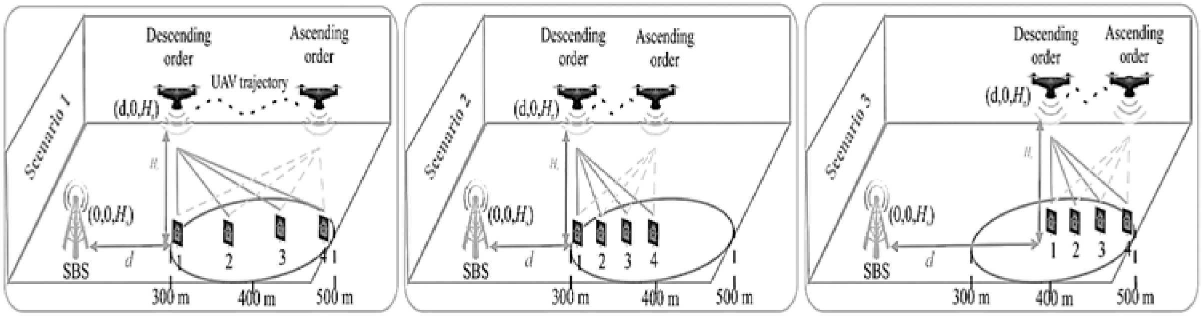

Fig. 6. Various hot-spot user distribution cases.

III. Generative AI for Wireless Networks

GMs demonstrate potential in tackling network optimization, organization, and resource management issues. GANs and other GMs can improve wireless network efficiency, mobile network slicing, and self-organization by producing artificial data and enhancing learning algorithms. This section shows how GMs effectively address resource allocation, network management, and performance optimization in various communication settings. GMs enhance RL/DRL agent learning by generating samples that demonstrate state-action value variation [27]. This reduces acquiring effects in nonstationary situations, minimizes action-value exaggeration and underestimation, and improves network improvement.

The work in [28] introduced a GAN-based Deep Distributional Q Network (GAN-DDQN) to tackle demand-aware resource allotment in 5G network segmentation. The GAN-DDQN model creates action tests, reflecting state-action values, and addresses nonstationary learning difficulties. The authors offer a reward-clipping approach to address training instability.

GMs can forecast user desires for resources, enabling efficient and adaptable network, computation, and storage control. Utilizing these estimates in dynamic service-oriented network slicing methods enhances resource provisioning and user experience (QoE). For allocation of resources forecasting in IoT usage, [29] introduced GANSlicing, a flexible service-oriented software-defined mobile network slicing scheme. This strategy prioritizes efficiency and flexibility in resource allocation to enhance user experience. GANs are used in GANSlicing to estimate user resource needs, enabling efficient and flexible control of network, compute, and storage equipment. Furthermore, in [30], Shahid et al. propose the production of realistic IoT network traffic utilizing a combination of AEs and GANs to enhance network-based intrusion detection systems (NIDS) and assess their effectiveness. The authors train an autoencoder to acquire the latent representation of actual sequences of packet sizes, thereafter training a WGAN in the latent space to provide latent vectors that can be decoded into realistic sequences. The artificial bidirectional flows produced by this technology closely mimic the actual traffic generated by a Google Home Mini, effectively deceiving anomaly detectors into perceiving them as valid traffic.

Recently, DL approaches have gained popularity for solving assignment issues. Additionally, VAE variations can be used to address linear sum allocation issues, a widely studied topic in wireless allocation of resources. A VAE variation can be used to tackle linear sum allocation issues, which are frequent in wireless resource allocation. This approach can replace the Hungarian algorithm and quickly and accurately solve huge cost matrices, as shown by simulation results in [31]. Fig. 6 shows the distribution of users in different scenarios where four NOMA users are positioned differently in each scenario. Users are scattered across the hot-spot region in Scenario 1, but before and after the center in Scenarios 2 and 3.

To overcome data shortage and imbalance in SONs, GMs can generate realistic artificial data for training powerful ML algorithms as shown [32], the authors propose a new cell outage detection approach for SONs using GAN and Adaboost to solve imbalanced data. GAN pre-processes imbalanced data, creating synthetic data for the minority class, while Adaboost classifies the balanced dataset. This method accurately detects cell outages in cellular networks, surpassing existing classification algorithms' limits in imbalanced data. The approach improves classification performance significantly, as measured by metrics like ROC, precision, recall rate, and F-value. Fig. 7 illustrates how the generator generates bogus samples from randomized noise samples. The discriminator determines if synthetic samples are authentic or not. If the discriminator finds synthetic samples more similar to real data, they are included in the minority group to create a fair dataset X'.

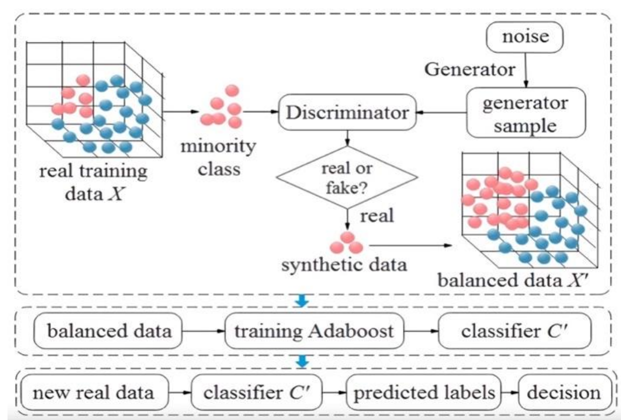

Fig. 7. Cell outage detection workflow using GAN and Adaboost [32].

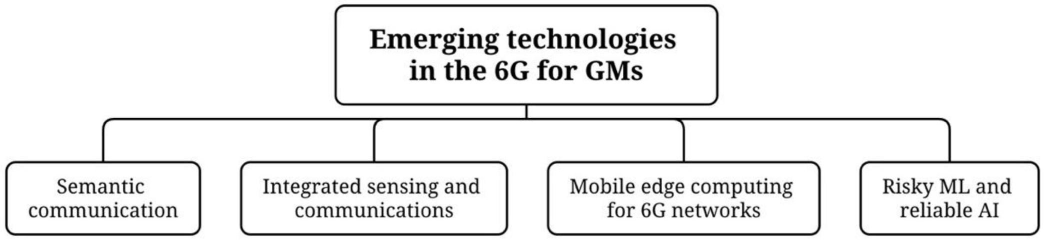

Fig. 8. Content of this section showing the technologies considered as the possibilities in the 6G for the GMs.

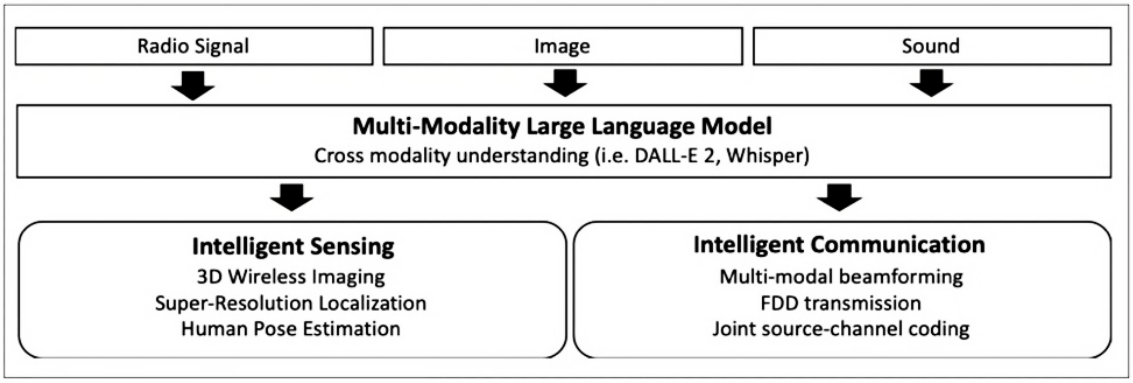

Fig. 9. Example on wireless sensor and communication LLM applications.

To improve algorithm flexibility to network shifts like UAV movement trends or infrequent URLLC events, GMs can generate synthetic data that records the basic architecture of these patterns. According to study [33], WS-GAN is a weakly-supervised GAN that uses additional data to predict wireless coverage using randomly distributed samples of received signal intensity. In contrast to standard methods like kNN or matrix finish, WS-GANs increase prediction effectiveness by including auxiliary information like terrain and building data, which greatly affects signal strength variation. In tests on an actual LTE dataset, WS-GAN demonstrated superior estimation accuracy and produced more practical wireless coverage maps compared to baseline approaches. In addition, [34] introduces a simpler approach for small cell coverage optimization utilizing GAN to obtain knowledge and transfer it to local SDN controllers. This approach focuses on creating effective GAN training for diverse topologies, even with insufficient data on network behavior and performance.

GANs and VAEs show potential for network administration and optimization. From improved learning algorithms to assignment solutions, GMs provide a versatile and effective toolkit for network researchers and practitioners. In non-stationary situations, GMs excel at forecasting user resource needs, handling imbalanced and sparse data, and adjusting to dynamic network conditions. GMs enhance network adaptability, efficiency, and robustness. By generating synthetic data, GMs can enhance actual information for training ML algorithms, enhancing performance in tasks like resource allocation and outage detection. Additionally, GMs improve the reliability of RL/DRL algorithms in non-stationary situations, enabling them more suitable for real-world deployments. Combining GMs with existing technology could change next-generation networks.

IV. The Role of Generative Models in Emerging 6G Capabilities

This section talks about emerging 6G capabilities included in the use of semantic communication, integrated sensing and communications (ISAC), mobile edge computing (MEC) and EAI for 6G networks, and Risky ML (RML) and reliable AI. Fig. 8 shows the content of this section.

Semantic communication (SC) is set to be a fundamental innovation in the advancement of 6G networks. In contrast to conventional communication models that emphasize the delivery of unadulterated bits with minimal distortion or data loss, semantic communication seeks to convey "meaningful" information, taking into account elements such as setting, the receiver's prior knowledge, and the transmission's intended purpose. This sophisticated technique designates SM as an essential element of forthcoming 6G networks, anticipated to utilize GenAI for comprehending, interpreting, and responding to extensive heterogeneous data flows.

Large Language Models (LLMs) are crucial in transforming the landscape of supply chains, ushering in an era of advanced, intelligent, and contextually aware data flows. LLMs are anticipated to provide as the foundation for developing self-governing, interacting AI agents that comprehend telecommunications language, ultimately guiding humanity towards collective intelligence, as opposed to the earlier notion of linked intelligence. Furthermore, LLMs can be developed as multimodal big models trained on telecommunications data and fine-tuned to execute various downstream tasks, thereby obviating the necessity for specialized models and facilitating the realization of artificial general intelligence (AGI)-enhanced wireless networks. LLMs can enhance wireless networks by providing predictability features, hence facilitating enhanced and proactive localization, beamforming, power allocation, transition, and spectrum administration, even in hitherto unencountered network conditions, as shown in Fig. 9. Conversely, wireless networks can link many GenAI models using innovative communication methods at both semantic and effectiveness levels, facilitating expedited detecting, inference, and action while minimizing the usage of resources.

With strong natural language comprehension potential, LLMs provide powerful database querying interfaces. Users can ask questions in normal language, and the system will understand and retrieve the desired data, instead of using structured searches. GANs are revolutionizing SM by producing more effective, flexible, and perceptive results. Additionally, GANs may simplify complex data into understandable visual illustrations, guaranteeing that the transmitted information is received and understood by the recipient. Using picture translations helps improve understanding and overcome the gap between raw data and actionable insights.

DGMs offer a unique technique to SM, tackling data transport and interpretation difficulties. DGMs can improve signal quality, preserving valuable data even in unfavourable situations. This feature is crucial when signal loss may obfuscate the meaning of communicated data. DGMs enable variable-rate communication for dynamic communication. As data complexity varies, DGMs can adjust transmission rates to ensure efficient data transfer without overburdening communication links. This allows DGMs to convey semantic depth despite data complexity.

ISAC brings new opportunities for network solutions by combining sensing and communication capabilities to react to shifts in the environment, resulting in improved effectiveness and intelligent processes. For ISAC, few factors can be considered important to discuss:

1) Data augmentation: the task involves creating synthetic, compelling sensor data to enhance real-world data repositories and provide a solid foundation for training. GANs excel in creating realistic and accurate data, making them ideal for augmentation jobs.

2) Anomaly detection: The objective is to identify data trends or spots that significantly depart from norms, ensuring fast notifications and system dependability. GANs have improved in identifying irregularities in sensor data spread. DGMs enhance anomaly identification by incorporating uncertainty quantification into their iterative approach.

3) Resource optimization: This involves simulating network settings and predicting future states to allocate resources efficiently. GANs excel at simulating various network contexts, enabling efficient model training for resource optimization. FGM's standardizing flows, which accurately describe complex network state distributions, are essential tools for decision-making in this environment.

4) Sensor/Data fusion: This responsibility involves combining data from several sensors to provide a comprehensive and accurate environment depiction. VAEs simplify complex tasks by reducing data into a simplified hidden space . Standardizing flows can improve this process by accurately simulating complex data patterns.

5) Decision making: This job supports consecutive decision-making based on sensor and communication data. GTMs excel at handling large data sets, making them useful in sequential decision-making situations. LSTMs, designed for data patterns, are essential for situations requiring a strong temporal or sequential backdrop.

MEC and EAI change 6G networks by decentralizing data execution. Standard models, relying on central servers or cloud computing, caused latency and inefficiencies, especially for time-sensitive operations or remote devices. Integrating compute and AI/ML capabilities at the network edge enables real-time data processing and decision-making for devices. This change is essential for meeting the needs of 6G and its various uses. GANs may reproduce real-world data through generated samples. GANs can enhance data at the edge in MEC contexts, particularly when significant datasets are unavailable for training or assessment.

Bayesian VAE models may estimate ambiguity, making them essential for edge devices [35]. Serial data is essential for edge applications like VR and AR. LSTMs and GTMs efficiently evaluate patterns, enabling real-time improvements in AR encounters based on user motions and activities. Edge devices frequently face complex data distributions, particularly in multi-modal or multi-sensor settings. Standardizing Flows models complex distributions, enabling localized AI to comprehend and respond to nuanced input. In cases of noisy or uncertain edge data, DGMs can be crucial. Their repeated output refinement improves accuracy continuously, making it useful for advanced robotics with unpredictable environmental variations.

RML studies how AI models can be deceived by particularly constructed inputs, leading to inaccurate predictions or classifications. Adversarial instances include modest, unnoticeable modifications to input data and manipulating model output, which may appear unmodified to humans. Studying AML is critical for understanding vulnerabilities and developing responses against prospective attacks.

GANs can be used to create antagonistic samples that deceive classifiers. The producer in GANs can produce fake samples that mislead a target classifier into making incorrect conclusions [36]. Conversely, GMs are able to identify and counter aggressive attacks. In GAN training, the generator generates adversarial instances and the discriminator learns to differentiate between authentic and adversarial samples. With proper training, the discriminator can identify adversarial samples in real-world settings.

AML handles adversarial assaults, enhancing AI system resilience and robustness. Although protections against adversarial attacks are being created, openness is needed to understand how they work and how the model processes data, which lies within trustworthy AI (TAI). Numerous frameworks have been suggested to direct the advancement of TAI, with the European Commission's High-Level Expert Group on

Artificial Intelligence being one of the most notable entities to have formalized TAI as a theory cantered on seven pillars that encompass diverse aspects of AI ethics and durability.

V. Conclusions

As the age of 6G begins, the amalgamation of innovative communication paradigms and nascent innovations is swiftly revolutionizing wireless communications, with machine learning and artificial intelligence proving to be pivotal in tackling intricate difficulties. Although DAI prevails in the AI-driven wireless scientific domain, the potential of GenAI to augment and enhance DAI methodologies is becoming increasingly apparent, particularly in contexts characterized by insufficient or partial data. This study offered insights into the principles of 6G and explored the critical function of GMs in diverse areas of wireless research. Moreover, by identifying potential problems and proposing effective techniques, we argue that our research offers scholars and industry professionals valuable insights, thereby positioning itself as a guide resource in this rapidly developing field.

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