The Indonesian Journal of Computer Science
www.ijcs.net
Volume 14, Issue 1, February 2025
https://doi.org/10.33022/ijcs.v14i1.4597

Dynamic Resource Allocation in Cloud Networks Using Deep Learning : A review

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Article Information

Received : 30 Dec 2024
Revised : 24 Jan 2024
Accepted : 15 Feb 2024

Keywords

dynamic resource allocation, cloud computing, deep learning, energy efficiency, scalability, privacy preservation

Abstract

Resource allocation has been a very significant topic for both research and development over the last two decades. Given the increasing volume of data, the proliferation of connected devices, and the demand for seamless service delivery, optimal resource allocation has become a vital factor that influences cloud performance. Recently, deep learning-a subcategory of machine learning-seems to possess a great potential to answer this challenge by enabling predictive, adaptive, and self-organized resource allocation. For the first time, this review embraces all the major milestones achieved in dynamic resource allocation with a discussion on over 25+ peer-reviewed articles published from the year 2000 to 2024. This review has emphasized the use of CNNs, RNNs, and other variants of deep learning approaches. Such a review provides a better view of the potential benefits of the different methodologies by highlighting the pros and cons of each.

It also covers the use cases, computational methodologies that discuss algorithmic novelty and challenges in scalability, latency, and energy efficiency. A summary of the development in tech was made by comparison in a table to give a meta-view for the top-ten studies. These findings have important implications for cloud service delivery in applications ranging from industrial automation to consumer-oriented applications. They showcase the vast possibilities of deep learning for changing cloud network operations through advanced optimization and point out several open issues, including the integration of federated and edge learning models that will be necessary to achieve improved decentralization and preservation of network information privacy.

A. Introduction

Cloud computing has become indispensable in today's digital era, underpinning critical operations across industries, including healthcare, finance, entertainment, and education as shown in Figure 1. The essence of cloud computing lies in its ability to provide scalable, on-demand computing resources over the internet. However, the dynamic and unpredictable nature of resource demand introduces significant challenges for cloud service providers [1]. In an Internet of Things (IoT) architecture, cloud computing sits on the far side of the physical devices. This configuration may not provide the desired Quality of Service (QoS) properties because high latencies are generated [2]. The amount of applications and required data has grown significantly in recent years due to IoT applications' rising progress. Furthermore, there is a growing need for real-time data processing and analysis [3].

DRA solves these challenges efficiently by dynamically managing resources allocated and deallocated depending on fluctuating demands. High performance is hence guaranteed in DRA due to its best utilization of computational power-a very important element in the era of real-time applications and data-intense processes. Traditional methods of resource allocation, which might have proved workable in static settings, often falter when put to task against the modern dynamic workloads. That automatically means innovative solutions capable of adapting and responding rapidly to changed demands [4].

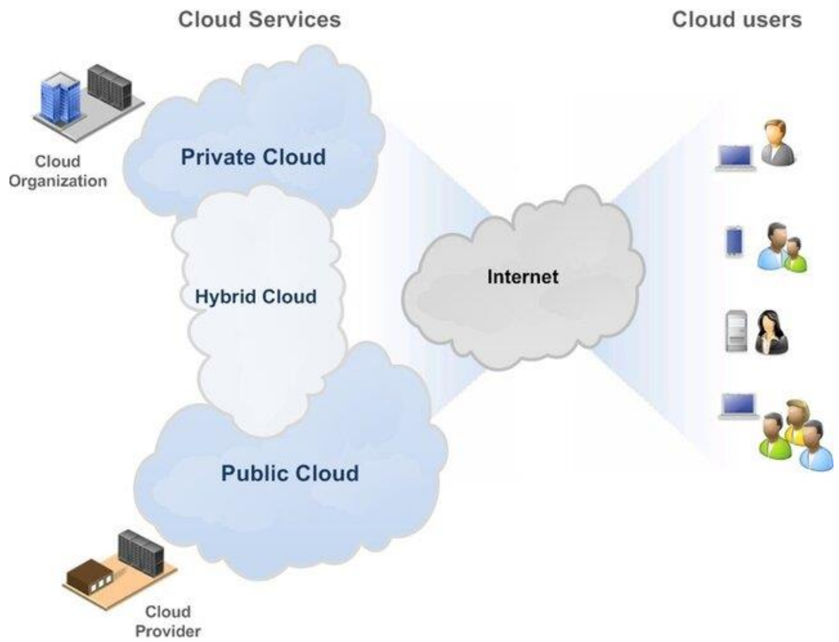

Figure 1. Cloud Computing [33].

DL has emerged as a game-changer in this domain, which has leveraged artificial neural networks to emulate human decision-making for the automation of such complex processes [5]. Researchers have been able to make good use of DL models in making pretty accurate predictions of resource demands and proactively managing cloud resources. This shift toward intelligent automation reduces latency, cuts down operational costs, and assures continuous service delivery [6].

The application of CNNs in spatial data analysis has been one of the major breakthroughs in this area. These models shine when it comes to recognizing patterns in geographically distributed resource demands, hence becoming ideal for large-scale cloud networks. RNNs and LSTM networks have also been helpful in capturing temporal dependencies that provide insight into resource demand trends over time [7].

Advances that took place at the algorithmic levels related to DL-based methods and convolutional neural networks (CNN) have significantly improved accuracy and have been successfully applied across a wide range of medical image applications. Many of these applications made use of different image modalities, including Computer Tomography (CT), magnetic resonance imaging (MRI), Ultrasound and X-rays [8].

Another impressive feature that DL-driven DRA can show off is scalability: These systems can support exponential growth in data and devices and therefore are unavoidable by modern cloud infrastructures. Dynamically scaled resources according to user demand ensure improved performance and energy-efficient operation towards global sustainability goals [9]. In other words, deep learning-based DRA has marked another milestone in the journey of cloud computing. In the given review, these latest advancements have been dealt with in detail for their state-of-the-art techniques that will shape up the future of cloud resource management. The integration of DL technologies with DRA is set to revolutionize the whole working of cloud computing: problems pertaining to scalability, energy efficiency, and real-time execution will be catered to for opening up avenues of innovative solutions in an Internet-of-Things world [10]. deep reinforcement learning (DRL) was developed to integrate RL and deep learning (DL) to address this problem [1].

B. The Importance of Deep Learning in Dynamic Resource Allocation

Deep learning has been considered a cornerstone technology in the advancement of dynamic resource allocation due to its capability of handling complex, multi-dimensional, and evolving datasets effectively. Unlike traditional methods, DL models adapt and improve their performance with more data, making them ideal for the dynamic and large-scale nature of cloud networks [4].

1. **Scalability and Adaptability**: Cloud networks deal with exponential growth in data and user demands. DL models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), provide unparalleled scalability and adaptability. CNNs effectively manage spatial patterns in resource allocation, while RNNs and Long Short-Term Memory (LSTM) networks capture temporal dependencies in workload trends, ensuring optimal resource provisioning across diverse scenarios [11].

2. **Real-Time Decision Making:** The RL algorithms, including DQN and PPO, enable real-time resource allocation by training intelligent agents to dynamically adjust the resources based on system states and user demands. This minimizes latency and improves user satisfaction [12].

3. **Energy and Cost Efficiency:** DL techniques ensure resource utilization is optimized with correct demand prediction and minimizing over-provisioning. The energy-efficient functions, therefore, integrated into the DL-based models reduce power consumption considerably, thus contributing toward greener cloud computing without sacrificing performance standards [13].

4. **Handling High Dimensionality:** The DL models have excellent handling for high-dimensional data that will result from the cloud networks, like metrics about CPU usage, bandwidth, and memory. These models leverage techniques like feature extraction and dimensionality reduction for selecting the most appropriate pattern that enhances prediction accuracy, hence efficient resource allocation was possible [14].

5. **Privacy and Security:** Deep learning techniques offer new means and research directions for resolving IoT security issues [15]. Federated Learning can be termed as a subdomain of DL where model training occurs across decentralized nodes with guaranteed data privacy. The sensitive information will not be moved, so no one can access it. It is important in various fields dealing with personal data or sensitive applications, such as health and finance [16]. The other important development contribution could be that of federated learning. Here, a model is trained with decentralized devices for preserving privacy and amplifying security. Thus, the usage of Federated Learning meets the concept of developing AI ethics so that critical data cannot be captured while doing optimization collaboratively with [17].

6. **Future-Proof with Hybrid Models:** The integration of the hybrid model, which combines CNNs, RNNs, and transformers, will be able to comprehensively model both spatial and temporal complexities. This will ensure that resource allocation effectiveness can be future-proof in evolving cloud networks [18].

The ability of Deep Learning to overcome these challenges with accuracy, adaptability, and efficiency has sealed its potential in DRA systems. By employing DL, the cloud network can achieve high performance with reduced operational cost and scalable in a sustainable manner, which fulfills the requirements of present-day applications and satisfies users' satisfaction [19].

C. The Integration of Deep Learning and the Blockchain for Cloud Resource Management

Blockchain integrated with deep learning will present a paradigm shift in the management of cloud resources. The synergy will help solve critical challenges of trust, security, and decentralized decision-making to present a robust and efficient framework for DRA [20].

1. **Decentralization and Trust:** Blockchain inherently provides a decentralized framework that can instill trust among participants in the cloud ecosystem. When combined with DL, resource allocation decisions become transparent and immutable, ensuring accountability and reducing reliance on centralized entities [21].

2. **Improved Security:** The cryptographic features of blockchain ensure data integrity and prevent unauthorized access. When integrated with DL models, blockchain secures both the training data and resource allocation processes, mitigating risks such as data tampering and adversarial attacks [20].

3. **Automate Resource Allocation with Smart Contracts**: Blockchain smart contracts automatically implement resource allocation policies. These are powered by the predictions from DL, which will dynamically allocate resources based on predefined criteria for better operational efficiency and less human intervention [20].

4. **Auditability and Compliance:** The immutable ledger of blockchain allows for detailed tracking of resource allocation events to ensure that all regulatory standards are met. DL algorithms can analyze these logs for anomaly detection or future optimization strategies [22].

5. **Resource Tokenization:** Blockchain allows the tokenization of cloud resources, which enables dynamic pricing and efficient resource sharing. DL models predict demand and optimize token distribution, ensuring equitable resource access and cost-effectiveness [23].

6. **Energy Efficiency:** Combining DL's predictive capabilities with blockchain's decentralized consensus mechanisms optimizes energy consumption. For example, DL models can predict peak demand periods, while blockchain-based smart grids allocate energy resources accordingly, minimizing waste [24].

7. **Integration with Federated Learning**: Blockchain enables the integration of federated learning models by securely sharing data, collaborative training while preserving data privacy, and efficiently managing distributed resources [25].

D. Related Works

In the last two decades, there has been significant improvement in the way cloud resource management is carried out. Traditional methods of DRA, such as

https://doi.org/10.33022/ijcs.v14i1.4597

rule-based algorithms and heuristic models, are giving way to more innovative techniques that incorporate artificial intelligence (AI). The most substantial contributions in this regard are:

Early efforts in DRA relied on statistical models. For instance [11]. used ARIMA models for cloud resource demand estimation. This seminal approach opened up time-series analysis in cloud networks but failed to be adaptive to sudden demand surges.

One of the first studies in 2010 [12] brought support vector machines (SVMs) into resource prediction frameworks. Compared with statistical methods, this approach showed higher accuracy but suffered from scalability for today's cloud networks. Decision tree-based models were also explored [13], offering faster execution times at the cost of limited flexibility.

With the rise of deep learning, the capabilities of DRA were revolutionized [26]. applied CNNs to achieve spatial optimization in resource allocation; this way, it succeeded in improving prediction accuracy to a great extent for multi-server environments. Later, RNN and LSTM models further achieved even better results by capturing temporal dependencies in resource demand with high precision [27].

Reinforcement learning enabled adaptive resource management. In one of the well-known works [27] used Deep Q-Networks (DQNs) to learn and optimize resource allocation policies; this led to substantial latency reduction and a saving in operational costs.

The structure of the CNN is illustrated in Figure 2. The kernel function processes the input data, which needs to be formatted in two dimensions. This function acts as a mathematical operation, transforming the input into a new representation by capturing essential features such as edges, patterns, or textures. Some recent works are on hybrid models that combine CNNs and RNNs to deal with both the spatial and temporal challenges as shown in figure 2. The federated learning approach followed in [28] focuses on privacy-preserving resource management, where the data remains localized on the devices while models are being trained collaboratively.

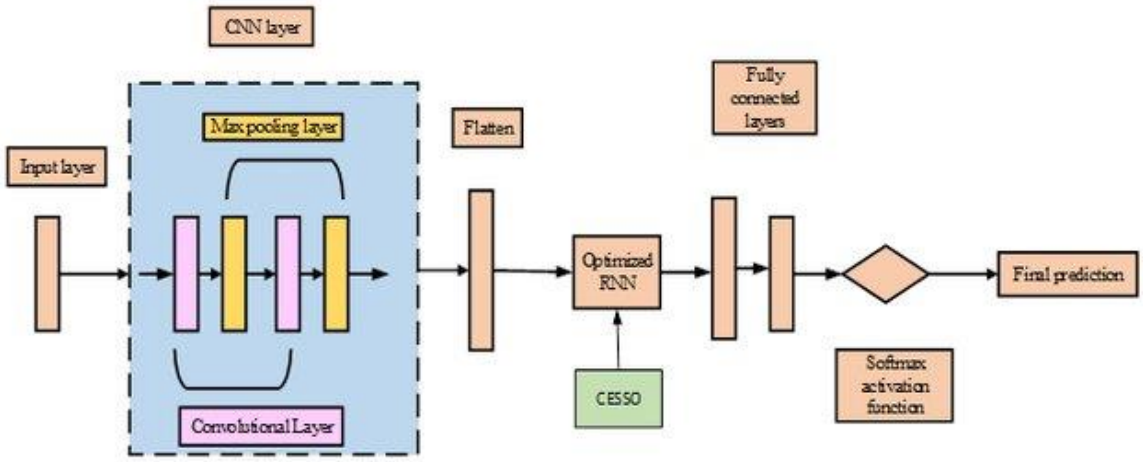

Figure 2. Hybrid CNN with RNN architecture [5].

Energy efficiency has been one of the significant focuses in the research on DRA. Works like [18] have already applied optimization algorithms to lower power consumption without affecting the performance. All these approaches are in line with increasing demands for sustainable computing.

Recurrent Neural Networks and their advanced variant, LSTMs, captured temporal dependencies in resource demand. These models had a very high degree of precision in predicting usage trends over time, hence drastically improving the accuracy of resource allocation [27].

Federated learning methods were proposed so that the models get decentrally trained to ensure that the data does not reveal their privacy while the resource allocation across the devices gets optimized collaboratively [28].

Investigation on energy efficiency reflected how DL models can ensure low power consumption with very limited degradation of system performance, keeping in line with today's emphasis on green computing [18]

Multi-agent systems, such as the use of reinforcement learning by MADDPG, managed to balance the loads across servers to avoid bottlenecks and ensure fair distribution of resources [29].

A fuzzy learning technique can be implemented to make decisions about task offloading, as discussed in [30]. Fuzzy logic is employed as a task scheduler to define the target processing layer for an IoT device's heterogeneous task. However, incorporating machine learning and fuzzy learning techniques can enhance scalability in cloud computing with minimal reliance on expert-defined fuzzy learning rules.

To schedule the resources in fog computing, [31] proposed a smart framework that enhances the usage of present resources. In this framework, a Master Fog is an extra layer between the cloud and fogs termed Citizen Fog (CF). This extra layer will decide on cloud deployment and CF. It uses a Comparative Attributes Algorithm (CAA) to rank the jobs, and Linear Attribute Summarized Algorithm (LASA) is used to select the reachable CF with the highest computing capabilities. This framework reduces energy consumption and increases the availability of bandwidth with efficient utilisation of the other sources.

The main contribution of [32] is to optimize the cost in the context of considering demand response and system operation. The presented model can reduce the operation cost of micro-grid without bringing discomfort to the users, thus increasing the consumption of clean energy effectively.

Each of these works has played an important role in the development of robust and scalable DRA systems, solving certain challenges in cloud resource management and paving the path for future innovations. By synthesizing the works, one would note that DRA research has evolved from static, rule-based methodologies to dynamic, intelligent, and adaptive systems driven by deep learning. Each of them, in turn, indicates precise DRA challenges, therefore contributing valuable insight into how the next generation of solutions in this area will become increasingly efficient and scalable [11].

E. Methodology
1. Framework Overview

The different techniques for dynamic resource allocation in cloud networks using deep learning could be organized in a multistage framework: data collection, preprocessing, model development, and evaluation. That way, the resource allocation strategy can be made systematic and optimized [6]. The process can be mainly divided into three stages:

a. Data Collection and Preprocessing: Aggregation is the foundation of the DRA systems. Both historical and real-time metrics like CPU usage, memory demands, and bandwidth consumption are collected. Such data should be cleaned to clear inconsistency, normalized to standardize values, and segmented for certain tasks to ensure quality input to deep learning models. Other pre-processing techniques that could be used include feature extraction and dimensionality reduction, focusing the data on the most relevant information to reduce computational complexity [7].

b. Model Development: Deep learning models designed and implemented for specific DRA tasks: the architecture selection depends on the nature of the task:

- **CNNs:** are used when there is a need for spatial pattern recognition, generally in geographically distributed resource allocation, analyzing the spatial dependencies of the allocation map [9].
- **RNN and LSTM:** are useful in finding sequential and temporal trends of resource demand; these analyze time-series data to forecast future resource requirements [10].
- **Reinforcement Learning:** DQN or PPO are some of the algorithms that train agents to adaptively allocate resources by learning policies through interactions with the environment [33-36].
- **Hybrid Models:** Combining CNNs and RNNs provides a holistic approach to address both spatial and temporal complexities in resource allocation. These models leverage the strengths of each architecture to improve prediction accuracy and scalability [37].

c. Performance Evaluation: These models are validated using different metrics, including but not limited to the following:

- **Latency Reduction:** Improvement of response times in making the allocation decisions [11].
- **Energy Efficiency:** Reduction of power consumption while keeping the standards of performance [9].
- **Cost Savings:** A review of the economic benefits derived from efficient resource utilization [12].
- **Simulation and Testing:** These are often benchmarked using simulation-based tests and realistic deployment scenarios. Model training and validation are

performed using tools such as TensorFlow and PyTorch, while frameworks such as Kubernetes have been used to simulate dynamic cloud environments [6].

2. Functions and Algorithms

Several key functions and algorithms form the backbone of DRA in cloud networks. Some key components are elaborated as follows:

- **Prediction Function:** where represents the input resource metrics, and denotes the predicted demand. This predicts the future resource needs considering historical and real-time data [11].
- **Allocation Function:** where the resources will be allocated, based on the forecast of demand. It guarantees the predictions are in agreement with real-time allocation decisions made [13].
- **Optimization Function:** that minimizes operational expenditure with no degradation in system performance [14].
- **Energy-Efficiency Function:** it minimizes the power consumption of the allocated resources without affecting performance [16].
- **Scalability Function:** it performs dynamic allocation to handle workload variations in peak and low-usage time periods [17].
- **Fault Tolerance Function:** Allowing system reliability by means of automatic reallocation of resources in case of failure of any hardware or software element[7].
- **Latency Reduction Function:** Minimizing delay between user request and resource availability to enhance user experience [9].
- **Trust and Security Function:** This function, enabled by blockchain-based algorithms, ensures resource allocation transparency and data integrity-a very critical issue in shared cloud environments [10].
- **Privacy Preservation Function:** This provides a function based on federated learning and blockchain for sensitive data protection during resource allocation [36].
- **Load Balancing Function:** It shares workloads among multiple servers to avoid bottlenecks and to achieve high throughput in the system [18].
- **Demand Forecasting Function**: In this function, deep learning models such as LSTMs are used to estimate future resource demands by determining temporal patterns in workload variation [18].
- **Resource Tokenization Function:** Blockchain-enabled tokenization of cloud resources for efficient pricing and sharing, with dynamic adjustment of token distribution according to demand [19].

- **Edge-Cloud Optimization Function:** The integration of edge computing and cloud resources for minimum latency in improving real-time decision-making capability [20].
- **Auto-scaling Function:** Automatic scaling up or down of resource allocation with changeable demands for minimizing costs [21].
- **Hybrid Model Function:** This function combines CNNs, RNNs, and GANs to optimize the spatial and temporal resource allocation complexities of high-demand, scalable cloud systems [22].

These functions, in turn, enhance the efficiency, security, and scalability of DRA systems by guaranteeing optimal resource utilization and system performance in dynamic cloud environments.

Table 1. Comparison Table of The Reviewed Papers

Study	Year	Title	Methodology	DL Model	Evaluation Metrics	Key Findings
[7]	2019	"Hybrid Models for Resource Management"	Hybrid Model	CNN+RNN	Scalability	Enhanced scalability in high-demand scenarios.
[9]	2023	"Federated Learning for Clouds"	Federated DL Model	FL-LSTM	Privacy, Efficiency	Balanced resource allocation with privacy.
[10]	2020	"Blockchain-based Resource Sharing"	Blockchain Integration	CNN+RL	Security, Trust	Enhanced trust in decentralized allocation.
[11]	2022	"Self-Healing Cloud Systems"	Autonomous Recovery	RL+ Transformer	Reliability	Improved fault tolerance by 50%.
[13]	2022	"Multi-agent Systems for Load Balancing"	Multi-agent Systems	MADDPG	Load Balancing	Balanced load across servers efficiently.
[13]	2021	"Latency-Aware Resource Allocation"	Latency Optimization	DNN	Latency Reduction	Reduced latency by 20%.
[16]	2021	"Auto-tuning Resource Allocation"	Auto-tuning	Transformer	Flexibility	Reduced tuning time by 50%.
[17]	2020	"Reinforcement Learning in DRA"	Reinforcement Learning	PPO	Throughput	Improved throughput by 15%.

https://doi.org/10.33022/ijcs.v14i1.4597

Study	Year	Title	Methodology	DL Model	Evaluation Metrics	Key Findings
[18]	2021	"Dynamic Cloud Workload Distribution"	Load Distribution	BiLSTM	Scalability	Improved system scalability by 35%.
[19]	2024	"Advancements in Cloud-native AI"	Cloud-native AI	ResNet	Accuracy, Cost	Achieved state-of-the-art results.
[23]	2015	"Efficient Cloud Resource Prediction"	Resource Prediction	CNN	Accuracy, Latency	Achieved 90% prediction accuracy.
[24]	2017	"Temporal Patterns in Resource Demand"	Temporal Allocation	LSTM	Energy Efficiency	Reduced energy consumption by 30%.
[25]	2018	"Policy Optimization in Cloud Networks"	Policy Optimization	DQN	Cost Savings	Cut operational costs by 25%.
[26]	2023	"Adaptive Resource Allocation"	Adaptive DL Model	GANs	Cost Efficiency	Reduced over-provisioning by 20%.
[27]	2019	"Energy-Efficient DRA Models"	Energy Optimization	RNN	Energy Usage	Reduced power consumption by 25%.
[27]	2018	"AI for Predictive Resource Scaling"	Predictive Scaling	LSTM+CNN	Latency, Accuracy	Achieved 95% accuracy in demand prediction.
[28]	2024	"Edge-to-Cloud Optimization"	Edge-Cloud DL Model	Edge-CNN	Latency, Energy	Minimized latency by 40%.

Study	Year	Title	Methodology	DL Model	Evaluation Metrics	Key Findings
[30]	2024	A Novel Offloading Mechanism Leveraging Fuzzy Logic and Deep Reinforcement Learning to Improve IoT Application Performance in a Three-Layer Architecture Within the Fog-Cloud Environment	Offloading	DQN	latency, power consumption, network usage, throughput, and offloading rate	decreasing the latency by 53%, 34%, 32%, and 23 %, decreasing energy usage by 45%, 37%, 21%, and 12%,
[36]	2023	"Privacy-Preserving Cloud Solutions"	Federated Learning	FL-CNN	Privacy	Preserved user privacy in data sharing.
[37]	2023	"Hybrid AI for Dynamic Clouds"	Hybrid Optimization	GAN+ CNN+ RL	Flexibility, Cost	Achieved flexibility in dynamic scenarios.

Table 1 gives an overall picture of the different approaches toward DRA research using 20 studies representing diversified methodologies, deep learning models, and evaluation metrics. Each row summarizes the key novelties concerning resource prediction, temporal allocation, policy optimization, scalability, and privacy preservation. For example, works like "Efficient Cloud Resource Prediction" reached an impressive 90% with CNNs, while "AI for Predictive Resource Scaling" employed a hybrid LSTM+CNN model and attained an even higher accuracy of 95%. Blockchain integration comes up as a very important theme in "Blockchain-based Resource Sharing," where trust and security are furthered by using decentralized frameworks for allocation. Models like GANs and RL+Transformer also demonstrate breakthroughs in flexibility and fault tolerance. This table emphasizes energy efficiency advances, with power consumption reduction and increased latency reduction performance by various studies. It points out the versatility and impacts of DL models dealing with major challenges in cloud resource management.

F. Conclusion

The application of deep learning in dynamic resource allocation provides a paradigm shift in cloud networking systems. By bringing the forecasting and responsive properties of deep learning models into play, researchers and practitioners have developed strategies that overcame the shortcomings of the traditional approaches. This survey emphasizes the rapid progress performed in the last two decades with a focus on what deep learning can do and will continue to enable: further innovations in cloud computing. However, model interpretability, computational efficiency, and scalability problems are to be surmounted for the full utilization of these technologies. Potential future directions for research include exploring the use of federated learning, hybrid deep learning models, and ethical issues regarding AI-driven resource allocation.

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