A Comprehensive Review of Cluster Head Selection

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Abstract*: The resource management, energy consumption and load balancing are important challenges in the dynamic and massive cloud systems. However, the dynamic and large-scale cloud systems pose a challenge to effective resource management, energy consumption and load balancing strategies. In this case, the cluster head (CH) selection plays an important role in improving the system performance by forming clusters, reducing communication cost, and improving resource utilization. The traditional CH selection techniques do not generally solve multi-objective optimization problems and hence face performance issues. Swarm intelligence algorithms have been widely applied to address these challenges as they are adaptable, resilient and can be applied to solve complex optimization problems. This review paper examines the existing approaches of cluster head selection and resource allocation in cloud computing using swarm intelligence and hybrid approaches. The review highlights the major research problems of high computation time, lack of real-time responsiveness, and generalization. It also highlights the opportunities and future research in developing efficient, lightweight, and intelligent optimization solutions. The study aims to provide useful insights to researchers to develop efficient and adaptive solutions to future cloud computing.*

Keywords: Cluster head selection; Swarm intelligence; Cloud computing; Load balancing; Energy efficient

1. Introduction

Cloud computing is an emerging paradigm that allows the on-demand delivery and sharing of computing resources (such as storage, network, processing, and applications) over the internet [1]. Cloud computing can make possible the provision of scalable, adaptable, and affordable services in various areas (including health, IoT, smart city, and big data analytics) without the need for local infrastructure [2]. The rapid development of data-intensive applications has also driven the adoption of the cloud environment, in which efficient resource utilization and the reliability of services are crucial [3]. To operate, cloud computing systems must satisfy a number of important requirements. These include scalability to manage an increasing workload, availability to provide a continuous service, resource efficiency to guarantee efficient use of the computing resources, and energy efficiency to reduce the cost of operation. Furthermore, security, fault tolerance and load balancing are critical requirements to ensure reliable and continuous services of the cloud services in dynamic environments [4].

Cloud computing has several benefits. This offers resource flexibility on demand, fast processing with distributed computing capabilities, and cost-effectiveness with reduced hardware and maintenance costs. Also, cloud computing is fast to deploy, the data is accessible and can be shared; hence they can be adapted to modern computing. But one of the challenges is to manage the widely distributed resources. Here the notion of cluster head (CH) is appropriate for cloud and distributed systems. A cluster head is a coordination agent that is responsible for task allocation, data collection and communication for a group of nodes. The right cluster head minimises communication costs, load balancing and enhances the performance of the system. Further, it helps enhance the scalability and efficiency of cloud environments, especially with edge computing and IoT-based systems. The cluster head selection process is a complex optimization problem that is influenced by several factors, including the energy level, computational capability, network condition, distance, and load distribution between nodes. These multi-objective constraints are often not addressed using traditional methods. So, to offer optimal CH selection in dynamic environments, intelligent and adaptive approaches are needed [5].

Swarm intelligence algorithms are becoming increasingly popular to tackle such complex optimization problems. Methods such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) and Grey Wolf Optimization (GWO) offer effective solutions to cluster head selection and resource optimization inspired by the collective behaviour of animals like ants, bees and wolves. These algorithms can be used in cloud or IoT systems, which have the features of fast convergence, adaptability, robustness, and avoiding local optima. The main aim of this review paper is to compare and analyse the existing solutions of resource allocation and selection of cluster heads in cloud computing using hybrid and swarm intelligence algorithms. The paper highlights the key techniques, their advantages and disadvantages, and the research challenges and opportunities. It also provides some perspectives on the future directions in creating efficient, scalable and intelligent optimization methods that can be employed to enhance the cloud-based system performance [6].

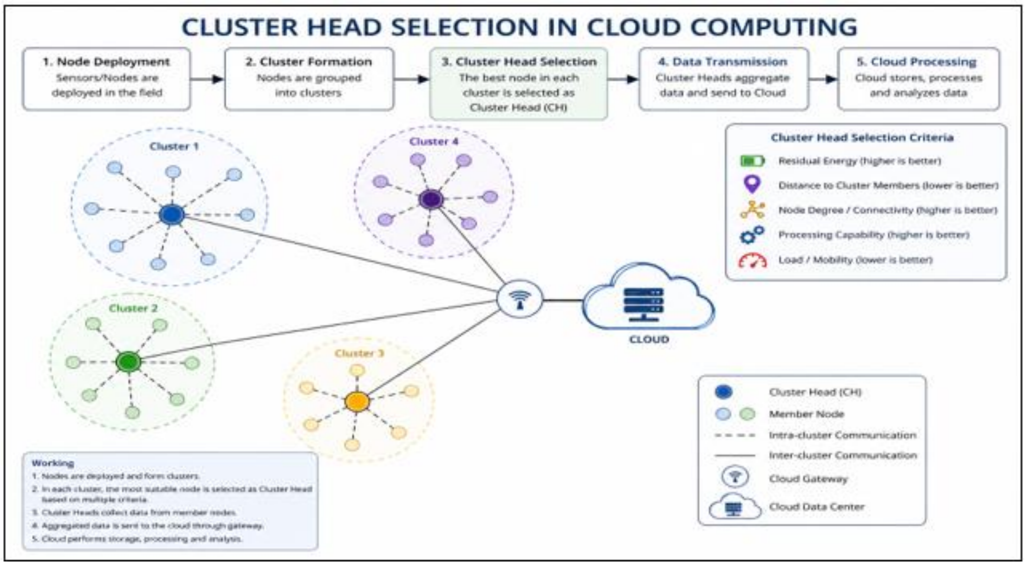

Figure 1 : Architecture of CH selections

2. Related Works

The following subsections are discussing about the recent studies related to CH selection based on different criteria.

2.1 Swarm Intelligence & Metaheuristic Optimization

Swarm intelligence techniques are generally applied for effective CH selection due to their global search capability. They efficiently trade off energy efficiency, speed of convergence, and increase the network lifetime. Hybrid approaches also improve performance by integrating several approaches of optimization, but can be more complex and need carefully tuned parameters. A great number of works, such as H. Alsuwat et al. [7] (2025), G. H. Alshammri [8] (2025), M. K. Reddy et al. [9] (2025), and S. Sathyamoorthy et al. [10] (2025) employ swarm intelligence algorithms (ABC, SSA, COA, PSO, ALO) for optimization. These approaches enhance convergence, power saving, and network life span. S. Harifi et al. [11] (2025) have established hybrid metaheuristic models like Hybrid AO-AOA, PSOGWO and WOA-based models, which further enhance the global search capacity and optimization performance.

Table 1: Swarm Intelligence & Metaheuristic Optimization

Ref	Methods	Key Contributions	Merits	Demerits
[7]	IQ-ABC (Q-learning + ABC)	Multi-objective CH selection using RL + swarm	High energy efficiency, longer lifetime	Complex computation
[8]	Improved SSA	Adaptive CH selection with local search	High PDR, low energy	Parameter tuning needed
[10]	Ant Lion Optimization	Energy-aware CH selection and routing	Improved throughput, low delay	Moderate complexity
[11]	Hybrid PSO + GPC	Improved optimization capability	Better convergence	High complexity

2.2 CH selection methods

CH selection approaches normally improve communication cost, energy, and distance. Traditional and modern clustering methods, including fuzzy logic and reinforcement learning, improve network stability and scalability. They help distribute the load evenly across nodes, but are sometimes expensive and less effective in dynamic, large-scale situations. The selection of CH is essential in such works as A. Selvaraj et al. (2025) [12], T. Kanimozhi et al. (2025) [13], and C. Lv et al. (2025) [14], in which energy, distance, and connectivity are minimized. These approaches improve the life of the network and decrease the use of energy. W. Osamy et al. [15] (2024) offer innovative clustering methods based on fuzzy logic, reinforcement learning, and trust mechanisms to expand reliability and fault tolerance.

Table 2 : Cluster head selection techniques

Ref	Methods	Key Contributions	Merits	Demerits
[12]	COA	Bio-inspired CH selection	Improved energy efficiency	Limited scalability
[13]	MGSO + MFCM	Energy-efficient clustering protocol	Extended network lifetime	High overhead
[14]	OERWCA	Optimized clustering for IoT	Improved PDR, reduced delay	Complex design
[15]	SCSO	Secure energy-aware clustering	High reliability	Computational cost

2.3 Hybrid AI & Deep Learning (DL) Models

DL and hybridization with optimization algorithms improve the decision-making and prediction skills of CH selection [16]. Approaches using the combination of neural networks with fast learning techniques increase classification accuracy, energy efficiency, and stability. However, such methods may be complex, requiring significant computational effort and data, which may be difficult to use in real-time networks. A. Khan et al. [17] (2025), S. Depuru et al. [18] (2025), and J. Cui et al. [19] (2025) introduce hybrid intelligent systems with the use of DL and optimization. These models enhance prediction performance, intrusion detection and classification. The addition of optimized DL models like

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ECSO-ICNN and SNGNN-RCGO by M. B. Dhivya et al. [20] (2025) and S. J. Rani et al. [21] (2025) further optimized energy consumption and network stability.

Table 3: Deep learning models

Ref	Methods	Key Contributions	Merits	Demerits
[17]	SONN + AFSA	Hybrid neural + swarm optimization	High accuracy, efficient scheduling	Complex model
[18]	IGWSO + RNN	Trust-based malware detection	High precision, recall	High training cost
[19]	EfficientNet + EFTTA	Intrusion detection using DL + optimization	High detection accuracy	Black-box issue
[20]	ECSO-ICNN	DL-based attack detection	High F-measure	Complexity

2.4 Cloud Computing & Resource Optimization

The use of cloud computing-based optimization algorithms helps with cluster head selection via resource scheduling and resource allocation. PSO and SSO improve resource allocation, reduce makespan and improve efficiency. But, problems such as latency, cloud reliance and scalability must be dealt with. Y. Wang [22] (2025), and B. K. R. Janumpally [23] (2025) provide cloud-based optimization models, i.e., SSO, PSO, and hybrid scheduling. Such strategies enhance efficient use of resources, makespan, and efficiency of the system. More sophisticated schemes such as SONN-AFSA and FQASO by A. Khan et al. [17] (2025) and B. Mohammad Hasani Zade et al. [24] (2025) also have superior SLA, energy efficiency, and scalability.

Table 4: Resource optimization methods

Ref	Methods	Key Contributions	Merits	Demerits
[22]	PSO + BiLSTM	Resource prediction & scheduling	High prediction accuracy	High computation
[23]	PSO	Task scheduling optimization	Reduced makespan	Static assumptions
[24]	FQASO	Energy-aware scheduling	High energy savings	Complex implementation

2.5 Routing & Communication Optimization

An efficient communication between nodes and CHs is significant for efficient routing. Fuzzy logic, bio-inspired and AI methods are improved the packet delivery ratio (PDR), delay, and throughput. These methods are enhancing the network performance, but with complexity and increased overhead. Optimization-based routing approaches are proposed by S. Othmen et al. [25] (2025), R. S. Abujassar [26] (2025), and F. Ajaz et al. [27] (2025). These techniques enhance the PDR, decrease latency and increase throughput. An IntelliBEF and DynaClusterNet are smart routing methods by S. Nimmala et al. [28] (2025) and R. Rajesh et al. [29] (2025) also donate to fault tolerance and dynamism in communication.

Table 5: Routing and communications optimization methods

Ref	Methods	Key Contributions	Merits	Demerits
[25]	Fuzzy + PSO	Routing optimization for IoT healthcare	Low delay, high throughput	Limited scalability
[26]	AI-SDN routing	Fault-tolerant routing	Reduced delay	Complexity
[27]	CLORP (Lion optimization)	Cluster-based routing	Improved performance	Overhead
[28]	IntelliBEF	Fault-tolerant routing + CNN	High reliability	Complex system

2.6 Security, Trust & Intrusion Detection

Security-based CH selection uses trust and reputation methods, intrusion detection and encryption to offer safe communication. These techniques enhance detection rate, minimise false positives and protect data integrity. But they can announce additional computational costs and impact network effectiveness due to extra security measures. Trust-based IDS and malware detection methods are recommended in security-related papers like M. Naghibi et al. [30] (2025), Such approaches improve the accuracy of detection and minimise false alarms. Narla et al. (2025) [31] and A. Choudhary et al. [32] (2024) present advanced safe frameworks combining optimization, trust, and encryption, trust, and optimization, which increase data integrity and secure communication.

Table 6 : Routing and communications optimization methods

Ref	Methods	Key Contributions	Merits	Demerits
[30]	Trust-based clustering	Secure CH selection	Improved security	Overhead
[31]	EfficientNet IDS	Intrusion detection	High detection rate	Black-box
[32]	RL + PSO	Secure clustering	Improved fault detection	Complexity

2.7 Federated learning (FL) & Distributed Frameworks

FL enables distributed CH selection by allowing nodes to learn from each other without exchanging data. This method offers privacy, communication efficiency, and scalability in distributed settings. However, synchronization and communication delays pose encounters to FL. A. K. Takele et al. [33] (2025) and T. Qayyum et al. [34] (2025) presents distributed learning techniques such as DHFL and parameter sharing. These methods decrease the communication costs and enhance scalability in edge computing. But there are issues with the synchronization delay and communication cost in the federated approaches.

Table 7: Routing and communications optimization methods

Ref	Methods	Key Contributions	Merits	Demerits
[33]	Federated Learning	Efficient parameter sharing	Reduced computation	Communication delay
[34]	DHFL + MCPSO	Hierarchical federated learning	Improved scalability	Synchronization issues

2.8 Emerging methods

Reinforcement learning, graph neural networks and UAV-assisted optimisation provide smart and dynamic CH selection. These methods improve decision making, robustness and adaptability. But their computational and execution complexity restrains their use in resource-limited settings. New works include reinforcement learning, graph neural networks, UAV optimization and advanced clustering as in X. Fan et al. [35] (2025), X. Liao et al. [36] (2025) and G. Han [37] (2025). Such techniques improve adaptability and responsiveness. New optimization models like OERWCA, WGWO and hybrid AI models demonstrate better scalability, energy, and accuracy.

Table 8: Routing and communications optimization methods

Ref	Methods	Key Contributions	Merits	Demerits
[35]	DRL + clustering	Fault detection & reliability	High efficiency	Complex
[36]	Multi-agent DRL	UAV clustering optimization	High adaptability	High cost
[37]	WGWO	UAV tracking optimization	High accuracy	Computational cost

3. Challenges

The following remarkable points discuss the challenges,

- The high computational complexity of swarm intelligence and hybrid optimization algorithms is one of the main issues that have been noted in the studies reviewed. Such techniques as PSO, GWO, ABC, and their hybrid versions are greatly enhanced in performance, though they demand a great number of parameters to be tuned and processed in an iterative manner, which does not suit real-time and resource-limited systems, such as wireless sensor networks (WSNs) and IoT systems.
- Imbalance of energy and inefficient cluster head (CH) choice is another problematic issue. Despite numerous algorithms that consider energy-sensitive CH selection, the imbalanced energy consumption between nodes still causes untimely node death and decreased network life. The current clustering schemes have been found to lack optimal balancing of loads, particularly in large and dynamic networks.
- The introduction of deep learning and hybrid AI models brings other difficulties, including a large amount of training time, large memory needs, and uninterpretability. The majority of the models are black-box systems, and it is hard to comprehend how decisions are made, which restricts their use in important systems, such as healthcare and security systems.
- One of the challenges for cloud and edge computing is resource allocation and task scheduling as workload is variable and resources are diverse. Many resource allocation and scheduling models based on optimization are static; therefore, they may not work well in dynamic conditions such as varying workloads.
- The other challenge is related to communication overhead. Optimization techniques improve the effectiveness of the routing scheme, but they can create additional control traffic, which leads to latency and energy increase. This affects the overall network performance, particularly in high-density IoT deployments.
- And there are significant security and trust issues. Some of these papers report the usage of trust and intrusion detection, but they all have the sub-problems of false positives/negatives, scalability and being vulnerable to high-level attacks. The question of how to provide efficient and secure communication is still a challenge.
- Moreover, federated and distributed learning systems, being potentially private, have issues of communication latency, synchronization and model drift across nodes. These limit their widespread adoption.
- Lastly, novel smart systems like reinforcement learning, UAV-aided optimisation, and graph neural networks are hard to deploy and scale due to the design and computational challenges. Some models are not thoroughly tested in real-time, hence they lack real-world applications.

4. Research gaps

- Although swarm intelligence and metaheuristic algorithms have been widely used in cluster head selection and routing, no effective hybrid optimization frameworks that can balance between exploration and exploitation without escalating the complexity of the computation are available. The existing methods mainly use single or loosely coupled optimizers that frequently result in premature convergence or suboptimal results in dynamic network settings.
- The other important gap is the energy-aware and balanced clustering mechanisms. Whereas residual energy and distance is used by most papers to select the cluster head, it does not guarantee that there is even distribution of energy among nodes, thus leading to fast drainage of energy in some of the nodes and shortening of the lifetime of the whole network. More dynamic and smart clustering strategies are needed, which adapt dynamically to network conditions.
- Moreover, existing models demonstrate a weak ability to manage the large-scale and highly dynamic IoT environments. Most algorithms are tested in a small scale or in a static situation, which limits their implementation in the real world. Scalability and adaptability are some of the issues that need more robust and flexible solutions.
- Deep learning, combined with optimization techniques, remains in its infancy, and there is a paucity of models that can be effectively used to combine lightweight architectures with high accuracy. The majority of hybrid AI systems are large-scale and incompatible with edge devices, which means that there is a break in the creation of resource-friendly intelligent systems.

- In addition, the absence of focus on real-time and online learning is also evident. Most of the existing methods are validated offline and cannot be applied to the issues of latency, the dynamic nature of traffic and real-time online decision making. This results in the gap between theoretical and practical results.
- In security research, the shortfalls in sound trust management and attack resilience are also observed. The majority of intrusion detection and trust models are not able to effectively handle advanced persistent threats (APTs) and zero-day attacks, and also have a high false positive rate.
- In addition, despite the advent of federated learning and distributed systems, problems of communication, synchronization and model drift are not well solved. This suggests the need for efficient distributed learning.
- Finally, new approaches such as reinforcement learning, UAV-assisted optimization and graph models are promising, but they are not refined and have not been tested in practical scenarios, so they are difficult to apply in real-life WSN and IoT applications.

5. Future Works

Adaptive and energy-balanced clustering mechanisms need to be designed that dynamically adapt to changing network conditions and increase overall network lifetime. One direction to consider is the combination of deep learning with effective optimization methods to create smart but resource-conscious systems that can be used on edge devices. Additional effort is needed to focus on real-time and online learning frameworks that would be capable of managing dynamic traffic and changing network environments. Moreover, the inclusion of sophisticated security systems and zero-day attack detection will enhance the robustness and reliability of the system. Lastly, scalable and distributed architectures (e.g., federated learning) with less communication overhead in large-scale IoT applications should be studied in the future.

6. Conclusions

The present review paper has discussed in detail the CH selection and resource allocation schemes in the context of cloud computing, and particularly the swarm intelligence and hybrid approaches. The paper focuses on optimal CH selection that is essential in improving energy efficiency, load balancing, scalability and efficiency. The flexibility and efficiency of the swarm intelligence algorithms like PSO, ACO, ABC and GWO have been proven to be effective in solving complex optimization problems due to their faster convergence. From the comparative study, it is evident that such hybrid algorithms, i.e., the use of optimization techniques in combination with artificial intelligence techniques, perform better than the conventional techniques. These techniques can be used to solve multi-constrained objectives and enhance dynamic decision-making. However, there are still some limitations, such as being computationally intensive, not being flexible in real-time, dependency on specific data or scenarios and not scalable for large-scale systems. Additionally, there are still issues with energy imbalance, communication overhead and a lack of security mechanisms that have an impact on system reliability. Although the results of new approaches, such as federated learning and the combination of deep learning and smart routing, have been encouraging, they still need to be further developed for practical use. Furthermore, the need to build lightweight, scalable, and smart optimization techniques for ensuring efficient resource management, enabling real-time adaptability and achieving high performance is evident. To overcome the current limitations and to support the next-generation cloud computing applications, future research should be focused on applying the most recent hybrid optimization techniques and adaptive learning models.

References

[1] U. Shankar, R. Jain, G. Radhakrishnan, A. Tiwari, S. Mahajan, and S. Tharewal, "A sustainable approach to cloud computing: A comprehensive analysis of load balancing techniques in cognitive environments," in *Cognitive Cloud Computing*: CRC Press, 2026, pp. 19-45.

[2] S. K. Chaurasiya, S. Saha, and S. Mondal, "A Survey on Clustering in Internet of Vehicles," in *Internet of Vehicles: Scope and Application of Artificial Intelligence-Based Technologies*: Springer, 2026, pp. 157-176.

[3] R. Kavitha, K. Saravanan, S. A. Jebakumari, and K. Velusamy, "Machine learning algorithms for IoT applications," in *Artificial Intelligence for Internet of Things*: CRC Press, 2022, pp. 185-214.

[4] A. K. M. Al-Qurabat, H. M. Lateef, A. Z. K. Matloob, and A. K. Mohammed, "Optimizing cluster heads for energy efficiency in WSNs using MADM approaches: A. Kadhum et al," *Telecommunication Systems,* vol. 89, no. 1, p. 26, 2026.

[5] C. B. Subramanian and R. Ramkumar, "A novel bacterial colony optimisation-based cluster head selection method for the internet of things," *International Journal of Networking and Virtual Organisations,* vol. 30, no. 4, pp. 366-386, 2024.

[6] B. Fathimamary, M. Nasreen, and K. Velusamy, "An Efficient DDoS Attack Detection Using Optimized Long Short-Term Optimization Based on Improved Brainstorm Optimization," *Indian Journal of Science and Technology,* vol. 19, no. 5, pp. 298-312, 2026.

[7] H. Alsuwat and E. Alsuwat, "Energy-aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee Colony algorithm," *Peer-to-Peer Networking and Applications,* vol. 18, no. 2, p. 65, 2025.

[8] G. H. Alshammri, "Enhancing wireless sensor network lifespan and efficiency through improved cluster head selection using improved squirrel search algorithm," *Artificial Intelligence Review,* vol. 58, no. 3, p. 79, 2025.

[9] M. K. Reddy, A. S. Veluswamy, S. Selvanayaki, C. Harini, P. Kumar, and S. Shameem, "Modeling of metaheuristic-based dual cluster head selection with routing protocol for energy-efficient wireless sensor networks," *Soft Computing,* vol. 29, no. 6, pp. 2999-3020, 2025.

[10] M. Sathyamoorthy, R. K. Dhanaraj, C. Vanitha, and M. S. Sayeed, "A hybrid Spatial Ant Lion optimization and utilitarian data transmission approach for intelligent optimization for energy-efficient wireless sensor

networks," *Scientific Reports,* vol. 15, no. 1, p. 21808, 2025.

[11] S. Harifi, F. Davachi, N. Mohammadi, and S. FaridMohammadzadegan, "Two competitive hybridization approaches based on combining of Giza Pyramids Construction with Particle Swarm Optimization for solving global optimization problems," *Inteligencia Artificial,* vol. 28, no. 75, pp. 114-139, 2025.

[12] A. Selvaraj and B. Sirumulasi Paramasivan, "Optimization and selection of cloud data center resources using salp swarm optimization," *International Journal of Research in Industrial Engineering,* vol. 14, no. 2, pp. 298-317, 2025.

[13] T. Kanimozhi and S. B. V. Sara, "Modified glowworm swarm optimisation-based cluster head selection and enhanced energy-efficient clustering protocol for IoT-WSN," *International Journal of Computational Science and Engineering,* vol. 28, no. 2, pp. 204-218, 2025.

[14] C. Lv and G. Long, "Energy-efficient cluster head selection in Internet of Things networks using an optimized evaporation rate water-cycle algorithm," *Journal of Engineering and Applied Science,* vol. 72, no. 1, p. 34, 2025.

[15] W. Osamy, A. M. Khedr, A. A. Elsawy, P. Pravija Raj, and A. Aziz, "SEACDSC: secure and energy-aware clustering based on discrete sand cat swarm optimization for IoT-enabled WSN applications," *Wireless Networks,* vol. 30, no. 4, pp. 2781-2800, 2024.

[16] K. Vijayakumari, J. Gnanadurai, S. Usharani, and K. Velusamy, "Deep Learning Models for Intelligent IoT Ecosystems," in *Intelligent Mobile and IoT Ecosystems*: Chapman and Hall/CRC, 2026, pp. 131-149.

[17] A. Khan *et al.*, "Self-Organizing Neural Networks Integrated with Artificial Fish Swarm Algorithm for Energy-Efficient Cloud Resource Management," *International Journal of Advanced Computer Science & Applications,* vol. 16, no. 2, 2025.

[18] S. Depuru, M. Sakthivel, A. D. Nandam, S. Sivanantham, K. Amala, and J. Sainath, "A hybrid trust based malware detection system using glow-worm swarm optimization and recurrent deep neural network for enhanced security for cloud applications," in *Hybrid and Advanced Technologies*: CRC Press, 2025, pp. 396-401.

[19] J. Cui, L. Shi, and A. Alkhayyat, "Enhanced security for IoT cloud environments using EfficientNet and enhanced football team training algorithm," *Scientific Reports,* vol. 15, no. 1, p. 20764, 2025.

[20] M. B. Dhivya and S. Thavamani, "Enhanced Chicken Swarm Optimization And Improved Convolutional Neural Network Algorithm For Attack Detection Over Iot Based Wireless Sensor Network," *Metallurgical and Materials Engineering,* pp. 1207-1221, 2025.

[21] S. J. Rani and D. Santhakumar, "Optimizing Network Energy In Cloud-Assisted IOT With Wireless Sensor Networks Using Similarity-Navigated Graph Neural Networks," in *2025 International Conference on Advanced Computing Technologies (ICoACT)*, 2025: IEEE, pp. 1-8.

[22] Y. Wang, "A Genetic Particle swarm optimization based Hybrid Scheduling Algorithm for Cloud Computing Resources," *INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL,* vol. 20, no. 4, 2025.

[23] B. K. R. Janumpally, "Intelligent Energy Aware Efficient Task Scheduling in Cloud Computing: Leveraging Swarm Optimization Algorithms for Improve Resource Utilization," in *2025 1st International Conference on Radio Frequency Communication and Networks (RFCoN)*, 2025: IEEE, pp. 1-6.

[24] B. Mohammad Hasani Zade, N. Mansouri, and M. M. Javidi, "An efficient task scheduling algorithm leveraging fuzzy quantum atom search optimizer with innovative migration for cloud computing," *Cluster Computing,* vol. 28, no. 4, p. 269, 2025.

[25] S. Othmen, R. Khdhir, A. Belghith, K. Hamouid, C. Lhioui, and D. Elmourssi, "Enhancing IoT-Enabled Healthcare Applications by Efficient Cluster Head and Path Selection Using Fuzzy Logic and Enhanced Particle Swarm Optimization," *International Journal of Communication Systems,* vol. 38, no. 3, p. e6096, 2025.

[26] R. S. Abujassar, "Intelligent IoT-driven optimization of large-scale healthcare networks: the INRwLF algorithm for adaptive efficiency," *Discover Computing,* vol. 28, no. 1, p. 93, 2025.

[27] F. Ajaz, M. Naseem, J. V. N. Ramesh, M. Shabaz, and G. Ahamad, "Cluster Based Lion Optimization Routing Protocol for Internet of Vehicles (CLORP)," *Transactions on Emerging Telecommunications Technologies,* vol. 36, no. 3, p. e70089, 2025.

[28] S. Nimmala, M. Mahendar, P. Manasa, K. Raghavendar, B. Rambabu, and D. D. Bhavani, "An Intelli BEF: An Intelligent Bio-Inspired Energy-Efficient and Fault-Tolerant Routing for IoT-Enabled WSNs," in *2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI)*, 2025: IEEE, pp. 942-947.

[29] R. Rajesh, R. Patgiri, and L. D. Singh, "DYNACLUSTERNET: A dynamic clustering network-based routing optimization for edge computing," *Radio Science,* vol. 60, no. 7, p. e2024RS008145, 2025.

[30] M. Naghibi, H. Barati, and A. Barati, "A dynamic trust based clustering method for secure data gathering in Internet of Things," *Computing,* vol. 107, no. 4, p. 97, 2025.

[31] S. Narla, S. Peddi, D. T. Valivarthi, S. S. Kethu, D. R. Natarajan, and D. Kurniadi, "FOG computing based energy efficient and secured iot data sharing using SGSOA and GMCC," *Sustainable Computing: Informatics and Systems,* vol. 46, p. 101109, 2025.

[32] A. Choudhary, N. Barwar, and V. Chouhan, "Energy Efficient Cluster Head Selection Using Hybrid RL-PSO Approach," *Journal of Intelligent Systems & Internet of Things,* vol. 11, no. 2, 2024.

[33] A. K. Takele and B. Villányi, "Resource-Efficient Clustered Federated Learning Framework for Industry 4.0 Edge Devices," *Ai,* vol. 6, no. 2, p. 30, 2025.

[34] T. Qayyum, Z. Trabelsi, A. W. Malik, A. Tariq, and I. ud Din, "DHFL: Decentralized Hierarchical Federated Learning With Dynamic Global Aggregation for Privacy-Aware Fog Computing," *IEEE Transactions on Consumer Electronics,* 2025.

[35] X. Fan *et al.*, "Co-Designed Communication and Computing for Data Reliability in Industrial Cyber-Physical Systems with Cloud-Fog Automation," *IEEE Journal on Selected Areas in Communications,* 2025.

[36] X. Liao, Y. Wang, Y. Han, Y. Li, C. Lin, and X. Zhu, "Heterogeneous Multi-Agent Deep Reinforcement Learning for Cluster-Based Spectrum Sharing in UAV Swarms," *Drones,* vol. 9, no. 5, p. 377, 2025.

[37] G. Han, "Bio-inspired swarm intelligence for enhanced real-time aerial tracking: integrating whale optimization and grey wolf optimizer algorithms," *Discover Artificial Intelligence,* vol. 5, no. 1, p. 18, 2025.