**Comparative Analysis of Hybrid Optimization Algorithms and Proposal of Novel QWhale and SARSA Whale Approaches**

**ABSTRACT**

In recent years, hybrid optimization algorithms have gained significant attention due to their ability to solve complex optimization problems efficiently. By combining the strengths of different algorithms, hybrid approaches often yield better performance compared to their individual counterparts. This paper aims to provide a comprehensive comparative analysis of popular hybrid algorithms, including Genetic PSO and Genetic Whale, and introduce two novel algorithms: QWhale and SARSA Whale. Our proposed algorithms integrate reinforcement learning techniques with the Whale Optimization Algorithm to enhance task scheduling and energy optimization in cloud computing environments.

The increasing complexity and energy demands of modern cloud computing environments necessitate advanced optimization techniques to enhance performance and efficiency. Hybrid optimization algorithms have emerged as a powerful solution, leveraging the strengths of multiple approaches to solve complex problems more effectively. This paper presents a comprehensive comparative analysis of prominent hybrid algorithms, such as Genetic Particle Swarm Optimization (Genetic PSO) and Genetic Whale Optimization (Genetic Whale), alongside the introduction of two novel algorithms: QWhale and SARSA Whale. Our proposed algorithms integrate reinforcement learning techniques with the Whale Optimization Algorithm to optimize task scheduling and energy management in cloud computing environments. Through extensive simulation and empirical evaluation, our study demonstrates the superior performance of these hybrid algorithms in reducing energy consumption and improving resource allocation, thereby addressing critical challenges in cloud data centers. The findings highlight the potential of hybrid approaches in advancing energy-efficient and resilient cloud infrastructures.

Hybrid optimization algorithms have garnered significant attention for their ability to address complex optimization problems efficiently by leveraging the strengths of multiple algorithms. This paper provides a comprehensive comparative analysis of popular hybrid algorithms, such as Genetic PSO and Genetic Whale, alongside the introduction of two novel algorithms: QWhale and SARSA Whale. These proposed algorithms integrate reinforcement learning techniques with the Whale Optimization Algorithm to enhance task scheduling and energy optimization in cloud computing environments. Our analysis reveals that hybrid approaches not only outperform their individual counterparts but also offer improved energy efficiency and resource management, crucial for modern data centers. By consolidating virtual machines and employing adaptive strategies, our methods demonstrate significant reductions in energy consumption and SLA violations. This study underscores the potential of hybrid optimization algorithms in advancing cloud computing infrastructure and contributes to the ongoing discourse on sustainable and efficient data center management.

### Comparison of Hybrid Algorithms

### 1. Genetic Algorithm - Particle Swarm Optimization (GeneticPSO)

* **Mechanism**:
  + **GA**: Uses a population of solutions that evolve over generations through selection, crossover, and mutation operations, mimicking natural evolution.
  + **PSO**: Employs a swarm of particles that explore the solution space based on their own and others' experiences, adjusting their positions to find optimal solutions.
* **Advantages**:
  + **Balanced Exploration and Exploitation**: GA’s global search capabilities combined with PSO’s local search enhancement lead to a well-balanced optimization process.
  + **Improved Convergence**: The hybrid approach accelerates convergence to global optima by leveraging both evolutionary and swarm intelligence techniques.
* **Applications**:
  + **Multi-Objective Optimization**: Solves problems with multiple conflicting objectives, such as engineering design and resource allocation.
  + **Engineering Design**: Optimizes complex design problems involving various constraints and objectives.
  + **Scheduling Problems**: Addresses complex scheduling tasks such as job shop scheduling and timetabling.

### 2. Genetic - Whale Optimization Algorithm (HGWO)

* **Mechanism**:
  + **GA**: Implements evolutionary strategies like selection, crossover, and mutation to evolve a population of candidate solutions.
  + **WOA**: Simulates humpback whale hunting behavior, including encircling and bubble-net feeding strategies, to explore and exploit the solution space.
* **Advantages**:
  + **Enhanced Solution Diversity**: Combines GA’s global search ability with WOA’s unique exploration strategies, improving diversity and avoiding local optima.
  + **Improved Optimization Performance**: Balances exploration and exploitation effectively, leading to better quality solutions.
* **Applications**:
  + **Feature Selection**: Optimizes the selection of relevant features in machine learning and pattern recognition.
  + **Image Processing**: Enhances techniques for image enhancement, segmentation, and restoration.
  + **Economic Load Dispatch**: Optimizes the distribution of power in electrical grids to minimize costs and improve efficiency.

### 3. Ant Colony Optimization - Particle Swarm Optimization (ACPSO)

* **Mechanism**:
  + **ACO**: Simulates ant behavior, using pheromone trails to find optimal paths and solutions.
  + **PSO**: Adjusts particles' positions based on individual and collective experiences to refine solutions.
* **Advantages**:
  + **Accelerated Convergence**: ACO’s exploration of diverse solutions combined with PSO’s refinement enhances convergence speed and solution quality.
  + **Improved Solution Quality**: The hybrid approach benefits from both pheromone-based and swarm-based optimization strategies.
* **Applications**:
  + **Network Routing**: Optimizes data routing paths in communication networks to enhance efficiency and reduce latency.
  + **Resource Allocation**: Solves complex allocation problems such as scheduling resources in manufacturing or project management.
  + **Combinatorial Optimization**: Addresses problems like the traveling salesman problem and job scheduling.

### 4. Hybrid Particle Whale Optimization (HPWO)

* **Mechanism**:
  + **PSO**: Uses particles that adjust their positions based on individual and swarm knowledge to search for optimal solutions.
  + **WOA**: Applies whale-inspired strategies to explore and exploit the search space, such as encircling prey and bubble-net feeding.
* **Advantages**:
  + **Efficient Search**: Combines PSO’s social information sharing with WOA’s encircling mechanism, leading to effective exploration and exploitation.
  + **Robust Performance**: Handles both dynamic and static optimization problems with improved accuracy and speed.
* **Applications**:
  + **Wireless Sensor Networks**: Optimizes sensor placement and communication strategies to enhance network performance.
  + **Image Processing**: Improves algorithms for tasks like image segmentation and feature extraction.
  + **Data Clustering**: Enhances clustering techniques for better data organization and pattern recognition.

### My Proposed Algorithms

### 1. QWhale (Q-Learning and Whale Optimization Algorithm)

* **Mechanism**:
  + **Q-Learning**: A model-free reinforcement learning algorithm that learns the value of actions in a given state to determine the best policy through trial-and-error.
  + **WOA**: Simulates the hunting behavior of humpback whales, utilizing techniques like encircling prey and bubble-net feeding to optimize solutions.
* **Advantages**:
  + **Dynamic Learning**: The combination of Q-Learning's ability to learn optimal policies and WOA’s optimization techniques provides a robust framework for dynamic environments.
  + **Enhanced Adaptability**: Balances exploration and exploitation effectively, improving efficiency and adaptability in changing scenarios.
* **Applications**:
  + **Task Scheduling**: Optimizes the allocation of tasks and resources in complex scheduling problems.
  + **Energy Optimization in Cloud Computing**: Improves energy efficiency by dynamically scheduling and managing resources.
  + **Real-Time Decision-Making Systems**: Enhances decision-making processes in systems that require quick and optimal responses.

### 2. SARSA Whale (SARSA and Whale Optimization Algorithm)

* **Mechanism**:
  + **SARSA**: A reinforcement learning algorithm that updates policies based on the agent’s current action and subsequent rewards, using the state-action-reward-state-action (SARSA) approach.
  + **WOA**: Applies whale-inspired strategies to explore and optimize solutions, including encircling and bubble-net feeding behaviors.
* **Advantages**:
  + **Conservative Strategy**: SARSA’s on-policy learning provides a cautious approach, beneficial in uncertain or dynamic environments.
  + **Optimized Exploration-Exploitation**: The hybrid approach combines SARSA’s learning with WOA’s optimization capabilities, enhancing the overall learning process and performance.
* **Applications**:
  + **Adaptive Systems**: Improves systems that require continuous adjustment and learning in response to changing conditions.
  + **Autonomous Navigation**: Optimizes navigation strategies for autonomous vehicles and robots.
  + **Systems Requiring Continuous Learning and Optimization**: Suitable for applications that need ongoing learning and refinement of strategies.

### Conclusion

The comparison highlights the unique strengths of each hybrid algorithm, with your proposed QWhale and SARSA Whale algorithms offering innovative solutions by combining reinforcement learning with WOA. These approaches are particularly promising for dynamic and complex environments, such as cloud computing and real-time decision-making systems, where adaptability and efficiency are crucial. The integration of learning algorithms with WOA's exploration capabilities provides a novel pathway for solving optimization problems more effectively.

This comparison provides a comprehensive overview of the hybrid algorithms, showcasing the distinct benefits and potential applications of each, including your innovative contributions with QWhale and SARSA Whale.

In conclusion, the integration of Q-learning and SARSA with the Whale Optimization Algorithm (WOA) has demonstrated significant improvements in solving complex optimization problems compared to conventional WOA and other benchmark algorithms. Our integrated variants consistently outperformed across various instances, achieving optimal solutions in several cases and demonstrating competitive performance close to optimal solutions on average.

Moreover, these integrated approaches streamlined the optimization process, significantly reducing tuning times. Detailed analysis of exploration and exploitation graphs revealed consistent convergence patterns with smaller variations and occurrences in our integrated variants, indicating potential for enhanced problem-solving capabilities.

Comparatively, other hybrid algorithms such as Genetic Algorithm - Particle Swarm Optimization (GeneticPSO), Genetic Whale Optimization Algorithm (HGWO), Ant Colony Optimization - Particle Swarm Optimization (ACPSO), and Hybrid Particle Whale Optimization (HPWO) have shown their strengths in specific applications. For instance, GeneticPSO excels in multi-objective optimization and scheduling problems, HGWO in feature selection and economic load dispatch, ACPSO in network routing and resource allocation, and HPWO in wireless sensor networks and data clustering. These hybrid approaches have provided balanced exploration and exploitation, enhanced solution diversity, and improved optimization performance across various domains.

Looking ahead, further validation and parameterization of results obtained from exploration and exploitation graphs are essential. Standardized metrics for comparison and incorporation into reinforcement learning agents' learning processes hold promise for advancing the optimization capabilities of metaheuristic algorithms. Furthermore, future endeavors should explore the potential of leveraging SARSA's capability to store experiences for further improving the performance of the integrated SARSA Whale Optimization Algorithm (WOA). By incorporating this feature, the SARSA WOA variant could effectively learn from past experiences, enabling it to adapt more efficiently to varying optimization landscapes. This iterative process of learning and adaptation holds promise for enhancing the robustness and effectiveness of the SARSA-integrated WOA in solving complex optimization problems.

Continued research into the parameterization of results obtained from exploration and exploitation graphs will be crucial in providing a standardized metric for comparison and further advancing the optimization capabilities of metaheuristic algorithms. Additionally, integrating Q-learning and SARSA with other optimization algorithms like Genetic Algorithm and Particle Swarm Optimization could offer new hybrid variants that leverage the strengths of multiple techniques.

Overall, these findings underscore the potential of integrating reinforcement learning techniques with metaheuristic algorithms for effectively tackling complex optimization challenges. The future directions highlighted emphasize continuous refinement and improvement, ultimately contributing to more efficient and effective solutions for challenging optimization tasks.

### Discussion

* **Innovations**: QWhale and SARSA Whale introduce reinforcement learning into the optimization domain, providing a new perspective on balancing exploration and exploitation. These algorithms can adapt to changing environments, making them suitable for dynamic and real-time applications.
* **Challenges**: Both QWhale and SARSA Whale require careful parameter tuning and might face challenges in convergence speed. Further research could focus on enhancing these algorithms' efficiency and scalability.

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