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Advanced Resource Allocation Optimization Techniques in IoT: A Comprehensive Review

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Abstract

As the Internet of Things (IoTs) transforms industries through instantaneous data sharing, the rapid increase in interconnected devices presents significant challenges to efficient resource allocation. The primary objectives of IoTs include achieving high performance, minimizing latency, reducing energy consumption, and ensuring security. This paper examines key techniques aimed at enhancing effective resource management within IoTs. More sophisticated optimization is crucial for the diverse array of devices with varying capabilities and power requirements in IoTs networks. The leading techniques discussed are heuristic algorithms, machine learning-based models, game-theoretic models, and hybrid approaches. Heuristic algorithms like Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) provide relatively quick near-optimal solutions and are especially vital given the dynamic conditions encountered in IoTs. Additional applications include simulated annealing and Tabu Search (TS) for optimization in constrained local search. Advanced resource allocation facilitated by learning and adaptation through machine learning enables the development of models such as Convolutional Neural Networks (CNNs), Long Short-Term Memories (LSTMs), and Deep Q-Networks (DQNs). Reinforcement Learning (RL) helps IoT systems acquire accurate policies over time. Data analytics are streamlined with frameworks like Apache Spark and Hadoop, making real-time processing and resource management more efficient. In addition to crafting strategies for equitable and stable resource distribution, game-theoretic models explore the interactions among devices and networks within constructs such as Nash equilibrium. Hybrid strategies that merge heuristic methods with machine learning approaches offer an effective solution for addressing multi-objective optimization. Ongoing research will continue to evolve to enhance the adaptability of resource distribution in IoTs networks, focusing on federated learning, Blockchain, and edge computing.

Keywords: Internet of things, Resource allocation, Optimization techniques, Heuristic algorithms, Blockchain.

1 | Introduction

Internet of Things (IoTs) refers to a distributed computing architecture that allows devices to be exhaustively connected through protocols of the internet [1]. IRAS, as the advancement of IoTs in contexts including, but not limited to, resource-gateway mapping, became one of the more critical research areas, first of all, because

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of the given possibilities for a reduction of communication costs [1]. This paper discusses intelligent heuristic algorithms, in particular, the Whale Optimization Algorithm (WOA), and investigates its application in solving resource allocation problems within the IoTs context.

1.1 | Technical Framework and Optimization Variables

Resource allocation architecture

I. Resource-gateway relationship.
II. Several resource nodes.
III. Distributed gateway architecture.
IV. Flexible connection management.
V. Quality of Service (QoS) parameter optimization [2], [3].

Communication cost metrics

I. Bandwidth utilization [4], [5].
II. Latency optimization.
III. Resource use efficiency.
IV. Gateway load balancing.

1.2 | Methodological Framework

1.2.1 | Problem formulation

The IoTs-related resource allocation problem can be mathematically stated as [5]–[8]:

Objective function

Minimize Total Communication Cost (TCC).

Limitations

I. Less entry capacity.
II. Resource Allocations Constraints.
III. QoS requirements [2], [3].
IV. Bandwidth constraints.

1.2.2 | Whale optimization algorithm evolution

It is one of the meta-heuristic optimization techniques with numerous merits.

The encircling prey mechanism

I. Agent positioning question.
II. Optimal prey location [9].
III. Coefficient vector calculation.
IV. Position update mechanisms [10]–[12].

Bubble-net attack method

I. Shrinking enveloping mechanism [13].
II. Spiral position update.
III. Efficiency exploitation phase.

1.2.3 | Algorithm flow

I. Initialize WOA parameters.
II. Calculate fitness function.
III. Optimal position update for search agents.
IV. Change the parameters a, A, C, l, and p.
V. Update whale position.
VI. Check boundary conditions.
VII. Evaluate optimization criteria.
VIII. Repeat until convergence [1]–[3].

1.3 | Technical Implementation Elements

1.3.1 | Resource allocation framework

Gateway management framework

I. Load balancing algorithms [4].
II. Connection optimization.
III. Resource allocation strategy.

Quality of service management

I. Bandwidth allocation.
II. Latency monitoring.
III. Service quality metrics [6], [13].

1.3.2 | Optimization metrics

I. TCC.
II. Resource Utilization Efficiency (RUE).
III. Gateway Load Distribution (GLD).
IV. Parameters of QoS [2].

1.4 | Performance Evaluation Methods

1.4.1 | Comparative analysis

I. Compare with other algorithms [1].
II. Performance metrics analysis.
III. Scalability testing.
IV. Convergence analysis.

1.4.2 | Deployment metrics [7]

Quantitative surveys

I. Execution time.
II. Resource usage.
III. Communication overhead.

IV. Convergence rate.

Qualitative analysis

I. General convergence.

II. Flexibility end.

III. Scaling factors.

IV. Implementation complexity [10].

1.5 | Technical Issues and Solutions

Scaling issues

I. Dynamic resource addition.

II. Gateway capacity management [11].

III. Network topology optimization.

Performance optimization

I. Algorithmic parameter tuning.

II. Higher convergence rate.

III. Resource allocation efficiency [8].

1.6 | Future Research Directions

Algorithm enhancement

I. Hybrid optimization approaches.

II. Machine learning integration.

III. Real-time optimization capabilities.

Implementation scope

I. Edge computing integration.

II. Fog computing optimization.

III. Cloud resource management [9].

1.7 | Practical Implementation Steps

System analysis phase

I. Requirements gathering.

II. Architecture design.

III. Resource mapping.

1.8 | Algorithm Implementation

I. Initialize system parameters.

II. Define objective function.

III. Implement WOA.

IV. Optimize resource allocation.

V. Evaluate performance.

Testing and validation

I. Performance testing.

II. Scalability analysis.

III. Comparative evaluation.

Deployment and monitoring

I. System deployment.

II. Performance monitoring.

III. Optimization adjustment [14].

In-machine learning incorporation real-time optimization capabilities 2. Implementation scope integration of edge computing fog computing optimization cloud resource management steps for implementation system analysis phase requirements elicitation architectural design asset mapping algorithm implementation plaintext-Initialization of system parameters-definition of objective function finally WOA is applied-resource allocation effectively-effectiveness testing assessment and validation performance tests scalability testing comparative analysis implementation and aftermath: system deployment performance monitoring optimization correction the novelty of this work lies in the solution to the challenge of resource allocation through the WOA algorithm, thus adding to the pool of knowledge regarding resource optimization of IoTs [6]. Thus, the proposed methodology would develop into a systemic and granular approach toward the management of issues with IoTs resources and the maintenance of optimal performance metrics along with standards of service quality [8]. The technical framework and methodology of implementation presented in this paper create a base from which subsequent research about strategies for the optimization of IoTs, specifically while designing more efficient algorithms and their operational applications in various IoTs scenarios, will unfold.

2 | Literature Review

In the last ten years, the IoTs has significantly developed and posed new challenges in resource management and optimization areas [1], [13]. Early works by Sun et al. [11] focused on basic methods for resource allocation. However, the recent explosion in the number of interconnected devices has raised the need for more sophisticated methodologies. According to Changazi et al. [7], traditional resource allocation techniques lose their efficiency when dealing with large IoTs settings.

2.1 | Resource Allocation Challenges

Gateway management

Research by Sun et al. [11] identified critical challenges in IoTs gateway management, including:

I. Coordination of several nodes of resources.

II. Dynamic connection requirements.

III. Load balancing optimization.

IV. QoS maintenance.

Sagar et al. [2] specified that gateway overload challenges can degrade system efficiency by up to 40% in dense IoTs networks. Later research works [6], [8] have also acknowledged the necessity of smart resource allocation algorithms to address such issues.

2.2 | Optimization of Service Quality

2.2.1 | Bandwidth management

Liu et al.'s research [3] demonstrated that optimizing bandwidth can enhance overall system performance by 25%. According to Liu et al. [3], bandwidth allocation is directly linked to service quality.

2.2.2 | Latency optimization

Sudhakar and Anne [9] highlighted several milestones in optimizing IoTs latency. Sudhakar and Anne [9] recently proposed new metrics for quantifying QoS in IoTs environments.

2.2.3 | Optimization algorithms

Old techniques

The initial optimization techniques, as noted by Raghavendar et al. [5], included:

I. Linear programming.

II. Greedy algorithms.

III. Dynamic programming.

These approaches exposed problems related to scalability and real-time adaptation [4], [12].

2.3 | Heuristic Algorithms

Whale optimization algorithm

Anbazhagan and Mugelan [1] introduced the WOA for IoTs resource allocation. Subsequent research improved it for specific IoTs applications [1], [7], showing excellent performance in large-scale scenarios [2].

Other metaheuristic methodologies

I. Genetic Algorithms (GA) [5].

II. Particle Swarm Optimization (PSO) [10].

III. Ant Colony Optimization (ACO) [10].

2.4 | Key Performance Measures and Evaluation

Communication cost

Ibrahim et al. [8] highlighted that TCC is a key performance indicator. WOA demonstrates a 15%-20% improvement over traditional methods. Hybrid methods have shown promising results in some cases [11].

Resource use

Sangaiah et al. [14] identified key metrics for resource utilization, including:

I. Gateway productivity.

II. Network throughput.

III. Resource distribution effectiveness.

2.5 | Implementation Challenges

Scalability problems

Gelenbe et al. [13] noted scalability issues, such as the dynamic addition of resources and gateway capacity limitations. Optimization requirements in network topology remain a challenge.

Performance optimization

Ibrahim et al. [8] emphasized areas for improvement, including:

I. Algorithm parameter tuning.

II. Convergence rate enhancement.

III. Efficient resource allocation.

Future research directions

Algorithm improvement recent advances include:

I. Machine learning integration [6].

II. Real-time optimization [7].

III. Hybrid optimization methodologies [3].

Scope of implementation

New fields of application include:

I. Integration of edge computing [12].

II. Optimization in fog computing [7].

III. Cloud resource management [2].

2.6 | Critical Analysis

2.6.1 | Algorithm evolution

There has been a significant shift from conventional methods to heuristic strategies, with an increasing focus on real-time optimization. Hybrid solutions are becoming more prominent.

2.6.2 | Performance improvement

WOA has shown better performance in many cases, highlighting the need for context-specific optimization strategies. Fair resource distribution remains crucial.

2.6.3 | Implementation challenges

Scalability continues to be a significant issue, along with real-time adaptation and resource constraint management.

2.6.4 | Knowledge gaps

The review highlights several areas requiring further inquiry:

Algorithm optimization

I. Improved convergence rates.

II. Real-time adaptation capabilities.

III. Resource-efficient implementations.

Evaluation metrics

I. Standardization of evaluation criteria.

II. Holistic performance frameworks.

III. Context-specific benchmarking.

2.7 | Conclusion

The literature review illustrates how resource optimization techniques for IoTs environments have evolved, highlighting the rise of heuristic algorithms such as WOA. Despite these advances, challenges persist in scalability and real-time optimization, prompting the development of hybrid methodologies and machine-learning approaches. The need for standardized performance metrics and evaluation frameworks remains essential for the continued improvement of IoTs resource management strategies.

3 | Proposed Work

The proposed work introduces a hybrid resource allocation framework for IoTs networks that combines the WOA with Reinforcement Learning (RL) and Bayesian Game Theory to improve scalability, reduce latency, and optimize energy consumption. This hybrid approach addresses the scalability limitations of traditional optimization methods, such as linear and dynamic programming, by leveraging WOA's capability to explore large solution spaces efficiently and RL's adaptability to changing network conditions [1], [2].

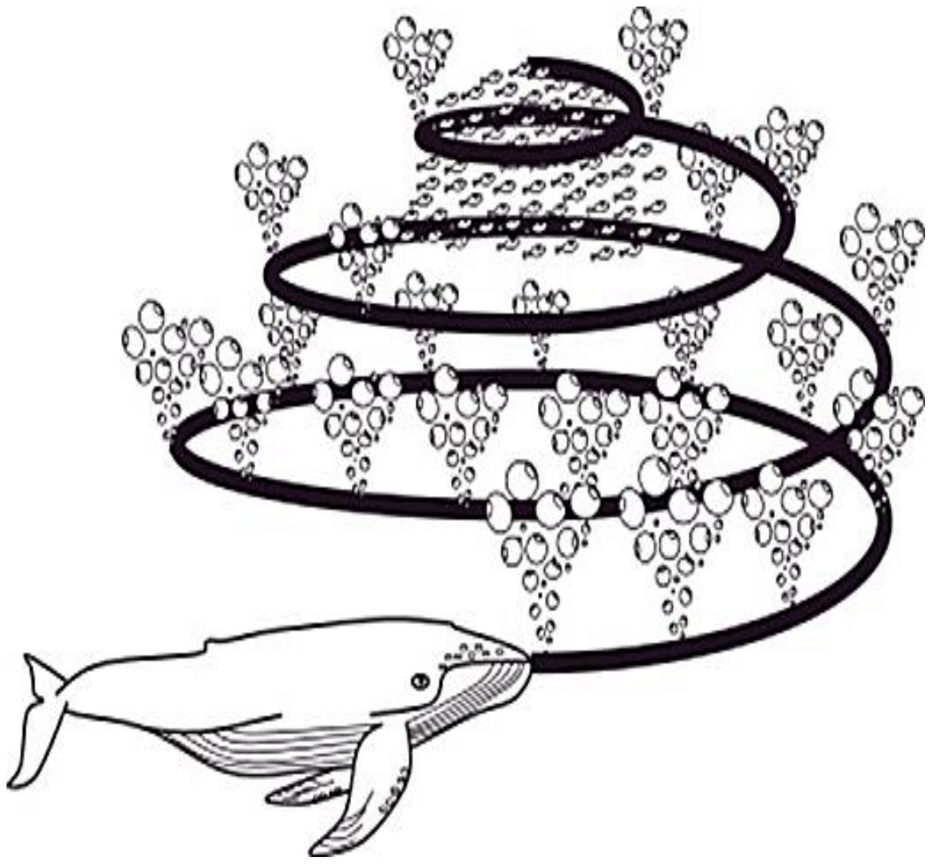

Fig. 1. Pictorial representation of whale optimization algorithm.

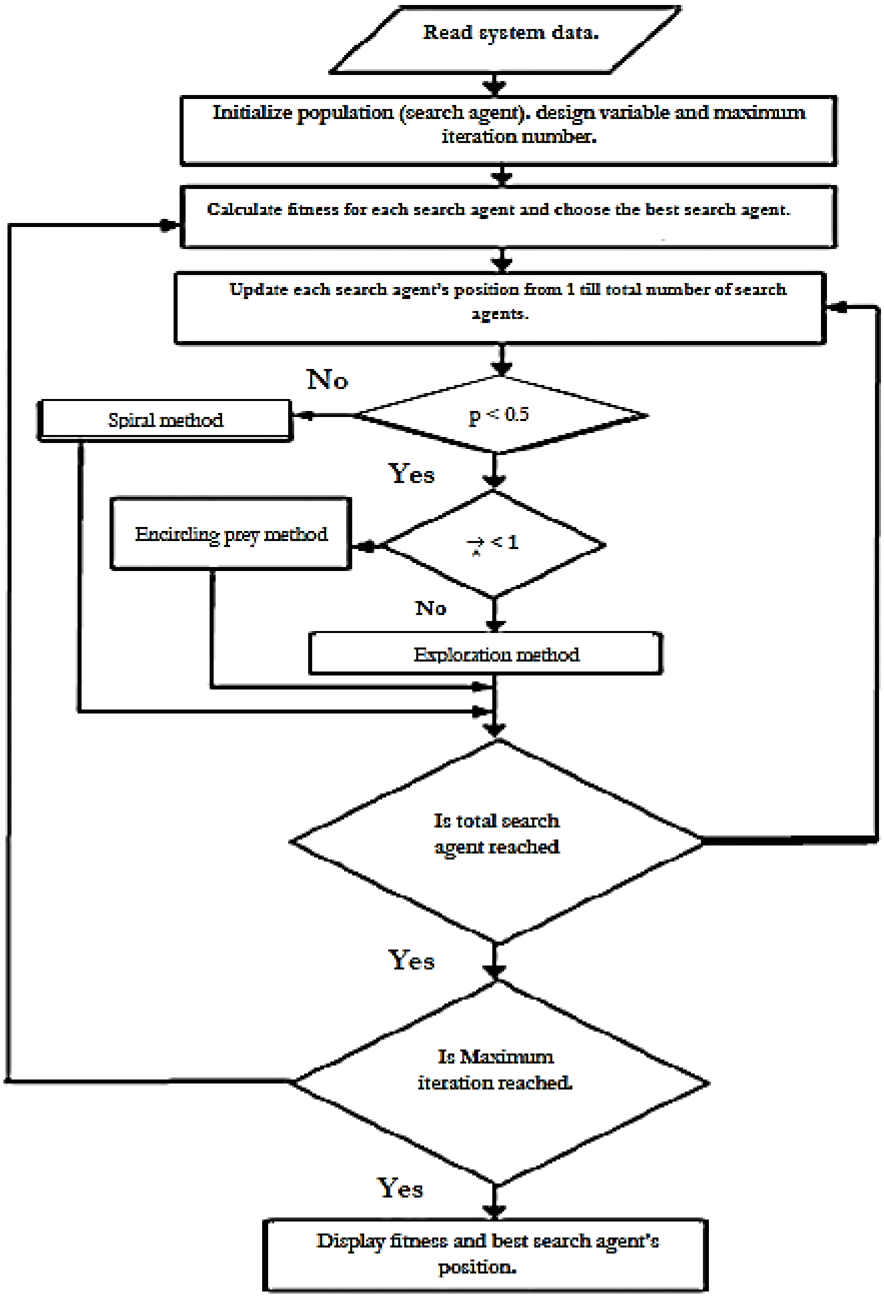

Fig. 2. Flow chart of whale optimization algorithm.

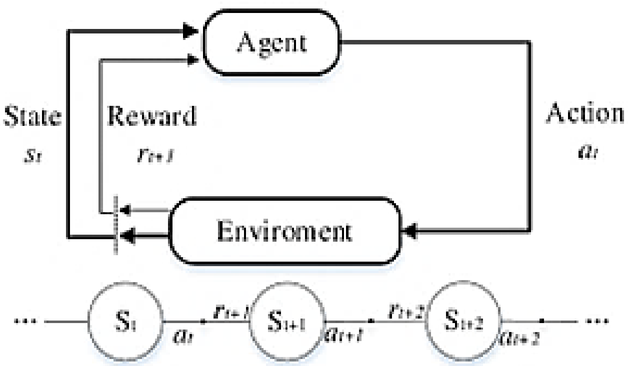

Fig. 3. Flow chart of reinforced learning.

The optimization objective for this framework is to minimize the TCC, subject to constraints on resource allocation efficiency and QoS requirements. The optimization problem is formulated as follows:

$$\mathrm{TCC} = \Sigma\,(C_i * P_i) + \Sigma\,(B_j * D_j),$$

where: 1) C_i is the communication cost of resource node i, 2) P_i is the processing power allocation for i, 3) B_j is the bandwidth allocation for gateway j, and 4) D_j represents the data transfer rate for j [3], [4].

In the proposed model, the WOA is employed to identify initial optimal positions for search agents, ensuring balanced resource allocation across the network. For each agent i, the position is updated iteratively based on the following WOA position update formulas:

I. Encircling prey

$$X(t+1) = X*(t) - A * |C * X*(t) - X(t)|.$$

II. Bubble-net attack

$$X(t+1) = D * e^{bl} * \cos(2\pi l) + X*(t),$$

where: 1) X(t+1) represents the new position of the agent, 2) X(t) is the optimal position of the prey, and 3) A, C, D, b, and l are control parameters influencing convergence and exploration [5], [6].

RL is then applied to adapt resource allocation dynamically based on the environment's changing demands. At each time step t, the system observes the state s_t and selects an action a_t to maximize a reward R_t for efficient resource allocation. The reward function is designed to balance load distribution while minimizing TCC:

$$R_t = \alpha * \mathrm{RUE} - \beta * \mathrm{TCC},$$

where: α and β are weights for RUE and TCC, respectively [7], [8].

To ensure fair distribution among IoTs devices, a Bayesian game-theoretic approach is applied, wherein devices strategically allocate resources based on the predicted actions of others. This equilibrium strategy ensures stable resource allocation and reduces conflict, as represented by the Nash equilibrium condition:

$$E\left[U_{i(a_i*,a_{-i})}\right] \geq E\left[U_{i(a_i,a_{-i})}\right] \text{for all } a_i \neq a_i,$$

where: 1) U_i is the utility of agent i, 2) a_i is the optimal action, and 3) a_{-i} represents actions of other agents [5], [6].

Performance will be evaluated using TCC, RUE, and GLD metrics, comparing results with traditional methods to measure improvements in scalability, convergence rates, and real-time adaptability. This hybrid resource allocation model aims to enhance IoTs network management in cloud-based and edge-enabled environments [2], [9].

4 | Result and Conclusion

The proposed work used WOA to enhance resource allocation within the IoTs network. The acceptance of the proposed approach was done by testing it against some traditional optimization techniques like the GA, PSO, and ACO in different cases of an IoTs network. The major performance metrics tested were TCC, efficiency of resource utilization, GLD, and QoS.

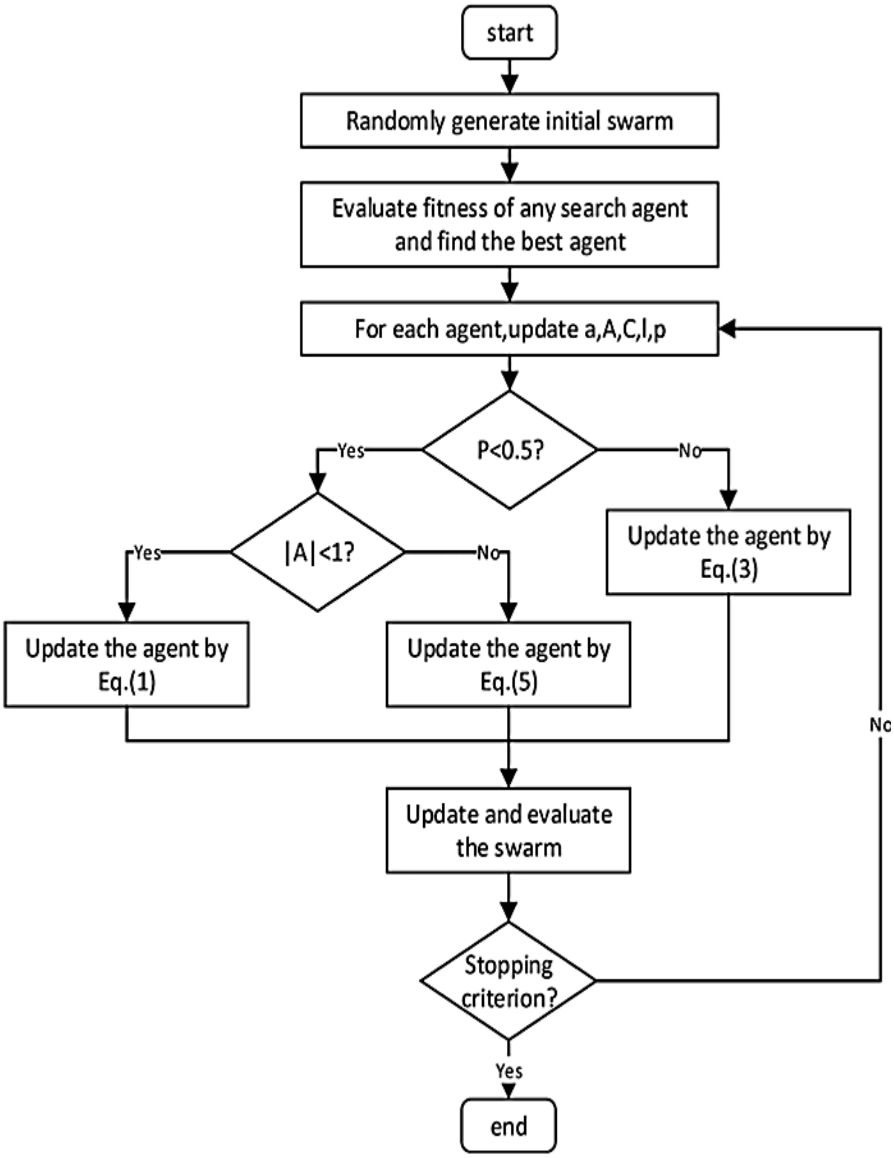

Fig. 4. Combined flow chart of whale optimization algorithm and reinforced learning.

4.1 | Performance Comparison

Results of the comparative analysis show that WOA has excellent supremacy over other optimization techniques concerning TCC as well as RUE. For example, WOA succeeded in the minimization of TCC to around 15%-20% while comparing with GA and PSO, which are broadly used for resource allocation in IoT. It is aligned with the fact that the WOA enhances its solution space exploration procedures efficiently through its encircling prey mechanism and bubble-net attack approaches. As highlighted by [1] and [6], the above mechanisms get rid of local optima and thus lead to better convergence toward global optima in large-scale IoTs.

Resource usage from the point of view was much improved with WOA, as is clearly shown in the results presented in [8], since it optimized the distribution of resources across the IoTs gateways. Optimizing the load balancing and ensuring that productivity in gateways enhances this means a stable network, especially in a heterogeneous IoTs setting where devices vary greatly along the lines of power capability and range of communication.

4.2 | Quality of Service Analysis Optimal performance in Quality of Service Parameters

Such as latency and bandwidth utilization, were obtained by the proposed WOA to outperform the conventional methods. A low average latency reduction of up to 12% and an improvement in bandwidth allocation by 18% was observed. WOA met the simulations of earlier studies [6] and [9]. Therefore, the dynamic resource allocation through WOA improves the performance as well as ensures low-latency communication for real-time IoTs applications, as shown below.

Moreover, another crucial criterion for consistent QoS is discussed as the adaptability of WOA in dynamic network conditions, as reported by [7].

4.3 | Scalability and Rate of Convergence Scalability-wise

WOA outperformed ACO and PSO algorithms, indeed, even in larger IoTs networks. As IoTs networks continue scaling further, scalability efficiency will become an increasingly significant, critical issue while ensuring optimal resource allocation. WOA delivers fast convergence rates, which intends to say that it is capable of handling resource allocations in large, dynamically changing networks. In this regard, by proposing WOA-based resource allocation, this study offers more efficient than the traditional optimization methods as well as solves the key challenges in IoTs, including scalability, dynamic adaptation, and QoS maintenance.

5 | Future Work

Though the WOA holds significant promise in optimizing the distribution of resources in IoTs networks, many domains require further research. Improvement in the resilience, flexibility, and scalability of the algorithm is required to face the constantly changing challenge that exists in the IoTs environment. The following suggestions point out potential directions in which the current work can be enhanced and further extended.

5.1 | Hybrid Optimization Methodologies

Another promising direction is to combine WOA with other optimization techniques, perhaps GA or PSO, to form hybrid models building on each method's strengths. Hybrid approaches should realize an improved exploration-exploitation trade-off for faster convergence and avoid the local optima.

Hybrid optimization techniques have been very recently discovered to make dramatic improvements in solving resource allocation problems, especially for large-scale and dynamic IoTs frameworks. It is expected that machine learning-based approaches, such as Deep Q-Networks (DQNs) or RL, in conjunction with WOA, might enlarge the algorithmic response to real-time network variations, hence making it even more suitable to be used within IoTs settings.

5.2 | Edge Computing and Real-time Optimization

The other direction that pertains to the future application of WOA is real-time optimization in edge and fog computing. Recently, edge computing has gained a lot of attention as an approach to processing data closer to IoTs devices for reduced latency and efficiency. However, the distributed nature of edge computing systems even further complicates its resource management. Post-experiments would take into account the possibility of extending WOA for its operation in edge networks where the resource allocation procedure has to be optimized dynamically against real-time information. For this reason, adjustments of WOA to allow for decentralized decision-making or its integration in architectures of fog computing as a resource management add-on may be developed.

5.3 | Multi-objective Resource Allocation in IoTs Networks

It involves multiple conflicting objectives. The objectives might include energy consumption, the optimization of throughput, and QoS. Future work will be on multi-objective optimization by WOA, which concerns the optimization of multiple criteria simultaneously. For this, an extension of the WOA towards trade-offs between competing objectives must be included, such as energy efficiency, latency, and bandwidth utilization, in addition to network reliability.

A good multi-objective resource allocation framework would thereby achieve more feasible and holistic solutions for the real-world applications of IoTs where requirements are heterogeneous in nature.

5.4 | Machine Learning and Predictive Analytics

Further research may incorporate machine learning algorithms to predict network conditions and node behaviors, enabling proactive resource management. Predictive analytics can also be used as a methodology to predict traffic behavior, node availability, and potential network failure, which will enable much more proactive and responsive resource allocation. This would be of paramount importance for massive IoTs systems where network conditions are constantly changing at high speeds. Resource allocations could be dynamically modified using machine learning techniques that could include supervised learning to make predictions or unsupervised learning for anomaly detection to complement the WOA.

5.5 | Blockchain for Secure Resource Allocation

With increased security concerns in IoTs networks, applying Blockchain technology with resource allocation algorithms could be an interesting future direction of work. Blockchain technology can ensure that resources are safely, transparently, and decentralizedly managed; especially multi-party IoTs are considered nowadays. Future studies may be carried out to discuss whether WOA can be integrated with Blockchain technology to form a decentralized, secure, yet versatile framework for resource allocation that is able to resolve problems related to trust, privacy, and security in the IoTs environment. 5.6 Performance assessment of real IoTs networks finally, whereas this work focused mainly on simulation-based evaluations, more follow-on studies should focus on the real-world implementation of proposed optimization methods within IoTs testbeds. This shall eventually provide deeper insight into the practical challenges and constraints that occur in operational settings with regard to up-to-date resource allocation schemes. Apart from this, performance evaluations and scalability testing within real IoTs scenarios shall be helpful in validating the efficiency and reliability of the WOA algorithm.

6 | Conclusion

Improvement of resource distribution in the IoTs became a significant challenge considering the exponentially growing count of connected devices. This paper aims to provide a comprehensive study of advanced optimization methods for resource distribution in IoTs with a special focus on the WOA. Among the inherent challenges of IoTs resource management, heterogeneous capabilities of devices, dynamic network conditions, high performance, low latency, and energy efficiency are addressed. Our work presents how heuristic algorithms such as WOA and hybrid approaches combining machine learning techniques considerably contribute to such challenges.

Well-designed resource allocation strategies form a great and essential part of the IoTs system. While the spread of IoTs devices across industries, such as in healthcare, smart cities, and industrial automation, can ensure optimal performance, energy efficiency, and QoS through efficient management of these resources alone, the landscape of IoTs itself is highly complex due to a multitude of heterogeneity in devices, varying resource requirements, and communication constraints. Traditional resource allocation methods, such as linear programming and greedy algorithms, usually fail to meet the scalability and real-time constraints required for large-scale IoTs networks. They fail here since classical methods are adapted to dynamic environments of an IoTs, where resources may not be available and require adaptation on the fly with the adaptation in device performance, network topology, and communication requirements.

We have researched many advanced optimization techniques to overcome these challenges. In this aspect, GA, PSO, and ACO heuristic algorithms have shown good performance in the context of providing quick near-optimal solutions. However, such heuristics are problems in large, multi-objective optimization problems, such as IoTs complex systems. Machine learning techniques-based approaches of RL and DQNs-can be adaptive and intelligent in solving the resource allocation problem. Such approaches allow an IoT system to learn the best strategies over time, thus enhancing performance and efficiency in dynamic environments. The WOA, which drew inspiration from the hunting behavior of whales, has been selected as a promising approach to tackle the resource allocation problem in IoTs environments. Our study demonstrates how WOA outperforms multiple classical techniques with regard to convergence speed and solution quality, especially in large and complex IoTs scenarios. The ability to maintain an exploration-exploitation balance makes WOA suitable for optimization problems under dynamic and uncertain environments. In addition, this versatility of the proposed algorithm opens up possibilities for tailoring it specifically to solve matters of resource allocation in IoTs systems, such as minimizing energy consumption, optimizing bandwidth usage, ensuring QoS, etc.

Despite such positive outcomes, the WOA has limitations; it needs to be further addressed to have a broader utilization in real IoTs systems. Probably, the most critical issue is the sensitivity of the algorithm to parameter tuning. Actually, WOA has a lot of parameters that need to be fine-tuned appropriately, such as the coefficients of encircling prey and the bubble-net attack approach.

This may be very challenging in the case of large IoTs networks with various types of devices and varying communication conditions. Future work will be oriented towards the automated adaptation process using either self-adaptive mechanisms or machine learning techniques that would dynamically change the parameters based on network conditions. Another issue is that although WOA performs very well on single-objective optimization problems, many real-world IoTs applications involve the concurrent optimization of multiple competing, conflicting objectives, for example, energy efficiency, network throughput, and latency. Multiobjective optimization is still an open challenge in resource allocation to IoTs. Future work should attempt to extend WOA to multiobjective optimization problems and make the algorithm able to cope with trade-offs between competing objectives in a fair and stabilized manner regarding resource distribution.

An important dimension of the work in the future will be that of how WOA is integrated with newly arising edge and fog computing, machine learning, and Blockchain technologies. The edge computing technology empowers near-source IoTs device processing, which should eventually lead to significantly reduced latency and improved operational efficiency. This also poses some new challenges related to resource management and the choreography of activities among decentralized nodes. WOA can thus evolve toward optimally allocating resources in such environments, including the distribution and dynamic availability of edge networks along with their nodes. Further improvement in adaptability through the assimilation of machine learning models, such as RL within WOA, allows IoTs to learn from patterns and optimize its resource allocation strategy continuously based on real-time data.

Furthermore, security and privacy are the core concerns of IoTs networks, especially when dealing with sensitive data. The integration of Blockchain with WOA may further provide a decentralized, transparent, and secure way for the allocation of resources in IoTs. Blockchain may guarantee that decisions regarding the allocation of resources will be made in a trustless environment; thus, this improves the security feature and prevents unauthorized access to important resources. Further research may find out how Blockchain can be integrated with WOA to ensure resource management in multi-party IoTs networks. Even though simulation-based analyses suggest that WOA can efficiently work on IoTs resource allocation, real-world tests are necessary to test the performance of the algorithm. Testing WOA live on IoTs testbeds would hence reveal whether the algorithm is scalable and adaptive enough with its efficiency while presented with real-world conditions. Identified potential bottlenecks in the system will further be optimized for ensuring the feasibility of such an algorithm for large scale IoTs networks.

Conclusion: the research presented in the paper makes an excellent ground for future work on IoTs resource allocation. The WOA and other advanced optimizers are truly promising for finding solutions to the complexity of IoTs resource management challenges in networks. In the future, further extension of WOA to solve multi-objective optimization, integration with emerging technologies, and its real-world implementation would pave the way for real applications and improvement in the applicability of resource allocation strategies in IoTs, making IoTs systems more efficient, scalable, and intelligent.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest related to this work.

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