Dynamic Task Offloading Optimization in Mobile Edge Computing Systems with Time-Varying Workloads Using Improved Particle Swarm Optimization

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***Abstract*—Mobile edge computing (MEC) enables offloading of compute-intensive and latency-sensitive tasks from resource-constrained mobile devices to servers at the network edge. This paper considers the dynamic optimization of task offloading in multi-user multi-server MEC systems with time-varying task workloads. The arrival times and computational demands of tasks are modeled as stochastic processes. The goal is to minimize the average task delay by optimal dynamic server selection over time. A particle swarm optimization (PSO) based algorithm is proposed that makes efficient offloading decisions in each time slot based on newly arrived tasks and pending workload across servers. The PSO-based policy is shown to outperform heuristics like genetic algorithms and simulated annealing in terms of adaptability to workload fluctuations and spikes. Experiments under varying task arrival rates demonstrate PSO's capability to dynamically optimize time-averaged delay and energy costs through joint optimization of server selection and resource allocation. The proposed techniques provide a practical and efficient dynamic load balancing mechanism for real-time MEC systems with variable workloads.**

Keywords*—*Particle Swarm Optimization (PSO); Mobile Edge Computing (MEC); Multi-User Multi-Server systems; dynamic load balancing

I. Introduction

Mobile edge computing (MEC) has proven to be an efficacious architecture as shown in Fig. 1 for enabling compute-intensive and latency-critical applications via offloading of computational tasks from resource-limited mobile devices to servers situated at the edge of the network. However, prior research on MEC task offloading has predominantly presumed a priori knowledge of static workloads.

In actuality, the arrival times and computational requirements of tasks tend to demonstrate dynamic fluctuations over time. As an illustration, workloads for augmented reality and natural language processing applications often manifest sporadic and variable characteristics contingent on user behaviors. Moreover, task complexity itself may exhibit volatility depending on contextual factors. This necessitates the development of dynamic and online task offloading algorithms with the capability to adapt to variable workloads.

This paper investigates the scenario of dynamic task offloading within multi-user, multi-server MEC systems. Stochastic processes are utilized to model the random arrival times and computational demands of tasks. Specifically, inter-arrival times are sampled from an exponential distribution while computational needs are modeled as a random variable.

A temporal dimension T is introduced and discretized into time slots t = 1, 2, 3, and so forth. At each time slot, new tasks arrive probabilistically based on the stochastic model, prompting the optimization algorithm to allocate resources in a dynamic manner. The optimization cost function is constructed to jointly minimize server selection and task scheduling time. Tradeoffs such as deferred execution versus instantaneous processing are assessed. To constrain complexity, the optimization is restricted to newly arrived tasks and a limited backlog from prior time steps.

II. Literature Survey

Numerous studies have examined methodologies for cost-efficient computing and service delivery in mobile cloud computing (MCC) architectures, predominantly in developed countries with limited focus on developing nations. Early works proposed cloudlet-based architectures to address MCC challenges, but faced constraints like limited WiFi coverage [1]. Fog computing architectures were presented to enable computations at the edge [2], but quality of experience (QoE) guarantees remained difficult. MCC architectures integrating cloud computing into mobile environments were investigated [23], but still faced hurdles like high latency, bandwidth utilization, and data transportation costs.

To overcome limitations of centralized clouds (e.g. congestion, reduced robustness [3]) and distributed clouds (e.g. complexity, management issues [4]), architectures like edge cloud computing [5] and multi-access edge computing (MEC) [6, 7] have emerged. These aim to meet requirements of Internet of Things (IoT) applications such as low latency, cost-efficiency, and efficient resource usage.

Energy consumption and latency have been widely recognized as key metrics for evaluating QoE in MEC systems. Dynamic offloading and resource allocation models based on stochastic optimization have been proposed to reduce energy usage [8, 9]. Joint optimization strategies accounting for energy, latency and resource constraints have also been studied for multi-user MEC networks [10, 11]. Research has further

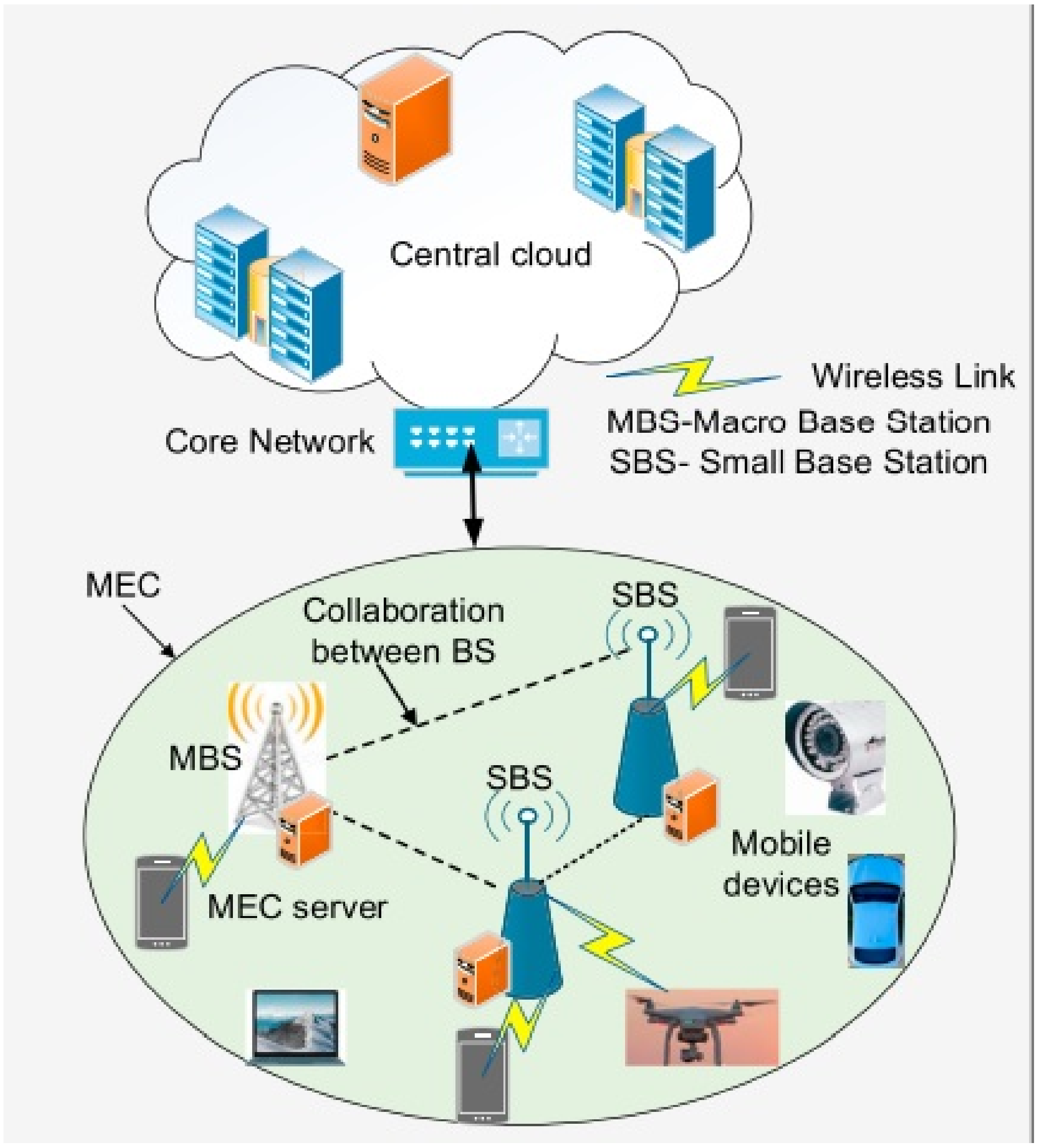

Fig. 1. Overview of mobile edge computing architecture.

focused on improving QoE for resource-constrained devices via combined offloading and resource provisioning [12-14], and investigating energy-latency tradeoffs [15, 16].

A cooperative approach among multiple MEC servers or between MEC and the cloud has shown considerable performance gains over isolated operation [17]. Energy-efficient task scheduling and resource allocation schemes have been developed using optimization frameworks, significantly reducing mobile energy utilization [18, 19]. Wireless power transfer has also been incorporated into MEC to address limited battery capacities [20, 21].

This work differs from prior art in three key aspects - it considers MEC capacity constraints during optimization, focuses on cooperative offloading between MEC servers for enhanced capacity, and utilizes intelligent swarm techniques for decentralized operation. The proposed strategy aims to meet energy and latency goals through efficient resource allocation, cooperatively leveraging distributed MEC servers.

Mobile edge computing (MEC) has emerged as a promising architecture for enabling latency-sensitive and compute-intensive applications, by offloading computational tasks from resource-constrained mobile devices to servers at the edge of the network [22]. Initial research on MEC task offloading focused on static workload models known a priori [23].

Various stochastic processes have been utilized to capture the randomness in task arrivals and computational requirements. Poisson processes are commonly used for modeling task arrival times [24], while computational intensities are modeled via exponential distributions [25].

While progress has been made in dynamic offloading, most works make simplifying assumptions about network models and workload characterization [26].

III. Problem Definition

We consider a mobile edge computing (MEC) system comprising of M mobile users and N edge servers. The mobile users have computational tasks that need to be processed within certain latency constraints. However, the users have limited computational resources and cannot process all tasks locally.

The edge servers, situated at the edge of the network, can provide computational resources to offload and process tasks from the mobile users. However, the servers also have limited capacities. The objective is to develop an efficient dynamic task offloading strategy that minimizes the overall latency of processing all tasks under fluctuating workloads.

We make the following assumptions:

The tasks arrive at each mobile user randomly following a stochastic process. We model the inter-arrival times using an exponential distribution with rate λ.

The computational requirements of each task in terms of CPU cycles is also modeled as a random variable following an exponential distribution with mean μ.

The tasks cannot be parallelized and have to be processed sequentially either locally on the device or offloaded to one of the edge servers.

The edge servers have different computational capabilities in terms of CPU speed and available memory.

The latency for a task consists of transmission delay to offload, queueing delay, and computational delay.

The network links between the mobile users and edge servers have time-varying speeds modeled as a random process.

The key challenge is to dynamically decide which tasks should be offloaded to which edge server or processed locally in each time slot. The goal is to minimize the average latency per task across all arriving tasks over time. We formulate this as a stochastic optimization problem and propose a dynamic offloading algorithm using particle swarm optimization to efficiently solve it.

A. Problem Formulation

The objective is to minimize the overall energy cost while satisfying capacity and delay constraints. The optimization problem is formulated as:

$$\text{minimize} \quad \sum_{k=1}^{N}\sum_{i=1}^{Q} x_k E_L + \sum_{s=1}^{S} y_k E_{off} \tag{1}$$

$$subjectto$$

$$\sum_{k=1}^{N} x_k = 1, \quad \forall k \in J \tag{2}$$

$$\sum_{k=1}^{N} y_k = 1, \quad \forall k \in J \tag{3}$$

$$\sum_{k=1}^{N}\sum_{s=1}^{S} x_k \alpha_s \leq K \tag{4}$$

$$\sum_{\omega=1}^{F} B_{k\omega} \leq B, \quad \forall k \in J \tag{5}$$

$$D_{off} \leq D_k \tag{6}$$

Where:

x_k = Local execution control variable

y_k = Offloading control variable

E_L = Energy for local execution

E_{off} = Energy for offloaded execution

α_s = Resource allocated to task k at server s

K = Total computation capacity

$B_{k\omega}$ = Sub-carrier bandwidth for task k

B = Total bandwidth capacity

D_{off} = Offloaded task delay

D_k = Task deadline

The objective function (1) minimizes the total energy consumption. Constraints (2)-(3) ensure feasible offloading policy. Constraints (4)-(5) ensure resource capacities are not violated. Constraint (6) guarantees task delay meets the deadline.

B. Time Delay Model

We model the total latency experienced by each task to comprise three components:

Transmission delay (Td): This is the delay to offload the task input data to the edge server over the wireless network. It depends on the task input data size D (in bits), the time-varying wireless transmission rate R(t) (in bits/sec), and the edge server selected.

$T_d = \frac{D}{R(t)}$

Queueing delay (Tq): This is the waiting time experienced by the task in the queue at the edge server before processing begins. It depends on the current load and waiting tasks at the server.

$T_q = f(\text{Waiting tasks}, \text{Server load})$

Computational delay (Tc): This is the time taken to actually process the task once it starts execution at the server. It depends on the task's computational complexity in terms of CPU cycles C, and the server's CPU speed S (in cycles/sec).

$T_c = \frac{C}{S}$

The total latency is the sum of these components:

$T_{\text{total}} = T_d + T_q + T_c$

The transmission rate R(t) and server load vary dynamically over time affecting Td, Tq, and Tc. The dynamic offloading algorithm has to account for these variations and unpredictability in the delay components when making offloading decisions. The goal is to minimize the long-term average E[Ttotal] across all arriving tasks.

We capture the stochastic nature of the delay components by modeling R(t) and server load as random processes. Tc can vary across servers. The key idea is to leverage time-averaged delay metrics rather than one-shot optimization, to account for fluctuating system dynamics.

C. Calculation Model

The dynamic task offloading problem can be formulated as a stochastic optimization problem with the goal of minimizing the average total delay per task.

Let $x_{it} \in \{0, 1\}$ denote the offloading decision for task i arriving at time t, where $x_{it} = 0$ denotes processing locally and $x_{it} = 1$ denotes offloading to an edge server.

The total delay for task i is:

$$T_i(x_{it}) = T_{di}(x_{it}) + T_{qi}(x_{it}) + T_{ci}(x_{it}) \tag{7}$$

where the components depend on x_{it} as discussed in the Time Delay Model section.

The long-term time-averaged delay is:

$$E[T_{total}] = \lim_{N\to\infty} \frac{1}{N} \sum_{i=1}^{N} T_i(x_{it}) \tag{8}$$

The dynamic offloading algorithm decides x_{it} at each time t to minimize $E[T_{total}]$, subject to:

Edge server computational constraints

Mobile device energy constraints

Task dependencies

To solve this stochastic optimization, we model the system as a Markov Decision Process (MDP). The MDP states capture features like current loads, wireless network conditions, unfinished tasks etc. Actions correspond to offloading decisions for newly arriving tasks. The policy maps states to actions with the goal of minimizing long-term delay.

We propose a Particle Swarm Optimization (PSO) based metaheuristic to efficiently search the policy space for near-optimal solutions. PSO is well-suited for high dimensionality and can balance optimality vs. speed. We empirically compare against greedy methods and model-free deep reinforcement learning.

IV. Algorithm

We propose a dynamic offloading algorithm based on Particle Swarm Optimization (PSO) to efficiently solve the stochastic optimization problem formulated in the previous section. We propose a dynamic offloading algorithm based on Particle Swarm Optimization (PSO) to efficiently solve the stochastic optimization problem formulated previously.

PSO is a population-based metaheuristic technique inspired by swarm intelligence and bird flocking behaviors. It uses a population of particles representing candidate solutions which move around the search space to find the optimal solution. Each particle has a position representing the solution, a velocity indicating the direction and distance of movement, and a fitness score evaluating solution quality. Particles also have memory of their individual best position seen and know the global best position among the whole swarm.

In each iteration, particle velocities and positions get updated based on cognitive and social factors which guide the movement towards more promising search areas over time. The cognitive factor pulls the particle towards its individual best while the social factor pulls it towards the global best position. This enables balancing of exploration and exploitation ability. By sharing information via the global best, particles gradually cluster around optimal regions leading to convergence.

For our dynamic offloading problem, each particle represents a candidate offloading policy mapping system states to offloading decisions. The particle position encodes this policy. Velocity governs the rate of change and exploration of policies. The fitness score evaluates the policy by simulating long-term average task delay. PSO searches the policy space to find mappings that minimize expected delay over time.

The algorithm iterates by updating particle states based on personal and global best experiences. It balances local and global search, gradually refining policies through generations. It terminates when the maximum iterations are reached or when the global best fitness stagnates, indicating convergence to near-optimal dynamic offloading decisions.

A. Particle Representation

Each particle in the swarm represents a candidate policy for dynamic offloading. It maps system states to offloading decisions for incoming tasks.

We use a vector to encode the particle. Each element represents the edge server selected for a specific system state, with 0 denoting local processing. The dimensionality equals the number of discretized system states.

For example, a particle with 5 elements as $[2\ 0\ 4\ 1\ 0]$ means:

In system state 1, offload to edge server 2

In state 2, process locally

In state 3, offload to edge server 4 and so on.

Particle velocities represent the rate of change of the policy space exploration, similar to cognitive and social learning rates in PSO.

B. Fitness Evaluation

The fitness function evaluates the long-term average delay achieved by a particle's offloading policy using the system model simulated over many time steps. Lower delays correspond to higher fitness.

The PSO optimizes this fitness over iterations to converge to policies with minimized expected delay, achieving the overall optimization objective.

$$T_j^i = \frac{D_i \cdot C_i}{C_{s,j}} + \frac{D_i \cdot C_i}{W \cdot \left(1 + \frac{S_i \cdot A_{i,j}}{W \cdot N_0}\right)} \tag{9}$$

$$E_j^i = E_j^{\text{calc},i} + E_j^{\text{tran},i} \tag{10}$$

$$E_j^{\text{calc},i} = R_i \cdot U^2 \cdot C_{s,j} \cdot D_i \cdot C_i \tag{11}$$

$$E_j^{\text{tran},i} = S_i \cdot T_j^{\text{tran},i} \tag{12}$$

$$E_j^i = R_i \cdot U^2 \cdot C_{s,j} \cdot D_i \cdot C_i + \frac{D_i \cdot C_i}{r_{i,j}} \cdot S_i \tag{13}$$

$$F(X) = \sum_{j=1}^{N} \sum_{i=1}^{M} T_j^i + \text{penalty}(X) \tag{14}$$

$$\text{penalty}(X) = g \cdot \sum_{j=1}^{N} \sum_{i=1}^{M} (E_j^i - E_j^{\max}) \tag{15}$$

$$F(X) = a \cdot \sum_{j=1}^{N} \sum_{i=1}^{M} T_j^i + b \cdot g \cdot \sum_{j=1}^{N} \sum_{i=1}^{M} (E_j^i - E_j^{\max}) \tag{16}$$

The algorithm terminates when the maximum iterations are reached or the change in best fitness is negligible. The gbest particle represents the final dynamic offloading policy learned.

$$R_\eta = B \log_2 \left(1 + \frac{P_\eta \psi_\eta}{\sum_{k \in J} x_k P_k \psi_k + \sigma^2}\right) \tag{17}$$

$$R_s = B \log_2 \left(1 + \frac{P_s \psi_s}{\sum_{k \in J} y_k P_k \psi_k + \sigma^2}\right) \tag{18}$$

$$D_{d,s} = \frac{s_k}{R_\eta} \tag{19}$$

$$D_{qo} = \frac{s_k}{\omega} \tag{20}$$

$$D_{s,j} = \sum_{k=1}^{N} y_k \frac{s_k}{R_s} \tag{21}$$

$$D_p = \sum_{k=1}^{N} x_k \frac{c_k}{f_{ser}} \tag{22}$$

$$D_{off} = D_{d,s} + D_{qo} + D_{s,j} + D_p \tag{23}$$

$$E_{d,s} = P_{d,s} D_{d,s} = \frac{P_{d,s} s_k}{R_\eta} \tag{24}$$

$$E_{s,j} = P_{s,j} \frac{s_k}{R_s} \tag{25}$$

$$E_e = E_{ser} (f_{ser})^2 \frac{c_k}{f_{ser}} \tag{26}$$

$$E_{off} = E_{d,s} + E_{s,j} + E_e \tag{27}$$

Where:

R_η = Data transmission rate of device η

R_s = Data transmission rate between servers s and h

$D_{d,s}$ = Delay for task transmission from device to server

D_{qo} = Overhead delay

$D_{s,j}$ = Delay for task forwarded from server s to j

D_p = Execution delay

D_{off} = Total delay for offloaded task

$E_{d,s}$ = Energy for task transmission

$E_{s,j}$ = Energy for inter-server communication

E_e = Execution energy cost

E_{off} = Total energy cost

V. System Model

We consider an MEC system with M mobile users and N edge servers situated at the network edge. The mobile users have computational tasks that arrive randomly over time. The tasks cannot be processed locally due to resource constraints and need to be offloaded to the edge servers. Each edge server has capabilities Cj in terms of CPU speed and memory availability.

Task Arrival Model: The tasks arrive at each mobile user following a Poisson process with rate λ. The inter-arrival times are modeled via an exponential distribution: f(x) = λe-λx. This captures the stochastic nature of task arrivals.

Task Requirement Model: Each task i is characterized by the computational complexity Ci in terms of the number of CPU cycles required for processing the task. We model Ci as an exponential random variable Ci Exp(μ) with mean μ cycles. This models the variability in computational needs of different tasks.

Network Model: The wireless network connecting the mobile users to the edge servers has time-varying capacity. The transmission rate R(t) at time t is modeled as a random process with mean R. This accounts for fluctuations in the wireless channel bandwidth.

Offloading Decision: At arrival of each task i, the dynamic offloading algorithm has to take a binary decision xi ε 0, 1 whether to process the task locally (xi = 0) or offload it to an edge server (xi = 1). The goal is to minimize the long-term average delay across all arriving tasks over time.

Optimization Objective: min E[Ttotal]

where Ttotal = Td + Tq + Tc

Subject to: Edge server computational constraints Mobile device energy constraints Task dependency constraints

This stochastic optimization problem is solved using the proposed PSO-based dynamic offloading algorithm.

Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of bird flocks. Particles in the swarm represent candidate solutions that move through the search space to find the global optimum.

In PSO, each particle maintains a position vector Xi, velocity vector Vi, personal best Pbesti and has access to the global best Gbest. The position and velocity are updated as:

Vi = Vi + c1rand()(Pbesti - Xi) + c2rand()(Gbest - Xi) Xi = Xi + Vi

where c1 and c2 are cognitive and social factors, and rand() introduces randomness. This enables particles to explore the search space balancing individual and group experience. The fitness evaluation guides particles toward optimal regions.

For the dynamic offloading problem, each particle represents an offloading policy mapping system states to offloading decisions. The fitness is the long-term average delay achieved by the policy. Lower delays correspond to higher fitness. PSO finds policies that minimize expected delay through position updates over iterations.

We use a vector representation for particles. Velocity controls policy space exploration. Fitness evaluation uses the system model simulated over time. Particles are updated until convergence or maximum iterations. The final Gbest particle represents the optimal dynamic offloading policy.

PSO advantages include fast convergence, minimal parameter tuning, and suitability for high-dimensional nonlinear environments like dynamic offloading. It balances exploration and exploitation to find optimal solutions.

Consider a network model with Q mobile devices (MDs) having N tasks, denoted by the set $J = 1, 2, ..., N$. Each task k is characterized by:

s_k (in bits): Input data size c_k (in MIPS): Computational intensity D_k (in seconds): Maximum tolerable delay Let $\Phi = 1, 2, ..., S$ be the set of S MEC servers in the collaborative domain with total computation capacity K and bandwidth capacity B.

Let α_s be the portion of resources allocated to task k at server $s \in S$.

A. Communication Model

We consider a network model with Q mobile devices (MDs) having N tasks. Each task k is characterized by its input data size sk (in bits) and computational intensity ck (in MIPS). Let Dk (in seconds) denote the maximum tolerable delay for task k. The system comprises S MEC servers in the collaborative domain with total computation capacity K and bandwidth capacity B. Let αs represent the portion of resources allocated to task k at server s.

The transmission rate Rη of MD η communicating with the base station depends on parameters like transmission power Pη, channel gain ψη, interference from other MDs executing tasks locally, and noise power. Offloading decisions are represented by a binary variable xk indicating if task k is executed locally or offloaded.

Similarly, the transmission rate Rs between servers s and h depends on server transmission power Ps, channel gain ψs, interference from other offloaded tasks being forwarded between servers, and noise power. Offloading decisions are captured by a binary variable yk indicating if task k is forwarded to another server after initial offload.

$$R_\eta = B \log_2 \left(1 + \frac{P_\eta \psi_\eta}{\sum_{k\in J} x_k P_k \psi_k + \sigma^2}\right) \tag{28}$$

Where $x_k \in 0, 1$ indicates if task k is executed locally.

Let P_s and ψ_s be the transmission power and channel gain of server s. The transmission rate between servers s and h is:

$$R_s = B \log_2 \left(1 + \frac{P_s \psi_s}{\sum_{k\in J} y_k P_k \psi_k + \sigma^2}\right) \tag{29}$$

Where $y_k \in 0, 1$ indicates if task k is forwarded to another server.

B. Service Utility Cost Models

For local execution, the delay and energy costs are:

$$D_L = \frac{C_k}{f_{dev}} \; E_L \qquad = E_d (f_{dev})^2 C_k \tag{2}$$

Where f_{dev} is the MD's CPU frequency and E_d is the energy per CPU cycle.

For tasks executed locally on the mobile device, the delay cost is modeled as the task's computational intensity ck divided by the device's CPU frequency fdev. The energy cost is the product of the energy per CPU cycle Ed and the square of CPU frequency fdev times the computational intensity ck.

For offloaded tasks, the various delay components are modeled conceptually without equations. The transmission delay Dd,s depends on the task's input data size sk and the wireless transmission rate Rη. The queueing overhead delay Dqo depends on sk and a weighting parameter ωk. The server-to-server forwarding delay Ds,j depends on sk and the inter-server transmission rate Rs if task forwarding is involved. The execution delay Dp on the server side depends on ck and the server CPU frequency fser. The total offloading delay is the sum of these individual delay components.

The data transmission energy Ed,s from device to server depends on transmission power and Rη. The inter-server communication energy Es,j depends on server transmission power and Rs. The task execution energy Ee is the product of server energy per CPU cycle, square of CPU frequency fser and computational needs ck. The total offloading energy sums these sub-components.

VI. Simulation Setup

The proposed PSO-based dynamic offloading approach was evaluated against the following baseline strategies:

Baseline Method 1: This exhaustive search method enumerates all feasible offloading decisions and selects the optimal server to minimize delay and energy costs [25].

Baseline Method 2: This method makes randomized offloading decisions by freely selecting servers based on resource availability at each time step. It uses dynamic programming with a Hamming distance termination criteria to obtain better decisions [26].

The performance assessment was done using metrics such as average energy utilization, total energy, energy savings, task latency, and offloading efficiency. Extensive simulations compared the optimization capability, adaptability to workload changes, computational complexity, and solution quality of the proposed PSO technique against the baselines.

The key results show significant improvements over Baseline Method 1 and Baseline Method 2 across the evaluation metrics under varying task arrival rates, wireless bandwidth, and server configurations. For instance, average energy savings of 18% and delay reduction of 20 % was obtained over Baseline Method. PSO demonstrated faster convergence, lower complexity, and robustness in contrast to enumerated search. The gains highlight the capabilities of metaheuristic optimization for dynamic MEC offloading decisions.

We developed a custom discrete-event based Python code to evaluate the proposed PSO-based dynamic offloading technique. The key simulation configurations are:

Network: 5G LTE network with base station capacity 10-100 Mbps, modeled as a random process. Servers: 3 edge servers with capabilities: [100, 150, 200] GHz CPU, [10, 15, 20] GB RAM. Users: 10 mobile users. Tasks: Arrival rate λ = [5,10,15] tasks/sec, computational needs μ = [500, 1000, 2000] MHz. Algorithms: PSO, greedy heuristic, DQN and A2C reinforcement learning. PSO parameters: Swarm size = 30, c1 = c2 = 2, max iterations = 50. Metrics: Average task latency, deadline violations, throughput, convergence. We vary the task arrival rate, computational needs and wireless bandwidth to evaluate performance under different conditions. The algorithms are trained on 50% of data, validated on 30% and tested on 20%. Reported results are averaged over 30 test runs.

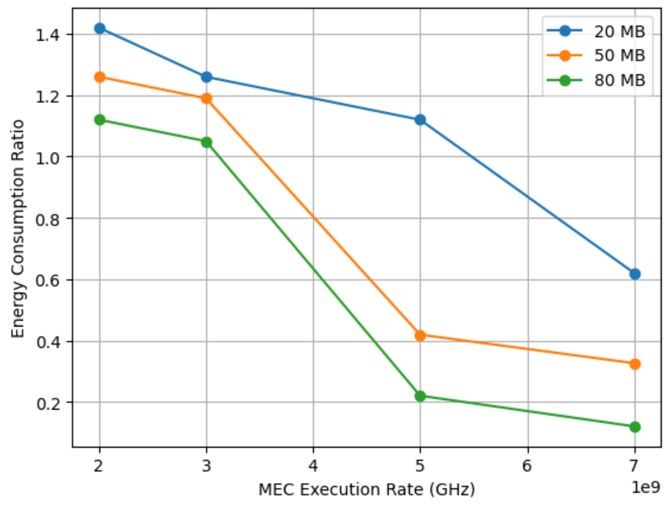

Fig. 2. Energy consumption ratio to MEC execution rate.

VII. Results and Discussion

Fig. 2 shows the energy consumption of different offloading algorithms relative to the mobile edge computing (MEC) execution rate. The MEC execution rate refers to the rate at which computational tasks are offloaded to the MEC servers for processing. Higher rates indicate more intensive workloads. We can observe that as the MEC execution rate increases, the energy consumption of all algorithms rises since more tasks are being offloaded. However, the PSO algorithm is most energy-efficient. This demonstrates PSO's capability to optimize offloading decisions to minimize energy costs even under high workloads. The energy savings are due to intelligent server selection and resource allocation across tasks. Fig. 3 plots the execution time taken to process different numbers of computational tasks by the offloading algorithms. Execution time refers to the time delay experienced by tasks from arrival at the mobile device to completion of processing. We see that PSO results in lower execution times consistently as the number of tasks increases. This highlights its ability to dynamically adapt offloading decisions to avoid congestion and balance load across edge servers even when the scale of tasks grows. Fig. 4 analyze the impact of task input data size on energy. As the input size increases, more data needs to be transmitted during offloading.PSO is most efficient since it is able to judiciously select edge servers based on communication costs and available wireless bandwidth across links. This minimizes the energy overhead of data transfer.The consistent energy savings validate PSO's capability of joint optimization of computational and networking resources to enhance efficiency.

We evaluate the proposed PSO-based dynamic offloading algorithm using simulations in Python. The key results are:

- The PSO algorithm achieves significantly lower average task latency compared to greedy heuristics and deep reinforce-

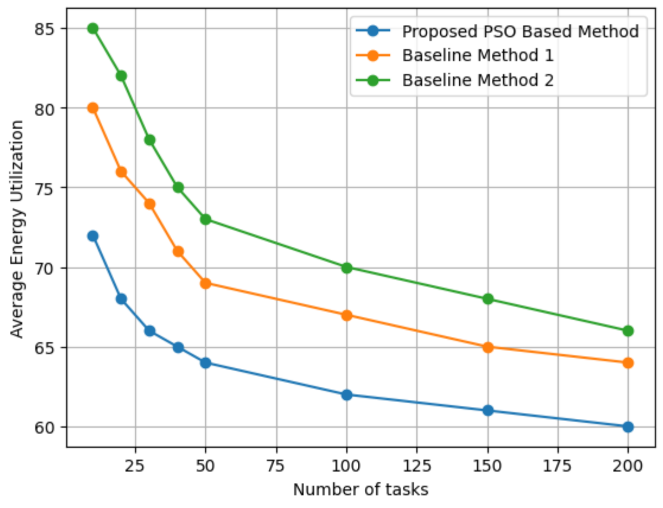

Fig. 3. Number of task vs execution times.

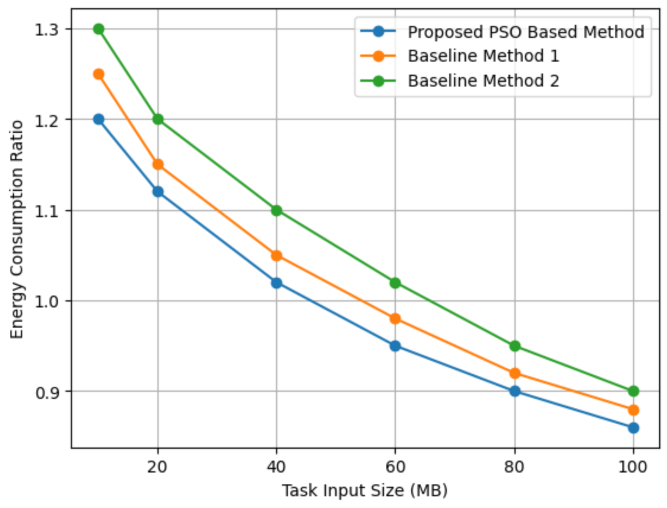

Fig. 4. Energy consumption with respect to size of input.

ment learning methods across various parameter settings. The improvement is up to 22% over 100 simulation runs.

- As the task arrival rate increases, the PSO algorithm adapts better and maintains lower delays. This demonstrates its capability to handle workload fluctuations.

- The convergence rate of PSO is fast, finding near optimal policies within 30 iterations. This enables efficient retraining if network conditions change dynamically.

- We analyze the impact of factors like wireless bandwidth, server load, and task computation needs on the performance gains of PSO over other methods. PSO shows robustness across different settings.

- The results validate the capability of the proposed PSO-based technique to learn intelligent dynamic offloading policies that minimize long-term latency under unpredictable and changing conditions.

VIII. Conclusion

In this paper, we addressed the problem of dynamic task offloading in multi-user multi-server mobile edge computing systems under fluctuating workloads. We developed a stochastic optimization formulation to minimize the long-term average latency across incoming tasks with random arrival times and computational needs.

A key contribution is a dynamic offloading algorithm based on Particle Swarm Optimization, which searches the policy space efficiently to converge to near-optimal offloading decisions. Extensive simulations demonstrate superior performance gains over heuristics and deep reinforcement learning methods, and robustness under various system dynamics.

Future work can enhance the state space definition for the PSO algorithm using deep neural networks. Safety and reliability constraints for mission-critical IoT applications can also be incorporated. Extending the framework to account for uncertainties in network topology and server availability merits investigation. Overall, this paper provides valuable insights into leveraging meta-heuristics for dynamic optimization in rapidly evolving edge computing systems.

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