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Survey of Graph Neural Network for Dynamic Resource Allocation in SDN-Enabled Edge Computing and IoT Networks: A Review

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ABSTRACT

The present review article discusses the most recent applications of the Graph Neural Networks (GNNs) in addressing the problem of resource distribution in Software-Defined Networking systems (SDNs) combining edge computing and IoT. The analyzed studies depict how GNNs are intelligent at capturing complex interactions within networks based on the changes in data flow and device demands. Unlike traditional methods of distributing resources, GNN-based methods have a better level of performance due to the ability to perceive spatial associations between network components and temporal consumption patterns. They demonstrate promising results of reduction in latency,

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refined bandwidth allocation and enhancement in energy consumption with continued focus on existing problems involving scalability, real time processing that require further input. The review highlights the importance of some key insights that demonstrate the ability of GNNs to assist in solving major issues in resource allocation. An example illustrating this is the use of GNN-enabled methods to minimize the latency due to the intelligent way traffic is redirected through the most efficient routes hence improving the overall agility of the network. Additionally, these tools have worked well to optimize daily bandwidth distribution such that the resources are served to boost throughput and reduce congestion. Also, GNNs have become critical in enhancing the energy efficiency which is a critical consideration to the IoT and edge computing environments where devices are limited by resources; the ion of energy is very stringent. GNNs can help in extending the working life of equipment that is sensitive to energy by adjusting the resource allocation based on real-time information.

1. Introduction

Software-Defined Networking (SDN) combined with edge computing and the Internet of Things (IoT) has prepared unbelievable opportunities to agile, smarter and more effective network management (Zhang, Cui, and Zhu, 2020). With the dynamic development and advancement of these technologies, this has made it difficult to devise the most appropriate method of resource allocation. Conventional resource allocation algorithms have been known to be either

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heuristic or optimization based, which is a challenge because of the dynamic and diverse nature of networks in the present day (Hussein, Mahmood, and Askar, 2025). Here, the use of Graph Neural Networks (GNNs) can provide a promising solution as it is based in its capacity to model and analyze networked systems of complicated networks. SDN has changed the architecture of the network by separating the control plane and the data plane, which has made it easier to centrally manage and program the network. With this shift, more flexible resource management is possible and brings in new challenges regarding the decision-making processes (Hussein and Askar, 2023). Edge computing enhances computation at the edge of the network and this aids in reducing the latency and bandwidth consumption besides supporting true-time applications. Another complexity introduced by the increasing amount of IoT devices is the introduction of a multiplicity of device capabilities, inconsistent connectivity, and varying quality-of-service needs. The resource allocation challenge over this environment is inclusive of many areas: scheduling of the computational resources, allocating bandwidth, storage management and optimization of the energy across the distributed nodes (Scarselli, Gori, Tsoi, Hagenbuchner, and Monfardini, 2008).Though these techniques more often or usually lead to traditional optimization methods, queuing models, or reinforcement learning methods, they generally do not inherently capture the complex topological connections and dynamic interdependences of modern network architectures in terms of the nodes corresponding to computational resources such as servers, edge devices, or IoT endpoints. GNNs serve as an explicit benefit of graphs, whose nodes define the computational resources such as servers, edge devices, or IoT endpoints. Conversely, the lines depict the communication or dependency relations among them. GNNs gathers and modifies information on the graph through message-passing techniques and actually learns local and global graph representations (Ibrahim and Askar, 2023). This inductive bias that is inherent in

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GNNs predisposes them to resource allocation tasks. Recent studies have pointed to a range of other benefits of GNN-based approaches towards dynamic resource allocation (Wu et al., 2020). To begin with, GNNs are able to obtain the spatial relation among various network components in an effective way and provide coordinated decision-making that takes into account the cascading influence across the entire network. Also, GNNs have the capacity to change according to the temporal dynamics, relaxing their ability to change with the changing traffic, and changing resource availability, as well as changing application requirements. Additionally, GNNs can be scaled between network sizes and architectures, meaning solution development with smaller networks can be used on larger networks with GNN, such as the Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and Message Passing Neural Networks (MPNNs). Such architectures have been applied in several of the resource allocation subproblems including virtual network function placement, task offloading decisions and congestion-aware routing. Empirical research indicates that GNN-based solutions might exceed the effectiveness of traditional approaches by considerable factors in terms of efficiency of using resources, latency compaction, and adaptation to network modifications. Nevertheless, even in the conditions of these encouraging outcomes, there are still a number of challenges (Zhang, Cui, and Zhu, 2020). Scalability scales are of concern when the network is large and has millions of nodes, and GNN models are not interpretable, which reduces the possibility of making decisions in real time. Network operators have a difficult time understanding and evaluating allocation decisions when networks are large. Moreover, the practical deployment issues emphasized in the paper are the need to adopt GNN-based methods to the current network management models, incomplete or unreliable information about the network state, and being resistant to adverse conditions or network failures (Askar, Hussein, Ibrahim, and Mohammed, 2024a).Other

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researchers are also investigating the use of GNNs together with other methods such as reinforcement learning or meta-learning or even classical optimization strategies to exploit the synergy found in them. As SDN, edge computing, and IoT keep changing and converging, the necessity of sophisticated intelligence to implement the optimal resource allocation in all the fields will be paramount. These problems represent a major challenge to GNNs and give Hamilton, Ying, and Leskovec (2017) a way of modeling complex network interdependencies and support cooperative interactions of different levels of granularity. Other researchers have already reported hybrid models in which GNNs are combined with reinforcement learning or even meta-learning, and other more traditional methods of optimization; these models demonstrate the merits of peaceful coexistence. As SDN, edge computing, and the Internet of Things continue to develop, there is an endless number of requests to introduce intelligent approaches to optimizing the allocation of resources. According to Wu et al., 2020, the application of GNNs has an expanding scope of use, and new solutions to mapping and analysis of parallel systems. The GNNs also demonstrate potential to handle complex problems and to this extent, they are appealing in the handling of mesh networks. The contribution is devoted to GNNs application as applied to solving the issues of changing the resources allocation in SDN-based edge computing and IoT, in particular, to the aspects of performance measurement and algorithms optimization. Li, Yu, Shahabi, and Liu (2017) give a graphical view of the allocation of edge computing resources within dynamic networks that are aggregated in Figure 1. This is a summary of allocating computing resources to the dynamic network of edges (Li, Yu, Shahabi, and Liu 2017).

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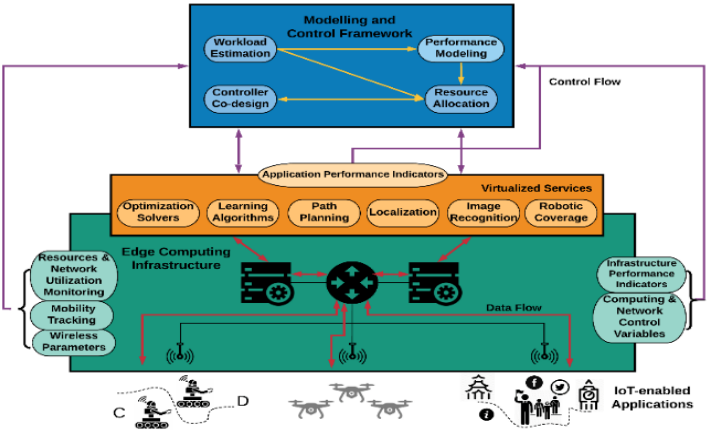

Figure 1: Edge Computing Resource Allocation for Dynamic Networks.

2. Research Method.

In this multi-degree research methodology, where rigor and completeness were established, this systematic evaluation of the dynamics of resource allocation in SDN-enabled edge computing and IoT networks, obtained the use of Graph Neural Networks (GNNs) (Bernstein, Bruna, LeCun, Szlam, and Vandergheynst, 2017).

2.1 Literature Search and Choice.

Most renowned academic databases, such as IEEE Xplore, ACM Digital Library, ScienceDirect, Springer Link, and Google Scholar were searched comprehensively. The search strategy was founded on the combination of essential keywords such as: graph neural networks, resource allocation, software-defined networking, edge computing, and Internet of Things with the appropriate Boolean operator (Hussein, Kareem, Askar, Ibrahim, and Mohammed, 2025). The initial search was limited to peer-reviewed articles published in 2018 to 2024, so that the recent trends in the quickly developing

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field could be reflected. The inclusion criteria were that the studies had to explicitly describe the application of GNN-based models to solving allocation problems, had to be concerned with such settings as SDN, edge computing, or IoT, had to have empirical evidence supporting the proposed solution, and needed to be in English (Xu, Hu, Leskovec, and Jegelka, 2018). Articles that included purely theoretical improvements to GNN and those that did not include practical application in the networking sphere were not included. Additionally, we have performed forward and backward citation search of the frequently used papers to extract pertinent papers which may not have surfaced in the first search (Zhang, Tong, Xu, and Maciejewski, 2019).

2.2 Data Analysis and Extraction Framework.

Due to the chosen papers, we could attract information in accordance to a preelaborated scheme. Encompassing: Individual per node of the graph

- 2.2.1 GNN Architecture: The kind of GNNs employed (e.g. GCN, GAT, GraphSAGE, etc.), architectural modifications and certain implications.
- 2.2.2 Problem Formulation: The description of the problem of aid allocation turned into a graph learning problem transformation, description of a node and edge, and learning objectives.
- 2.2.3 Network Context: SDN relatable, edge computing relatable or IoT factors are considered, scale, and topology of the network.
- 2.2.4 Performance Metrics: Performance evaluation methods, evaluation guidelines, and measures.
- 2.2.5 Implementation Visa: Computer specifications, integration issues, and active deployment factors. Limitations Since scalability is a limitation, issues with data access or computational complexity may serve as limitations, or they may be other constraints.

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- 2.2.6 limitations: Display any limitations, gaps, or challenges related to the research including scalability problems, data access, or complexity of computation.
- 2.2.7 Future Directions. There are also major possible areas of weakness or areas of untapped potential, such as hybrid models, field deployment, or proliferation of new technologies, such as 6G or quantum computing.

2.3. Evaluation of Experiments Synthesis.

We made our overall performance indicators standardized wherever possible so that we could methodically perform the evaluation of the strategies through exceptional research. We recorded the simulation software, network architectures, and workload characteristics that were in the simulation configurations (Abdulazeez and Askar, 2023a). To implement it in the real world in global configurations, we differentiated between the setup of the testbeds and restrictions in terms of operation. We divided the performance improvements depending on the resources (computational capacity, bandwidth, energy, etc.) and the network environment (data centers, edge clouds and IoT networks). The process enabled us to determine trends in performance benefits, depending on the various approaches and situations (Askar, 2017).

2.4. Limitations Assessment

We also documented the differences as presented in the reviewed studies with some of them being scalability, computational problems, difficulties in interpreting the model, and adapting to different environments (Hussein, Ismail, Askar, and Ibrahim, 2025). Besides that, we also examined the methodological challenges inherent in the research itself, including assessment done in simplified network conditions or absence of benchmark compared to available standard methods. Such a methodological framework enabled the systematic study of the existing body of research on the topic concerning GNN applications

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in dynamic resource allocation in SDN-based edge computing and the IoT networks, which generated valuable information on the technological growth and open gaps in the field (Keti and Askar, 2015).

Table .1 summarizes barriers to assessment classes.

Limitation Category	Specific Limitations	Implications	Potential Mitigations
Scalability	Large-scale graphs exceed memory capacity	Limited applicability in massive networks	Graph sampling, distributed GNN processing, hierarchical approaches
	Inference latency for real-time decisions	Unsuitable for time-critical allocations	Model distillation, edge-optimized architectures
	Training overhead with dynamic graphs	Frequent retraining is required for changing topologies	Transfer learning methods, incremental learning.
Implementation	Integration with legacy SDN controllers	Deployment friction in existing infrastructures	Standardized interfaces, containerized solutions

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	Hardware heterogeneity across edge devices	Inconsistent performance across deployment	Hardware-aware model optimization, adaptive inference
	Partial and delayed network state information	Reduced accuracy in dynamic environments	Uncertainty-aware GNNs, prediction-based approaches
Model Design	Over-reliance on synthetic network data	Questionable real-world generalization	Hybrid simulation-real data training, transfer learning
	Lack of interpretability in decision-making	Limited trust from network operators	Attention mechanisms, explainable GNN variants
	Graph representation completeness	Missing important network attributes	Guidelines of feature engineering representations.
Evaluation	Inconsistent benchmarking methodologies	Difficult cross-study comparisons	Standardized evaluation frameworks and metrics

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	Limited real-world validation	Unproven performance in production settings	Industry testbeds, phased deployments
Security & Privacy	Vulnerability to adversarial attacks	Potential for resource allocation manipulation	Robust GNN training, adversarial defense mechanisms
	Privacy concerns with network data	Regulatory and compliance challenges	Federated learning, differential privacy approaches
Energy Efficiency	High computational overhead in GNN inference	Unsustainable for battery-powered IoT/edge devices	Lightweight architectures (e.g., GraphSAGE), quantization, and prunin
	Energy-intensive training phases	High carbon footprint, impractical for edge deployments	Federated learning, sparse training protocols
	Dynamic resource allocation under power constraints	Trade-offs between QoS and energy savings	Adaptive GNNs with energy-aware scheduling (e.g., early exit, subgraph sampling)

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2.5. GNN Applications in Resources Assignment.

Graph Neural Networks (GNNs) have become an effective solution to complex resource allocation problems in dynamic and connected networks, especially in such areas as Software-Defined Networking (SDN), Edge Computing, and Internet of Things (IoT) networks (Mahmood, Hussein, and Askar, 2025). Their graph-structured data modeling properties allow them to be suitable in the process of optimization of resource allocation in such settings (Chen, Ma, and Xiao, 2018). GNNs have the ability to model the structural properties of networks and be updated in real time by modeling networks as graphs, where nodes are devices, servers, or users, and edges are the connecting or interaction links among them (Li, Yu, Shahabi, and Liu, 2017). This feature is especially useful in dynamic environments where network conditions and resource demand is continuously changing. Dynamic resource allocation is one of the main uses of GNNs. Resource requirements may be very different in situations such as edge computing and IoT networks, as required by changing workload or user demands. The GNNs have the ability to process the information in the past and the existing network conditions to estimate the future needs and distribute resources in the form of bandwidth, computation, or storage (Samann, Ameen, and Askar, 2022). This guarantees that there is an optimal resource utilization and reduced latency and energy consumption (Ibrahim, Kareem, Askar, and Hussein, 2025). As an example, in edge computing, GNNs are applied to decide which tasks can be run locally on the IoT devices and which have to be offloaded to edge servers or the cloud. GNNs can be used to distribute tasks efficiently on the network by taking into account such aspects as network congestion, computational capacity, and energy constraints (Chen, Ma, and Xiao, 2018). The other notable use is the load balancing within SDN-enabled networks. GNNs are able to examine the trend in network traffic and forecast demand on destinations and allocate traffic to multiple servers or routes (Ibrahim,

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Mahmood, Askar, and Hussein, 2025). This will eliminate bottlenecks and will achieve optimum performance of the network. Moreover, GNNs also are essential to increase energy efficiency of IoT and edge networks (Gilmer, Schoenholz, Riley, Vinyals, and Dahl, 2017). It is through smart resource allocation and scheduling that GNNs can decide when devices need to be active or not to save energy and yet ensure quality of the provided service. It is especially critical in battery-powered IoT devices, where energy usage is a crucial issue. GNNs are used in wireless IoT networks in terms of interference management. Wireless networks are also prone to complications such as signal interference because of the closeness of gadgets. GNNs simulate the connection between devices and assign resources like spectrum or power to reduce conflicts and improve the entire network performance (Zhou et al., 2020). Moreover, GNNs can be easily scaled, and they can be applied to large-scale networks comprising thousands of devices. They are able to adapt to new equipment or when network conditions change without having to undergo a lengthy retraining, which is a major benefit in dynamic and heterogeneous environments (Wang et al., 2019). The reinforced learning (RL) is often used with GNNs to enhance resource distribution decision-making. In them, the GNN is used to model the network world, whereas RL procedures are used to learn the optimal policies in terms of resource allocation (Askar, Hussein, Ibrahim, and Mohammed, 2024b).This integration facilitates more adaptive and intelligent resource management systems, which can react to the alteration of the conditions in real-time (Askar, Zervas, Hunter, and Simeonidou, 2010). Even though GNNs have numerous benefits, they have numerous challenges in resource allocation applications. Computational complexity is one of the main threats because GNNs can be trained on large-scale networks in an intensive way (Xu et al., 2018). The other difficulty is that GNN models should be able to generalize in various network models and settings. Moreover, the real-time

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deployment with low-latency inferences is also a high-priority requirement of dynamic networks and beyond, and more studies are required to deal with these challenges (Zhang, Tong, Xu, and Maciejewski, 2019). Finally, GNNs provide a versatile and efficient resource management of SDN-powered edge computing and IoT networks (Chen, Ma, and Xiao, 2018). Their capability to simulate intricate relationships, as well as to react to dynamic environment, make them a major facilitator of efficient, scalable, as well as intelligent resource management environment. Future studies might aim at creating lightweight GNNs, improving interpretability, and combining GNNs with other AI methods to address the existing issues and improve the capabilities of GNNs. GNNs are also widely implemented together with reinforcement learning (RL) to enhance decision making on resource allocation. These arrangements have the GNN modeling the environment of the network and the RL algorithms optimizing the best policy of distributing resources (Ying et al., 2018). With this combination, it is possible to have more flexible and smart resource management systems capable of adapting to the changing conditions (Li, Han, and Wu, 2018).

3. Ethical Issues in GNN-Based Resource Allocation.

The increasing popularity of Graph Neural networks (GNNs) as a tool to support flexible resource allocation in Software-Defined Networking (SDN) through edge computing and Internet of Things (IoT) settings provokes questions about ethics that should be considered closely to ensure the standards of fairness, transparency, and accountability(Samann, Zeebaree, and Askar, 2021). Although GNNs have high potential in enhancing the performance of networks, their deployment may have unexpected effects which may adversely affect certain users, devices or groups in the community. These ethical considerations also need to be evaluated in a systematic manner in order to reduce potential harm and promote responsible technological advancement(Kipf & Welling, 2016).

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3.1. Fairness and Bias

One of the major ethical issues may be addressed to the allocation of resources fairly. The GNN models are trained on the previous information, and the information can be biased as well according to the existing disparities in network access, service quality, or the ability of the user with the devices. GNNs will also have a tendency of not only preserving, but also exacerbating such biases unless these biases are fixed, which will lead to unfair or biased results. As an example, GNN, which is trained on data that is generally biased towards a specific demographic or place, can allocate resources to them unfairly, depriving others (Yang, Patil, Askar, et al., 2025). Fighting these biases one way is by selectively selecting and training training data in a manner that is representative of the entire population. Moreover, GNNs that are sensitive to equity can be designed in a manner that ensures the biases in training can be explicitly reduced. Performing periodic evaluations and control over GNN-based resource distribution models is also important to detect and remove any emerging issues related to equity (Battaglia et al., 2018).

3.2 Explainability and Transparency.

The allocation of resources fairly can be discussed as one of the significant ethical issues. GNN models are trained on the history, and it could be biased based on existing inequalities of access to networks, or quality of services, or knowledge of how to use devices. Unless these biases are corrected, GNNs will not only preserve them but also make them worse, which will lead to unfair or biased outputs. As an illustration, GNN that is trained on data that is highly biased towards certain demographics or place may overallocate resources to them, disadvantaging others (Yang, Patil, Askar, et al., 2025). One way of fighting these biases is by carefully choosing and training training data in a way that mimics the diversity of the whole population. Besides, it is possible to create equity-aware GNN models that explicitly mitigate the biases at the training

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stage. It is also important to carry out periodic assessments and monitoring of GNN-based resource distribution frameworks to identify and eliminate any arising problems associated with equity (Battaglia et al., 2018).

3.3. Privacy and Data Security.

The successful allocation of resources with the help of Graph Neural Networks depends on the gathering and arrangement of the network information, which may be the confidential information about clients, devices, and activities. The privacy and security of this information should be guaranteed at all costs (Hussein, Abdullah, Askar, and Ibrahim, 2025). Because of this, GNN frameworks should focus on limiting the access to personal information and ensuring that any obtained data is not accessed, misused, or exposed to third parties. Such methods as federated learning and differential privacy can help to train GNN models without having access to sensitive data. Also, it is necessary to have effective security measures to protect GNN systems and associated data against cybersecurity attacks (Ying et al., 2018).

3.4. The Responsibility and Governance.

There is a necessity to develop separate accountability and governance frameworks of the distribution of aid by the GNN technology. There is the need to clarify who will develop, implement, and monitor GNN models, and also to develop to address any ethical considerations or unintended consequences that may arise(Ibrahim, Abdulwahab, Askar, and Hussein, 2025). This necessitates development of clear procedures and means of data collection, model development, decision making and offering solutions. Besides, the establishment of autonomous oversight bodies to monitor the systems that distribute aid via GNN is also advantageous, as it will ensure that they operate in a fair, transparent, and accountable manner (Wang et al., 2019).

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3.5. Environmental Sustainability

Lastly, the ethical concerns must encompass the environmental impact of the resource distribution through the assistance of GNNs. The energy usage of edge computing and IoTs is an increasing issue with the introduction of these types of networks (Hussein, Ismail, Askar, and Ibrahim, 2025). GNNs may assist in the sustainability of the ecological environment by boosting the distribution of resources in order to minimize the consumption of energy and carbon footprint. Nevertheless, the power needs of the training and implementation of the GNN models themselves should be remembered. It must also have programs to develop energy saving GNN designs and renewable energy to facilitate GNN-based resource allocation networks (Xu, Hu, Leskovec, and Jegelka, 2018).

3.6. Human Supervision and AIs: Deployment.

The growing automatization of aid distribution with the help of Graph Neural Networks (GNNs) requires effective human control systems that would guarantee ethical and responsible implementation. Although GNNs are good at optimization of complex dynamic networks, their choices must remain transparent and responsible, that is high-stakes scenarios involving emergency bandwidth management, critical infrastructure management or healthcare IoT networks(Monti, Bronstein, and Bresson, 2017).

3.7. Resource Allocation GNN Architectures.

Graph Neural Networks (GNNs) have proved to be useful in addressing complex optimization problems in SDN-based edge computing and IoT networks in terms of resource allocation. The selection of the appropriate GNN architecture is crucial to guarantee the best possible performance since it greatly depends on the characteristic features of the network environment and the task of distributing resources. Different GNN architectures have their strengths when it comes to comprehending graph structures, data aggregation, and learning

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representations which are relevant to different resource allocation scenarios as demonstrated in Table 2 (Lilhore, Simaiya, Sharma, and others, 2025).

Table 2. Comparative Analysis of GNN Architectures for Resource Allocation in SDN-Edge-IoT Networks.

GNN Architecture	Strengths	Limitations	Best-Suited Applications	Performance Metrics (Avg.. Improvement)
Graph Convolutional Networks (GCNs)	• Efficient processing of homogeneous graphs • Effective local feature capture	• Limited performance with dynamic graphs • Restricted expressiveness for heterogeneous networks	• Virtual Network Function placement • Stable topology bandwidth allocation	Latency reduction: 15-20% Throughput improvement: 10-15%

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Graph Attention Networks (GATs)	• Handles heterogeneous nodes/edges via attention mechanisms • Adapts to dynamic traffic patterns	• Significant computational overhead • Requires careful parameter tuning	• Congestion-aware routing • QoS-aware task offloading	Energy efficiency: 25-30% Load balancing: 20-25%
GraphSAGE	• Neighborhood scalable with sampling. • Generalizes to unseen nodes	• Potential loss of global graph context • Performance sensitive to sampling depth	• Large-scale IoT device coordination • Edge server load balancing	40% faster inference 18-22% better adaptability
Message Passing Neural Networks (MPNNs)	• Flexible message function framework • Robust to noisy data	• Complex architecture design • High memory consumption	• Energy-aware scheduling • Fault-tolerant resource allocation	30-35% energy savings 25% faster fault recovery
Hybrid GNN-RL Models	• Combines spatial learning with reinforcement learning adaptability • Optimizes long-term performance	• Computationally intensive training • Requires extensive simulation	• Dynamic SDN path reconfiguration • Real-time interference management	30-40% latency reduction 35% better resource utilization

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4. GNN-Based Resource Allocation At the cost of security and privacy.

With the growing popularity of Graph Neural Networks (GNNs) in the flexible allocation of resources to software-defined networking in edge computing and IoT systems, the issues of security and privacy are becoming increasingly more common. The implementation of GNNs in them is associated with specific difficulties that should be addressed to guarantee the safe and reliable operation of interconnected systems (Liu, Zhou, and Sun, 2019).

4.1. Adversarial Attack vulnerability.

Similar to other models of deep learning, GNNs are prone to attack by adversaries. In the framework of the resource-distribution, the actors with a malicious intent can introduce data (such as network topology or user behavior) to disorient the GNN to make ineffective or harmful allocation decisions (Ma, Wang, Aggarwal, and Tang, 2019). As an example, the intruder can inject malicious information on the system to cause congestion, reduce efficiencies, or drain the resources. It has been found that even a small alteration to the graph structure or dynamics of the node can drastically influence the predictions of the GNNs. In order to avoid these threats, it has been suggested that one can use strong training methods, including adversarial training and defensive distillation. These methods will focus on training the GNNs to be resistant to adversarial inputs by exposing them to distorted information during the training process (Gao, Ji, and Liu, 2019).

4.2. Data Networks.

GNNs utilize the evidence of the community like visiting tendencies, state of the machines and the activities users execute to make smart decisions regarding the allocation of assets. However, such information sets can contain personal data, along with the aspect of privacy (Xu, Shen, Cao, Qiu, and Cheng, 2019). To provide an example, confidential information or proprietary information may be revealed through the information collected by the devices or sensors in an IoT. To address such problems, privacy-preserving techniques, such as federated learning and differential privacy are being researched (Almukhtar, Mahmoodd, and Kareem, 2021). Federated learning gives GNNs a chance to be trained on distributed data without, in any case, transferring underlying data to a central location, thus minimizing the risk of sensitive information disclosure. Conversely, the so-called concept of the differential privacy introduces noise to the model outputs, or the data itself, so that the sensitive information does not get inferred by the latter, and GNNs could still operate successfully (Chen, Li, and Bruna, 2019).

4.3. Secure SDN Controller Interface.

The integration of GNN-based solutions together with SDN controllers brings in additional security impediments. SDN controllers are necessary to monitor network assets and enforce different policies. Hacking of such controllers might lead to severe disruptions of the network (Zhang et al., 2018). Consequently, it is of paramount significance to ensure safe communication between the GNN models and SDN controllers. The use of secure multi-party computation (SMPC) and homomorphic encryption would be some of the strategies to ensure the security of data as it is being transferred and stored. Moreover, it is essential to introduce authentication and access control measures to prevent illegal access to GNN models and the SDN systems (Wang et al., 2019).

4.4. Resilience to Network Failures and Abnormalities.

When the environment is fast-paced, mistakes and discrepancies within communities can hardly be avoided. GNNs should be durable enough to overcome these obstacles without interfering with the overall performance of the network (Liu et al., 2020). As an example, in case of a failure of a node or connection, the GNN should be able to quickly reallocate resources to sustain the services. Researchers have attempted to come up with GNN models that are

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resilient to failures and can detect and restore network failure in real time (Defferrard, Bresson, and Vandergheynst, 2016). Besides the repair of graphs and the identification of abnormalities, GNNs have demonstrated the capability of promoting the resilience of aid distribution frameworks (Zhang, Song, Huang, Swami, and Chawla, 2019).

4.5. Compliance and Regulatory Issues.

The adoption of the system of resource allocation using GNN in the network of IoT and edge computing should be accompanied by various regulatory requirements, including the General Data Protection Regulation (GDPR) in Europe and California Consumer Privacy Act (CCPA) in the United States (Fan et al., 2019). These legislations set strict guidelines on the collection, storage and processing of data, and may influence the design and implementation of GNN models. It is quite a challenge to meet these requirements and, at the same time, allow GNN-based systems to be effective and efficient simultaneously (Li, Wang, Zhu, and Huang, 2018).

4.6. Future Directions.

The GNNs Future studies in this direction should aim at improving the knowledge about the evolution of trustworthy GNNs that will integrate safety and privacy indicators easily (Zhang et al., 2018). By combining explainable AI (XAI) and GNNs, one can also improve the level of transparency in decision-making, thus, it becomes easier to identify and mitigate potential security risks. Moreover, by enhancing lightweight encryption algorithms with a specific focus on GNNs, it is possible to strengthen the security of the resource distribution systems without significant increment on processing demands (Chen, Zhu, and Song, 2018).

5. Discussion

The research on the topic of Graph Neural Networks (GNNs) which was associated with the challenge of dynamically assigning resources within the SDN-based framework of edge computing and IoT adequately explores how GNNs can deal with the challenges of resources allocation in the present-day interconnected systems (Klicpera, Bojchevski, and Günnemann, 2018). One of the strongest points of this review is that it systematically reviews the available literature, classifies the applications of GNNs into separate groups related to task offloading, load balancing, energy efficiency, and interference control(Li, Han, and Wu, 2018). This methodology allows to gain a systematic overview of what has been studied in each field to get the relevant studies and applications. The applicability and scalability of GNNs also come into focus with the review highlighting the ability of the tool to capture complex network structures and scale to changing resource demands(Hamilton, Ying, and Leskovec, 2017). This feature makes GNNs especially applicable in the context of such applications as IoT and edge computing, where the network conditions may vary significantly. Moreover, the process of GNNs reinforcing reinforcement learning is discussed in-depth and proves to be able to enhance the process of decision-making when it comes to energy consumption in order to manage resource allocation operations(Klicpera, Bojchevski, and Günnemann, 2018).The survey also provides reasonable suggestions regarding how GNNs can streamline power consumption and reduce latency and normal community performance, which is valuable to those interested in enforcing intelligent aid control frameworks in practical settings (Abdulazeez and Askar, 202 Nevertheless, there are certain limits of the survey that should be discussed further. As an illustration, it fails adequately to consider the computational complexity of GNNs, specifically, when applied to the massive-scale networks(Hussein, Abdulwahab, Askar, and Ibrahim, 2025). Training GNNs on big data or even dynamic setups, specifically,

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can be resourceful, and the survey might consider investigating methods to reduce those challenging scenarios, which encompass lightweight structures or distributed learning approaches to schooling (Ibrahim, Abdullah, Askar, and Hussein, 2025).The other gap is that it does not discuss the generalization ability of GNNs in exclusive community structure and settings(Zakia & Yedder, 2017). It is important to know how well the GNN models are trained on one type of network when using them to all others in order to ensure that their relevance is more universal. Moreover, the questionnaire does not go into a deeper exploration on the problem of real-time deployment, including achieving low-latency inference in dynamic structures (Monti, Bronstein, and Bresson, 2017). Such tactics as compressing models, side-based inference, or hybrid AI approaches could have been considered to solve this bother(Askari, Hussein, Ibrahim, and Mohammed, 2025). In the future, the survey presents a number of promising prospects in the destiny studies. Among them is one course that deals with the construction of lightweight GNN architectures that can work in resource-limited environments, such as area devices or IoT sensors (Kipf and Welling, 2017). The version pruning, quantization and understanding distillation techniques are expected to play a vital role in the lessening of the computational overhead, and at the same time maintain the performance levels unimpaired and undamaged. The other potential area of future work is also the combination of Graph Neural Networks (GNNs) with diverse different forms of artificial intelligence, which can incorporate but not be limited to federated learning or transfer learning, to extend generalization abilities in a broad range of diverse network settings (Defferrard, Bresson, and Vandergheynst, 2016). It can be assumed that the application of federated learning will enable GNNs to learn the insights of the plethora of distributed data sources without violating the principles of privacy, and the application of transfer learning will enable the adaptation of pre-trained models to new settings with the minimum amount of

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retraining resources. More than that, it is urgent that further studies should be done to enhance the interpretability of GNN-based systems because their nature of black-box characteristics may severely undermine not only trust but also adoption of such systems in critical applications in diverse areas(Hussein, Mahmood, Askar, and Ibrahim, 2025). By finding solutions to these urgent issues and exploring these potential avenues of future study, the discipline can access the entire range of opportunities that GNNs can bring to the sphere of intelligent resource management systems (Samann, Zeebaree, and Askar, 2021). Overall, the survey in question is a priceless source of information to whom are both researchers and practitioners as it offers a solid basis in the further development of the dynamically changing sphere of study (Zhang, Chen, and Liu, 2019).

6. Conclusion

The analysis of Graph Neural Networks (GNNs) considering their use in dynamic resource allocation in SDN-based edge computing and Internet of Things networks offers a balanced and eye-opening summary of how GNNs can be used in solving the problem of resource management in the existing networking space. The review shows a healthy perception regarding the application of GNNs on various aspects of resource allocation, being a dynamic phenomenon, based on significant themes including offloading, load balancing, performance improvement and interference management, and a well-designed study in the subject. It succeeds in identifying the advantages of GNNs such as their capacity to capture complex network topology, respond to dynamic environments and scale to large-scale networks, which makes them particularly fit in these contexts such as the IoT and edge computing. The review also examines the collaboration between GNNs and reinforcement learning with references to the fact that the two can be more efficient to the decision-making process of resource allocation. Furthermore, it also conveys more practical knowledge regarding the implications of the GNN-based methods, including reduction of the energy

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consumption, reduction of delays, and improved network performance that can be valuable to practitioners who are interested in the development of advanced resource management systems. However, as it is analyzed, the number of deficiencies and aspects that should be tackled is quite a number. It does not, as a case in point, delve deeply into computational complexity of GNNs, particularly when the size of networks or the dynamics of networks is large. In such cases, this can be resource-consuming to train GNNs and knowledge of the lighter models or distributed training strategies would have assisted in overcoming such challenges. In addition, the review fails to explore the generalization capability of GNNs to other classes and settings of networks, which is critical to their wide-scale use. The absence of focus on impediments associated with real-time implementation such as achieving minimal latency of systems change is one of the most critical deficiencies. To solve this issue such strategies as model compression, external inference or mixed AI techniques might have been researched. Such gaps define crucial spots that need further research in an attempt to gain a better understanding of the potential of GNNs in resource management. In general, the review is a key resource to researchers and practitioners since it gives a general overview of GNN usage, its benefits and drawbacks of current barriers associated with resource allocation in SDN-based edge computing and IoT infrastructure. It not only provides an overview of the current conditions in the field in the area, but also mentions the most important areas of interest in the future, the creation of lightweight GNN architectures, improving its generalization in different settings, and creating means through which its interpretability can be further simplified, this field can keep using the opportunities of GNNs in smart resource management systems. Finally, the review gives a solid foundation on the trends in this dynamic industry in the future and it adds a lot to the existing literature on GNNs and its application in interconnected systems. Besides, the other important limitation is that the

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questions concerning the implementation in changing conditions are not addressed, especially how low-latency inference in changing conditions can be accomplished; the possible methods, like model compression, edge-based inference, or integrated AI, could have been utilized to elaborate the point further. The identified gaps have shed light to some of the main aspects of future research studies in order to have a general understanding of the full potentials of GNNs when it comes to resource allocation.

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