Survey on Deep Learning-Based Cloud Computing Resource Management Technologies

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Abstract

Cloud computing resource management faces core challenges, such as dynamics, heterogeneity, and resource supply-demand matching. Deep learning offers significant advantages in addressing these issues, including adaptive decision-making and complex pattern mining. This paper targets the application of deep learning in cloud computing resource management for summary and analysis, dividing it into three categories: resource scheduling and allocation, load prediction and elastic scaling, and energy efficiency optimization. Based on these categories, we summarize mainstream methods, technical frameworks, and application scenarios, analyze their advantages and disadvantages, and discuss future trends.

Keywords

Cloud computing; Deep learning; Resource management; Resource scheduling; Load prediction.

1. Introduction

As a new computing paradigm, cloud computing provides dynamically scalable virtualized resources by the Internet [1]. In today's digital era, it is pretty much essential for supporting large-scale distributed applications, and efficient resource management is crucial for improving resource utilization, ensuring service quality, and reducing operational costs. However, traditional cloud resource management mainly relies on manually designed rules and strategies like round-robin scheduling, greedy algorithms, and static threshold-based allocation, which have limitations [2]. They cannot adapt to the dynamics of real-world cloud environments, often optimize single objectives without considering trade-offs between multiple metrics, and face scalability issues as the cloud scales, requiring constant manual updates with high maintenance costs and delayed responses to new challenges. Hence, efficient resource management is crucial, driving the exploration of deep learning-based technologies. Deep learning brings substantial benefits to cloud computing resource management by enabling adaptive decision-making through learning from vast amounts of data, mining complex patterns in heterogeneous environments, and optimizing multiple objectives simultaneously. These advantages allow for higher resource utilization, reduced energy consumption, and improved service reliability in dynamic scenarios, making it important for handling the increasing complexity of cloud systems. Given that numerous researchers have explored deep learning applications in this field due to its proven effectiveness in similar domains like AI-driven automation, we undertake this study to further advance the understanding and implementation of these technologies. Existing surveys often focus solely on specific aspects, such as load prediction or scheduling, lacking a comprehensive analysis of multi-objective optimizations and emerging application scenarios. In contrast, this paper provides a more thorough review by covering three core technology categories, their frame-works, advantages, disadvantages, practical applications, challenges,

and frontier directions, highlighting its uniqueness in offering a systematic and innovative perspective.

This paper aims to systematically review the development of deep learning-based cloud resource management technologies, compare the strengths and weaknesses of mainstream methods, and summarize current challenges and future directions. It introduces foundational theories, including core tasks of cloud resource management and key deep learning technologies. Next, it elaborates on critical deep learning-based management techniques, analyzes application scenarios and cases, discusses challenges and future trends, and concludes with a summary. Overall, this article not only offers clear and accessible guidance for beginners to quickly grasp the core concepts and practical methods of deep learning-based cloud resource management but also provides valuable insights and research directions for industry practitioners and researchers, thereby contributing significantly to advancing technological innovation and practical application in the field of cloud computing. (Figure 1)

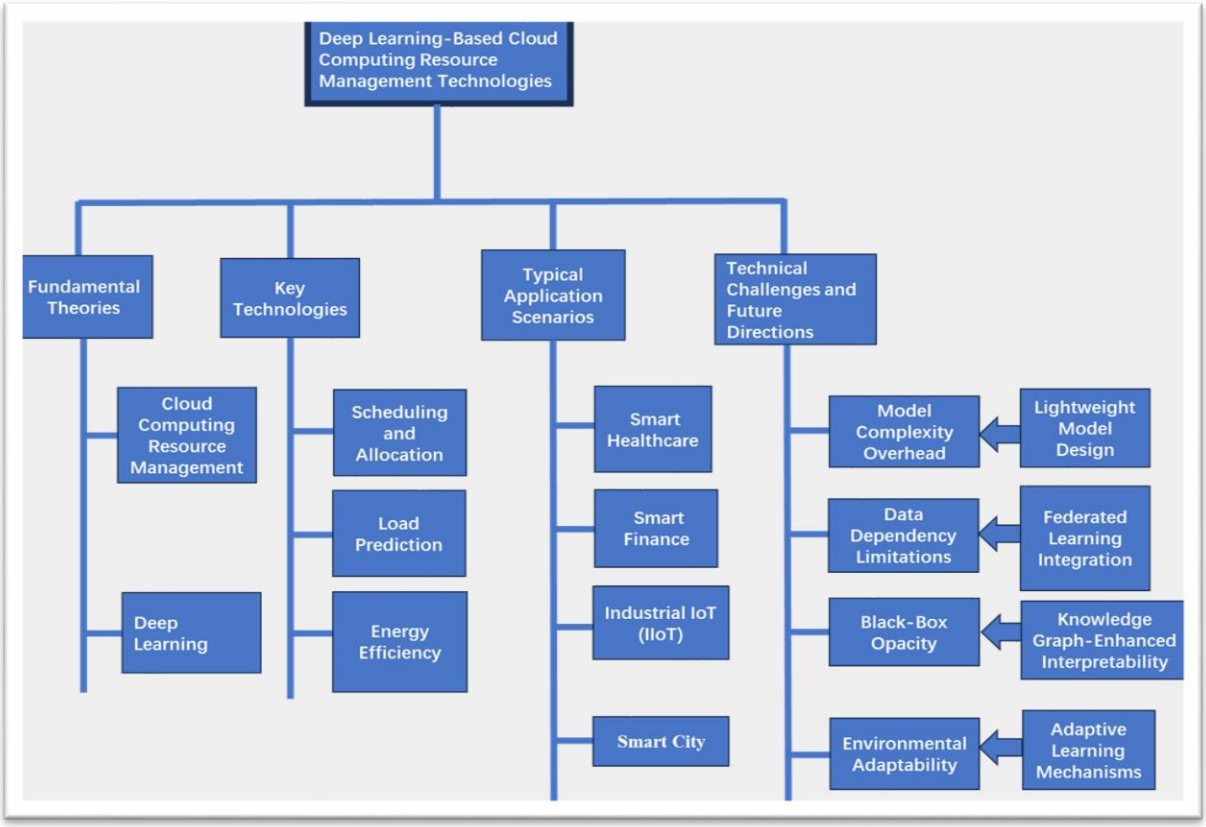


Figure 1: Key Technologies Figure

2. Fundamental Theories

2.1. Cloud Computing Resource Management

Cloud computing resource management refers to the comprehensive process of allocating, scheduling, monitoring, and optimizing virtualized resources such as virtual machines, containers, and storage in cloud environments to ensure efficient operation, meet service requirements, and minimize costs [3]. These resources include virtual machines (VMs), containers, storage systems, and network bandwidth, all of which are dynamically provisioned to support diverse user applications and services.

2.2. Deep Learning

Deep learning is a part of machine learning which helps computers learn to represent data hierarchies using multi-layer neural networks, just as the human brain does. In cloud computing resource management, it is very important because it can automatically extract features and patterns from a large number of data, make adaptive decisions in a changing and various environment, and improve the efficiency of the system without manual feature treatment.

3. Key Technologies

Based on analysis and combing, the core technologies are divided into the following three categories, as shown in Table 1:

Table 1: Key Technologies Categories

Resource Management Methods	Introduction	References
Scheduling and Allocation	It refers to methods using deep learning to dynamically allocate virtualized resources and prioritize tasks, aiming to optimize utilization, reduce latency, and meet service agreements, including DQN-based dynamic scheduling and neural network-driven task-resource matching.	[1] [4] [5] [6]
Load Prediction	It refers to methods leveraging deep learning to forecast resource demands from historical data and automatically adjust resource capacity, avoiding over/under-provisioning, with key models like LSTMs, Transformers, and edge-optimized lightweight models.	[7] [8] [9] [10]
Energy Efficiency	It refers to methods using deep learning to predict power consumption, optimizing energy use while maintaining service quality, including multi- objective models balancing efficiency.	[3][11][12]

3.1. Resource Management Methods Based on Scheduling and Allocation

Resource scheduling and allocation in cloud computing involve dynamically assigning virtualized resources like virtual machines and containers to physical infrastructure and prioritizing tasks to optimize resource utilization, minimize latency, and meet service-level agreements. This process must adapt to varying workloads, node capacities, and task priorities to avoid bottlenecks and underutilization, especially in large-scale cloud environments where thousands of tasks and resources interact in complex ways. With the rapid growth of cloud services, traditional static scheduling methods have become inadequate, making deep learning-driven dynamic scheduling a critical area of research.

Recently, lots of professors, scholars, have started studying this method. The author [4] proposed DQN-based dynamic scheduling algorithm for inefficient VM deployment in dynamic cloud environment. It regards VM placement as a MDP problem. treating a deployed VM as a state change, rewards like reducing latencies makes it plausible to permit the algorithm to let the agents continuously learn from trial and errors the best strategy resulting in scheduling with much less delay and better use of resource than using a greedy algorithm. Johnson et al. [5] studied the difficulty of combining different requirements of a task with an appropriate resource in order to develop a new multi-layered neural network based on extracting the relevant data from the task attributes (such as its deadline and amount of computing power) and the status of the available resources such as CPU and RAM. This model can also do automatic prioritization of the given work and allocate resources, so the system should have

good throughput in a real time and batch task situation. Smith et al.[1] studied scalable resource scheduling in largescale cloud environment, which proposed a deep reinforcement learning framework with integrating graph neural networks to model resource dependency. framework keeps up with the changes of load between many nodes at any moment; it readjusts allocating resources so that fewer tasks are rejected in case of high traffic. Also, Zhang et al. [6] provide a hybrid CNN-LSTM model for scheduling in edge-cloud hybrid systems which CNN extracts the spatial feature of the distribution of edge nodes and LSTM extracts the temporal feature of the workload, and the end-to-end latency is reduced as compared to traditional round-robin scheduling.

These advancements demonstrate that deep learning-based scheduling methods outperform traditional rule- based approaches by dynamically adapting to environmental changes, balancing multiple objectives like latency, utilization, and energy consumption, and scaling efficiently. By leveraging neural networks and reinforcement learning, they enable more precise and adaptive resource allocation, significantly improving overall cloud system efficiency. However, these methods have drawbacks, such as high computational overhead during training, potential slow convergence in DQN leading to delayed responses in real-time scenarios, and over-fitting in MLP models when dealing with highly heterogeneous tasks, which can reduce generalization and require large datasets for effective performance. The integration of diverse deep learning architectures from DQNs for decision-making to GNNs for modeling complex resource relationships highlights the versatility of deep learning in addressing the multifaceted challenges of cloud resource scheduling, though future improvements are needed to mitigate these limitations.

3.2. Resource Management Methods Based on Load Prediction

Load and Elastic Scaling forecast future needs like CPU usage, Network traffic and storage from the past and change the amount of resources, such as up or down scaling VM instances or pod copies, to fit the expected load. It is very important when there's fluctuating loads, like high traffic during e-commerce promotions, people using an enterprise app more in the day than at night, or suddenly lots of IoT devices sending information. The correct prediction guarantees that resources won't be over-provisioned, which would waste money, or under-provisioned, which would reduce service quality, so it's a part of managing cloud resources.

This facilitates elastic scaling by adjusting resources dynamically, reducing over-provisioning and latency. For example, hybrid CNN-BiLSTM models have demonstrated superior performance in multi-dimensional load forecasting, achieving mean absolute percentage errors in real-world cloud traces, particularly effective for handling non-stationary workloads in edge-cloud setups with fluctuating IoT data streams [7]. Research shows LSTM-based methods achieve accuracy in predicting cloud workloads, outperforming ARIMA models in dynamic environments, with Transformers excelling in capturing long-range dependencies like seasonal trends over extended periods [8]. Lightweight CNN-LSTM variants further optimize for edge devices, reducing model size through pruning while maintaining high precision in resource-constrained IoT scenarios, enabling seamless integration with container orchestration tools [9]. Comprehensive reviews highlight how these deep neural networks integrate seamlessly into cloud systems for proactive scaling, supporting multi-objective optimizations in hybrid cloud architectures [10]. Drawbacks include sensitivity to noisy data, which can degrade accuracy, and the need for large datasets, making them less effective in sparse or cold-start environments. Furthermore, prediction errors during sudden spikes may lead to resource shortages or inefficiencies, high training times—often exceeding hours on standard hardware—can delay deployment in time-sensitive systems, and overfitting risks require careful regularization strategies like dropout or early stopping to mitigate generalization issues, especially in volatile multi-tenant clouds.

This has proved the superiority of deep learning in load prediction, making proactive and precise scale-in scaling. They correctly predict demands and allow for automated resource adjustment, reducing over allocation, cutting down on operation costs, improve service dependability with resources available when required. But there are limitations with LSTM, as it can suffer from vanishing gradients in very long sequences, Transformer needs a lot of computing resources which make it hard to use on edge devices and hybrid models are more complicated, so they might need longer training times and could be more likely to over if we don't have lots of data. The combination of diverse deep learning architectures and optimization techniques like hybridization and quantization makes load prediction and elastic scaling more robust and adaptable to various cloud scenarios, from centralized data centers to distributed edge environments, though addressing these drawbacks is essential for broader adoption.

3.3. Resource Management Methods Based on Energy Efficiency

Energy efficiency for cloud resource management is doing as much as you can with as little energy as possible. It means lowering idle server energy consumption, streamlining resource gathering, and making sure resources are given out according to what the work is like. With data centers accounting for a significant portion of global energy consumption, these optimizations are critical for sustainability.

Many scholars have conducted in-depth explorations in this field. Muller et al. [11] developed a deep learning model to predict data center server power consumption by integrating real-time CPU/memory utilization, network traffic, and ambient temperature data. The model uses a stacked autoencoder for feature extraction and a regression head for power prediction, enabling targeted energy-saving measures such as dynamic voltage scaling and server hibernation during low-load periods. Field tests showed a reduction in energy consumption without impacting service availability. Schmidt et al. [3] demonstrated how deep learning-driven resource consolidation reduces energy waste in large data centers: their model uses a CNN to identify underutilized servers from resource status heatmaps and a DQN to decide which VMs to migrate, achieving a reduction in idle server time and a drop in energy use. Additionally, Lee et al. [12] developed a multi-objective deep reinforcement learning model that balances energy consumption, optimizing the trade-off between server power usage and performance. The model achieved an improvement in energy efficiency compared to single-objective optimizations.

These methods have advanced green cloud computing by leveraging deep learning's predictive capabilities to balance performance and energy use. They enable data centers to operate more sustainably by reducing carbon footprints. However, disadvantages include the models' sensitivity to environmental data variations like temperature fluctuations leading to prediction inaccuracies, and DQN's potential for local optima in multi- objective scenarios, which can result in suboptimal energy savings. The integration of multi-source data like resource usage and environmental factors highlights deep learning's ability to address the complex trade-offs in energy management, but overcoming these limitations is key to enhancing reliability.

4. Typical Application Scenarios

4.1. Smart Healthcare

Smart healthcare involves processing real-time medical data such as MRI image analysis and patient monitoring to support diagnosis and treatment. This scenario relates to cloud computing resource management by requiring dynamic allocation of resources to handle variable data volumes, ensuring low latency for critical tasks to avoid delays in patient care.

Deep learning plays a key role by optimizing resource allocation; for example, CNNs can prioritize urgent diagnostic tasks by analyzing image complexity and patient criticality, ensuring faster processing for life-threatening cases and reducing diagnostic latency while maintaining accuracy, thus improving patient outcomes.

4.2. Smart Finance

Smart finance includes low latency in transaction, secure in dealing with transactions in finance platform It has to connect to the cloud resource management because it requires elastic scaling to cope with the peak trading hours and balance the load to preserve service quality and security. Deep learning helps by predicting trans-action volumes using hybrid LSTM-Transformer models, which can adjust resources proactively when the market is changing, so there's less chance of something not being available and it takes up less space than just having everything ready all the time.

4.3. Industrial IoT (IIoT)

Industrial IoT manages massive sensor data from manufacturing equipment for real-time analytics and predictive maintenance. This ties to cloud resource management via the demand for reliable edge-cloud coordination to process data efficiently, preventing downtime. Deep learning facilitates this through DQNs for scheduling re- sources, prioritizing critical machinery data like assembly line robots, reducing equipment failures and enhancing utilization via dynamic task routing.

4.4. Smart City

Smart cities, integrating thousands of IoT devices such as traffic sensors, waste management systems, and public lighting that generate massive real-time data, leverage deep learning to enable centralized resource management across urban cloud-edge layers, where this technology dynamically coordinates computing resources to handle the diverse and fluctuating demands of urban operations—whether it's allocating cloud computing power for traffic signal adjustments to reduce congestion, using Transformer-based models to optimize energy distribution by analyzing consumption patterns and rerouting energy to high-demand zones, or deploying lightweight CNNs on edge nodes to process street camera feeds for public safety anomaly detection and allocate extra power for emergency analysis—all working in tandem to ensure efficient, responsive, and adaptive resource utilization that enhances the overall functionality and livability of the city.

5. Technical Challenges and Future Directions

5.1. Technical Challenges

5.1.1. Model Complexity Overhead

Deep learning models are computationally demanding, requiring millions of floating-point operations and relying on high-performance hardware like GPUs for training and deployment. This not only consumes excessive energy and computing resources but also delays real-time tasks in cloud resource management, such as instant scheduling during workload surges or rapid fault detection—delays that can lead to service bottlenecks. In edge environments, IoT devices and edge servers have less processing power deployed complex models which causes latency above 100ms. To be slow down real time decisions like smart city traffic adjustments, the increased energy usage by running hardware for longer times, all against the goals of being efficient [13].

5.1.2. Data Dependency Limitations

Performance of every model depends always upon the quantity, quality, and representative of train data Insufficient data, e.g., sparse workload traces results in poor capturing pattern;

biased data, e.g., infrequent rare event, e.g., sudden traffic surge, causes bias in prediction resulting in under-provisioning and disruption. Privacy regulation, commercial competition creates “data silos” which leads to limited data diversity thus making models less generalizable for example in a cloud that does support multiple tenant user data is isolated [2].

5.1.3. Black-Box Opacity

Deep learning model’s decision making is opaque due to the complex architecture of a thousand connected neurons so explaining to why a scheduling model would choose to give one job priority over the other for instance is next to impossible. The opacity is damaging when it comes to important stuff like money or health-care cloud networks, where people can't see the choices that are being made. And makes the models easy to launch unknown adversarial attacks like giving the model false workload data to get the model to do waste allocation which is dangerous for the cloud’s safety [5].

5.1.4. 4. Environmental Adaptability

The models learned based on historical data have difficulty adapting to sudden changes in cloud environments, like an unexpected surge in traffic due to a viral trend or hardware breakage, so the resource management isn't good enough. and also cannot learn how to recognize unseen things like new cyber-attacks and regulations. In multi-user clouds, static pre-trained models can't adapt to the need of dynamic resources and changes in regional regulations, which breaks context-aware management [1].

5.2. Future Research Directions

5.2.1. Lightweight Model Design

Compact models through pruning techniques, quantization techniques, neural architecture search etc. Pruning: remove redundant neurons to make a model structure simpler; Quantization: lower parameter precision for smaller memory and faster computing needs; Neural Architecture Search: automatically design best model configuration; All those approaches help cut down computational costs and cut down on the use of resources but keep most of the models’ performance. That makes them good matches for deploying on edge devices and IoT sensors with limited resources, letting them do real-time data work in edge-cloud setups, and solving problems like delays and too much power use in changing places [13].

5.2.2. Federated Learning Integration

Implement federated learning to facilitate collaborative model training across multiple cloud providers without the need to share raw data. This approach directly addresses privacy concerns that restrict data sharing and alleviates data scarcity by aggregating learning results from diverse sources. To enhance security, integrate blockchain technology to establish a decentralized trust mechanism. Additionally, explore multi-task learning to enable the models to handle various tasks simultaneously, such as threat detection, thereby improving the adaptability of resource management strategies in complex cloud environments [2].

5.2.3. Knowledge Graph-Enhanced Interpretability

Knowledge graph is combined with explainable AI such as feature importance & visual decision tracing. Knowledge graphs give a nicely structured framework for creating connections among significant ideas and connections. Explainable AI methods make it simpler to grasp what the model is accomplishing inside. They can also make it clearer how decisions on managing resources are being made, make models more resistant to malicious attacks with hybrid models, and build trust with important applications like financial and healthcare cloud services [5].

5.2.4. Adaptive Learning Mechanisms

Create real-time updating frameworks by combining transfer learning and edge/fog computing. Transfer learning allows models to reuse knowledge from pre-trained models, enabling faster adaptation to new scenarios. Edge and fog computing bring processing closer to data sources, reducing latency and improving responsiveness. These mechanisms enable models to quickly adjust to sudden changes in cloud environments, such as unexpected workload spikes or hardware fluctuations. They also enhance robustness in processing IoT data and support automated incident response to evolving cloud threats, ensuring more flexible and reliable resource management [1].

6. Conclusion

This paper systematically summarizes and analyzes deep learning-based cloud computing resource management technologies. It categorizes key methods into three types: resource management based on scheduling and allocation, load prediction and elastic scaling, and energy efficiency optimization. For each category, the paper reviews core concepts, related work including key studies, and progress achieved. It also explores four revised application scenarios—smart healthcare, smart healthcare, Industrial IoT (IIoT) and smart city—detailing how deep learning enhances efficiency and reliability. Additionally, the paper identifies four critical challenges which are model complexity, data dependency, black-box opacity and environmental adaptability and proposes corresponding future directions which are lightweight models, federated learning, knowledge graph integration, and adaptive mechanisms. These insights highlight the transformative role of deep learning in cloud resource management and provide a roadmap for future innovation in the field.

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