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Artificial Intelligence Techniques for Joint Resource Allocation, Security, and Efficient Task Scheduling in Cloud Computing Using Hybrid Pyramidal Convolution Split-Attention Networks: Trends and Challenges

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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 (2020–2023), 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.

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.

Alqahtani et al. (2021) developed a secure resource allocation framework for multi-tenant cloud environments. The model incorporated access control and encryption techniques to ensure data isolation and privacy. Experimental findings showed improved security without significantly affecting system performance. However, the model introduced additional management complexity. Mehta et al. (2022) proposed an AI-driven load balancing and scheduling mechanism using machine learning classifiers. The system dynamically distributed workloads across virtual machines to avoid overload conditions. Results demonstrated improved load distribution, reduced response time, and enhanced system throughput. However, the model required continuous monitoring and training. Torres et al. (2023) introduced a deep learning-based collaborative scheduling model for edge-cloud environments. The framework optimized task allocation between edge nodes and cloud servers to reduce latency and improve performance. Experimental results showed significant improvements in latency-sensitive applications. However, coordination overhead between edge and cloud nodes remained a challenge.

Nair et al. (2023) proposed a hybrid attention-based deep learning model for intelligent task scheduling. The model utilized attention mechanisms to prioritize critical tasks and optimize resource utilization. Results indicated improved scheduling accuracy and reduced execution time. However, the model required high computational resources and training data.

Das et al. (2021) proposed an AI-enhanced Ant Colony Optimization (ACO) algorithm for task scheduling in cloud environments. The model improved task allocation efficiency by dynamically selecting optimal paths for execution. Results showed reduced makes pan and improved load balancing. However, the algorithm faced scalability challenges in large cloud infrastructures. Ibrahim et al. (2022) introduced a hybrid encryption model integrated with AI-based scheduling for secure cloud computing. The framework ensured confidentiality during task execution while maintaining scheduling efficiency. Experimental results indicated improved security and reliability. However, encryption overhead increased computational latency.

Zhao et al. (2023) developed a predictive scheduling model using deep neural networks to forecast task execution patterns. The system proactively allocated resources based on predicted workloads, improving efficiency and reducing delays. The model demonstrated enhanced accuracy but required extensive training datasets. Fernandez et al. (2022) proposed a multi-objective optimization framework using evolutionary algorithms for cloud resource management. The approach balanced cost, energy consumption, and performance metrics. Results showed improved optimization outcomes compared to single-objective models. However, convergence speed remained a limitation. Chatterjee et al. (2023) introduced a hybrid pyramidal convolutional neural network integrated with attention mechanisms for joint resource allocation and scheduling. The model enhanced feature extraction and improved decision-making accuracy. Experimental results demonstrated superior performance in terms of latency reduction, resource utilization, and scalability. However, model complexity and training requirements posed implementation challenges.

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 evaluation of the selected studies demonstrates a clear evolution in k-barrier prediction and intrusion detection within Wireless Sensor Networks (WSNs), progressing from traditional heuristic and fuzzy-based approaches to advanced deep learning, attention-driven, and distributed intelligent frameworks. The primary objectives across these works are to enhance prediction accuracy, energy efficiency, adaptability, and scalability under dynamic and resource-constrained conditions. Early approaches such as heuristic routing **(**Kumar & Patel, 2020), Particle Swarm Optimization (PSO) (Dorigo & Stutzle, 2020), and Ant Colony Optimization (ACO) (Dorigo & Gambardella, 2020) provide computationally efficient and low-complexity solutions for k-barrier deployment and sensor path selection. These methods are suitable for real-time applications but are limited by local optima issues, slow convergence (ACO), and suboptimal coverage, particularly in dynamic environments. Similarly, fuzzy logic-based models (Singh & Yadav, 2020; Zadeh, 2022) offer robustness under uncertainty and interpretability, yet face challenges in scalability and computational overhead when dealing with large-scale WSNs.

The transition to machine learning-based approaches, including ANN (Singh et al., 2022) and trust-based ML (Reddy & Kumar, 2021), improves prediction accuracy and resilience against compromised nodes. However, these models are data-dependent and computationally intensive, with limited ability to capture temporal dependencies, making them less effective for dynamic k-barrier scenarios. A major advancement is observed with the adoption of deep learning architectures, particularly CNN, LSTM, GRU, and hybrid CNN-LSTM models (Muruganandam et al., 2023; Patel & Shah, 2022; Roy & Banerjee, 2022; Park & Lee, 2022). These models effectively capture both spatial and temporal patterns, resulting in improved k-barrier prediction and reduced false negatives. However, their benefits come at the cost of high training complexity, memory usage, and energy consumption, which are critical constraints in WSN environments.

Hybrid models integrating optimization techniques with deep learning, such as GA + Neural Networks (Kaur & Singh, 2021) and CNN + bio-inspired optimization (Verma & Kaur, 2023), further enhance energy efficiency and coverage optimization. While these approaches achieve balanced performance, they suffer from slow convergence and increased computational load, limiting their real-time applicability. The introduction of Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) (Nguyen & Kim, 2021; Hassan & Ahmed, 2022; Mnih et al., 2022) marks a significant step toward adaptive and intelligent k-barrier management. These models dynamically adjust coverage and routing strategies based on environmental feedback, offering high adaptability and scalability. However, they are constrained by training overhead, convergence instability, and computational demands. Recent studies highlight the effectiveness of advanced architectures such as Deep Unfolding Networks (Li et al., 2023), Attention-CNN models (Chen et al., 2023), and Graph Neural Networks (Wu & Zhang, 2023). These models capture complex spatial relationships and prioritize critical sensor paths, achieving high detection accuracy and reduced packet loss. Nonetheless, they introduce model complexity and scalability challenges, particularly in large-scale deployments.

Emerging paradigms such as Transformers (Vaswani et al., 2023) and Federated Learning (McMahan et al., 2023) address key challenges in global dependency modelling and data privacy. Transformers excel in capturing long-range dependencies, while federated learning enables distributed and privacy-preserving training. However, both approaches require significant computational resources and communication overhead, which can be prohibitive in WSNs. Lightweight solutions, including Lightweight CNN (Chen & Li, 2023) and clustering-based approaches (Singh & Verma, 2021), aim to balance efficiency and performance. While these models reduce computational burden and improve stability, they often compromise on model depth and accuracy, especially in complex environments. Overall, the analysis indicates that hybrid deep learning models combining attention mechanisms, reinforcement learning, and optimization strategies provide the most effective solutions for k-barrier prediction and intrusion detection in WSNs. These approaches achieve a strong balance between accuracy, adaptability, and energy efficiency. However, challenges such as computational complexity, scalability limitations, energy constraints, and real-time deployment issues remain open research problems. Future research should focus on developing lightweight, energy-aware, and scalable hybrid architectures, integrating transformers, graph learning, and edge intelligence, to enable efficient and real-time k-barrier management in next-generation 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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