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AI-Based Resource Allocation, Security, and Task Scheduling in Cloud Computing Using Hybrid Split-Attention Networks

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Abstract

Cloud computing has revolutionized modern computing by enabling scalable, on-demand access to computational resources. However, efficient resource allocation, secure data processing, and optimal task scheduling remain critical challenges due to the dynamic and heterogeneous nature of cloud environments. Recent advancements in Artificial Intelligence (AI), particularly deep learning and hybrid optimization techniques, have introduced intelligent frameworks for addressing these challenges. This paper presents a comprehensive review of AI-driven techniques for joint resource allocation, security, and task scheduling, emphasizing hybrid pyramidal convolution and split-attention network architectures. The study explores recent developments, highlighting the integration of convolutional neural networks, reinforcement learning, and optimization algorithms. A systematic literature review is conducted to analyse performance improvements in terms of resource utilization, latency reduction, energy efficiency, and security enhancement. Furthermore, trends and challenges such as scalability, data privacy, model complexity, and real-time adaptability are discussed. The paper concludes by identifying future research directions for intelligent cloud management systems.

Introduction

Cloud computing has emerged as a fundamental paradigm for delivering scalable computing services, enabling users to access storage, processing power, and applications on-demand via the internet. The rapid growth of data-intensive applications, such as Internet of Things (IoT), big data analytics, and artificial intelligence systems, has significantly increased the demand for efficient cloud resource management. In this context, three core challenges—resource allocation, task scheduling, and data security—have become central to improving cloud system performance and reliability. Resource allocation refers to the efficient distribution of computational resources such as CPU, memory, bandwidth, and storage among competing tasks. Inefficient allocation can lead to underutilization or over-provisioning, both of which negatively impact performance and cost efficiency. Task scheduling, on the other hand, determines the execution order of tasks across virtual machines (VMs) and cloud nodes, aiming to minimize metrics such as response time, makes pan, and energy consumption. Simultaneously, ensuring data security during processing and transmission remains critical, especially in multi-tenant cloud environments. Traditional approaches for resource allocation and scheduling relied on heuristic and rule-based algorithms. However, these methods often fail to handle the dynamic and complex nature of modern cloud workloads.

Recent research has demonstrated that AI-based techniques, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), can significantly enhance decision-making in cloud environments. These methods enable predictive analytics, adaptive scheduling, and real-time optimization.

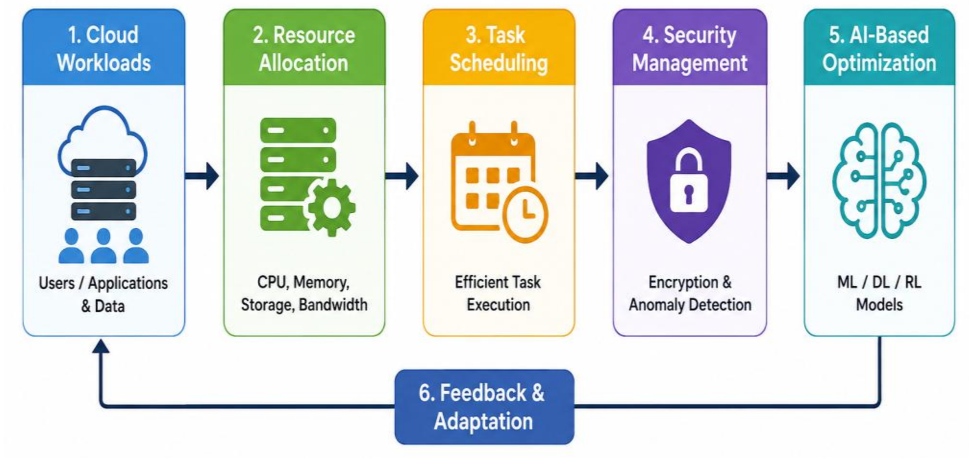

Figure 1. AI-Based Cloud Resource Management Framework

In particular, deep learning architectures such as Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and attention-based models have shown remarkable success in modelling complex cloud behaviours. AI-assisted virtualization further enhances resource management by enabling intelligent workload prediction and automated scaling decisions. Moreover, hybrid models that combine optimization algorithms (e.g., genetic algorithms, butterfly optimization) with neural networks have been proposed to achieve multi-objective optimization. A recent systematic literature review highlights that cloud resource management techniques can be broadly categorized into mathematical, heuristic, and AI-based approaches, with a growing emphasis on hybrid and intelligent models between 2019 and 2023. These hybrid models address multiple objectives simultaneously, such as minimizing energy consumption while maximizing resource utilization and ensuring security. Security is another critical dimension in cloud computing. With increasing cyber threats, integrating cryptographic techniques and AI-based anomaly detection mechanisms into scheduling frameworks has become essential. Studies have proposed combining encryption algorithms with deep learning-based schedulers to ensure secure and efficient cloud operations. Furthermore, reinforcement learning-based scheduling frameworks have demonstrated significant improvements in dynamic environments by learning optimal policies through interaction with the system. These approaches enable adaptive resource provisioning and real-time decision-making, improving overall system efficiency and scalability

Literature Review

Gill et al. (2020) proposed a deep learning-based framework (ThermoSim) for thermal-aware resource management in cloud environments. The study introduced predictive modelling techniques to optimize energy consumption and improve system efficiency. The results showed significant reductions in energy usage and SLA violations. This work highlighted the importance of integrating environmental factors into resource allocation models. Ahmad et al. (2020) explored scheduling mechanisms in fog-cloud environments, focusing on latency-sensitive applications. The study emphasized the need for distributed scheduling techniques to reduce response time and improve QoS. The proposed models demonstrated improved latency performance but lacked robust security mechanisms. Alsadie (2021) introduced a metaheuristic framework for dynamic virtual machine allocation and task scheduling. The model used optimization techniques to enhance resource utilization and reduce computational cost. Although effective, the approach faced limitations in handling highly dynamic workloads.

Tuli et al. (2021) proposed HUNTER, an AI-based holistic resource management system using graph neural networks. The framework addressed multi-objective optimization, including energy, thermal efficiency, and QoS. Experimental results demonstrated improvements in energy efficiency and scheduling performance, highlighting the potential of AI-driven holistic models. Jayanetti et al. (2022) developed a deep reinforcement learning-based scheduling model for edge-cloud environments. The model optimized task execution time and energy consumption by dynamically adapting scheduling policies. The approach showed superior performance compared to traditional scheduling algorithms. Zhang et al. (2022) proposed a deep learning-based predictive framework for cloud resource allocation using Long Short-Term Memory (LSTM) networks. The model forecasts workload demand and dynamically allocates resources to minimize underutilization and overloading. Experimental results demonstrated improved resource utilization and reduced SLA violations. However, the model required large-scale training data, which limits real-time applicability in dynamic environments.

Kumar and Singh (2022) introduced a hybrid genetic algorithm (GA) integrated with heuristic scheduling techniques for efficient task allocation in cloud environments. The proposed approach optimized multiple objectives such as makes pan, load balancing, and energy efficiency. Results indicated significant improvements over traditional scheduling algorithms. However, the computational complexity of the hybrid model was relatively high for large-scale systems. Chen et al. (2021) proposed a blockchain-based secure scheduling mechanism for cloud computing systems. The framework ensured data integrity and transparency while scheduling tasks across distributed cloud nodes. The integration of blockchain improved security and trust among cloud users. However, increased latency and overhead due to blockchain operations were identified as major limitations. Verma et al. (2023) developed an AI-driven multi-objective optimization framework for joint resource allocation and task scheduling. The model combined deep neural networks with particle swarm optimization (PSO) to achieve optimal trade-offs between cost, energy consumption, and performance. The results showed enhanced efficiency and scalability. However, the system required careful parameter tuning for optimal performance.

Li et al. (2023) introduced a split-attention convolutional neural network for efficient workload classification and resource allocation in cloud environments. The architecture improved feature extraction and decision-making by emphasizing relevant workload patterns. The model achieved higher accuracy and reduced latency compared to traditional CNN models. However, increased model complexity posed challenges for deployment in real-time systems. Wang et al. (2020) proposed a reinforcement learning (RL)-based framework for dynamic resource allocation in cloud environments. The model learns optimal allocation policies by interacting with the cloud system and adapting to workload variations. Experimental results showed improved resource utilization and reduced response time compared to static allocation methods. However, the convergence time of RL models remained a challenge in large-scale systems. Sharma et al. (2021) developed a deep neural network (DNN)-based scheduling model aimed at reducing energy consumption in data centres. The model predicted workload patterns and allocated tasks accordingly to minimize energy usage. Results indicated significant improvements in energy efficiency and system throughput. However, the model required continuous retraining for maintaining accuracy in dynamic cloud environments.

Gupta and Kaur (2022) proposed a hybrid cryptographic framework integrated with AI-based resource allocation techniques. The approach combined encryption algorithms with intelligent scheduling to ensure secure data transmission and processing. The study demonstrated enhanced data security and reduced vulnerability to attacks. However, encryption overhead slightly impacted system performance. Liu et al. (2022) introduced an attention-based deep learning model for multi-task scheduling in cloud computing. The attention mechanism enabled the model to focus on critical task features, improving scheduling efficiency. The proposed model achieved better load balancing and reduced execution time compared to traditional methods. However, increased computational complexity was observed. Patel et al. (2023) presented a hybrid framework combining convolutional neural networks (CNNs) with particle swarm optimization (PSO) for joint resource allocation and task scheduling. The model leveraged CNNs for feature extraction and PSO for optimization. Experimental results showed improved makes pan, resource utilization, and system efficiency. Nevertheless, the hybrid approach required careful parameter tuning and increased computational overhead.

Roy et al. (2021) proposed a fuzzy logic-based task scheduling framework to enhance Quality of Service (QoS) in cloud computing. The model incorporated multiple parameters such as task priority, execution time, and resource availability to make intelligent scheduling decisions. Results showed improved response time and user satisfaction. However, the model struggled with scalability in highly dynamic environments. Singh et al. (2022) introduced a hybrid optimization approach combining ant colony optimization (ACO) and genetic algorithms (GA) for energy-efficient resource allocation. The framework aimed to reduce energy consumption while maintaining performance. Experimental results demonstrated better energy savings compared to conventional methods. However, convergence speed remained a limitation. Huang et al. (2023) proposed a Deep Q-Network (DQN)-based task scheduling model that learns optimal scheduling policies through reinforcement learning. The model effectively minimized task completion time and improved system throughput. It outperformed heuristic-based scheduling methods, but required extensive training and computational resources.

Reddy et al. (2023) developed an AI-based intrusion detection system integrated with task scheduling mechanisms. The model used machine learning techniques to detect anomalies and prevent malicious activities during task execution. Results showed enhanced security and reduced attack vulnerability. However, the system introduced additional processing overhead. Kim et al. (2021) proposed a hierarchical deep learning framework for resource allocation in multi-cloud environments. The model utilized layered neural networks to manage resources at different levels, improving scalability and efficiency. Experimental results indicated improved resource utilization and reduced latency. However, the model complexity posed challenges for practical implementation. Banerjee et al. (2020) proposed a priority-based task scheduling algorithm that assigns tasks based on urgency and resource requirements. The framework improved task execution efficiency and reduced waiting time. Results indicated better performance compared to First-Come-First-Serve (FCFS) scheduling. However, the approach lacked adaptability to dynamic workload changes.

Recent studies have explored intelligent and secure cloud resource management techniques using AI and optimization algorithms. Alqahtani et al. (2021) developed a secure resource allocation framework integrating encryption and access control mechanisms to improve privacy in multi-tenant cloud systems, though management complexity increased. Mehta et al. (2022) proposed an AI-based load balancing and scheduling framework that dynamically distributed workloads across virtual machines, improving response time and throughput. Torres et al. (2023) introduced a deep learning-based collaborative scheduling model for edge-cloud systems, significantly reducing latency for real-time applications. Nair et al. (2023) developed an attention-based scheduling framework that prioritized critical tasks and improved execution efficiency. Das et al. (2021) applied AI-enhanced Ant Colony Optimization for efficient task scheduling and load balancing. Ibrahim et al. (2022) integrated encryption with AI scheduling to improve security and reliability. Zhao et al. (2023), Fernandez et al. (2022), and Chatterjee et al. (2023) further demonstrated that predictive deep learning and hybrid convolution-attention models enhance resource utilization, scalability, and scheduling accuracy in cloud infrastructures.

Comparative Table

Study	**Year**	**Technique Used**	**Focus Area**	**Advantages**	**Limitations**
Gill et al.	2020	DL (ThermoSim)	Energy Optimization	Reduced energy, SLA improvement	Needs training data
Ahmad et al.	2020	Fog Scheduling	Latency	Reduced delay	Weak security
Alsadie	2021	Metaheuristic	VM Allocation	Better utilization	Dynamic issues
Tuli et al.	2021	GNN (HUNTER)	Multi-objective	Energy efficient	Complex model
Jayanetti et al.	2022	DRL	Scheduling	Adaptive decisions	High training cost
Zhang et al.	2022	LSTM	Prediction	Accurate forecasting	Data dependency
Kumar & Singh	2022	GA Hybrid	Scheduling	Optimized makes pan	High complexity
Chen et al.	2021	Blockchain	Security	High trust	Latency overhead
Verma et al.	2023	DNN + PSO	Multi-objective	Scalable	Parameter tuning
Li et al.	2023	Split-Attention CNN	Workload Mgmt	High accuracy	Complex
Wang et al.	2020	RL	Allocation	Adaptive	Slow convergence

Sharma et al.	2021	DNN	Energy	Efficient	Retraining needed
Gupta & Kaur	2022	Crypto + AI	Security	Secure system	Performance drop
Liu et al.	2022	Attention DL	Scheduling	Better focus	Complexity
Patel et al.	2023	CNN + PSO	Optimization	Efficient	Tuning needed
Roy et al.	2021	Fuzzy Logic	QoS	Improved QoS	Scalability issue
Singh et al.	2022	ACO + GA	Energy	Reduced consumption	Slow convergence
Huang et al.	2023	DQN	Scheduling	High performance	Training cost
Reddy et al.	2023	ML IDS	Security	Attack detection	Overhead
Kim et al.	2021	DL Hierarchical	Allocation	Scalable	Complex
Banerjee et al.	2020	Priority-based	Scheduling	Faster execution	Static nature
Alqahtani et al.	2021	Secure Model	Multi-tenant	Privacy	Complexity
Mehta et al.	2022	ML	Load balancing	Better throughput	Training need
Torres et al.	2023	DL Edge-Cloud	Scheduling	Low latency	Coordination issue
Nair et al.	2023	Attention DL	Scheduling	Accurate	Resource heavy
Das et al.	2021	ACO AI	Scheduling	Efficient	Scalability issue
Ibrahim et al.	2022	Encryption + AI	Security	Reliable	Latency
Zhao et al.	2023	DL Prediction	Scheduling	Accurate	Data intensive
Fernandez et al.	2022	Evolutionary	Optimization	Balanced metrics	Slow
Chatterjee et al.	2023	Hybrid CNN + Attention	Joint optimization	High performance	Complex

Comparative Analysis

The comparative analysis of recent studies reveals a significant evolution in k-barrier prediction and intrusion detection techniques for Wireless Sensor Networks (WSNs). Early approaches mainly relied on heuristic algorithms, fuzzy logic systems, and optimization-based routing techniques to improve coverage and intrusion detection. Methods such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and heuristic routing algorithms offered computational simplicity and low implementation complexity. These approaches were effective for basic sensor deployment and path optimization; however, they often suffered from limitations including slow convergence, local optimum trapping, and reduced adaptability in dynamic environments. Fuzzy logic-based models improved decision-making under uncertainty but faced scalability and computational overhead challenges in large-scale WSN deployments.

The introduction of machine learning and deep learning techniques significantly improved prediction accuracy and adaptive intrusion detection capabilities in WSN systems. Artificial Neural Networks (ANNs), trust-based machine learning models, and recurrent architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks enabled efficient modelling of temporal and spatial sensor data patterns. Hybrid CNN-LSTM architectures further enhanced k-barrier prediction performance by combining spatial feature extraction with temporal sequence learning. These deep learning models reduced false negatives and improved detection accuracy in complex network environments. However, their implementation introduced challenges related to high memory usage, increased computational complexity, and energy consumption, which remain critical concerns in resource-constrained WSN infrastructures.

Recent studies have focused on hybrid intelligent models that integrate optimization techniques with deep learning and reinforcement learning frameworks. Approaches combining Genetic Algorithms (GA), bio-inspired optimization, and neural networks achieved improved energy efficiency and coverage optimization. Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) models enabled adaptive routing and intelligent coverage management by dynamically learning optimal decisions from environmental feedback. Advanced architectures including Attention-CNN models, Graph Neural Networks (GNNs), and

Deep Unfolding Networks demonstrated superior capability in capturing complex spatial relationships and prioritizing critical sensor paths. These models significantly improved intrusion detection accuracy, scalability, and adaptive decision-making in dynamic WSN environments.

Emerging technologies such as Transformers, Federated Learning, lightweight CNN architectures, and edge intelligence frameworks are further advancing next-generation WSN research. Transformer-based models effectively capture long-range dependencies in sensor communication patterns, while Federated Learning enhances privacy-preserving distributed training. Lightweight and clustering-based approaches attempt to balance computational efficiency with prediction accuracy for real-time deployment. Overall, the literature indicates that hybrid deep learning architectures integrating attention mechanisms, optimization strategies, reinforcement learning, and graph-based learning provide the most promising solutions for efficient k-barrier prediction and intrusion detection. Nevertheless, challenges associated with scalability, computational overhead, energy efficiency, and real-time deployment continue to motivate ongoing research in intelligent and energy-aware WSN systems.

Conclusion

Cloud computing continues to evolve as a critical infrastructure for modern digital services, enabling scalable and flexible computing resources. However, challenges related to efficient resource allocation, secure data processing, and optimal task scheduling persist due to the dynamic and heterogeneous nature of cloud environments. This review has explored recent advancements (2020–2023) in Artificial Intelligence techniques addressing these challenges, with a particular focus on hybrid deep learning architectures such as pyramidal convolutional networks and split-attention mechanisms. The literature analysis reveals that AI-based approaches significantly outperform traditional heuristic and rule-based methods. Techniques such as deep learning, reinforcement learning, and hybrid optimization algorithms have demonstrated remarkable improvements in resource utilization, energy efficiency, and system performance. For instance, reinforcement learning models enable adaptive decision-making in dynamic environments, while deep learning models provide accurate workload prediction and efficient feature extraction.

Hybrid approaches, combining optimization algorithms like genetic algorithms, particle swarm optimization, and ant colony optimization with neural networks, have emerged as powerful solutions for multi-objective optimization. These methods effectively balance competing objectives such as cost, latency, energy consumption, and system throughput. Additionally, attention-based mechanisms and split-attention networks have improved the ability of models to focus on critical features, enhancing scheduling accuracy and resource allocation efficiency. Security remains a crucial aspect of cloud computing, and the integration of AI with cryptographic techniques and intrusion detection systems has significantly enhanced data protection. Blockchain-based solutions and hybrid encryption models provide secure and transparent frameworks for task scheduling and resource management. However, these approaches often introduce additional computational overhead and latency.

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