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Job Scheduling in Cloud and Fog Computing: A Recent Systematic Review

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ABSTRACT

Cloud and Fog computing have emerged as pivotal paradigms in the field of distributed computing, offering flexible and scalable resources for various applications. Efficient job scheduling is a critical factor in optimizing resource utilization and enhancing the performance of these systems. Job scheduling is a complex challenge in Cloud and Fog computing due to their dynamic and heterogeneous nature. The need to balance resource allocation, minimize latency, and enhance energy efficiency poses significant research questions. To address these issues, this article systematically reviews existing literature to identify trends, challenges, and recent advancements in job scheduling strategies. The objectives of this work were to: assess the current landscape of job scheduling techniques in Cloud and Fog computing; analyze the key challenges and trends in job scheduling research; and highlight recent advancements and innovations in this domain, which further provide insights for future research directions in these computing environments. We conducted an advance searching and comprehensive systematic review of peer-reviewed articles (n=48) published in 2023 from Scopus and IEEE databases based on PRISMA framework. Our search and selection criteria ensured the inclusion of relevant studies, and a rigorous analysis was performed to extract key findings and identify emerging trends. By summarizing the state-of-the-art, it offers valuable insights for researchers and practitioners in the field, guiding future research efforts to address the evolving demands of these dynamic computing paradigms.

1. Introduction

The convergence of Cloud and Fog computing has led to transformative shifts in the utilization of computational resources [1-4]. Within these dynamic environments, the intricate task of job scheduling plays a pivotal role in allocating tasks to resources for optimal performance, efficient resource utilization, and improved user experiences. This systematic review focuses on the critical domain of job scheduling in Cloud and Fog computing, presenting a comprehensive analysis of recent developments, methodologies, and trends.

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The distributed nature of these paradigms has spurred innovative advancements in job scheduling, given the challenges presented by Cloud computing's expansive resource pool and Fog computing's edge-centric architecture [5].The objective of this article is to synthesize and critically evaluate recent research in this area. By systematically exploring a wide array of scheduling strategies, algorithms, and models, the review aims to uncover the fundamental principles guiding resource allocation efficiency. Furthermore, it endeavors to uncover novel methodologies employing machine learning, artificial intelligence, and optimization techniques to address the complexities of scheduling tasks within intricate, distributed environments [6-8].

This systematic review is poised to be an indispensable resource for researchers, practitioners, and decision-makers, offering insights into current job scheduling practices in Cloud and Fog computing. Beyond illuminating existing advancements, it aims to identify gaps and potential avenues for further research. In a continually evolving landscape, understanding job scheduling approaches becomes increasingly vital for harnessing the transformative potential of Cloud and Fog computing paradigms.

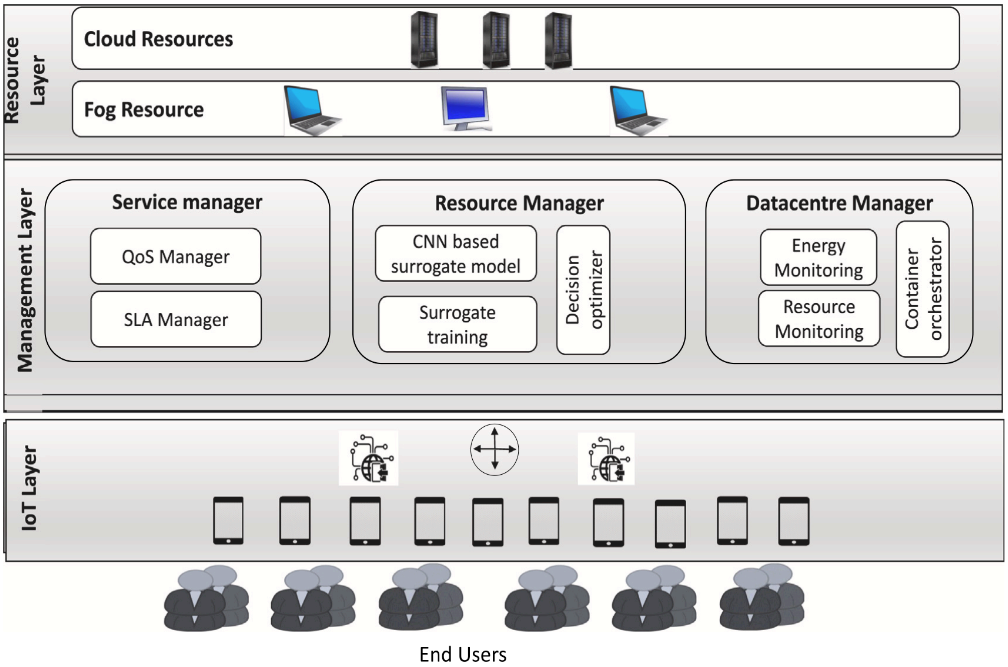

Fig. 1: An example of system architecture considering Cloud and Fog computing [8]

2. Literature Review

In contemporary technology, cloud computing plays a vital role by offering scalable and cost-efficient solutions; however, it has also led to amplified expenses for cloud providers due to hardware provisioning and maintenance. To address this cost challenge, one study focuses on energy consumption reduction through intelligent task-scheduling algorithms, introducing the "HunterPlus" model, which combines Convolutional Neural Networks (CNNs) with Gated Recurrent Units to refine cloud-fog task scheduling. Empirical findings reveal that the CNN scheduler outperforms Gated Graph Convolution Network (GGCN)-based models with significant improvements in energy consumption and job completion rates. Another study tackles the optimization challenge of Dynamic Workflow Scheduling in Fog Computing (DWSFC), introducing a Multi-Tree Genetic Programming (MTGP) approach to efficiently address routing and sequencing decision points [8]. Further, in Xu *et al.*, [9], a new approach called Multi-Tree Genetic Programming (MTGP) approach is developed. The MTGP demonstrates remarkable reductions in makespan across diverse scenarios, outperforming state-of-the-art methods. Next, a new research effort is developed which focuses on categorizing IoT application jobs and allocating resources based on Quality of Service (QoS) parameters, resulting in a novel scheduling framework that surpasses traditional cloud and fog computing paradigms in terms of performance [10]. This framework combines application types with fog computing's computational capabilities, contributing to the advancement of the field.

The continuous expansion and diversity of Industrial Internet of Things (IIoT) applications within fog networks present energy consumption challenges, particularly for time-sensitive tasks. Traditional cloud technology struggles to meet the stringent latency requirements of these IIoT applications due to long-distance data transmission. To address this, a novel energy-delay optimization framework called transmission scheduling and computation offloading (TSCO) is introduced in Hazra *et al.*, [11]. TSCO employs a heuristic-based transmission scheduling strategy and a graph-based task-offloading strategy using mixed linear programming, resulting in a substantial 12%-17% improvement in energy consumption and delay optimization compared to traditional baseline algorithms. Additionally, fog computing extends cloud capabilities to the network edge, requiring reliable task scheduling systems for efficient application deployment. Two scheduling approaches are introduced in the context of cloud and fog computing, surpassing established methods like Randomized and Round Robin approaches in Ranjan *et al.*, [12]. This research aims to enhance IoT system task execution efficiency by selectively allocating real-time tasks to the fog layer using fuzzy logic, achieving superior performance in various metrics. Furthermore, for efficient robot task execution, a model is presented in Alirezazadeh *et al.*, [13] which optimally allocates computational tasks to cloud infrastructure based on memory, computational power, and communication constraints, offering significant advantages in robot design and deployment efficiency.

Fog computing extends cloud capabilities to the network's edge, enabling faster data processing using local resources. Machine learning plays a vital role in optimizing resource allocation and job scheduling, and the XaaS paradigm emphasizes service flexibility and scalability. A research work done in Pittalà *et al.*, [14] discusses an early-stage PhD project aimed at designing a fog orchestrator that leverages AI and a service-centric approach to enhance user experiences in fog computing. Meanwhile, in another study in Altin *et al.*, [15], scheduling tasks in fog computing environments presents unique challenges due to heterogeneity and dynamism. A multi-objective task scheduling model and a MOMRank scheduling algorithm tailored for fog computing are introduced, demonstrating significant reductions in data transfer costs through empirical evaluations. Additionally, fog computing addresses real-time requirements for latency-constrained data processing by bringing processing closer to data sources. The RTH2S scheduling algorithm is presented in Kaur *et al.*, [16] for real-time tasks in a hierarchical fog-cloud architecture, showcasing its real-time performance and scalability through simulation and practical testing.

Fog computing is essential for efficiently meeting various user resource demands over the internet, but optimizing resource utilization and task execution time is crucial. Task scheduling is a key component in achieving these objectives within the fog computing environment, where tasks must be assigned to specific resources at specific times. A study in Mishra *et al.*, [17] explores the challenges of task scheduling in fog computing, providing a comprehensive overview of existing research on task scheduling and resource allocation strategies, while also highlighting unresolved issues for future exploration. Furthermore, fog computing, with its cloud-like capabilities at the network edge, is instrumental for latency-sensitive applications. However, it faces privacy, security, and trust challenges. To address these issues and improve real-time performance, the RT-TADS scheduling algorithm is introduced in Kaur *et al.*, [18], considering both direct and recommended trust techniques for fog devices. RT-TADS intelligently maps tasks to trustworthy fog devices based on privacy constraints, leading to substantial improvements in task success ratios compared to other algorithms. Next, the article in Dustda *et al*., [19] emphasizes the need for innovative management technologies to handle complex distributed "computing continuum" systems across various tiers, introducing the concept of the Markov Blanket and equilibrium as alternative management frameworks, with the understanding that implementing these methods will require significant effort and learning techniques.

In response to the growing number of IoT sensing devices and the resulting increase in cloud server traffic, study in Saurabh and Dhanaraj [20] emphasizes the importance of efficient job scheduling in fog-based cloud systems to enhance Quality of Service (QoS) and reduce data delays. The study introduces a novel hybrid model that combines features of Genetic and optimization algorithms with load balancing scheduling on fog nodes, aiming to address QoS challenges exacerbated by heavy traffic. Comparative evaluations against established algorithms like Round Robin (RR), Hybrid RR, Hybrid Threshold-based, and Hybrid Predictive-Based models demonstrate the significant improvement in the task scheduling process achieved by the proposed load balancing model, highlighting its effectiveness in enhancing QoS within the fog environment. Additionally, as the demand for IoT-based smart home automation systems continues to grow, research in Tran *et al*., [21] addresses scheduling challenges specific to fog computing environments, where fog nodes function as mini-clouds with limited resources. These fog nodes handle real-time home automation tasks by processing inputs locally, minimizing latency, a key limitation in contemporary cloud computing. The study reviews various scheduling techniques and introduces a unique task scheduling model tailored for smart home environments within fog computing. Leveraging machine learning mechanisms, this model optimizes task scheduling and allocates tasks to appropriate nodes, providing a comprehensive solution to these challenges. Furthermore, study in Ruchika *et al*., [22] underscores the significance of fog computing in meeting IoT application requirements, such as low latency, locality awareness, reduced network traffic, and mobility support, making it a suitable alternative to traditional cloud computing for IoT applications.

The growth of IoT devices has led to a surge in IoT applications, resulting in massive data generation that necessitates processing and storage, often exceeding the capacity of IoT devices alone. This has led to the practice of offloading tasks to remote cloud data centers, which can introduce challenges such as high bandwidth usage, service latency, and increased energy consumption. To address these issues, fog computing has emerged as a solution by bringing cloud services closer to end-users. Efficient task scheduling and resource allocation mechanisms are vital to balance demand while considering task unpredictability and user Quality of Service (QoS) requirements. In Jain *et al*., [23], the study formulates the task offloading problem as a Markov Decision Process (MDP) and proposes three model-free, off-policy Deep Reinforcement Learning (DRL)-based solutions to maximize resource utilization and rewards. Extensive experiments validate these mechanisms, showing an average increase of 8.25% in task deadline satisfaction, reaching 96.23%. In addition, the study in Chakraborty *et al*., [24] introduces a fuzzy logic technique to prioritize tasks based on resource needs and deadlines, along with an elitism-based multipopulation Jaya algorithm for scheduling diverse task groups onto heterogeneous computing nodes. A compatibility-based heuristic offloading strategy is also presented, resulting in significant improvements, with the proposed algorithm achieving a 35% reduction in average waiting time and a 28% reduction in average service latency compared to existing algorithms. These approaches collectively contribute to addressing challenges in resource management and latency reduction in IoT applications.

3. Material and Methods

3.1 Identification

The systematic review process consists of three basic phases that were used to choose many relevant papers for this study. The first phase entails the identification of keywords and the search for associated, related terms using thesaurus, dictionaries, encyclopedias, and prior research. Following the selection of all pertinent keywords, search strings on the Scopus and IEEE databases (see Table 1) have been developed. The current study project was able to successfully obtain 2,396 articles from both databases during the first stage of the systematic review process.

Table 1
The search string

Database	Search String
Scopus	TITLE (("Job* Scheduling" OR "Job* Selection*" OR "Job* Allocation" OR "Task* Scheduling" OR "Task* Selection*" OR "Task* Allocation" OR "Resource* Management*" OR "Resource* Selection*" OR "Resource* Allocation*") AND ("Cloud Computing" OR "Cloud Environment*" OR "Cloud System*") OR "Fog Computing" OR "Fog-Cloud System*" OR "Fog-Cloud Environment*") AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SUBJAREA , "COMP")) AND (LIMIT-TO (PUBYEAR , 2023)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j")) Date of Access: 30 August 2023
IEEE	Scheduling AND Cloud Computing AND Fog Computing ("All Metadata": Scheduling) AND ("All Metadata": Cloud Computing) AND ("All Metadata":Fog Computing Date of Access: 30 August 2023

3.2 Screening

In the initial screening phase, redundant papers were removed, resulting in the exclusion of 2 papers during the first stage of the study. The second stage involved the evaluation of 2,394 papers against a set of inclusion and exclusion criteria established by the scholars. It includes the exclusion from the current study of publications in the form of systematic review, review, meta-analysis, meta-synthesis, book series, books, chapters, and conference proceedings. Additionally, the review was restricted to publications in the English language, and it is noteworthy that this study's framework was developed in 2023. To align with the study's analytical objectives, only research conducted within the field of computer science was considered. Ultimately, 2,279 publications were excluded based on specific criteria.

3.2 Eligibility

The third level, termed "eligibility," encompasses a selection of 115 articles. During this phase, a meticulous examination of article titles and key textual content was conducted to ascertain compliance with the inclusion criteria and alignment with the research goals of the present study.

Consequently, 67 papers were excluded due to their title and abstract were not substantially aligning with the study's objectives, as substantiated by empirical data. Ultimately, 48 articles were deemed suitable for further review, as detailed in Table 2.

Table 2
The selection criterion of searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Time line	2023	< 2023
Literature type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press
Subject	Computer Science	Besides Computer Science
Language	English	Non-English

3.3 Data Abstraction and Analysis

In this research, an integrative analysis approach was employed as a key assessment strategy to comprehensively examine and synthesize various research designs, predominantly employing quantitative methods. The objective of this expert study was to identify pertinent topics and subtopics within the research domain. The data collection phase served as the initial step in shaping the overarching themes. As illustrated in Fig. 2, a rigorous examination was conducted on a compilation of 48 publications to identify statements or content relevant to the specific research topics under investigation. Subsequently, the authors proceeded to evaluate the domain of job scheduling in the context of both Cloud and Fog computing. Two primary focal points emerged from this methodological exploration: detection and classification impacts. Building upon these core themes, the authors further developed subthemes, concepts, and ideas through collaborative efforts with co-authors, grounded in empirical evidence. Throughout the data analysis process, a detailed log was maintained to document analyses, perspectives, questions, or any other insights relevant to data interpretation. To ensure coherence and consistency, the authors conducted a comparative analysis of the results, addressing any disparities in theme development through internal discussions. It is important to note that any discordance among concepts was diligently deliberated and resolved among the authors. Ultimately, the generated themes underwent refinement to ensure their harmonious alignment. Domain experts, specializing in cloud computing and distributed systems, were engaged to validate the research's robustness. This expert review phase, focused on domain validation, contributed to confirming the clarity, significance, and relevance of each subtheme. In response to expert feedback and professional judgments, the researcher made necessary refinements to their analyses and interpretations.

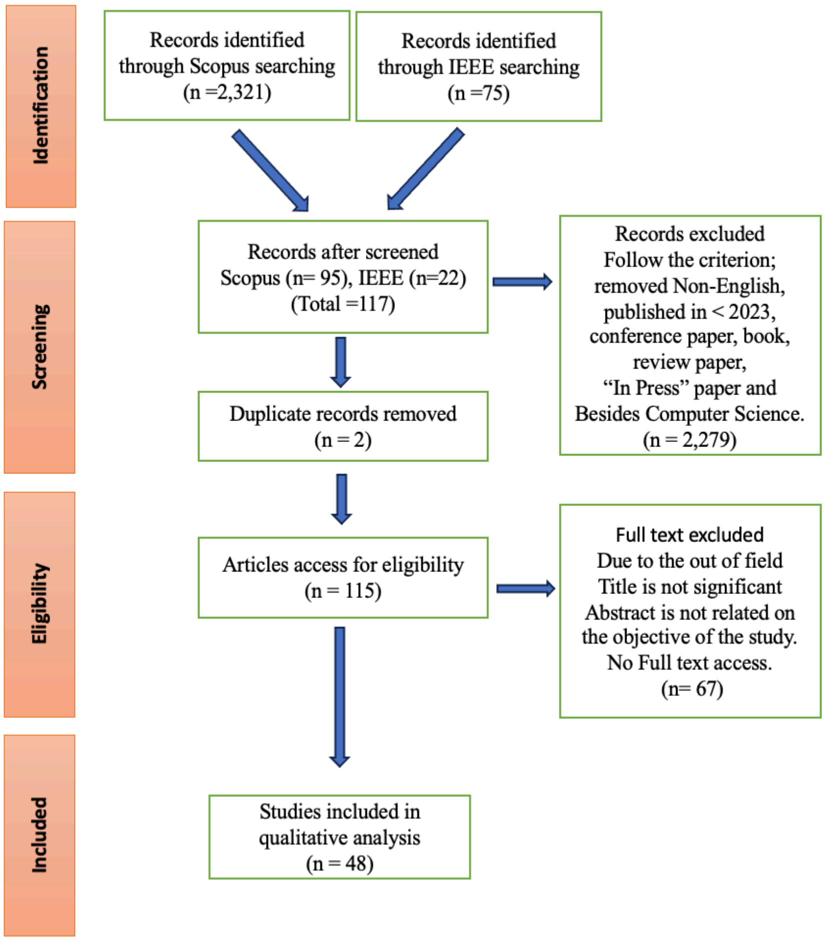

Fig. 2: Flow diagram of the proposed searching study [25]

4. Results and Finding

Job scheduling in cloud and fog computing is a critical aspect of optimizing resource utilization and system performance in distributed computing environments. Cloud computing leverages vast data centers to deliver scalable and on-demand services, while fog computing extends computing capabilities to the network edge. Efficient job scheduling in these contexts involves allocating computing resources to tasks, optimizing load balancing, minimizing latency, and considering energy efficiency. This dynamic field of research explores innovative algorithms, heuristics, and optimization strategies to address the unique challenges posed by cloud and fog computing, ultimately enhancing the quality of service, resource utilization, and energy conservation in these environments.

Based on the searching technique, 48 articles were extracted and analyzed. All articles were categorized into three main themes, namely an Edge Intelligence and Machine Learning Driven Scheduling (13 articles), Multi-objective and QoS-aware Scheduling (24 articles) and Energy-Aware Scheduling (11 articles), as shown in Table 3, 4 and 5, respectively.

Table 3
The research article finding based on the proposed searching criterion for the theme: "Edge Intelligence and Machine Learning-driven Scheduling".

Authors	Title	Year	Source title	Method	Result / Advantages
Zhang X. [26]	A fine-grained task scheduling mechanism for digital economy services based on intelligent edge and cloud computing	2023	Journal of Cloud Computing	• Encompasses both end-device and edge layers. • Accomodate resource-intensive tasks • Tasks are intelligently relocated to suitable resources	• Improves task scheduling performance with regards to energy consumption and delays.
Qadeer A.; Lee M.J. [27]	Deep-Deterministic Policy Gradient Based Multi-Resource Allocation in Edge-Cloud System: A Distributed Approach	2023	IEEE Access	• Uses a deep-deterministic policy gradient (DDPG)-based temporal feature learning attentional network (TFLAN) model. • Integrates convolution, gated recurrent units, and attention layers to extract local and long-term temporal information from task sequences, facilitating precise function approximation. • Proposed a novel heuristic-based priority experience replay (hPER).	• Fast convergence • Operational cost: 28% • Rejection rate reductions: 72% • Average quality of experience improvement: 32%.
Chellapraba B.; Manohari D.; Periyakaruppan K.; Kavitha M.S. [28]	Oppositional Red Fox Optimization Based Task Scheduling Scheme for Cloud Environment	2023	Computer Systems Science and Engineering	• Developed an oppositional red fox optimization-based task scheduling scheme (ORFO-TSS) tailored for IoT-enabled cloud environments. • The ORFO-TSS allocates resources within the IoT-based cloud platform, optimizing task scheduling procedures to minimize makespan across various incoming tasks. • Incorporate the concept of oppositional-based learning (OBL)	• Results underscored the superior effectiveness of the ORFO-TSS technique when compared to established methods.
Atiq H.U.; Ahmad Z.; uz Zaman S.K.; Khan M.A.; Shaikh A.A.; Al-Rasheed A. [29]	Reliable Resource Allocation and Management for IoT Transportation Using Fog Computing	2023	Electronics (Switzerland)	• Prioritize latency and energy efficiency. • Users can opt for cost-effectiveness over speed within a fog environment. • The simulation was conducted using the iFogSim2 simulation tool.	• Reduction of Latency: 10.3% • Decrease in energy consumption: 21.85%
Bouhouch L.; Zbakh M.; Tadonki C. [30]	Online Task Scheduling of Big Data Applications in the Cloud Environment	2023	Information (Switzerland)	• It introduces an Online Task Scheduling algorithm based on Data Migration and Data Replication (OTS-DMDR).	• Reduction in response time: 78% compared to the First Come First Served scheduler (FCFS) and 58%

				• The primary goal is to efficiently assign incoming tasks to available servers, considering dataset access times, task execution durations across different machines, and machine computational capabilities.	decrease compared to Delay Scheduling.
Gao Z.; Yang L.; Dai Y. [31]	Fast Adaptive Task Offloading and Resource Allocation via Multiagent Reinforcement Learning in Heterogeneous Vehicular Fog Computing	2023	IEEE Internet of Things Journal	• Proposes a decentralized task offloading approach called Transformer and Policy Decoupling-based Multiagent Actor-Critic (TPDMAAC). • Adapts to varying input sizes using a versatile transformer. • Mapped between transformer-based embedding features and offloading policies.	• TPDMAAC lowers the system cost from 11.01% to 12.03% • Enhances task completion rates by 10.45% to 13.56%.
Yakubu I.Z.; Murali M. [32]	An efficient meta-heuristic resource allocation with load balancing in IoT-Fog-cloud computing environment	2023	Journal of Ambient Intelligence and Humanized Computing	• Presents a layer-fit algorithm that equitably distributes tasks between the fog and cloud layers • Presents a Modified Harris-Hawks Optimization (MHHO)-based meta-heuristic approach to assign the optimal available resource to tasks within each layer. • The objective is to minimize makespan time, task execution costs, and power consumption	• Reduces makespan time, cutting down execution costs, and minimizing energy consumption. • Outperformed traditional HHO and various other optimization algorithms.
Mseddi A.; Jaafar W.; Elbiaze H.; Ajib W. [33]	Centralized and Collaborative RL-Based Resource Allocation in Virtualized Dynamic Fog Computing	2023	IEEE Internet of Things Journal	• Investigates and proposes online resource allocation solutions with the primary aim of maximizing user satisfaction within predefined latency constraints. • Applies a reinforcement learning (RL) approach.	• Utilizing real-world mobility datasets • Good efficiency and favoring the collaborative approach.
Wang Y.; Dong S.; Fan W. [34]	Task Scheduling Mechanism Based on Reinforcement Learning in Cloud Computing	2023	Mathematics	• Proposes a Q-learning-based Multi-Task Scheduling Framework (QMTSF) • Involves two stages: first, dynamic task allocation to suitable servers based on server types, and second, the application of an enhanced Q-learning algorithm termed UCB-based Q-Reinforcement Learning (UQRL) for task assignment to Virtual Machines (VMs).	• Surpasses alternative scheduling methods in both makespan and average task processing time.
Singh J.; Singh P.; Hedabou M.; Kumar N. [35]	An Efficient Machine Learning-Based Resource Allocation Scheme for SDN-Enabled Fog Computing Environment	2023	IEEE Transactions on Vehicular Technology	• Presents a technique tailored for SDN-enabled fog computing, integrating Collaborative Machine Learning (CML). • Seamlessly incorporated into the resource allocation process within the SDN-enabled fog computing environment.	• Reduction of: Processing time: 19.35%, Response time: 18.14%, Time delay 25.29%. execution time: 21%, network usage: 9% energy consumption: 7%

Li S.; Zhang Y.; Sun W.; Liu J. [36]	A Combinatorial Auction Mechanism for Time-Varying Multidimensional Resource Allocation and Pricing in Fog Computing	2023	International Journal of Applied Mathematics and Computer Science	• Uses an integer programming model for time-varying multidimensional resource allocation in fog computing. • The aim is to maximize utility within the fog resource pool. • Approximate the model's solution, incorporating a dominant resource-based strategy for enhanced resource utilization and critical value theory for improved resource pricing within the fog resource pool.	• Enhances resource utilization and optimizes the utilization of the fog resource pool.
Kadhim A.R.; Rabee F. [37]	Deadline and Cost Aware Dynamic Task Scheduling in Cloud Computing Based on Stackelberg Game	2023	International Journal of Intelligent Engineering and Systems	• Introduces a dynamic Stackelberg game model (DTSSG) • Captures the interactions among tasks, schedulers, and cloud resources, aiming to find an equilibrium while considering both budget and deadline constraints. • Incorporates pricing and satisfaction factors to select the optimal virtual machine for task processing	• Reduction of: Makespan: 30% Number of deadline violations: 52% Total cost: 27.13% Makespan: 27.95% • Increase of: Provider profit: 19.15% Throughput: 59.4%
Badri S.; Alghazzawi D.M.; Hasan S.H.; Alfayez F.; Hasan S.H.; Rahman M.; Bhatia S. [38]	An Efficient and Secure Model Using Adaptive Optimal Deep Learning for Task Scheduling in Cloud Computing	2023	Electronics (Switzerland)	• Developed a novel Convolutional Neural Network Optimized Modified Butterfly Optimization (CNN-MBO) algorithm. • It optimizes task scheduling, maximizing throughput and minimizing makespan. • Applies a modified RSA algorithm is applied to encrypt data for secure transmission.	• Energy consumption: 180 kWh, • Response time:20 seconds, • Execution time: 0.43 seconds, • Resource utilization: 98%, when applied to tasks of size 100.

Table 4
The research article finding based on the proposed searching criterion for the theme: "Multi-objective and QoS-aware Scheduling".

Authors	Title	Year	Source title	Method	Result / Advantages
Khaleel M.I. [39]	Efficient job scheduling paradigm based on hybrid sparrow search algorithm and differential evolution optimization for heterogeneous	2023	Internet of Things (Netherlands)	• Introduces CSSA-DE, a dual-phase metaheuristic algorithm. • Node offering the highest Performance-to-Power Ratio (PPR) is selected as the mega cluster head (MCH). • The Sparrow Search Algorithm (SSA) is merged with the Differential Evolution (DE) algorithm to enhance search efficiency in identifying suitable task-VM pairs.	• Exhibits robust performance and consistently outperforms state-of-the-art algorithms in various scenarios.

	cloud computing platforms				
Zhao M.; Zhang Z.; Fan T.; Guo W.; Cui Z. [40]	Many-Objective Optimization-Based Task Scheduling in Hybrid Cloud Environments	2023	CMES - Computer Modeling in Engineering and Sciences	• Presents a many-objective optimization model for hybrid cloud task scheduling (HCTSO), considering risk rate, resource utilization, total cost, and task completion time. • Introduces an opposition-based learning knee point-driven many-objective evolutionary algorithm (OBL-KnEA) to enhance model performance.	• OBL-KnEA stands out with exceptional results in various aspects, including evaluation metrics, initial population considerations, and model optimization effectiveness.
Mangalampalli S.; Swain S.K.; Chakrabarti T.; Chakrabarti P.; Karri G.R.; Margala M.; Unhelkar B.; Krishnan S.B. [41]	Prioritized Task-Scheduling Algorithm in Cloud Computing Using Cat Swarm Optimization	2023	Sensors	• Introduces a novel algorithm that considers task priorities upon entering the cloud platform. • Calculates task VM priorities and presents to the scheduler, which selects tasks for VMs based on these priorities. • Using the cat swarm optimization algorithm, inspired by cat behavior.	• Consistently outperforms PSO, ACO, and RATS-HM across various parameters.
Nanjappan M.; Natesan G.; Krishnadoss P. [42]	HFTO: Hybrid Firebug Tunicate Optimizer for Fault Tolerance and Dynamic Task Scheduling in Cloud Computing	2023	Wireless Personal Communications	• Introduces the Hybrid Firebug and Tunicate Optimization (HFTO) algorithm. • Leveraging past scheduling data, generates various Virtual Machine (VM) variants, reducing VM creation time. • Strives to optimize Quality of Service (QoS) parameters like fault tolerance, response time, efficiency, and makespan. • The HFTO algorithm broadens solution search space and formulates an optimal task scheduling strategy for virtual machines, offering advantages like improved search capability and faster convergence.	• Enhances load balancing efficiency and improved performance in cloud task scheduling.
Hu Q.; Wu X.; Dong S. [43]	A Two-Stage Multi-Objective Task Scheduling Framework Based on Invasive Tumor Growth Optimization Algorithm for Cloud Computing	2023	Journal of Grid Computing	• Introduces the Multi-Objective Scheduling framework MSITGO, focused on optimizing batch task completion time, energy consumption, and idle resource costs simultaneously. • MSITGO leverages the Invasive Tumor Growth Optimization (ITGO) approach, incorporating characteristics of tumor cell growth models, Pareto optimality, and packing problems to enable a detailed and efficient exploration of solution space. This enhances solution diversity and accelerates convergence.	• Offers a superior solution to the multi-objective task scheduling problem as compared to other state-of-the-art algorithms.

Senthil Kumar A.M.; Padmanaban K.; Velmurugan A.K.; Asha Shiny X.S.; Anguraj D.K. [44]	A novel resource management framework in a cloud computing environment using hybrid cat swarm BAT (HCSBAT) algorithm	2023	Distributed and Parallel Databases	• Introduces an innovative task allocation algorithm that combines Cat Swarm Optimization (CSO) with the BAT algorithm to address pre-convergence challenges. • Aids in mitigating convergence issues. • Rigorously evaluated and benchmarked against well-known algorithms, including CSO and BAT algorithms, to assess its performance and effectiveness.	• In terms of availability and throughput, the results obtained from HGCSBAT surpass those achieved by Genetic algorithm, Cat Swarm Optimization, and BAT algorithms.
Zhang X. [45]	A Hybrid Method Based on Gravitational Search and Genetic Algorithms for Task Scheduling in Cloud Computing	2023	International Journal of Advanced Computer Science and Applications	• Presents a hybrid approach that merges Gravitational Search and Genetic Algorithm • It capitalizes on the complementary strengths of both algorithms to improve scheduling performance.	• Demonstrated superior performance compared to prior scheduling methods • Optimizes resource allocation and cost reduction.
Yin L.; Sun C.; Gao M.; Fang Y.; Li M.; Zhou F. [46]	Hyper-Heuristic Task Scheduling Algorithm Based on Reinforcement Learning in Cloud Computing	2023	Intelligent Automation and Soft Computing	• Introduces a hyper-heuristic algorithm driven by reinforcement learning (HHRL) for optimizing task sequence completion times. • HHRL algorithm employs a reward table setup that integrates population diversity and maximum time considerations. • Introduces a task computational complexity estimation approach, combining it with linear regression to influence task scheduling priorities. • A candidate solution migration method enhances the continuity and diversity of the solving process, ensuring high-quality solutions.	• Demonstrates rapid acquisition of task complexity • Adapt selection of suitable heuristic strategies for task scheduling, • Pursuit of the best makespan • Superior disturbance detection capability for maintaining population diversity.
Li X. [47]	An IFWA-BSA Based Approach for Task Scheduling in Cloud Computing	2023	Journal of ICT Standardization	• Introduces the Integration of Fireworks Algorithm and Bird Swarm Algorithm (IFWA-BSA). • Establishes a cloud computing task scheduling model, incorporating time and cost constraints. • FWA initialization phase utilizes chaotic backward learning and Coasean distribution for optimization.	• Clear advantages over ACO, PSO, and FWA in terms of execution time and cost consumption metrics, resulting in reduced scheduling time and cost in cloud computing.
Pirozmand P.; Jalalinejad H.; Hosseinabadi	An improved particle swarm optimization algorithm for task	2023	Journal of Ambient Intelligence and	• Presents an Improved Particle Swarm Optimization (IPSO) algorithm. • Coorporate a multi-adaptive learning strategy.	• Attain the optimal solution for the majority of the criteria, i.e., makespan, load

A.A.R.; Mirkamali S.; Li Y. [48]	scheduling in cloud computing		Humanized Computing	• The Multi Adaptive Learning for Particle Swarm Optimization (MALPSO) is introduced to distinguishes between ordinary particles and locally best particles.	balancing, stability, and efficiency,
Nanjappan M.; Krishnadoss P.; Ali J.; Natesan G.; Ananthakrishnan B. [49]	Task Scheduling Based on Cost and Execution Time Using Ameliorate Grey Wolf Optimizer Algorithm in Cloud Computing	2023	International Journal of Intelligent Engineering and Systems	• Proposed a Grey Wolf Optimizer Cuckoo (GWOC) algorithm to represents a meta-heuristic hybrid combining elements from the Grey Wolf Optimizer and Cuckoo Search algorithms.	• Enhancements of 2.11%, 3.5%, and 5.17% for makespan and reduces costs by 7.71%, 11.3%, and 15.4% when compared to the gravitational search algorithm (GSA), whale optimization algorithm (WOA), and grey wolf optimizer (GWO), respectively.
Mangalampalli S.; Swain S.K.; Karri G.R.; Mishra S. [50]	SLA Aware Task-Scheduling Algorithm in Cloud Computing Using Whale Optimization Algorithm	2023	Scientific Programming	• Employs a Whale Optimization Algorithm, • Enables the scheduler to make precise task scheduling decisions onto virtual resources.	• Enhance makespan compared to PSO, ACO, GA, and W-schedulers, with improvements of 20.07%, 17.55%, 19.9%, and 6.35%, respectively, and 17.3%, 17.86%, 17.64%, and 5.93%, respectively • Improves SLA violations over PSO, ACO, GA, and W-Scheduler by 56.76%, 42.17%, 35.29%, and 24.53%, respectively, and 63.42%, 23.33%, 55.51%, and 40.1%, respectively.
Ghazy N.; Abdelkader A.; Zaki M.S.; Eldahshan K.A. [51]	An ameliorated Round Robin algorithm in the cloud computing for task scheduling	2023	Bulletin of Electrical Engineering and Informatics	• Introduces the Enhanced Round Robin Algorithm (ERRA). • Improves time quantum determination method by considering both fixed and dynamic approaches, optimizing it based on the average task burst time.	• Perform better over other algorithms, including improved RR, enhanced RR, dynamic time quantum approach (ARR), and enhanced RR (RAST ERR), in

					terms of average waiting time, average turnaround time, and response time.
Karimunnisa S.; Pachipala Y. [52]	An AHP based Task Scheduling and Optimal Resource Allocation in Cloud Computing	2023	International Journal of Advanced Computer Science and Applications	• Introduces a modified approach driven by the Analytical Hierarchy Process (AHP). • Ensures functionality in two phases: Task ranking and optimized scheduling algorithms, leading to enhanced resource utilization. • The task ranking phase leverages an improved AHP with extensive use of fuzzy clustering, followed by the application of an enhanced CUCMCA (Chimp Updated and Cauchy Mutated Coot Algorithm) for optimal resource allocation in cloud applications.	• Improves performance with significant gains of 32% in memory usage, 33.5% in execution time, 29% in makespan, and 18% in communication cost compared to conventional pre-existing models.
Abdullahi M.; Ngadi M.A.; Dishing S.I.; Abdulhamid S.M. [53]	An adaptive symbiotic organisms search for constrained task scheduling in cloud computing	2023	Journal of Ambient Intelligence and Humanized Computing	• Introduces the Adaptive Benefit Factors based Symbiotic Organisms Search (ABFSOS) • Dynamically adjusts SOS control parameters to strike a balance between local and global search processes, resulting in accelerated convergence. • An adaptive constrained handling strategy is integrated into the algorithm, effectively fine-tuning penalty function values to prevent infeasible solutions and premature convergence. • Evaluates the performance of the Constrained Multi-Objective ABFSOS (CMABFSOS) using both standard and synthetic workloads on the CloudSim simulator.	• CMABFSOS exhibits performance enhancements over EMS-C within the range of 17.02% to 47.73% across various workloads, and it outperforms ECMSMOO with improvements ranging from 19.98% to 52.18%.
Sreenu K.; Malempati S. [54]	Multiple Resource Attributes and Conditional Logic Assisted Task Scheduling in Cloud Computing	2023	International Journal of Intelligent Engineering and Systems	• Introduces an efficient task scheduling mechanism aimed at achieving faster convergence and improved Quality of Service (QoS). • It leverages multiple resource attributes, including resource reaction time, resource location, resource availability, and resource reliability rate. • These attributes are utilized to create a task scheduling index (TSI) that guides the allocation of tasks to resources. • TSI is generated through a novel conditional logic, prioritizing resources with higher TSI values.	• Exhibits a Makespan reduction of 48.22% for GOCJ and 46.87% for Synthetic datasets.
Abu-Amssimir N.; Al-Haj A. [55]	A QoS-aware resource management	2023	Multimedia Tools and Applications	• Introduce a QoS-aware edge placement scheme designed to optimize the end-to-end latency of real-time IoT applications by strategically distributing application modules across fog devices.	• Enhances Quality of Service (QoS) by reducing end-to-

	scheme over fog computing infrastructures in IoT systems			• Encompasses two key stages: an initial stage focusing on the selection of application modules to minimize delay and a subsequent stage dedicated to the placement of these modules to further reduce latency.	end latency, network usage, and energy consumption.
Suganya R.; Joseph N.P.; Rajadevi R.; Ramamoorthy S. [56]	Enhancing the job scheduling procedure to develop an efficient cloud environment using near optimal clustering algorithm	2023	International Journal of Cloud Computing	• Focuses on resource clustering in the cloud environment • Introduces an efficient resource clustering algorithm called Identicalness Split Up Periodic Node Size (ISPNS).	• Able to generate near-optimal solutions for the resource clustering problem.
Muniyappa V.; Hattibelagal C. [57]	Cloud Computing for Task Scheduling Using Estimate of Distribution Algorithm – KrillHerd Method	2023	International Journal of Intelligent Engineering and Systems	• Presents the Estimation of Distribution Algorithm for Krill Herd (EDA-KrillHerd), • Conducts a comparative analysis with particle swarm optimization (PSO) and the Krill Herd algorithms. • The primary goal is to efficiently leverage EDA in conjunction with the KrillHerd algorithm to significantly reduce task completion times.	• EDA-Krill Herd algorithm exhibits superior performance, achieving notable efficiency with a Makespan of 1000.74 seconds, a throughput of 64.30%, and resource utilization of 99.90%.
Hai T.; Zhou J.; Jawawi D.; Wang D.; Oduah U.; Biamba C.; Jain S.K. [58]	Task scheduling in cloud environment: optimization, security prioritization and processor selection schemes	2023	Journal of Cloud Computing	• Introduces an enhanced variant of the Heterogeneous Earliest Finish Time (HEFT) algorithm, focusing on improving its performance. • Incorporates modifications in two key stages. First, in the rank generation stage, various methodologies are applied to compute task priorities. Second, alterations are made to the process of selecting empty slots for task scheduling.	• The modified versions of the HEFT algorithm outperform the original HEFT algorithm in terms of reducing the schedule length for workflow problems.
Chandrashekar C.; Krishnadoss P.; Kedalu Poornachary V.; Ananthakrishnan B.; Rangasamy K. [59]	HWACOA Scheduler: Hybrid Weighted Ant Colony Optimization Algorithm for Task Scheduling in Cloud Computing	2023	Applied Sciences (Switzerland)	• Introduces an ideal and efficient task scheduling algorithm, which is evaluated and benchmarked against existing methods in terms of efficiency, makespan, and cost parameters. • It tackles the scheduling problem through the utilization of the Hybrid Weighted Ant Colony Optimization (HWACO) algorithm, • The objective is to demonstrate the algorithm's superior performance in optimizing task scheduling in comparison to established alternatives.	• HWACO algorithm achieves rapid convergence, surpassing traditional algorithms such as Ant Colony Optimization (ACO), Quantum-Based Avian Navigation Optimizer Algorithm (QANA), Modified-Transfer-Function-Based Binary Particle Swarm

					Optimization (MTF-BPSO), MIN-MIN Algorithm (MM), and First-Come-First-Serve (FCFS).
Saif F.A.; Latip R.; Hanapi Z.M.; Shafinah K. [60]	Multi-Objective Grey Wolf Optimizer Algorithm for Task Scheduling in Cloud-Fog Computing	2023	IEEE Access	• Introduces the Multi-Objectives Grey Wolf Optimizer (MGWO) algorithm aimed at minimizing QoS objectives, particularly reducing delay and energy consumption. • The algorithm is applied within the context of a fog broker • Seek to enhance the efficiency of fog computing systems, thereby improving QoS parameters such as latency and energy usage.	• The MGWO algorithm is more efficient when compared to state-of-the-art algorithms in terms of reducing both delay and energy consumption.
Hamed A.Y.; Elnahary M.Kh.; Alsubaei F.S.; El-Sayed H.H. [61]	Optimization Task Scheduling Using Cooperation Search Algorithm for Heterogeneous Cloud Computing Systems	2023	Computers, Materials and Continua	• Presents an innovative approach to efficiently schedule tasks within cloud computing systems, leveraging the cooperative search algorithm to address the inherent challenges of managing heterogeneous cloud computing workloads. • The core concept involves harnessing the capabilities of meta-heuristic algorithms to attain optimal solutions.	• It outperforms existing methods: New Genetic Algorithm (NGA), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), Gravitational Search Algorithm (GSA), and Hybrid Heuristic and Genetic (HHG), achieving a superiority ranging from 2.1% to 8.8% concerning makespan.
Ya-Meng B.; Yang W.; Shen-shen W. [62]	Deadline-aware Task Scheduling for Cloud Computing using Firefly Optimization Algorithm	2023	International Journal of Advanced Computer Science and Applications	• Introduces a novel task scheduling algorithm for cloud environments that prioritizes deadlines. • This algorithm is based on the Firefly Optimization Algorithm (FOA).	• Enhances execution time, waiting time, resource utilization, missed task percentage, power consumption, and makespan.

Table 5

The research article finding based on the proposed searching criterion for the theme: "Energy-Aware Scheduling "

Authors	Title	Year	Source title	Method	Result / Advantages
Grewal S.K.; Mangla N. [63]	EETSQ: Energy Efficient Task Scheduling based on QoS Parameters in Cloud Computing Environment	2023	International Journal on Recent and Innovation Trends in Computing and Communication	• Introduces an energy-efficient task scheduling approach, taking into account Quality of Service (QoS) parameters. • Incoming tasks are categorized into four distinct classes using specific attributes, and these classes are subsequently prioritized based on their relative significance. • A list of Physical Machine (PM) types is compiled, considering the available resource blocks, and from this list, the PM with the highest QoS value is selected.	• Experimental evaluation conducted using CloudSim confirms the effectiveness and efficiency of the proposed approach.
Himanshu; Mangla N. [64]	A Hybrid Secure and Optimized Execution Pattern Analysis Based O-HMACSHA 3 Resource Allocation in Cloud Environment	2023	International Journal of Computer Networks and Applications	• Introduces the Optimized-Hybrid Medium Access Control Secure Hash Algorithm 3 (O-HMACSHA3). • Ensure reliable resource scheduling access for diverse tasks • Focusing to reduce turnaround time (TAT) and energy consumption (EC). • Leverages optimization techniques, employing Particle Swarm Optimization (PSO)	• Energy consumption decreasing to 47.7 joules • TAT reduced to 316 milliseconds
Razaak M.P.A.; Ansari G.A. [65]	Greedy-based task scheduling algorithm for minimising energy and power consumption for virtual machines in cloud environment.	2023	International Journal of Cloud Computing	• Introduces a Virtual Machine Placement (VMP) to reduce the number of physical servers. • Schedule underutilized servers. • Establish a connection between the task scheduler and cloud server through VMP. • Incorporates the Minimization Algorithm for Active Physical Servers (MAPS).	• Outperforms existing state-of-the-art methods in terms of energy efficiency.
Iftikhar S.; Ahmad M.M.M.; Tuli S.; Chowdhury D.; Xu M.; Gill S.S.; Uhlig S. [66]	HunterPlus: AI based energy-efficient task scheduling for cloud–fog computing environments	2023	Internet of Things (Netherlands)	• Introduces HunterPlus • Investigates the impact of extending the Bidirectional Gated Recurrent Unit (Bi-GRU) in contrast to the Gated Graph Convolution Network (GGCN). • Explores the integration of Convolutional Neural Networks (CNNs) to enhance the optimization of cloud-fog task scheduling.	• CNN scheduler surpasses the GGCN-based models in terms of energy consumption and job completion rate metrics by 17% and 10.4%, respectively.

Sun W.-B.; Xie J.; Yang X.; Wang L.; Meng W.-X. [67]	Efficient Computation Offloading and Resource Allocation Scheme for Opportunistic Access Fog-Cloud Computing Networks	2023	IEEE Transactions on Cognitive Communications and Networking	• To minimize data transmission and computation latency and enhance energy efficiency, this paper • Introduces the concept of an opportunistic access fog-cloud computing network (OFCN). • Formulates an optimization problem, taking into account resource allocation and computation offloading while adhering to user quality of service (QoS) criteria.	• OFCN reduced latency and lower energy consumption compared to traditional fog-cloud computing networks.
Jambulingam U.; Balasubadra K. [68]	An Energy-Aware Agent-Based Resource Allocation Using Targeted Load Balancer for Improving Quality of Service in Cloud Environment	2023	Cybernetics and Systems	• Propose an energy-aware agent-based resource allocation approach utilizing a targeted load balancer (TLB). • Energy levels are monitored by Cloudwatch to determine the typical payload size of resource execution. • Introduces a novel instance state mechanism for resource assignment based on payload weight. • Developed a dynamic hyper-switching model.	• Achieves up to a 95.5% enhancement for execution time through state-of-execution switching. • Reduced CPU consumption by effectively reducing temporal complexity.
Vispute S.D.; Vashisht P. [69]	Energy-Efficient Task Scheduling in Fog Computing Based on Particle Swarm Optimization	2023	SN Computer Science	• Introduces the Energy-Efficient Task Scheduling in Fog Computing based on Particle Swarm Optimization (EETSPSO) algorithm. • Focus on key evaluation parameters, including makespan, energy consumption, and execution time.	• Decreases: Makespan: 6.39% Energy consumption:9.12% Execution time: 9.83%
Jakwa A.G.; Gital A.Y.; Boukari S.; Zambuk F.U. [70]	Performance Evaluation of Hybrid Meta-Heuristics-Based Task Scheduling Algorithm for Energy Efficiency in Fog Computing	2023	International Journal of Cloud Applications and Computing	• Introduces Hybrid Meta-Heuristic Optimization Algorithm (HMOA), designed for the energy-efficient task scheduling. • Combines the Modified Particle Swarm Optimization (MPSO) meta-heuristic and the Deterministic Spanning Tree (SPT) algorithm.	• Superior performance with regards to energy efficiency, resource utilization, and response time.
Agarwal G.; Gupta S.; Ahuja R.; Rai A.K. [71]	Multiprocessor task scheduling using multi-objective hybrid genetic	2023	Knowledge-Based Systems	• Presented Hybrid Genetic Algorithm and Energy-Conscious Scheduling. • Integrates Genetic Algorithm and an Energy-Conscious Scheduling model.	• Perform better than genetic algorithms, particle swarm optimization, gravitational search

	Algorithm in Fog–cloud computing				algorithms, ant colony optimization, and round-robin models.
Kalai Arasan K.; Anandhakumar P. [72]	Energy-efficient task scheduling and resource management in a cloud environment using optimized hybrid technology	2023	Software - Practice and Experience	• Introduced a Unique Ranking based on Technique for Order Preference by Similarity to Ideal Solution (uRank-TOPSIS) and Hybrid State-Action-Reward-State-Action (SARSA) Reinforcement Learning with the Black Widow Algorithm (HSRLBA). • Employs uRank-TOPSIS to generate a unique set of weights and rank alternative solutions. • HSRLBA is utilized for resource allocation, incorporating the Black Widow Algorithm (BWA) to expedite the convergence of parallel agents within the SARSA-based Reinforcement Learning model.	• Energy consumption: 325KWh • Response time: 15.42 s, • Makespan: 1150 s, • TCR: 98%, • Resource utilization rate: 92%.
Gao Y.; Wang L.; Xie Z.; Qi Z.; Zhou J. [73]	Energy- and Quality of Experience-Aware Dynamic Resource Allocation for Massively Multiplayer Online Games in Heterogeneous Cloud Computing Systems	2023	IEEE Transactions on Services Computing	• Introduces a dynamic resource allocation strategy for Massively multiplayer online games (MMOGs) in heterogeneous cloud systems, • Present a novel hybrid algorithm combining differential evolution and a modified first-fit heuristic for VM consolidation.	• Energy savings: 44.8%

4. Discussions and Conclusion

From the erspective of "Edge Intelligence and Machine Learning-driven Scheduling", the proposed methods leverage advanced machine learning techniques, deep learning models, and intelligent algorithms to optimize task scheduling, resource allocation, and decision-making processes within cloud computing and IoT-enabled environments. By incorporating features like convolutional neural networks, reinforcement learning, collaborative machine learning, and attention mechanisms, these approaches harness the power of machine learning-driven scheduling to enhance efficiency, reduce energy consumption, and improve overall performance. This theme underscores the critical role of machine learning in addressing scheduling challenges at the edge, making these methodologies highly relevant and contributory to this evolving field.

Menawhile, from the point of view of "Multi-objective and QoS-aware Scheduling", the proposed methods emphasized the importance of optimizing cloud and edge resources while considering multiple objectives and quality of service (QoS) parameters. They introduce innovative algorithms and techniques that aim to strike a balance between various conflicting objectives such as makespan reduction, energy consumption minimization, resource utilization improvement, and QoS enhancement. By integrating multi-objective optimization, machine learning, and meta-heuristic approaches, these methodologies address the complex challenges of scheduling tasks in cloud and edge computing environments. They contribute to the development of intelligent scheduling solutions that prioritize efficiency, cost-effectiveness, and user satisfaction, making them highly relevant to the overarching theme of multi-objective and QoS-aware scheduling in cloud and edge computing.

Furthermore, when "Energy-Aware Scheduling" is concerned, the proposed methods were dedicated to optimizing energy efficiency in various computing environments, including cloud, fog, and IoT systems. They employ a range of innovative techniques such as meta-heuristics, machine learning, and hybrid algorithms to achieve energy-efficient task scheduling. Additionally, they take into account factors like resource allocation, load balancing, and QoS improvement to minimize energy consumption while ensuring effective task management. By addressing the critical issue of energy efficiency, these methodologies contribute significantly to the development of sustainable and environmentally conscious computing systems.

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