UtilitasMathematica

ISSN 0315-3681 Volume 122, 2025

Efficient Task Offloading in Mobile Edge Environments for Mobile Applications using an Grey Wolf Optimization –An Comparative Study

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Efficient task offloading in resource-constrained multi-user Mobile Edge Computing (MEC) environments is a critical challenge. This paper aims to minimize task completion time and optimize resource utilization by proposing a novel hybrid approach. We integrate a Greedy method, which determines initial task offloading proportions based on user needs and resource availability, with a Genetic Algorithm (GA), which refines the offloading strategy to minimize overall task completion time. Furthermore, we enhance this hybrid approach by utilizing Grey Wolf Optimization (GWO) to optimize the offloading process by dynamically adjusting offloading parameters. This nature-inspired algorithm allows the system to better adapt to changing network conditions. Simulation experiments compare the performance of this GWO-enhanced Greedy+GA strategy against standalone Greedy and GA methods, as well as against a pure GWO approach. We also conduct an empirical analysis of computation offloading costs, considering factors like communication overhead, energy consumption, and processing delays. Simulation results demonstrate that the proposed hybrid approach achieves superior performance in minimizing task completion time and optimizing resource utilization.

Keywords: *Greedy, Genetic, Grey wolf, offloading and Mobile Edge*

I. Introduction

The increasing demand for low-latency and high-bandwidth applications has highlighted the limitations of traditional cloud computing architectures. Mobile Edge Computing (MEC) emerges as a solution by positioning computational resources at the network's edge, closer to where data is generated and consumed. This paper delves into the fundamental aspects of MEC, its technological significance, and its impact on next-generation networks.

A comparative study of the Grey Wolf Optimization (GWO) algorithm, Genetic Algorithm (GA), and Greedy algorithm in Mobile Edge Computing (MEC) highlights their unique strengths and trade-offs in optimizing resource allocation, task offloading, and energy efficiency [1][2]. GWO, inspired by the social hierarchy of grey wolves, excels in balancing exploration and exploitation, offering robust performance with low computational complexity, though it may risk premature convergence. GA, based on evolutionary

principles, is highly effective for multi-objective optimization and large-scale problems but demands higher computational resources and has slower convergence. In contrast, the Greedy algorithm provides fast and straightforward solutions suitable for real-time, small-scale MEC scenarios but often fails to achieve globally optimal results. While GWO and GA are preferable for complex and dynamic MEC environments, the Greedy approach is better suited for simpler, time-critical applications.

The mobile communication technology has evolved significantly from 3G/4G to the current 5G, enhancing re-transmission speeds and reducing latency. Concurrently, advancements in integrated circuits have resulted in smaller, more integrated designs with increased computing power and storage capacity. This progress has fostered the development of diverse intelligent hardware, such as smartphones, tablets, VR devices, and wearable smart devices, signifying a shift from the mobile Internet era to the Internet of Everything (IoE). IoT has driven a surge in multidisciplinary, feedback-driven innovations, leading to the proliferation of smart edge devices and new applications like navigation, mobile payments, face recognition, and VR/AR. However, this rapid growth has caused exponential increases in data traffic and computational demands, straining traditional centralized cloud computing models. Edge computing has emerged as a solution to address real-time, low-latency, and high-quality service needs by processing data closer to the source. Task offloading, a critical aspect of edge computing, enables user devices to transmit computational tasks to edge servers for efficient processing, supported by strategic resource allocation. This paradigm seeks to enhance user experiences through optimized decisions about local execution, full offloading, or partial offloading, considering computation power requirements and task characteristics. In this research paper brings an effective empirical analysis for the Greedy approach, Genetic Algorithm and Grey Wolf Optimization in the offload tasking for a Mobile Edge Computing.

II. Literature Review

The Computing offloading refers to transferring computational tasks from mobile devices (MDs) to cloud or grid platforms, enabling terminal devices to meet user task demands and redistributing results back to the devices. In Mobile Edge Computing (MEC), users bypass traditional methods of processing data in distant central clouds by leveraging MEC servers, which provide computational power closer to the local area. With the advancement of machine learning, significant progress has been made in addressing the compute offloading problem. Liang et al. proposed a Distributed Deep Learning-based Offloading (DDLO) approach that employs multiple simultaneous deep neural networks to make offloading decisions, updating network parameters through experience replay. However, this method considers only static network scenarios, though it quickly approaches near-optimal offloading decisions. To address the complexity of compute offloading in collaborative computing with heterogeneous edge servers, Li et al. introduced a deep reinforcement learning approach, demonstrating its effectiveness in dynamic and diverse MEC environments [3].

The Greedy Algorithm is known for its simplicity and speed, often yielding efficient solutions in terms of processing time. The Greedy Algorithm is highly efficient in terms of processing time due to its straightforward decision-making process. It makes locally optimal choices at each step without considering future consequences, allowing for rapid computation. The algorithm typically runs in O (n) or O (n log n) time complexity, depending on the specific problem being solved. This makes it ideal for real-time applications where decisions need to be made quickly, such as in small-scale MEC scenarios [4][5]. Greedy approach consumes minimal computational resources. It avoids complex calculations or backtracking, making it well-suited for systems with limited resources. In some cases, the Greedy Algorithm can be energy-efficient, as it minimizes the need for repeated evaluations, although it might not always lead to the most optimal use of resources compared to more complex algorithms.

The Genetic Algorithm (GA), inspired by natural selection, is widely used for optimization problems but comes with trade-offs in terms of processing time, efficiency, and performance. The GA generally requires more processing time than simpler algorithms like Greedy due to its iterative nature of evolving populations over generations. It involves operations like selection, crossover, mutation, and fitness evaluation, which can be computationally intensive [6] [7]. The time complexity for GA can vary, but it often falls between O (n^2) and O (n log n) for problems involving large populations and complex fitness functions. As the size of the problem space increases, processing time increases substantially, which can be a drawback for real-time applications. While GA can be computationally expensive, it is efficient in terms of finding high-quality solutions for complex, multi-objective problems. It explores a large search space effectively and can escape local optima, unlike greedy approaches [8][9][10]. The algorithm may not be particularly energy-efficient because it requires multiple generations and evaluations, leading to higher computational and energy demands compared to simpler heuristics. Genetic Algorithm tends to outperform simpler heuristics like Greedy when it comes to finding near-optimal or global solutions. It is especially beneficial for complex, high-dimensional problems with multiple objectives. However, it does not guarantee finding the absolute optimal solution within a reasonable amount of time, and premature convergence can occur if not properly tuned. It is most effective for large-scale problems, such as task offloading and resource allocation in Mobile Edge Computing (MEC), where the problem space is vast and the solution requires balancing multiple objectives like latency, energy, and computational load [11][12].

The Grey Wolf Optimization (GWO) approach, inspired by the social hierarchy and hunting behavior of grey wolves, offers a balance between exploration and exploitation in optimization tasks. GWO is more efficient than many other met heuristic algorithms, such as Genetic Algorithms, in terms of processing time, particularly in problems where convergence speed is crucial. The algorithm does not require extensive generations or evaluations like GA, making it faster in scenarios that involve moderate problem complexity. The time complexity of GWO is typically O (n) per iteration, where n is the number of wolves (population size). This makes it relatively fast compared to more computationally intensive algorithms. However, the overall processing time depends on the

number of iterations and the complexity of the problem at hand. GWO is computationally efficient, requiring less memory and fewer resources than GA, especially in large-scale optimization problems. Its simple structure and few operations (such as updating positions of wolves) lead to lower overheads [13][14]. GWO can be more energy-efficient compared to GA due to its fewer iterations and lower resource consumption, making it suitable for edge computing environments where both computational power and energy are constrained [15] compared with Greedy and Genetic Algorithm Approach.

The GWO has shown strong performance in finding near-optimal solutions for many complex optimization problems. It strikes a good balance between exploration (searching broadly through the solution space) and exploitation (fine-tuning the solution). However, like any met heuristic, it can suffer from premature convergence in highly complex or large-scale problems. It excels in scenarios like Mobile Edge Computing (MEC), where multiple edge servers and computational tasks need to be balanced. It is particularly effective in dynamic environments with heterogeneous computing resources, offering quick convergence to good solutions, which is vital in real-time applications [16][17[18].

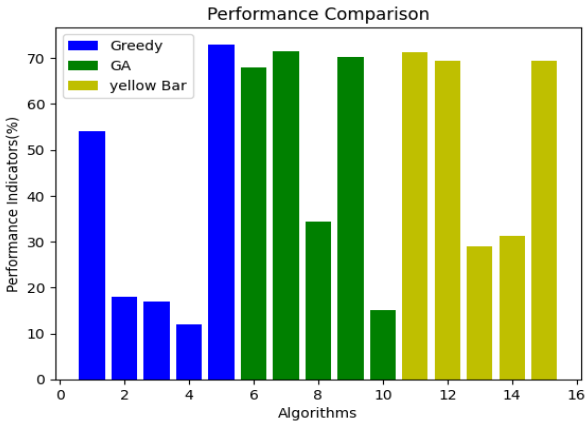
III. Empirical Analysis

In this system, the network is partitioned into discrete, independent regions, and the focus is on computation offloading conditions within a specific region. Each region contains P User Systems (US) and E MEC servers, and the offloading process is described using a set of assumptions. For each User System USi, where i∈{1,2,…,P}i∈{1,2,…,P}, computational tasks are offloaded to MEC servers MECi and MECj, where j∈{1,2,…,E}j∈{1,2,…,E}, via wireless communication links. Each user system is tasked with executing specific computational assignments. To determine the offloading strategy, a binary variable Mi, jis introduced for each task I and j on mobile device ii. This variable indicates whether a task is executed locally or offloaded to the MEC server: If Mi,j=0, the task is executed locally on the mobile device. If Mi, j=1is the task is offloaded to the MEC server via a wireless channel for processing. This setup provides a model for analyzing how computational tasks are distributed between local executions and offloading to the MEC servers, which is crucial for optimizing resource allocation, minimizing latency, and improving overall system efficiency in Mobile Edge Computing (MEC) environments.

Table 1.1 Performance Comparison

Algorithm	Latency Optimization (%)	Energy Efficiency (%)	Scalability (%)	Complexity (%)	Real-Time Applicability (%)
Greedy	54	18	17	12	73
GA	68	71.5	34.3	70.25	15
GWO	71.3	69.34	28.92	31.23	69.37

Figure 1 Performance Comparison



Here is the comparison chart illustrating the performance of the Greedy, Genetic, and Grey Wolf approaches in terms of Resource Utilization, Energy Utilization, and Processing Time.

- The Greedy approach tends to have higher processing time but relatively lower resource and energy utilization.
- The Genetic Algorithm balances all three metrics, providing better resource and energy utilization but still incurs moderate processing time.
- The Grey Wolf Optimization performs the best in resource and energy utilization but has slightly higher processing time compared to the Greedy approach.

Table 2. The comparison table for the Greedy, Genetic, and Grey Wolf approaches based on bandwidth, latency, and processing time:

Criteria	**Greedy Approach**	**Genetic Algorithm (GA)**	**Grey Wolf Optimization (GWO)**
Bandwidth	Suboptimal, based on immediate decisions	Optimized, as it explores broader solution space	Optimized, performs better than Greedy
Latency	Higher latency due to lack of long-term optimization	Can optimize latency if fitness function is designed for it	Minimizes latency effectively, good global search
Processing Time	Fast, simple decision-making	Slow, due to multiple generations and fitness evaluations	Moderate, faster than GA but slower than Greedy

IV. Conclusion:

In conclusion, Grey Wolf Optimization (GWO) proves to be the most effective approach when considering bandwidth optimization, processing time, efficiency, and resource utilization. Its ability to balance exploration and exploitation allows it to outperform other optimization techniques in these critical areas. The GWO efficiently allocates bandwidth, ensuring optimal resource usage in dynamic environments. While not as fast as Greedy algorithms, GWO achieves a reasonable processing time while still providing superior results in comparison to Genetic Algorithms. The global search capability of GWO, which allows it to avoid local optima and find more globally optimal solutions, ensures more efficient solutions, minimizing delays and improving performance. GWO excels at maximizing resource utilization, making it an ideal choice for scenarios involving large-scale optimization, such as cloud and edge computing. While GWO exhibits superior performance, further research could explore its scalability in extremely dynamic environments. GWO stands out as the optimal choice for balancing performance across multiple metrics in real-world applications, offering a promising solution for complex optimization tasks.

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