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Review

Review on Machine Learning for Intelligent Routing, Key Requirement and Challenges Towards 6G

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Abstract: The constant desire for faster data rates, lower latency, improved reliability, global device integration, and pervasiveness are some of the factors driving the development of next-generation communication systems. Sixth-generation (6G) networks have received a lot of attention from the industry and academics as fifth-generation (5G) communications are being rolled out globally. With the proliferation of smart devices and the Internet of Things (IoT), 6G networks will require ultra-reliable and low-latency communication. Routing protocols have a significant role in improving the performance of a network. Traditional routing techniques will have difficulty coping with the highly complex and dynamic 6G environments. Recently, machine learning (ML), a key component of artificial intelligence, is emerging as the key to managing complex and dynamic networks efficiently. However, there are still several significant challenges that need to be addressed. In this paper, we provide an overview of current machine-learning techniques used in network routing. Lastly, we highlight open research problems that need to be addressed and prospects for future research.

Keywords: machine learning (ML), 6G networks, routing protocols, reinforcement learning, intelligent routing

1. Introduction

The ever-increasing demand for higher data rates, minimal latency, better reliability, global integration of diverse devices, and pervasiveness are some of the drivers for newer-generation wireless communication. Introduced in the 1980s, the first generation (1G) of cellular communication was the first commercially available mobile network. The data rate was minimal, supporting the most fundamental voice calls. The second generation (2G) networks emerged in the 1990s, supported text message service, email, web browsing, and voice communication, and brought significant improvements over 1G. 2G networks adopted the GSM cellular communication standard. Mobile technology advanced significantly with the advent of third-generation (3G) networks in the early 2000s. 3G networks provided services to access multimedia and video communication and greatly improved mobile networks' capacity and effectiveness, enabling faster data rates and better voice quality. The fourth generation (4G), introduced in the early 2010s, supported high-definition TV, online gaming, and mobile TV with improved QoS over the predecessors. In the early 2020s, the fifth generation (5G) is being deployed globally with additional services, including telemedicine, industrial control, virtual and augmented reality, and the Internet of Things (IoT) with enhanced broadband, massive access, and ultra-reliable and low latency [1,2].

The three primary aspects of 5G are enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC). The enhanced eMBB feature of 5G allows for high data rates of up to 10 Gbps. Furthermore, compared to 4G, mMTC in 5G supports over 100 times as many devices per unit area, and uRLLC achieves a latency reduction of 1 millisecond. An

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extremely high connection density of 1 million devices/km2 is expected to be supported [3]. Technologies such as Software Defined Network (SDN), Device to Devices (D2D), Non-Orthogonal Multiple Access (NOMA), and massive MIMO have been introduced to improve performance by reducing network traffic, saving energy, and increasing data rate. However, the capabilities of 5G wireless systems are likely to be outperformed by the rapid inclusion of smart devices and automated IoT devices in the networks. On the other hand, as new IoT services and applications grow, such as robotic surgery, automated cars, and extended reality, which require further advancement in the current generation. The 5G-enabled Internet of Things (IoT) is evolving into the Internet of Everything (IoE), aiming to associate with vast numbers of devices, people, and organizations, exceeding the capabilities of 5G. The current network design cannot guarantee service quality for applications in the future that need high throughput, very low latency, and global coverage [4]. Therefore, investigation of the upcoming network design is important.

Overcoming these challenges necessitates the development of 6G networks, which are expected to provide data speeds exceeding 100 Gbps, latency of 0.1 milliseconds, and support for high connection densities of up to 10 million devices/km2 [3]. Network reliability and availability are expected to go beyond the requirement of 5G. Increase in application based on positioning are expected due to 5G networks' anticipated ability to find devices with sub-meter accuracy. However, the advent of applications like extended reality, telemedicine, V2X, and autonomous industrial systems often compromises the positioning accuracy of current 5G. The 6G network will have to conform down to centimetre-level positioning accuracy or even sub-centimetre-level positioning accuracy to support such applications [5]. The sixth generation aims to present the space-air-ground-sea integrated network and areas within human activities to increase capacity and offers worldwide coverage, providing a completely integrated user experience that works as a fully intelligent system [3,6,7]. 6G communication networks may address the shortcomings of the 5G system by incorporating new future services such as THz communications [8], edge intelligence [9], reconfigurable intelligent surfaces (RISs) [10], a pervasive introduction of AI [11], space–air–ground–underwater communications [6], massive URLLC communications [12], and blockchain [13]. An overview of 6G wireless communication networks is shown in Figure 1.

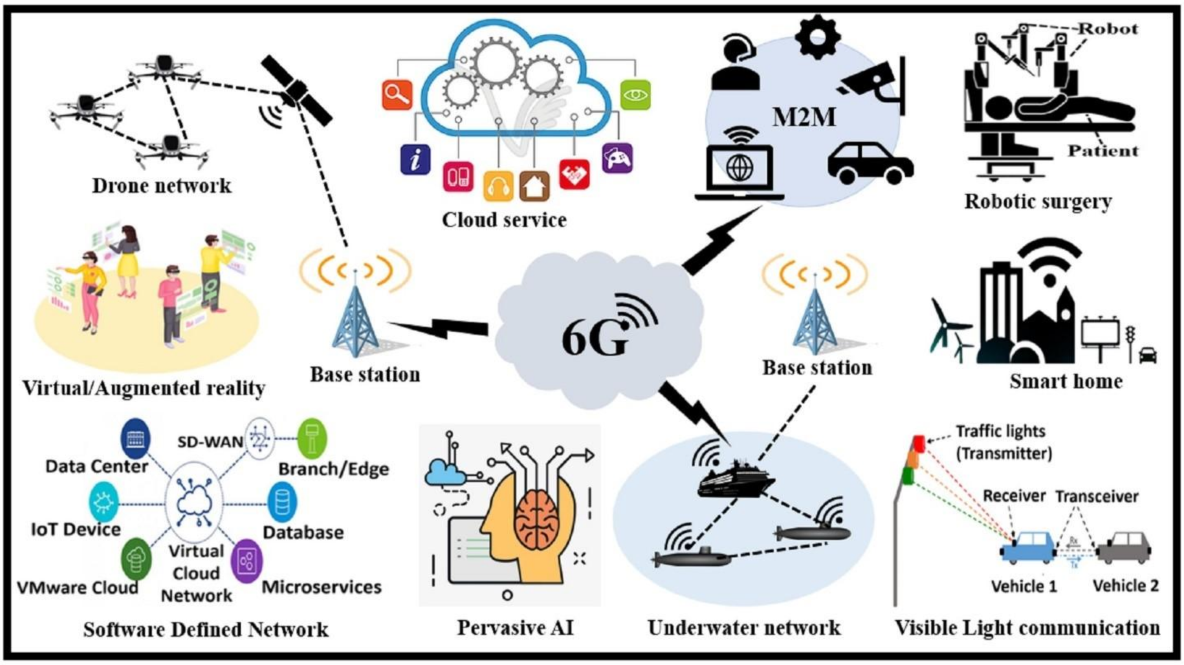

Figure 1. An overview of 6G networks.

Wireless communication technologies are improving rapidly to meet the demand of ever-increasing data-hungry applications, demanding higher data rates, very low latency, and better service quality. 6G network is designed to provide pervasive intelligent services from the core network to its endpoints, making its widespread deployment of machine learning systems feasible. With the assistance of Artificial Intelligence (AI) technology over a large spectrum, 6G is envisioned to offer a higher data rate with improved QoS and reliability with ultra-low latency. AI-assisted 6G offer computational power and intelligent data transfer with caching to enhance network performance [14,15]. The network architecture design for 6G has considered high dynamism, dense distribution, and heterogeneity. Effective connectivity to support real-time processing of large amounts of data generated from terminal devices has been considered one of the main challenges for 6G networks. The existing wireless infrastructure needs improvement to support rapidly increasing connectivity that can ensure end-to-end QoS as well as QoE. Some machine learning methods and protocols are being studied in recent times to enhance some aspects of network functionality, including network traffic prediction, traffic classification, and congestion control.

Routing strategy plays an important key role in improving network performance. One of the major challenges with traditional routing protocols is that, it relies on finding the shortest path between a source and its destination without considering the real-time network scenario. Furthermore, the traditional routing methods do not have the scope of learning from past information with similar conditions, that resulted in severe congestion or increased delays, because of wrong decisions. Traditional routing algorithms are inefficient in large-scale systems because it involves enormous computational complexity. Moreover, the rapid growth in network traffic and rapidly changing network environments in next-generation networks may give rise to new challenges for routing strategy design with application demands large amounts of data, high data rates, and low latency [14,16]. Thus, traditional routing solutions require a scope for improvement to meet the requirement of 6G with the assistance of Machine Learning techniques, thereby predicting the optimum path and estimating the minimum cost to route the packet in real-time. This paper provides an in-depth review of machine learning based on intelligent routing and makes the following contributions:

- An analysis of the 6G convergence, beginning with the evolution of cellular network generations and limitations of 5G.
- The expected service requirements of 6G are briefly discussed.
- The overview of Machine Learning techniques and existing machine learning-based routing techniques are enumerated.
- Research challenges and potential future research directions toward 6G are discussed.

The paper is organized as follows; the first section of this paper gives an overview of cellular communication emphasizing on 6G. The second section lists the key requirement of the 6G Network. The third section discusses the background of different machine-learning techniques, followed by an elaborate discussion of existing machine-learning-based routing algorithms. In the fifth section, we list some open research challenges that need further investigation for future prospect and finally, we conclusion the manuscript.

2. Requirements of 6G network

The specifications for 6G network are covered in this section. Applications such as remote surgery, virtual reality/augmented reality, unmanned aerial vehicles (UAVs), Internet of Things (IoT), Vehicle to Everything (V2X), and machine-to-machine communication are expected to be supported by 6G networks. In addition, 6G mobile network are expected to provide these services with high reliability, high efficiency, capacity, and low latency.

2.1 *Massive Connectivity*

The future 6G networks are anticipated to host a sizable number of IoT devices. IoT applications require frequent data exchange which may be from sensing, processing, managing and storing. Machine-type communication is a significant focus of next-generation communication networks due to the demand for seamless communication among multiple networked devices. As the number of devices increases, networks need to support huge connections with efficient utilization of resources. Massive device deployment may exacerbate network resources, packet loss, and latency [17]. A mmWave-based NOMA strategy for mMTC, where several devices share the same assigned base station resources, was proposed in [18]. The author in [19] suggests a reinforcement-learning-based ML strategy to overcome channel limitations, because connected devices use the same spectrum. Depending on the distance between the devices themselves or between the device and the base station, the devices sharing the resources that works in pairs. With non-terrestrial technologies like satellite connectivity and wireless communication supported by UAVs, 6G are expected to provide total coverage. These applications require an efficient spectrum and capacity to accomplish this connectivity [20].

2.2 *Massive Ultra-Reliable and Low-Latency*

Relatively low latency and dependability link are key requirement in IoT-based application domains such as autonomous vehicles, remote surgery, machine-to-machine communications, smart grids, and virtual reality /

augmented reality. Vehicles will need a high URLLC to send information, and video information to improve traffic efficiency on the roadway while maintaining safety. The efficiency and delay for applications such as remote surgery and remote medication, which use robots to monitor or treat patients located at far distance, can directly impact a patient, as their well-being relies on the effectiveness and efficiency of these network parameters [21]. Machine learning methodologies will be crucial for the development of intelligent network resource allocation strategies for URLLC requirements. The author in [22] presents a framework that aims to enhance time and frequency resources in such communication system, thereby increasing the capacity to support lifesaving devices. With this approach, latency and reliability restrictions are guaranteed with improved spectrum utilization. The author in [23], suggested approach with prediction and communication co-design for improving performance in remotely-controlled system. The author also pointed the challenges of simultaneous achievement of 5G NR's ultra-reliability and high latency demand. Thus, Massive MIMO and multi-connectivity were studied in order to attain high reliability. The author in [24] has concentrated on using machine learning techniques to acquire prior environmental knowledge. In order to enable URLLC services utilizing cognitive radio under perfect or imperfect channel state information, the author introduces low-complexity algorithms in a cellular environment. The suggested techniques improved the uplink and downlink access scenario.

2.3 *High Energy Efficiency*

For real-time applications like smart automobiles, smart cities, smart health, and smart industries, high power is required. Mobile devices with poor battery life, running services demanding high energy consumption seriously impair smooth connectivity. 6G devices will demand more energy because they are projected to operate in a higher frequency range. Power optimization and energy-efficient methods must be designed to meet the challenges of next-generation networks. A fresh approach for 6G network was proposed by the author of [25] and is known as Multivariate Regressive Deep Stochastic Artificial Structure, learning to adjust the different data packets to improve communication that is energy and cost-conscious. In order to locate the useful node in the hidden layer, multivariate regression is performed. The suggested approach examines node statuses like energy, signal intensity, and spectrum usage. According to the author's discussion in [26], a machine learning-assisted 6G network can achieve energy efficiency, enabling energy efficiency at the access, edge, and core networks. Machine learning can boost performance while lowering energy efficiency concerns in future networks. In order to increase the network lifetime, radio frequency (RF) energy harvesting, for instance, can harness energy from RF waves. A novel alternating optimization technique is proposed to enhance the energy efficiency of the backscatter-enabled cooperative NOMA system, which is affected by poor channel conditions [27].

2.4 *High Security and Privacy*

The protection of data, privacy and confidentiality in existing IoT networks is another crucial requirement. Edge devices will regularly use AI applications, and every edge device in 6G is anticipated to have an Internet connection. The security and privacy of data that is acquired must be addressed because bulk of AI applications rely on data. Distributed Denial of Service (DDoS) attacks on a large scale may become more frequent as more IoT devices are connected to the internet. The broad distribution of 6G systems renders edge computing prone to physical security concerns, DDoS attacks, and man-in-the-middle attacks [28]. In order to intelligently recognize and address potential threats, it is crucial to employ a security design that utilizes machine learning techniques that can analyze network anomalies throughout the network. Future networks should also include strong security safeguards to protect user privacy, and the vast amounts of obtained healthcare data, describing how ML can be used to improve the security of 6G networks in health care [29]. UAVs have emerged as an effective way to reduce security risks. An approach based on UAV-assisted communications is carried out by the author in [30] to enhance URLLC systems' secrecy by reducing the risk of eavesdroppers.

2.5 *Resource Management/Optimization*

Edge computing (EC) is viewed as a potential enabling technology for the sixth generation (6G), able to meet enhanced service needs. Moreover, Edge computing in 6G will include edge devices with advanced technologies such as artificial intelligence and autonomous decision-making that handle real-time data analysis, extract insightful knowledge, and react autonomously to local events, enabling quicker and more effective decision-making [8]. With the support of base stations, wireless network controllers and other aggregation sites, EC enables the development of virtualized infrastructures at the network's edge. Researcher have been investigating on enabling edge intelligence in 6G-IoT use cases. The development of EC reduces the network's potential data transmission bottlenecks as well as the data processing load assigned to the core network. However, the frequent changes in these edge devices and resources result in uncertainty in EC systems. The author in [31] offered a brief overview of RL-based EC-enabled networks and identified the challenges with optimization based on an analysis of the network uncertainty. The author in [32] proposes an effective edge computing framework for smart cities to reduce energy consumption, enhance system performance, and implement real-time applications. The proposed technique acts at the application layer between EC servers and creates an information structure to store the characteristics of EC services that are performed by EC servers.

2.6 *Global Coverage*

It is anticipated that wireless broadcasts will be completely available everywhere. Multiple devices, such as smartphones, automobiles, sensors, robotics, and maritime users, must be seamlessly connected via 6G. The next generation of wireless communication networks will integrate air-space-ground-sea networks to attain worldwide coverage. Satellites and UAVs collaborate to create a cognitive satellite-UAV network in order to smoothly connect Internet of Everything (IoE) that are outside the range of terrestrial cellular networks. Enabling communication via satellites is especially challenging due to the inherent delay and limited data capacity. Wide-area IoT networks are anticipated to be connected in 6G using swarm UAVs. Incorporating swarm UAVs into terrestrial and satellite networks will allow for 3D networking and cell-free communication [20]. Such technology is anticipated to be used in the next generation of mobile communication networks.

3. Overviews of Machine Learning Techniques

Machine learning (ML), being an integral part of artificial intelligence that does not require explicit programming, allows systems to learn from examples and data. Regression, categorization, and interactions between an intelligent agent and its environment, uses these models. For cases where there is no optimal solution using a conventional technique, ML approach may be the candidate of choice. ML is data-driven and uses past data to predict application scenarios dynamically, allowing it to adapt to various situations and changes in the network environment. Based on an enormous number of predictions about the application scenarios, the ML-based routing algorithm can be used for suitable decisions making in accordance with the QoS standards [14]. Adopting ML techniques that can automatically acquire knowledge from previous data gives a more effective method of replacing traditional techniques that depends on lengthy rule lists. Figure 2a depicts the relationships between artificial intelligence, machine learning, and deep learning.

3.1 *Supervised Learning*

ML technique known as supervised learning maps the input function to the output function using labelled datasets. Supervised learning (SL) is divided into regression and classification based on network continuity. Applications that have access to large volumes of data for algorithm training have benefited from supervised learning since the robustness of an algorithm is directly correlated with the number of instances [11]. Compared to the conventional technique, supervised learning-based routing algorithms can significantly reduce the computing and signalling overhead, making them a desirable solution for intelligent routing. Support Vector Machine (SVM), Gaussian Process Regression (DPR), Support Vector Regression (SVR), and K-Nearest Neighbours (KNN) methods are a few examples of SL techniques.

3.2 *Unsupervised Learning*

Unsupervised machine learning learns the functions that can be used to describe hidden data structures and patterns using unlabelled datasets. These methods are suited for wireless network problems where - the findings are unknown in advance or where data annotation is difficult to put into practice. The extraction of system knowledge and behaviour in difficult environments is made possible by data analysis utilizing unsupervised learning techniques, such as analyzing the effects of frequency changes, dynamic interference, changing user density over time, dynamic traffic patterns, and cell switching [11]. The techniques for unsupervised learning are K-means clustering, Principal Component Analysis (PCA), isometric Mapping (ISOMAP), and hierarchical clustering algorithms.

3.3 *Reinforcement Learning*

Reinforcement learning (RL) focuses on producing appropriate decisions by mapping situations to actions and determining which actions must be considered to maximize a long-term reward. Wireless networks operate under unpredictable stochastic conditions, such as the location of a node and its available power level. The goal of the RL task is to determine the optimal action taken to maximize rewards by making the best decision under a given circumstance [11,14]. RL gains the ability to manipulate a system to achieve a long-term goal. The controlled system's current state, as well as the reward linked to the most recent state change, are sent to the controller. As a result, the controller makes a decision and update the system about the changes. The system then transitions to a new state in response. This loop keeps iterating until the controller discovers a way to interact with the system so that the overall reward is maximized. Reinforcement learning techniques include the Markov decision process (MDP), a multi-armed bandit (MAB), Q-Learning and policy learning, and actor-critic (AC).

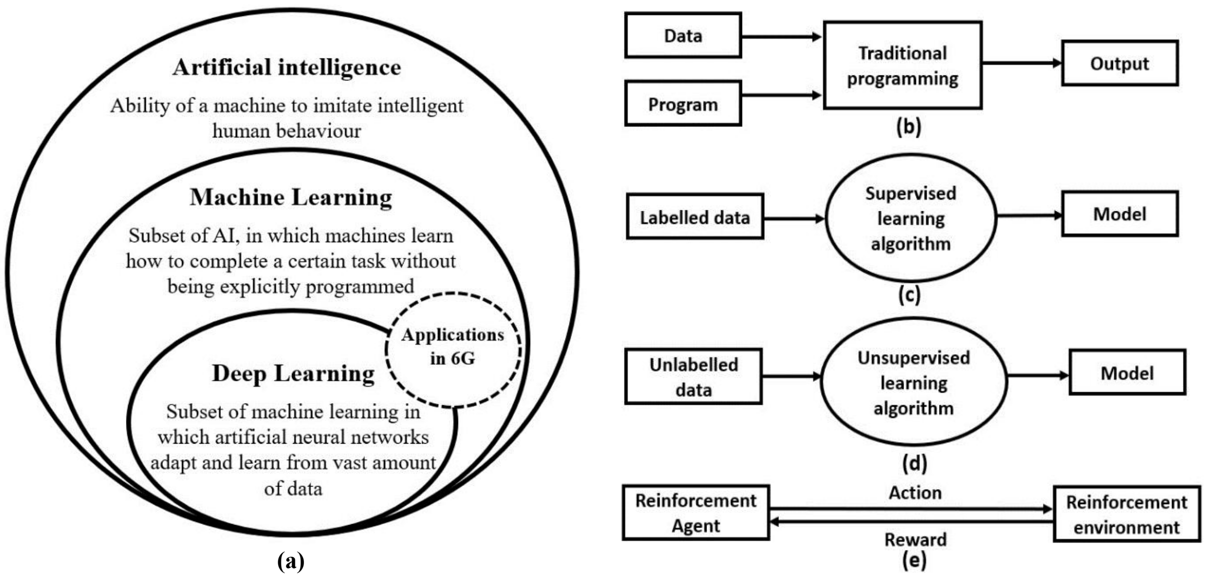

Figure 2. (a) Gives the relationship between artificial intelligence, machine learning, and deep learning. (b) Traditional programming (c) Supervised learning (d) Unsupervised learning (e) Reinforcement learning.

3.4 *Deep Learning*

Deep learning is an AI function that analyses how human brains work and uses that knowledge to build patterns on artificial neural networks with numerous layers of neurons. The accessibility of large datasets and the availability of adequate computing power have been the key drivers for deep learning paradigm's growth [14,15]. By using nonlinear processing units to extract information from raw data - layer by layer, DL techniques produce predictions based on predetermined goals, as shown in Figure 3. Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNN) are some DL methods. Deep neural networks (DNNs) use straightforward nonlinear functions on input data to approximate complex functions. The model parameters are produced when a loss function reaches its minimal value by employing stochastic gradient descent (SGD) techniques and a back-propagation mechanism, which abides by the fundamental chain principle of differentiation.

4. Machine Learning-Based Routing Algorithms

The process of selecting a path for transferring the data from source to destination is known as network routing. The end-to-end delivery of packets is mostly handled by the network routing algorithm. Traditional routing protocols primarily rely on distance vectors or link metrics. Several ideas have also been offered for the conceptual explanation of routing and its application. These traditional routing protocols may not be adequate for rapidly changing network and handle heterogeneity of connectivity, resulting in ineffective routing decisions and insufficient resource utilization [14]. These methods have shortcomings, such as slow network recovery speeds for large networks and poor scalability in dynamic context. The classical shortest path technique, which incurs high computational complexity with the increase and dynamic of the node, routes packets based on variables like hop count or delay [16,17]. Additionally, because these traditional protocols make their routing decisions on limited information, existing techniques may be challenging to adapt to dynamic traffic. Moreover, traditional routing techniques send all traffic to a link as per the current state information, which may lead to bottleneck problems as available bandwidth fluctuates over time in the actual network environment. The user experience will be significantly reduced as a result, leading to major network congestion and significant resource wastage [33]. Intelligent network routing systems based on machine learning have received a lot of interest in a variety of network environments for their ability to take advantage of the intricate relationships among the many parameters to choose the optimum route. Recently, researchers are adopting machine learning techniques to address network routing issues. Figure 3 depicts the architecture of a machine learning-based routing system for a varying packet with respect to time.

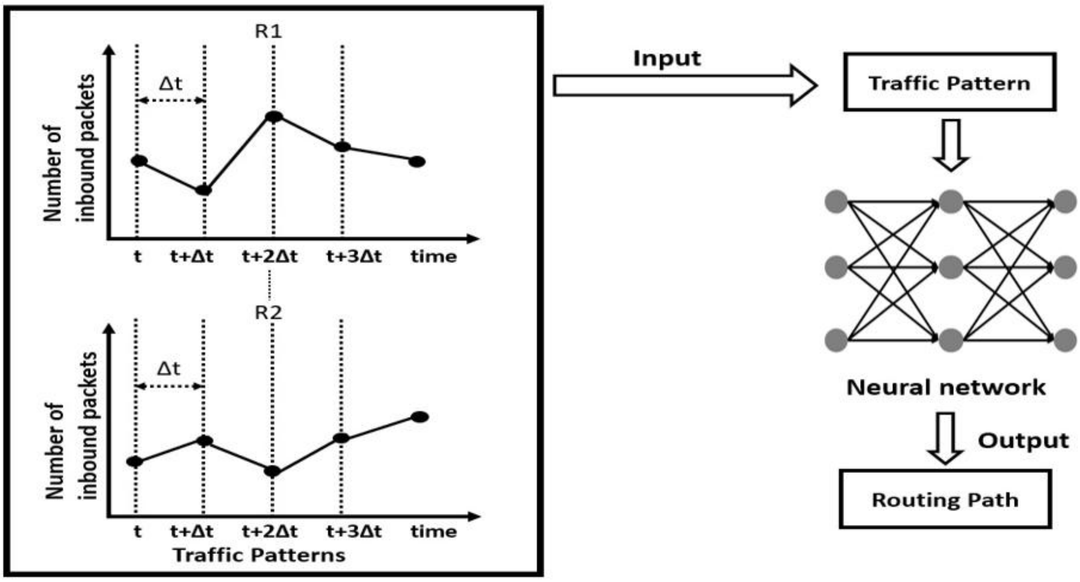

Figure 3. Deep learning-based routing.

4.1 *Supervised Learning Based Routing Algorithm*

Deep learning based on supervised learning techniques can provide the opportunity to implement routing techniques in complex network topologies by obtaining insight from labelled data. The author in [34] proposes the use of supervised classification methods to handle the routing and wavelength assignment problem. The combined wavelength distribution and routing challenge is defined as an ML task classification problem, and the software-defined optical network is trained using logistic regression and DNN from the training data set that was gathered. A QoS-aware routing method is proposed using supervised ML to classify and determine a path with the highest average route residual capacity based on the QoS requirements of each application. DNN model is then used in the SDN controller to perform dynamic QoS classification for each request that enters the network [35]. In [36], the author proposed a routing protocol for D2D communication to reduce routing overhead and energy consumption resulting from delivering various parameters separately. The model was trained using four supervised ML techniques to find the best technique for the proposed protocol. When compared to the conventional approach, the proposed approach reduces routing overhead, increases network lifetime, and enhances connection quality. The author in [37], address complex decision-making problems by using a deep learning-based routing method to choose the shortest path required for data transmission. The suggested routing approach learn the nodes' connection behaviour for shortest path identification to avoid congestion and improve energy efficiency. Compared to the traditional method, which uses the distance between nodes as metrics, the work in [38] uses four distinct metrics, such as latency, bandwidth, SNR, and distance, to determine the best routes with the use of Dijkstra's algorithm in real-time. In [39], the author considering the significance of maintaining IoT networks and the difficulty of achieving energy optimization in various environments. A hybrid method based on support vector regression is suggested to enhance IoT routing and reduce energy consumption. The suggested technique outperforms alternative approaches in terms of power consumption, end-to-end delay, load balancing, overhead, and network longevity. In [40], the author suggested a novel approach based on stochastic gradient descent to verify the accuracy of the node's parameter updates and integrity of aggregating the node's parameter updates. The suggested approach guarantees data privacy and improves QoS. Table 1 summarizes the supervised learning based routing algorithms.

Table 1. Summary of supervised learning based routing algorithm.

Ref.	Technique	Year	Path	Deployment	Outcome
[34]	Deep Neural Networks	2019	Single-path	Distributed	Reduce network congestion dynamically
[35]	Deep Neural Network	2022	Single-path	Distributed	Improve the link capacity and throughput
[36]	Supervised Learning	2022	Multi-path	Distributed	Minimize routing overhead and improves link quality
[37]	Deep Belief Network	2022	Single-path	Distributed	Improve energy efficiency, number of active nodes, and packet delivery rate
[38]	Supervised Learning	2023	Multi-path	Distributed	Improve delay and throughput
[39]	Support Vector Regression	2023	Multi-path	Distributed	Reduce computational overhead, end-to-end delay, and improve load balancing
[40]	Supervised Learning	2023	Multi-path	Distributed	Improve data privacy within the acceptable overhead

4.2 *Imitation Learning Based Routing Algorithm*

Imitation learning is learning from experts and imitating the best behaviours without the redundant exploration process. The key concept is to consider network routing with the optimal routing decision as an expert behaviour, and the network's agent continuously imitates the optimal decision as it learns from the current state. The author in [41], highlight the drawback of traditional network, that is traditional networks are unable to perform self-adaptation intern SDN controllers' computing resources are wasted. The CNN approach, which is based on real-time traffic traces, is used to intelligently compute the paths by following the concept of imitation learning. The suggested method is highly accurate at determining the appropriate path combinations. The author in [42] analyses the effect of route prediction on the performance of the transport network. In order to effectively perform fast inference and lower the cost of control information exchange, the central controller uses a DNN classifier to predict the path sequence. A network model based on the GNN that can adjust to various topologies, routing protocols, and traffic quantities was proposed in [43]. Even with topologies, routing, and congestion that was not present during training, the author claims their approach accurately predict the delay distribution and loss. The study in [44] pointed out that certain issues exist with the deep learning-based network traffic control methods in use, including sub-optimal routing performance, longer training durations, and high data demand. The study shows the use of three deep learning models to train and test a large number of network sub-blocks via a recursive partition technique to address these issues. The work in [45], presents an extreme learning machine method to address the issue of longer training durations, and high data demand. With the aid of both past and current data, the authors in their study learned the attack rule and anticipated the attacker's subsequent behaviour in the edge computation system.

The work in [45] presents an extreme learning machine method to address the issue of longer training durations, which in turn will have penalty during network congestion and attacks in EC. With the aid of both past and current data, the authors in this study learned the attack rule and anticipated the attacker's subsequent behaviour in the EC system. The QoS-aware multipath routing issue was addressed by the author in [46], using DNN-based multipath routing. The suggested approach develops a mapping function that relates the routing configurations at the central network controller to the projected network state. The proposed framework also exhibits a higher gain in computing efficiency. Table 2 summarizes the imitation learning based routing algorithms.

Table 2. Summary of imitation learning based routing algorithm.

Ref.	Technique	Year	Path	Deployment	Outcome
[41]	Convolutional Neural Networks	2019	Single-path	Distributed	Minimize the packet loss rate, prevent congestion, and increase throughput
[42]	Deep Neural Networks	2020	Single path	Centralized	Decrease the signalling overhead of the transport network
[43]	Graph Neural Networks	2020	Single-path	Centralized	Increase network performance metrics including jitter, packet delay, and latency
[44]	Convolutional Neural Networks	2020	Single-path	Centralized	Achieves less time complexity while obtaining higher accuracy
[45]	Extreme Learning Machine	2020	Single-path	Centralized	Improve network reliability and avoid congestion
[46]	Deep Neural Network	2021	Multi-path	Centralized	High prediction accuracy and improved computational efficiency

4.3 *Reinforcement Learning Based Routing Algorithm*

Reinforcement learning are more dominant approach adopted for optimization and dynamic problem, as RL does not rely on instruction and therefore does not require manual data labelling, which is a significant benefit of RL over supervised learning. Some researchers propose using deep reinforcement learning for multi-hop routing since it achieves lower latency. To reduce congestion problems and reducing delay in transmitting data, the author in [47] employs DRL for route selection in networks with high traffic. Two distinct DQN based algorithms have been created to minimize the possibility of network congestion using short-range routes. The other focuses on shortening the transmission route, while the former aims to reduce the possibility of congestion. The proposed algorithms claim to have increase network throughput in situations with high network traffic. The author [48] incorporated a modified deep Q-network into each router to assess its neighbours. By updating their Q-networks, the model updates to improve the packet routing technique. The network's routers can function decentralized to lower computation complexity if the reward structure and learning process are appropriate. The suggested strategy can also enhance network performance by lowering the likelihood of congestion.

In recent years, new network application scenarios like data centre network traffic scheduling and backbone network traffic engineering have emerged. The authors of [49] propose a direct flow routing technique that is based on SDN and allows packets belonging to the same flow to follow the same routing path. In this work, single-path routing and conventional routing techniques are greatly outperformed in terms of performance by using simple Q learning algorithm. A constrained intelligent routing methodology built on deep learning was developed by the author in [50]. It combines the advantages of the Lagrange multiplier method for dealing with constrained situations with the exceptional feature learning capabilities of deep learning. The routing service learns a variety of properties in order to adapt to the ever-changing network traffic environment and enhance network performance. The authors in [51], suggested Q-routing, which treats each routing node as a state in the MDP, the current routing node select the next routing hop based on the MDP action. An intelligent routing algorithm was proposed in [52], which utilize deep learning and global optimization techniques to improve performance for newly developed network application scenarios. By merging erasure coding and DQN to learn constantly changing network parts, the author proposed DQN erasure coding to address routing issues. The proposed approach gathers information about the status, quantity, and block size of nodes that have stored blocks during erasure coding using the SDN controller. A routing algorithm based on reinforcement learning was presented in [53] with the objective of balancing the network load and improving network connection. Based on the current input status, the technique predicts the ideal routing plan in the current traffic environment. The suggested method outperforms conventional algorithms by attaining better average delay, reduced packet loss rate, greater throughput, and improved load distribution performance.

In [54], the author suggests a dynamic routing method selection approach that utilizes Q Learning. The suggested algorithm is trained to select the best traditional routing method to apply to the traffic flows in an SDN environment and decide which QoS-based traffic class offers the optimum balance between throughput, packet loss, and rate of rejection. For the purpose of offloading in 5G cellular IoT, the author in [55] proposed reinforcement learning-based V2V routing, which is used to balance each vehicle's energy usage and conserve energy. However, strict energy consumption limits are not imposed on vehicle models. As a result, certain vehicles may end up using a lot of energy to transmit packets. Moreover, due to the continuously changing network topology and short coherence periods caused by high levels of mobility and hybrid vehicle types, a quick adaptation is required. A new routing protocol with reinforcement learning capabilities incorporates information on the potential movements of mobile agents. The RL-based routing technique has been shown to suffer from short-term impacts in urban environments. A hybrid ML approach added a timer-based technique to the update process in order to classify radio environment prototypes. This allows the protocol to adapt autonomously based on the situation [56].

The author of [57] presented a routing model based on RNN that takes service delays into consideration while calculating routes, that complies with the traffic routing principle. The suggested technique quickly calculates every route between every pair of nodes in the meta-graph, and it determines how reliable a link is by tracking the cost variance over time. The suggested method results in constant-time convergence. In order to authenticate the nodes, the work in [58] presents a unique routing protocol based on ML for IoT-WSN. When compared to other protocols, the suggested protocol outperforms in terms of throughput, latency, and overhead. However, convergence speed and model generalization are the main concerns with regard to progress in the real world. The author in [59], proposed a method in order to speed up convergence and meet the current 3GPP standard. The work introduces Soft Actor-Critic, a DRL algorithm based on maximum entropy reinforcement learning for achieving its objective.

In order to communicate between nodes in an energy-efficient manner, Distributed AI is first adopted in [60], and power usage for the communicating nodes is determined mathematically. The consumed power values of the nodes for various time instants serve as the training data for the neural network approach employing self-organizing maps (SOM), which creates a cluster. This power-based node design produces effective routing for operation of specific application. The suggested strategy turns out to be more efficient in terms of the network's overall energy use as well as minimizing computational complexity. However, strict energy consumption limits are not imposed on vehicle models throughout the routing process. As a result, certain vehicles may end up using a lot of energy to transmit packets. For the purpose of offloading 5G cellular IoT, reinforcement learning-based V2V routing is used to balance each vehicle's energy use and conserve energy [61].

According to the research of [62], each link's bottleneck was predicted using a deep neural network predictor based on multitask learning using past information, and the results were compared to rule-driven congestion mitigation and replay. In contrast to passively compensating for congestion once it occurs, the integration of routing techniques enables routing approaches to continuously adjust routing before congestion arises. The technique presents more robustness against topology changes and reduces the network's average end-to-end delay. The author [63] addressed the issue of the Q-learning algorithm's slow convergence. Based on the Q-learning algorithm, the author enhances the reward mechanism, boost the guiding function, decrease the possibility of random behavior in an agent's decision-making process, reduce delay and packet loss rates, and use the periodic data of satellites to establish the network model. The LEO satellite network features a guiding function that improves the algorithm's convergence by including in Q learning algorithm.

In order to optimize connection stability, range and to increase the packet delivery rate of the IoV, the sending node uses the multi-weight decision algorithm for decision-making process [64]. The author in [65] aims to solve dynamic load balance problem in real-time topology and improve the QoS of the system using the proximity of each of the paths and priority-based categorization. The suggested approach keeps track of each link's load and, if necessary, re-routes traffic in real-time. The result shows significantly improvement in bandwidth utilization and throughput. In [66], the author proposed an efficient method to address the issue of call drops due to a lack of resources, which causes an additional network delay. The proposed technique distributes the user's power according to their needs, provides stable connectivity for latency-sensitive applications, and reroutes users if there is network congestion. Table 3 summarizes the reinforcement learning based routing algorithms.

Machine learning routing technique perform better for heterogeneous networks and has promising feature learning capabilities that can be exploited for highly dynamic network. The ML-based routing algorithm can cope with higher dimensional network state feature information as compare to traditional routing algorithm. Furthermore, the development of the SDN architecture allows the ML-based routing algorithm to operate as an application on the SDN server with significant processing capacity with efficient management of traffic [44,48]. Existing deep reinforcement learning-based intelligent routing schemes have achieved improvements in network traffic engineering [44], complicated optimization tasks [37], and congestion control [38,39]. However, with changing network deployment environments, such as when the topology and traffic-generating model are altered, performance measures like accuracy, latency, and throughput may change. As the network environment changes, it could be necessary for some application scenarios to gather training data and retrain continuously [67]. Reducing the cost of training is a challenging task when dealing with machine learning methodology. Deep reinforcement learning techniques are often associated with high training costs [38]. These issues have a negative impact on QoS and will be challenging to meet the needs of the massive, extremely dynamic future 6G network. Moreover, overall network throughput may be affected because of frequent fluctuations in network behaviour due to node mobility and varying network resources. Future 6G systems will have to take into account more than just communication performance, including the cost of computing and storage, in order to achieve full intelligence. Therefore, it is crucial to develop adaptable machine-learning models that can be applied to heterogeneous network.

Table 3. Summary of reinforcement learning based routing algorithm.

Ref.	Technique	Year	Path	Deployment	Outcome
[47]	Deep Reinforcement Learning	2019	Single-path	Centralized	Reduce congestion probability and minimize the path length over heavy traffic
[48]	Deep Q-Network	2019	Single-path	Distributed	Achieve higher network throughput with less transmission path
[49]	Q Learning	2020	Multi-path	Centralized	Low latency and flow integrity is maintained in small multipath networks
[50]	Long Short-Term Memory	2021	Multi-path	Distributed	Adapt to constantly changing networks
[51]	Reinforcement Learning	2021	Multi-path	Distributed	Reduce the network overhead and delay
[52]	Deep Q-Network	2021	Single-path	Distributed	Increase network throughput and reduce link cost
[53]	Reinforcement Learning	2021	Single-path	Distributed	Increase throughput and improve load distribution
[54]	Reinforcement Learning	2021	Single-path	Centralized	Determines the optimal balance between packet loss, rejection rate, and throughput
[55]	Reinforcement Learning	2021	Multi-path	Distributed	Less traffic load and improve packet delivery ratio
[56]	Reinforcement Learning	2021	Multi-path	Distributed	Provides high PDR and low latency
[57]	Recurrent Neural Network, LSTM	2022	Multi-path	Centralized	Reduced end-to-end latency
[58]	Deep CNN	2022	Multi-path	Distributed	Higher accuracy with less overhead
[59]	Reinforcement Learning	2022	Multi-path	Distributed	Improve reliability and minimized latency
[60]	SOM Neural Networks	2022	Single-path	Distributed	Minimizes energy consumption
[61]	Reinforcement Learning	2022	Multi-path	Distributed	Minimize energy consumption, delivery ratio and average delay
[62]	Deep Reinforcement Learning	2022	Multi-path	Centralized	Minimize delay and improve robustness over topology changes
[63]	Q learning	2022	Single-path	Distributed	Reduce delay and accelerate the convergence
[64]	Multi-weight decision algorithm	2023	Multi-path	Distributed	Reduce packet loss and improve bandwidth utilization
[65]	Deep Neural Network	2023	Single path	Centralized	Improve the transmission bandwidth utilization and throughput
[66]	Reinforcement Learning	2023	Multi-path	Centralized	Allocates resources efficiently and minimize the delay

5. Open Research Challenges

5.1 *Quality of Service (QoS) and Quality of Experience (QoE)*

The next-generation network with ultra-reliable and low-latency communications is strongly dependent on end-to-end QoS and QoE. For large data stream applications with high dependability on security, users, for instance, demand high throughput and low delay. Furthermore, the next-generation network's complex and incredibly dynamic circumstances are difficult for traditional network optimization techniques to handle. ML techniques can be essential for balancing network resources and meeting a variety of criteria. An efficient cross-layer design can be achieved by using machine learning-based network routing algorithms to predict potential applications based on historical patterns and intelligently route the packet. However, the upcoming 6G systems will focus more on improving several metrics than just one, outperforming the capacity of present mathematical models to define their complex relationships accurately. Utilizing several purpose-based learning approaches is essential to overcome these problems effectively.

5.2 *Dynamic Power Control*

The future network will require more power due to connectivity for applications such as vehicle networks, UAVs, and satellite networks. Most of these devices are powered by batteries, which demand large amounts of energy. High energy efficiency is expected in 6G networks to provide efficient communication. Traditional power control systems often look for near-optimal power distribution strategies by addressing optimal problems. Due to their high computational cost and immediate channel state information precision requirements, such approaches are difficult to apply to large-scale networks [26]. To address these issues in large-scale heterogeneous 6G networks, employing energy-aware optimization methods is critical to dynamically allocating resources to ML approaches depending on their needs and priorities.

5.3 *Scalability*

Scalability is one of the requirements that routing methods must fulfill. In some dynamic applications, ML approaches can consider dynamic factors such as changing link connections, varying network resources, and producing high accuracy [41,42,46]. Future intelligent routing algorithm design challenges include ensuring the algorithm can still produce decent results in a large topology. Additionally, when the topology is complicated, the centralized routing control mechanism may cause high information exchange costs and lengthy network state transfers, which limits scalability. However, the accuracy can lead to frequent network dynamics caused by node relocation and the reconstruction of virtual subnetworks. Therefore, it is crucial to develop scalable machine-learning models that may replicate in various networks to achieve global intelligence.

5.4 *Interpretability*

The machine learning models at the foundation of 6G are expected to increase in sophistication and complexity. The unpredictable nature and difficulty of interpretability in routing techniques is another issue with intelligent routing solutions. Deep neural networks are among the many machine learning models that are regarded as black box models and frequently have unpredictable behaviours [14]. It becomes difficult for the operator to identify the source of a problem when incorrect routing decisions are taken, and it is very challenging to fix the model. This lack of interpretability could lead to problems in figuring out the rationale behind a specific routing choice and can cast doubt on the reliability and accountability of the system. Therefore, improving the interpretability of intelligent routing techniques remains an open challenge in developing intelligent routing systems.

5.5 *High Propagation and Atmospheric Loss of Terahertz (THz)*

Terahertz communication is expected to increase 6G network capacity by supplying more spectrum ranges. THz has a short wavelength and a high frequency. In the THz range, long-distance data transmission becomes problematic. To enable high-frequency bandwidth, a small-sized transceiver must be redesigned in the THz band. Due to the size of tiny particles like water vapor and oxygen being close to the wavelength of the THz band, the THz frequency is affected by atmospheric absorption. As a result, terahertz channels cannot be modeled using conventional channel models that are based on the assumption that they are stationary or quasi-stationary. In a known or unknown environment, ML algorithms can assess communication data and forecast likely signal loss. Therefore, a wide range of AI or ML techniques can be used to solve the problems with terahertz channel modeling and estimation in 6G networks.

5.6 *Ultra-Reliable Low Latency*

The ultra-low latency requirement of 6G network is predicted to be less than a millisecond. To ensure seamless connectivity, IoT applications like the Internet of Things, UAVs, holographic communication, and VR/AR demand incredibly low latency. Furthermore, rapid resource allocation, network reconfiguration, and service adaption require effective, low-latency, and adaptive network management. Mobility management and offloading solutions must provide ultra-reliable and low-latency communications to meet these demands. The computational complexity of traditional machine learning techniques may prevent them from meeting these latency requirements. Developing machine learning models that can quickly predict outcomes within the required time frame and can perform well with minimal computational resources is a challenge in URLLC.

5.7 *Dynamic Spectrum Allocation*

In 6G network, spectrum efficiency must be taken into consideration. New spectrum resources are needed as a result of the rise in user numbers, as the current spectrum resources cannot support the increase in users and devices with high data demands. Due to the limited spectrum resources, interference increases and becomes a significant problem in heterogeneous networks. In dynamic wireless environments, the availability and utilization of the spectrum may vary quickly. Channel availability, interference levels, and user requirements are all vulnerable to change throughout time and space. Moreover, it is difficult to obtain a significant and diverse dataset for the purpose of training machine learning models. Designing machine learning models that efficiently collect and utilize the data for reliable spectrum allocation choices is difficult due to the high-dimensional and complicated data. It is challenging to explore approaches to tackle these problems and enable effective and adaptive spectrum allocation in dynamic wireless environments.

5.8 *Trust, Security, and Privacy*

The proliferation of IoT devices has led to new security flaws and wireless interface assaults. Due to the demanding communication requirements and high-performance requirements of 6G applications, many applications require strong security at the same time maintaining performance [29]. When individuals switch between their interconnected network services, security and privacy risks appear. IoT devices and services will make it harder to monitor and execute privacy and security solutions. Although IoT systems and devices' embedded intelligence are used by ML-based security technologies to address these security concerns, more challenges pertaining to the authenticity of devices and trust need further study.

6. Conclusions

The next-generation communication network with extremely stable and effective communications is in high demand. As such, intelligent routing design is crucial for network performance. However, the complex and extremely dynamic environment of the next-generation networks is challenging using conventional methods. Machine learning-assisted 6G networks can be the significant candidate of choice for resolving some of these issues. We have covered some of the criteria of 6G in this paper. To create dependable transmission links and handle high dynamics, we have also enumerated machine-learning techniques and examined several machine-learning-based network routing strategies. The research concerns and potential future scope are discussed in the final section.

Conflict of Interest

There is no conflict of interest for this study.

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