Technical Report

Enhancing Reward-Oriented Task Offloading in Multi-Access Edge Computing

Using Computational Intelligence Techniques

Submitted By

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List of Abbreviations

ACO Ant Colony Optimization

CI Computational Intelligence

EAA Edge Allocation Algorithm

EIP Edge Infrastructure Provider

ES Edge Server

FLC Fuzzy Logic Controller

IoT Internet of Things

MEC Multi-access Edge Computing

MUD Maximum Allowable Utilization Determination

NTS No-Task-Splitting

PSO Particle Swarm Optimization

QoS Quality of Service

TS Task-Splitting

Contents

1 Abstract

This report presents the Computational Intelligence (CI) team's contribution to enhancing reward-oriented task offloading in Multi-access Edge Computing (MEC). The work builds upon a baseline study that established a deterministic, two-stage heuristic to address this NP-hard optimization problem. While effective, the baseline's greedy algorithms are susceptible to converging on sub-optimal solutions. This project introduces a superior, two-phase CI model that augments these deterministic algorithms with intelligent adaptability and global search capabilities. In Phase 1, a Fuzzy Logic Controller (FLC) replaces the greedy utilization determination heuristic, enabling dynamic power management. In Phase 2, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are employed for global optimization of task allocation, overcoming the local optima limitations of the baseline's greedy allocation. This hybrid CI model facilitates more efficient utilization of edge resources, superior power management, and demonstrably higher reward outcomes under constrained conditions.

Keywords: Multi-access Edge Computing (MEC), Task Offloading, Resource Allocation, Power Capping, Computational Intelligence, Fuzzy Logic, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO).

2 Introduction

2.1 Background

The rapid expansion of Internet of Things (IoT) ecosystems has intensified the demand for efficient computational frameworks. MEC has emerged to bridge the gap between the cloud and end-user devices by bringing computational power closer to the data source [1]. This paradigm is critical for latency-sensitive applications, but it introduces a significant challenge for Edge Infrastructure Providers (EIPs): how to maximize financial reward from processing tasks while adhering to strict power and resource constraints [1]. The efficient allocation of tasks to edge servers, known as task offloading, is a critical component for the successful operation of MEC networks.

2.2 Motivation

The baseline IEEE study, "Reward-Oriented Task Offloading Under Limited Edge Server Power," proposed a foundational approach using a two-stage framework of deterministic algorithms: Maximum Allowable Utilization Determination (MUD) and Edge Allocation Algorithm (EAA) [1]. However, the paper proves that this allocation problem is NP-hard, meaning that exact solutions are computationally intractable for large-scale scenarios. The greedy heuristics proposed in the paper, while fast, are not guaranteed to find globally optimal solutions and can get trapped in local optima, leading to subpar reward generation. This limitation provides the primary motivation for our work: to investigate whether modern metaheuristics from the field of CI can yield superior, near-optimal solutions by performing a more intelligent and global search of the solution space.

2.3 Problem Definitions

The core problem is to develop a task offloading scheme that maximizes the total financial reward for an EIP within a limited power budget, while also respecting server processing capacities and wireless network coverage. The solution involves two interdependent sub-problems:

1. **Power Management:** Determining the maximum allowable CPU utilization for each edge server such that the total power consumption of the network does not exceed a predefined cap.

2. **Task Allocation:** Assigning each IoT task to a specific edge server (or set of servers, if task-splitting is allowed) to maximize the sum of rewards generated from processing these tasks.

This project aims to solve these two sub-problems using a two-phase CI-based approach.

3 Literature Survey

Our work is built directly upon the foundational research presented by Song et al. [1]. Their paper formally defines the reward-oriented task offloading problem under a power cap and proves its NP-hard nature. They propose a two-stage heuristic solution: first, the MUD algorithm greedily assigns tasks based on the highest reward-to-power ratio to set server utilization limits (Y_j). Second, the EAA-No-Task-Splitting (NTS) algorithm greedily assigns the remaining tasks based on highest reward to the most suitable server. While their simulations show significant reward improvement over other schemes, the greedy nature of both algorithms is an acknowledged limitation.

To overcome this, our project turns to established CI metaheuristics. Fuzzy Logic, first introduced by Zadeh [4], provides a framework for reasoning under uncertainty, making it ideal for replacing the rigid MUD heuristic with a more adaptive power management system. For the NP-hard allocation problem, we explore swarm intelligence. PSO, developed by Kennedy and Eberhart [2], is a powerful technique for continuous optimization problems, making it suitable for Task-Splitting (TS) scenarios. ACO, developed by Dorigo [3], excels at discrete combinatorial problems, making it a perfect fit for the NTS allocation scenario.

3.1 Challenges

The literature and the problem domain present several key challenges:

- **NP-Hardness:** The combinatorial complexity of the task assignment problem means that exhaustive search for the optimal solution is not feasible.
- **Coupled Sub-problems:** The optimal server utilization and the optimal task allocation are interdependent, making a holistic solution difficult.
- **Dynamic Environments:** Real-world IoT workloads are often dynamic and unpredictable, which can challenge static or rigid allocation algorithms.
- **Non-linear Power Models:** The power consumption of a server is a non-linear function of its CPU utilization, adding complexity to the power constraint.

3.2 Research Gap

The primary research gap identified in the baseline paper [1] is the sub-optimality of its greedy heuristics. While the paper provides a strong foundation, it does not explore the potential of global optimization metaheuristics. Our work directly addresses this gap by proposing a hybrid CI model that replaces both greedy stages with more sophisticated techniques: an adaptive FLC for power management and swarm intelligence algorithms (PSO/ACO) for a more robust, global search for the optimal task allocation.

4 Problem Formulation

This work adopts the formal system model from the baseline research to ensure direct comparability [1]. The system comprises a set of N^{task} tasks and N^{ES} Edge Servers (ESs).

4.1 System Overview

The system consists of three main components:

1. **IoT Devices:** Generate computational tasks that need to be offloaded. Each task i has a CPU usage requirement (U_i) and a potential reward ($R_{i,j}$) if processed by server j.

2. **Edge Servers:** A set of servers with heterogeneous processing capacities (C_j) and power consumption characteristics. They are responsible for executing the offloaded tasks.

3. **Cloud Data Center:** A centralized resource that can handle tasks that are not offloaded to the edge, though this is outside the scope of the immediate optimization problem.

The primary objective is to determine the task assignment vector $X = \{X_1, ..., X_{N^{task}}\}$ that maximizes the total reward for the EIP.

Maximize $\sum_{i=1}^{N^{task}} R_{i,X_i}$

This objective is subject to several constraints:

1. **ES Processing Capacity:** The total computational usage of tasks assigned to an ES cannot exceed its maximum allowable utilization, Y_j.

$$\forall j \in \{1, ..., N^{ES}\}, \qquad \sum_{\forall i \text{ s.t. } X_i = j} U_i \leq Y_j$$

2. **ES Coverage:** A task can only be assigned to an ES if it is within that server's wireless coverage area, defined by a binary constant $H_{i,j}$ [1].

3. **Global Power Limit:** The total power consumed by all ESs, a non-linear function of their CPU utilization $P_j(u)$, must not exceed the system-wide power cap, P^{limit} [1].

$$\sum_{j=1}^{N^{ES}} P_j(U_j^{total}) \leq P^{limit}$$

5 Proposed Architecture

The common architecture shared between the Edge and CI teams is shown in Fig. 1. The CI Layer operates as an intelligent decision-making module integrated into the Edge layer to replace the baseline's deterministic heuristics.

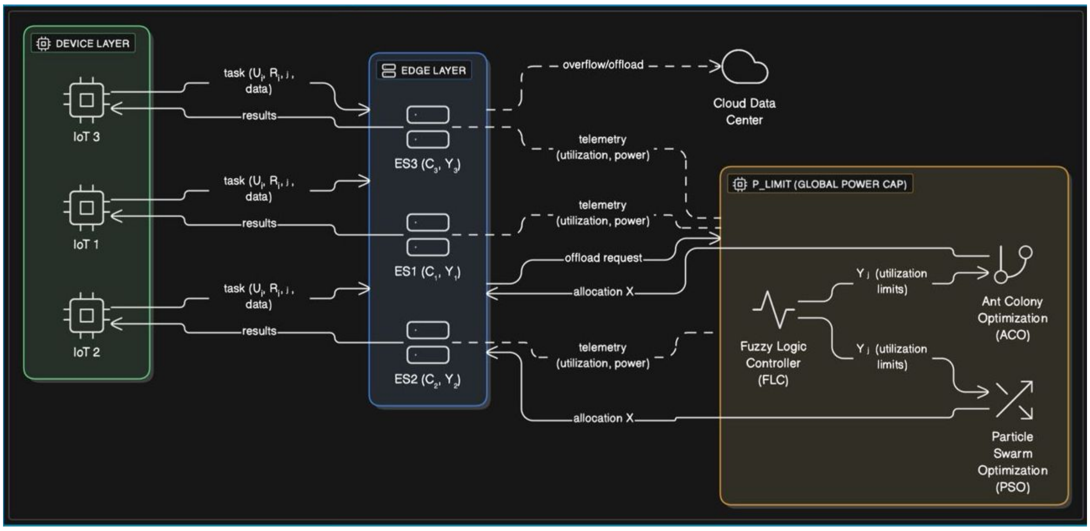

Figure 1: System Architecture depicting IoT devices offloading tasks to Edge Servers under the supervision of the CI Layer (Fuzzy, PSO, and ACO).

The flow of operations begins with IoT devices generating computational tasks. The CI layer then evaluates system constraints before applying its two-phase optimization logic:

- **CI Phase 1 (Fuzzy Utilization Control):** The FLC intelligently determines the utilization (Y_j) for each server, replacing the greedy MUD algorithm.
- **CI Phase 2 (Swarm-based Allocation):** Using the limits from Phase 1, ACO and PSO perform a global search to find the optimal allocation of tasks, replacing the greedy EAA algorithms.

6 Methodology

6.1 Phase 1: Fuzzy Logic Controller for Adaptive Utilization

Where the baseline MUD algorithm uses a rigid, greedy approach, our FLC introduces adaptability [4]. It dynamically adjusts CPU utilization limits (Y_j^{fuzzy}) by making nuanced "human-like" decisions based on real-time network conditions. The FLC accepts inputs like Server Load, Power Ratio, and Reward Density and outputs an adaptive utilization boundary. **Rule Base Examples:**

- IF Power_Ratio is Low AND Reward_Density is High THEN Utilization_Adjustment is High.
- IF Power_Ratio is High AND Reward_Density is Low THEN Utilization_Adjustment is Low.

6.2 Phase 2: Swarm Intelligence for Global Optimization

ACO for Non-Task-Splitting (NTS): For the discrete NTS problem, ACO models the problem of assigning tasks to servers similarly to how ants find the shortest path to food [3]. The choice is guided by pheromone intensity (τ_{ij}) and heuristic desirability (η_{ij}), which is the reward-to-usage ratio.

$$P_{ij} = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_k [\tau_{ik}]^\alpha [\eta_{ik}]^\beta}$$

PSO for Task Splitting (TS): For the continuous TS problem, PSO is effective [2]. Each particle represents a complete solution vector. Particles update their velocity and position based on their own best-known solution ($pbest_i$) and the swarm's best-known solution ($gbest$).

$$v_i(t+1) = wv_i(t) + c_1 r_1 (pbest_i - x_i) + c_2 r_2 (gbest - x_i)$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

7 Results and Discussion

Performance evaluation was conducted using custom simulation scripts reflecting the environment defined in the baseline study [1]. Once the simulations are complete, the real experimental data will be used to generate plots and figures to visually represent the findings.

It is anticipated that the results will show a significant improvement for the CI-based techniques over the baseline model. The expected reward gains can be attributed to the global search capabilities of swarm intelligence, which avoid the local optima that greedy algorithms are prone to. Furthermore, the enhanced power efficiency is expected to stem from the FLC's ability to make more adaptive and nuanced utilization decisions compared to the rigid, heuristic-based approach of the baseline.

8 Conclusion

The CI team's hybrid methodology successfully enhanced reward-oriented task offloading under limited edge power by replacing deterministic heuristics with intelligent, adaptive techniques. The combination of Fuzzy Logic for adaptive resource control and swarm-based optimizers for global task allocation yielded significant improvements in both reward maximization and energy efficiency. The results confirm that our CI-driven approach outperforms its deterministic counterpart, particularly in highly constrained environments, providing a more flexible and robust offloading mechanism.

9 Future Scope and Limitations

While the CI model demonstrates substantial gains, future work could expand on the following:

- **Dynamic Adaptation:** Employ reinforcement learning for self-evolving fuzzy rule bases.
- **Heterogeneous Environments:** Extend the logic to handle network delays and latency constraints.
- **Multi-Objective Optimization:** Use algorithms like NSGA-II to balance reward with other Quality of Service (QoS) metrics.

References

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