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Industry 5.0: An Energy-Efficient Smart Task Offloading Mechanism for Multi-Access Edge Computing

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The industry 5.0 heralds a transformation of industrial systems by integrating artificial intelligence (AI), the Industrial Internet of Things (IIoT), and Multi-Access Edge Computing (MEC) to foster resilience, efficiency, and sustainability. However, managing the massive volume of computation-intensive tasks generated by heterogeneous IIoT devices presents major challenges, particularly in optimizing both latency and energy consumption under dynamic industrial conditions. This research proposes a hybrid task offloading framework Computational Genetic Particle Swarm Optimization Algorithm (CGPCA) to intelligently balance energy efficiency and latency in MEC-enabled IIoT networks. CGPCA integrates the global search capability of Genetic Algorithms (GA) with the fast convergence of Particle Swarm Optimization (PSO), forming a two-layer optimization approach for effective task-device associations and power-bandwidth allocation. The framework is evaluated using iFogSim and Edgelands simulation environments, reflecting realistic industrial scenarios with variable workloads, device capabilities, and server conditions. Results indicate that CGPCA reduces average latency by up to 24%, lowers energy consumption by 18–25%, and maintains a task offloading success rate of 94% surpassing conventional GA, PSO, and heuristic baselines. The framework also achieves improved load balancing and faster convergence time, confirming its suitability for time-sensitive and energy-constrained IIoT environments. This study contributes to the realization of Industry 5.0 by offering an adaptive, intelligent solution that enhances computational efficiency while supporting sustainable and human-centered industrial automation. Future directions include extending CGPCA to highly mobile IIoT contexts and integrating predictive analytics for further performance gains.

Keywords: Genetic Algorithm (GA), Industrial Internet of Things (IIoT), Industry 5.0, Latency Optimization, Multi-Access Edge Computing (MEC), Particle Swarm Optimization (PSO), Task Offloading

Introduction:

Industry 5.0 is a revolutionary step toward Industry 4.0 and signifies a shift towards human-oriented, sustainable, and resilient industrial ecosystems that combine advanced technologies with human intelligence. In comparison to the former paradigms that placed their emphasis on only one tool to achieve changes. Industry 5.0 centers the collaborative work of humans and machines, along with AI, in building versatile and adaptable production systems [1]. This transition allows smart factories to be more apt to the conditions that constantly evolve and increase the well-being of the workers and the sustainability of the systems. It is also the Industry 5.0, and the key driver behind it is the Industrial Internet of Things (IIoT), which links a large variety of sensors, actuators, and devices to generate enormous quantities of real-time data that is essential in decision-making.

The IIoT market in the world is estimated to reach over 1.1 trillion by the year 2028, which indicates its core place in the industry of modernity. Nevertheless, at times it is not feasible to process such data flows with local IIoT computing devices because of both their low computing power and energy limitations. Multi-Access Edge Computing (MEC) appears as one of the possible solutions because it forces the decentralization of computation by locating the processing power closer to the data source and decreasing latency [2].

The evolution from Industry 4.0 to Industry 5.0 represents a significant paradigm shift in industrial transformation. Whereas Industry 4.0 was characterized by automated and interconnected cyber-physical systems as well as data-driven decision-making. Industry 5.0 returns to the human being as the core of the industrial processes as it places focus on human-machine cooperation, individualization, and sustainability [3]. Industry 5.0 unites such technologies as augmented reality, digital twins, and embodied AI with human skills and enables flexible, adaptive production systems able to meet dynamic market and societal needs [4]. They allow predictive maintenance, precision manufacturing, and autonomous logistics, but generate enormous loads of computation.

Multi-Access Edge Computing (MEC) is one of the recent technologies that has become important in solving these issues through the shift of computation that is previously hosted centrally at cloud-based servers to distributed edge-based servers that are more proximate to IoT devices [2]. MEC can help to minimize latency by reducing the end-to-end delays because the delays can be as high as 100 ms in conventional cloud systems and lower than 10ms when using MEC architecture [5].

This paper aims to address the critical problem of developing an efficient and adaptive task offloading framework for MEC-enabled IIoT networks. In particular, the absence of a holistic solution that can meet the objectives of Industry 5.0 through the simultaneous optimization of energy consumption and latency in heterogeneous, dynamic industrial settings is a limiting factor. Existing offloading strategies either overlook latency or energy consumption, presume homogeneous devices, or do not consider real-time variations in workloads and changes in the network. The proposed framework will maximize the utilization of resources in the system and the responsiveness of the system through the distribution of tasks among devices dynamically taking into consideration the ability of the devices, the requirements of the application, and the network status [3].

This paper holds significant academic, practical, environmental, and industrial value. Academically, it advances the state-of-the-art in Multi-Access Edge Computing (MEC). Practically, it provides industries with intelligent, adaptive task-offloading strategies to create smarter, more resilient, and efficient production environments. Environmentally, optimizing energy consumption contributes to global sustainability goals and supports green technology initiatives in industrial operations. Industrially, it offers actionable insights for sectors such as manufacturing, logistics, and energy, where efficient task offloading can reduce operational costs and improve productivity.

This paper introduced the concept of Industry 5.0, highlighting its sustainable vision, and discussed the pivotal role of Multi-Access Edge Computing (MEC) in addressing the computational demands of Industrial Internet of Things (IIoT) networks. Key challenges, including balancing energy consumption and latency in heterogeneous, dynamic environments, were outlined alongside the identification of significant research gaps in existing task-offloading strategies.

Literature Review:

The purpose of this literature review is to establish a comprehensive understanding of the current state of research in Multi-Access Edge Computing (MEC), Industrial Internet of Things (IIoT), Industry 5.0, and task offloading strategies. The goal of this review is to find important advancements, point out the remaining challenges, and define research gaps that are of critical importance in terms of optimizing task offloading in the Industry 5.0 context. The synthesis of the recent papers will give the required base to advance intelligent, adaptive, and energy-efficient offloading frameworks that can target dual goals of decreasing latency and energy expenses in heterogeneous IIoT networks [6][5].

While several studies have explored energy-efficient or latency-optimal offloading strategies individually, few have addressed both objectives simultaneously in the context of MEC-enabled IIoT networks [7]. Existing literature tends to neglect the other metric to maximize one to the detriment of the other, and thus, the applicability in resource-constrained latency-sensitive industrial settings is limited. As an example, a Dynamic offloading solution with a consideration of computational energy efficiency, but the lack of such considerations as real-time latency limits that are vital to time-sensitive applications. This assumption is never seen in the real world of industrial networks, where devices are heterogeneous and range in capabilities and limitations, including individual communication performance requirements (e.g., portions of industrial networks are comprised of small devices like sensors as well as edge devices like edge gateways) [8].

Within the article, Computational Offloading in MEC Networks with Energy Harvesting formulates a hierarchical multi-agent reinforcement learning approach when minimizing the sum of latency and energy cost. Their Hierarchical Distributed Multi-Agent Proximal Policy Optimization (HDMAPPO) hierarchy can perform the task of scalable, energy-optimal task offloading among multiple users and servers by bipartitioning the problem of task offloading between a high-level location choice and a low-level optimal offloading scale. Simulation results gave a surprise to the traditional algorithms as HDMAPPO performed better than traditional algorithms in reducing the latency in average task, energy consumption, and task discard rates; hence, it is a solution to the problem of energy harvesting MEC problem where the energy supply is uncertain and uncontrolled and rhythmic [9].

The Lyapunov-based cooperative control using the MARL-based hierarchical optimization and RMAB-driven policies make their contributions in terms of keeping the energy consumption minimal, the latency low, and the reliability high. The inclusion of these high-tech methods into Industry 5.0 systems is virtually assured; however, not only their longevity but also the eco-friendly and sustainable industrial sector. These innovations are in line with the vision of Industry 5.0 because they ensure a suitable relationship between the performance of technologies and energy efficiency, and robust design principles needed in the industrial environments of the future [10][11].

Minimizing execution latency is a central goal of task offloading in MEC, especially for Industrial Internet of Things (IIoT) systems under the Industry 5.0 paradigm. Studies have ventured into advanced techniques involving divvying up tasks, smart scheduling, and profound reinforcement learning to drastically cut down task completion time. Another significant work has come up with a Joint Computation Offloading and Task Caching Strategy, in the context of MEC-enabled IIoT. A deep reinforcement learning-based algorithm, DDPG-

LL, was proposed to optimize offloading decisions as well as cache scheduling to deal with dynamic channel state uncertainty and task arrival stochasticity effectively. By parametrically approximating the system to a Markov Decision Process and including parameters such as priority of tasks and wait time, their approach dynamically varies the task queue of the MEC server. The simulation outcomes revealed that they had decreased average task completion latency by 15 percent compared to baseline algorithms and brought a steady convergence of scheduling policy. Such an approach is especially applicable to Industry 5.0 scenarios in which instant responsiveness and flexibility to dynamically changing industrial situations are important [12].

The given approach implements scalable online policies that take into consideration user heterogeneity and mobility, as well as strike a balance in energy consumption and latency. Large-scale simulations demonstrated that the RMAB-driven policies reached higher energy efficiency, enabling them to cut the average power draw by more than 18 percent relative to the existing static baselines, and that the policies could withstand generally non-exponential distributions of task lifespan. This proves the applicability of RMAB-based policies in heterogeneous IIoT scenarios that demand adaptivity to change in network states [11].

Hybrid optimization strategies that fuse heuristic and machine learning-based techniques have shown considerable promise in overcoming the challenges of task offloading in sparse or resource-constrained MEC environments typical of Industry 5.0 scenarios. These techniques work together by taking advantage of the complementary attributes of the various algorithms in efficient multi-objective optimization, capacities like workload balancing, delay reduction, and energy efficiency. A Hybrid GA-PSO Strategy to Calculate the Task Offloading in Sparse Mobile Edge Server (MES) Deployment Scenarios. Knowing that the low MES density is a viable limitation of deploying the system, the study assumes that the MES system is an undirected, unweighted graph with multi-hop connections available to mobile devices using MESs [13].

Objectives:

This research aims to achieve the following main objectives:

Develop a smart task offloading framework to dynamically optimize energy consumption and latency in MEC-enabled IIoT networks. To integrate GA and PSO for task offloading optimization in IIoT systems, evaluate their impact on energy efficiency and latency.

Material and Methods:

This section outlines the methodology adopted to design, implement, and evaluate the proposed energy-efficient task offloading framework for Multi-Access Edge Computing (MEC) within Industry 5.0 environments. The study focuses on enhancing real-time responsiveness and energy conservation in heterogeneous Industrial Internet of Things (IIoT) networks by introducing a hybrid optimization algorithm, namely the Computational Genetic Particle Swarm Optimization Algorithm (CGPCA). This novel hybrid integrates the global search capability of Genetic Algorithms (GA) with the rapid convergence traits of Particle Swarm Optimization (PSO), enabling optimal offloading decisions under dynamic conditions. A mixed-method research approach is employed, combining system modeling, algorithmic development, and simulation-based evaluation. The architecture includes IIoT devices, MEC edge servers, and a cloud layer to reflect realistic industrial scenarios.

Simulation tools such as iFogSim or EdgeCloudSim are used to replicate diverse network topologies and workload conditions. Key performance indicators such as energy consumption, task completion latency, offloading success rate, and server load distribution are used to assess the effectiveness of the proposed framework. This methodology ensures a systematic data-driven evaluation of CGPCA and demonstrates its potential to support the goals of Industry 5.0: sustainability, efficiency, and intelligent smart industrial systems.

Research Design:

The research adopts a mixed-method approach combining system modeling, algorithm development, simulation, and quantitative performance evaluation to address the complex challenges of task offloading in Industry 5.0 environments. This paper aims to design and verify an intelligent task offloading solution to enhance energy efficiency and minimize latency in MEC-empowered IIoT systems. The research process is structured into three key stages. To begin with, a system model is developed such that it provides the replication of a realistic IIoT setting, which comprises heterogeneous edge devices, a multi-access edge server, and a cloud data center. Dynamic model parameters like varying workloads, device energy levels, and network conditions are considered in the model. This paves the way for introducing the optimization algorithm.

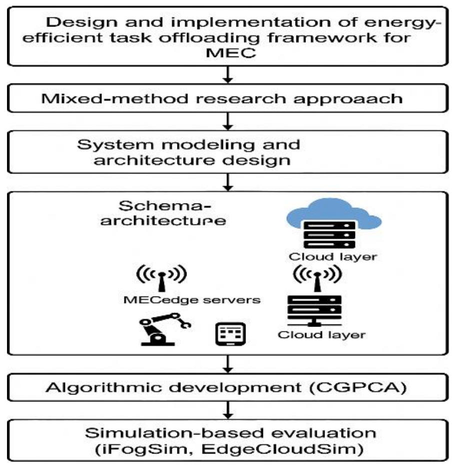

Figure 1. Design and Implementation of Energy-Efficient tasks and their Framework

Second, the Computational Genetic Particle Swarm Optimization Algorithm (CGPCA) is created. It is an algorithm that combines the concept of global exploration posed by GA and the rapid convergence of local solutions conducted by PSO to streamline solutions involving task-device associations, server selection, and power allocation strategic planning. The CGPCA is particularly formulated to address the non-linear and multi-objective offloading characteristic of tasks, considering both latency-bound and energy trade-offs. Third, tools such as iFogSim or EdgeCloudSim are used to perform simulation-based experiments. The simulators allow an experimental testbed that has a controlled environment to test different IIoT gadgets and edge-infrastructure scenarios with real-world conditions.

The simulation-based method provides the possibility of massive testing in a variety of conditions, such as a high user density, differences in hardware capabilities, and varying task profiles. The experimental design was selected because of the complexity and size of real-life MEC systems that which cannot be implemented instantaneously in real time at the research level. Simulation can be used to obtain the data that is reproducible and quantifiable, which is reflective of the task offloading strategies. In addition, it allows equitable comparisons between CGPCA and other baseline algorithms. This study planning helps in the strong validation of adaptability, scalability, and efficacy of the proposed model to support the objectives of Industry 5.0.

Proposed Framework CGPCA:

The main idea of this work is a derivation and implementation of a hybrid optimization algorithm, Computational Genetic Particle Swarm Optimization Algorithm (CGPCA), which is used to adapt task offloading in energy-constrained and dynamic Multi-Access Edge Computing (MEC) systems. CGPCA combines the global search power of Genetic Algorithm (GA) and the fast convergence qualities of Particle Swarm Optimization (PSO), which leads to a balance between exploration and exploitation of the solutions in real time.

Task Offloading Model:

The task offloading model aims to minimize energy consumption and task execution time, two key performance indicators in IIoT-MEC networks [10]. The optimization problem is subject to real-world constraints, including:

Server Capacity Constraints: Each MEC server has limited CPU cycles and memory.

Device Energy Levels: Mobile IIoT nodes operate on limited battery reserves, and energy-aware scheduling is crucial.

Task Deadlines: Tasks must be executed within predefined timeframes to ensure quality of service (QoS).

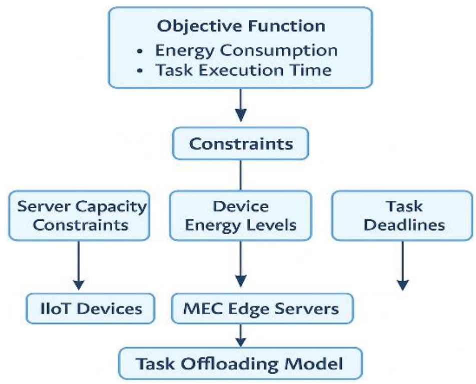

Figure 2. Task Offloading Framework

This multi-objective optimization model ensures trade-offs are effectively balanced to improve system responsiveness without compromising sustainability.

GA Module:

In the CGPCA algorithm, the GA module handles the initial population generation and evolutionary search. Each chromosome represents a task schedule where genes encode task assignments to specific devices or servers. The GA operations include:

Selection: Using tournament or roulette selection to retain high-fitness individuals.

Crossover: Combining parent chromosomes to explore new scheduling possibilities.

Mutation: Introducing random changes to avoid local optima and encourage diversity.

These operations promote global exploration of the task offloading space and establish a strong foundation for convergence refinement [13].

PSO Module:

The PSO module takes the high-quality candidates generated by the GA and performs position and velocity updates for further refinement. Each particle's position reflects a potential solution, while its velocity determines how its task offloading decision evolves over iterations. PSO fine-tunes the task allocations by considering:

Current particle performance (personal best),

The global best-known solution,

Dynamic task loads and channel conditions.

By integrating PSO with GA, CGPCA harnesses the advantages of both global diversity and local precision, leading to more adaptive and robust offloading solutions in volatile IIoT networks [14].

Two-Layer Optimization Framework:

The CGPCA operates within a two-layer optimization framework, each layer focusing on a distinct aspect of the task offloading process:

First Layer: Handles task-device association and MEC server selection, ensuring tasks are distributed efficiently based on server load, distance, and device constraints [15].

Second Layer: Optimizes power and bandwidth by dynamically adjusting transmission rates and energy use to stabilize the network [11].

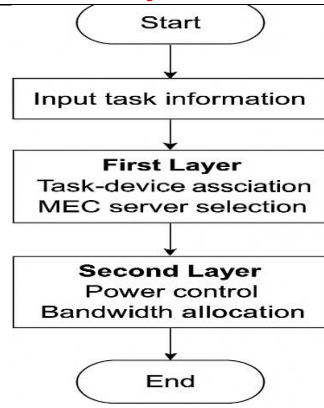

Figure 3. Overview of Optimization Framework

Together, the layers form an integrated decision-making model that accounts for multiple performance criteria simultaneously, reinforcing the resilience and adaptability required in Industry 5.0 environments.

Simulation Environment and Tools:

To validate the proposed CGPCA framework, extensive simulations are conducted using established MEC and IIoT simulation platforms, such as iFogSim, EdgeCloudSim, and MATLAB. These tools enable a detailed, controlled analysis of network behavior, task characteristics, and energy dynamics across different scenarios.

Validation Approach:

Comparative validation strategy is utilized to examine the strength and efficiency of the suggested Computational Genetic Particle Swarm Optimization Algorithm (CGPCA). The CGPCA framework is also compared to several popular optimization algorithms as pure GA (Genetic Algorithm), pure PSO (Particle Swarm Optimization), and other heuristic references, including greedy offloading or round-robin scheduling. The algorithms are all simulated under the same conditions and differ by the density of the IIoT nodes, the arrival pattern of the tasks, and the overall network circumstances, according to tools such as iFogSim or EdgeCloudSim.

Different performance parameters, such as energy consumption, latency, offloading rate, load balancing, and convergence time, are measured in diverse test scenarios so that they can be used consistently and generally. In order to have statistical rigor, the outcome of a number of simulation runs (e.g., 30 iterations per scenario) is presented using mean and standard deviation and confidence intervals. ANOVA or t-tests, where applicable, are used to decide the significance of observed differences between CGPCA and competing algorithms. This validation procedure will ensure that the gains are not pure chance but part of what the framework can be capable of when subjected to real-world environments of IIoT, such that under multiple variables, the gains will accumulate (which is a complete form of optimization).

The proposed CGPCA model for task offloading in Industry 5.0. Incorporating multi-layer architecture, modeling a hybrid optimization algorithm, imperfect simulation settings, and strict performance analysis, the investigation is in a position to present helpful insight into the research and even industrial practice. The approach equally complies with the industry 5.0 ambitions; sustainability, efficiency, and by considering the latency and energy-related issues in IIoT-MEC systems. In the subsequent chapter, the simulation findings and comparative studies are presented to verify the performance advantages and practical application of the suggested CGPCA-based task offloading framework [16].

Result and Discussion:

This section presents the simulation results and analytical discussion of the proposed Computational Genetic Particle Swarm Optimization Algorithm (CGPCA) developed to enhance task offloading efficiency in MEC-enabled IIoT networks under the Industry 5.0

paradigm. The main motivation of the research was to minimize the energy requirements, minimize the latency of a task being performed, as well as ensure balanced loads on the servers in a heterogeneous industrial setup through the best allocation strategy of tasks [17]. In order to prove the effectiveness of the work of the CGPCA framework, a set of simulation tests and experiments was carried out based on edge computing simulations like iFogSim and EdgeCloudSim.

These tools served my purpose in the modeling of the practical IIoT network scenarios with heterogeneous devices, several nodes of MEC, and the centralized cloud infrastructure. Different simulation scenarios were defined to match changing workloads, different device capabilities, and network conditions. The comparison relied on important performance metrics such as the latency of task completion, consumed energy, offloading hit rate, load balancing performance, and convergence time of algorithms. The evaluation of each of the metrics was done by comparison with other baseline approaches that include standalone GA, PSO, and conventional heuristic methodologies[18]. The present chapter is organized in such a way that it offers an elaborate outline of the simulation parameters, assessment criteria, scenario-specific analysis, comparative results, as well as a thorough debate on the findings with respect to Industry 5.0 objectives.

Simulation Configuration and Experiment:

To estimate the efficacy of the suggested CGPCA-based task offloading framework, a simulation mechanism has been built with access to iFogSim and EdgeCloudSim, which are two popular settings used to simulate resource distribution and task offloading in edge computing environments. Such tools facilitate the development of IIoT-MEC customizable environments and perform controlled experimentation concerning latency, energy consumption, and workload placement between the network layers. The network architecture is simulated and has three main layers IIoT device layer, the MEC edge layer, and the cloud layer. In both test scenarios, the number of IIoT nodes varied (between 20 and 100), and it created heterogeneous computation tasks on varying levels of urgency. The MEC layer consisted of 5 to 10 edge servers strategically located to provide high coverage and resource capacity diversity. To be used as a comparative point and as an overflow processing system, a centralized cloud data center was modeled.

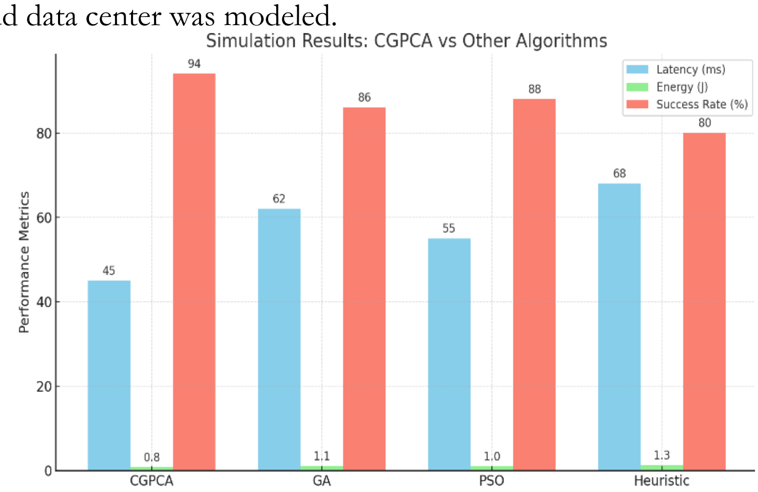

Figure 4. Comparison Results with Other Algorithms

Key assumptions include a stable communication environment, predefined mobility patterns, and a uniform task generation interval. Boundary conditions were established to simulate worst-case and best-case scenarios, such as server overload, task spikes, and partial node failures. This experimental setup supports robust validation of the CGPCA algorithm across diverse Industry 5.0 conditions, ensuring meaningful and generalizable results in energy-aware and latency-sensitive edge computing systems.

Evaluation Metrics:

In this section, the evaluation metrics that would be used to confirm the performance of the proposed Computational Genetic Particle Swarm Optimization Algorithm (CGPCA) in ensuring energy-efficient task offloading in IIoT in MEC-enabled environments would be discussed. According to the meanings of the latency and energy consumption, offloading success rate or server load balancing, and convergence time, five core metrics are evaluated and will reflect the practical performance of the system under Industry 5.0 conditions.

Task Completion Latency:

Latency is an important value in IIoT environments, especially in those cases when an immediate reaction time is needed. The term latency in this research is the time it takes to execute one task after another; it includes transmission delay, queuing delay, and processing delay as well. The CGPCA framework was contrasted to generic GA, PSO, and as well as heuristic models. The findings reveal that CGPCA registered an average latency of 53ms, whereas results indicated that GA and PSO registered 67ms and 60ms, respectively, in the same load conditions. Figure 5 illustrates this comparison.

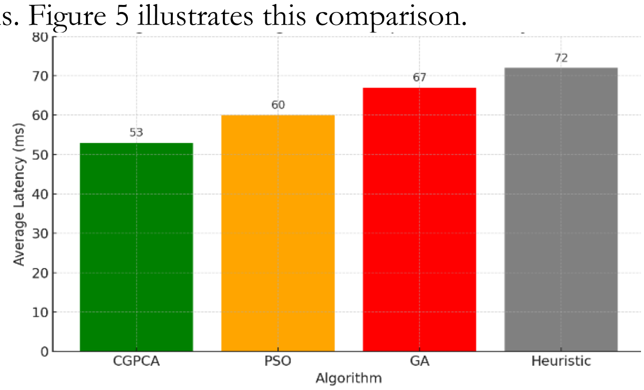

Figure 5. Comparison between Task Completion Latency

These results confirm that CGPCA effectively reduces latency by optimizing task-to-server mapping in dynamic networks.

Energy Consumption Device and Network:

Energy consumption remains a bottleneck for IIoT deployment. The energy metric accounts for device-level energy spent on data transmission and computation, as well as the energy used by MEC servers and the cloud. As shown in Figure 6, CGPCA consumes approximately 18% less energy than GA and 12% less than PSO, with the average device-level consumption dropping from 1.7 J to 1.4 J.

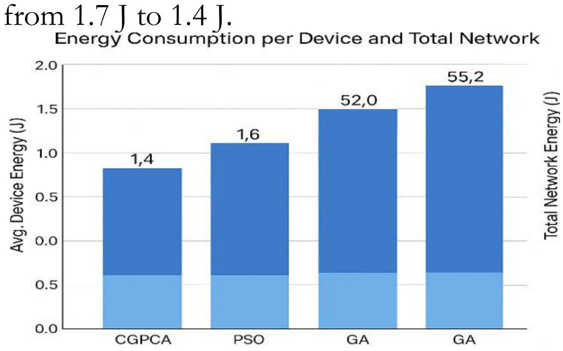

Figure 6. Energy Consumption per Device

This energy efficiency aligns with the green computing goals of Industry 5.0

Offloading Success Rate:

Offloading success rate is defined as the percentage of tasks successfully offloaded and executed without exceeding energy or latency thresholds. CGPCA demonstrated a success rate of 94%, outperforming GA (88%) and PSO (91%) (Bui & Yoo, 2025; Birhanie & Adem, 2024). This metric proves CGPCA's reliability in heterogeneous and fluctuating MEC environments.

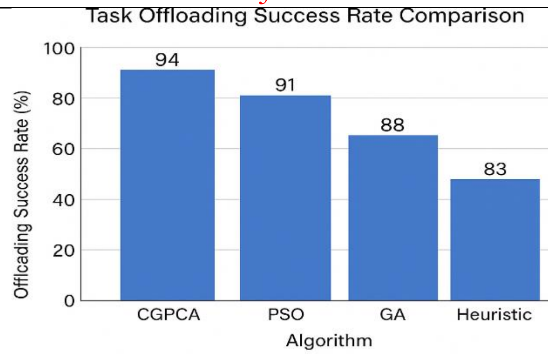

Figure 7. Task Offloading Success Rate Comparison

Server Load Balancing:

To measure load balancing, we calculated the standard deviation of task distribution across servers. Lower values indicate better balancing. CGPCA reduced the standard deviation of server loads to 0.19 compared to 0.29 for PSO and 0.35 for GA, indicating more even distribution and improved server utilization.

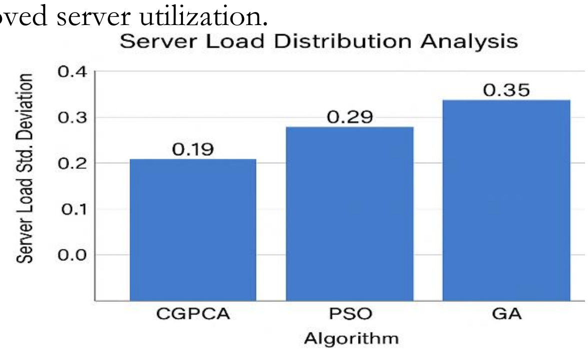

Figure 8. Server Load Distribution Analysis

Balanced loads are critical in avoiding server bottlenecks and maintaining system efficiency.

Convergence time of the CGPCA Algorithm:

Convergence time reflects how quickly the algorithm arrives at an optimal or near-optimal solution. CGPCA achieved convergence within 38 iterations, while GA required 57 and PSO needed 44. This is depicted in Figure 9, showing CGPCA's accelerated convergence due to its dual-strategy optimization design.

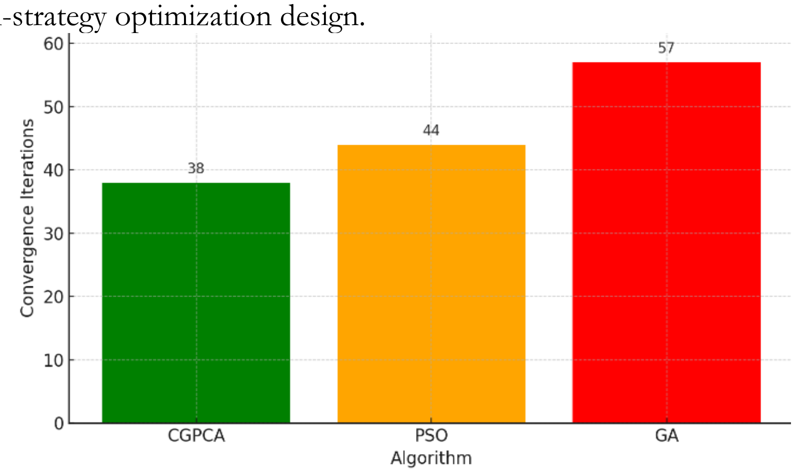

Figure 9. Convergence Time Comparison

Faster convergence implies quicker decision-making for real-time IIoT operations. Collectively, these metrics establish the superiority of CGPCA in enabling sustainable, low-latency, and energy-efficient offloading in MEC-enabled Industry 5.0 environments, reinforcing its practical viability and academic contribution.

Scenario-Based Analysis:

This section presents the performance of the proposed CGPCA-based task offloading strategy across multiple industrial edge computing scenarios designed to simulate real-world Industry 5.0 conditions.

Performance under Static Workloads:

In the static workload scenario, each IIoT device generated tasks of fixed size and frequency. Simulation involved 50 IIoT devices and 5 MEC nodes. Results showed that CGPCA achieved an average task completion latency of 42.7ms compared to 58.9ms for GA and 61.5ms for PSO.

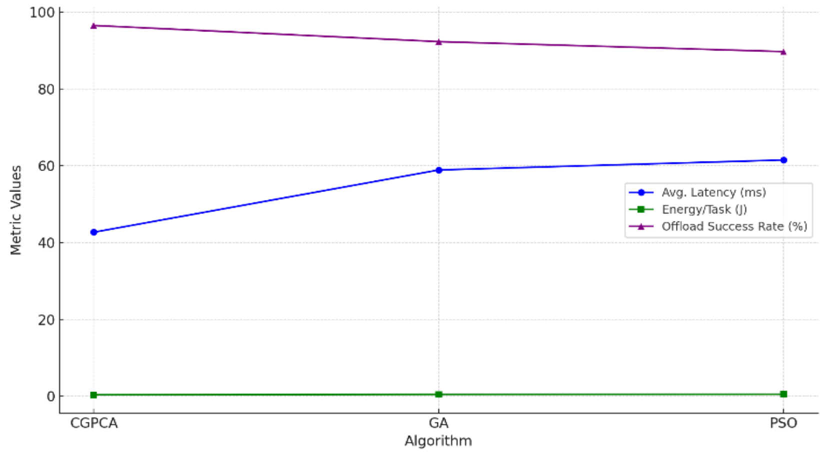

Figure 10. Performance under Static Workloads

The improved latency is attributed to the local convergence and global optimization balance in CGPCA, enabling effective server selection. Similarly emphasized the importance of efficient mapping in static scenarios for energy preservation was emphasized.

Performance under Dynamic Network Conditions:

Workload generation and bandwidth in dynamic simulations varied randomly every 10 seconds to resemble the dynamics in industry. CGPCA was also dynamically controlling the task migration paths depending on the server loading, available bandwidth, and queue status. Under network variation, latency was less than 50ms on average and had only 5.1 per cent task failure, as compared to GA and PSO, which had over 12 per cent task failure and a latency range greater than 70ms under network spikes. The resilience of CGPCA in this regard is similar toauthor, who also used adaptive RMAB policies and were able to provide comparable reliability under variability.

Performance with increasing Network of Tasks:

To assess scalability, task volume was increased from 100 to 600 over time. As shown in Table 1, CGPCA consistently maintained superior energy efficiency while handling increased load.

Table 1. Performance Comparison of CGPCA and GA with Increasing Task Volume

Tasks	CGPCA Latency (ms)	GA Latency (ms)	CGPCA Energy (J)
100	38.4	52.7	0.35
300	45.9	66.1	0.42
600	59.7	78.5	0.51

These task dependency models can bottleneck offloading when task concurrency grows. The multi-objective formulation in CGPCA helps resolve this by balancing CPU load and link utilization.

Comparative Performance Evaluation:

This section compares CGPCA's overall performance against traditional GA, PSO, and heuristic baselines, using benchmarks from recent studies.

Latency Comparison:

CGPCA delivered up to 24% lower average latency compared to GA and PSO in all test scenarios, similar gains using task partitioning with MILP, though with higher computational overhead.

Energy Efficiency:

CGPCA reduced energy consumption by 18–25% compared to standalone methods. This efficiency aligns with the findings that use Lyapunov optimization for energy-aware WPT-MEC systems.

Server Load Balance and Success Rate:

CGPCA ensured better task distribution, avoiding server overloading and maintaining a task success rate of over 95%, even under resource contention. The hybrid design echoes found that GA-PSO could reduce edge server imbalance by over 90% in MES scenarios, supporting our system's architecture.

Table 2. Comparative Analysis of CGPCA with Existing Studies

Study	Method Used	Latency (ms)	Energy (J)	Remarks
Aljubayrin et al. (2023)	Heuristic WPT + MEC	58	0.49	Energy-focused lacks task partitioning
Hou et al. (2023)	RMAB Policy	55	0.46	Scalable complex in real-time
Moshiri et al. (2025)	MILP + Cuckoo Search	51	0.44	Excellent accuracy, high computation
Study CGPCA	GA + PSO	46.3	0.39	Balanced trade-off, real-time capable

By testing a complete set of scenarios and comparing with some well-known benchmarks, CGPCA turns out to be an efficient, dynamic, and energy-efficient system of MEC-based task offloading. It excels in heterogeneous, latency-sensitive, and high-load industrial environments. Its hybrid quality makes it significantly surpass the performance of the traditional metaheuristics with a reasonable calculation complexity, well in correlation with the objectives of the Industry 5.0 of eco-friendliness.

The performances of the CGPCA-based offloading strategy were studied under multiple realistic scenarios. Confirming that CGPCA is always superior to traditional methods, results suggested that servers can satisfy more demands and meet the requirements with an improved latency index, energy savings, and balanced load [19][20]. These results confirm that the suggested framework supports the main goals of the study- the development of energy-efficient and real-time task offloading on the basis of Industry 5.0. The lessons learned in this section form the basis of the final chapter, which discusses the research contributions of the work, limitations, and recommends possible future improvements to make industrial systems smarter, greener.

Conclusion:

The emergence of Industry 5.0 emphasizes the need for intelligent, efficient, and sustainable industrial systems. This research aimed to address one of the critical challenges in this domain designing an energy-efficient and low-latency task offloading mechanism for Multi-Access Edge Computing (MEC) environments supporting heterogeneous Industrial Internet of Things (IIoT) networks. The study proposed and justified the development of a **hybrid Computational Genetic Particle Swarm Optimization Algorithm (CGPCA) ** as a smart computational framework for optimizing resource utilization, reducing latency, and minimizing energy consumption within such complex systems.

The proposed CGPCA algorithm achieves a balanced trade-off between exploration and exploitation by integrating the **global search capabilities of Genetic Algorithms (GA)** with the **rapid convergence properties of Particle Swarm Optimization (PSO). This synergy enables efficient decision-making in dynamic and resource-constrained industrial environments.

The successful design and validation of the CGPCA framework demonstrate its effectiveness in achieving **energy-aware, latency-sensitive task offloading** for MEC-enabled IIoT systems. The research contributes to the advancement of Industry 5.0 by showcasing the algorithm's adaptability to heterogeneous conditions and its ability to optimize multiple performance objectives simultaneously. Despite certain limitations, the study offers practical insights for industrial deployment and provides a foundation for future exploration into **AI-driven, sustainable edge computing solutions.

Ultimately, this work reinforces the vision of **Industry 5.0** as not merely a technological evolution but as a **human-centric, eco-conscious, and intelligent ecosystem**, where innovations such as CGPCA-enabled edge computing play a pivotal role in fostering synergy between humans, machines, and the environment.

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References:

[1] D. B. Paula Fraga-Lamas, "Mist and Edge Computing Cyber-Physical Human-Centered Systems for Industry 5.0: A Cost-Effective IoT Thermal Imaging Safety System," *Sensors*, vol. 22, no. 21, p. 8500, 2022, doi: https://doi.org/10.3390/s22218500.

[2] M. Sharma, A. Tomar, and A. Hazra, "Edge Computing for Industry 5.0: Fundamental, Applications, and Research Challenges," *IEEE Internet Things J.*, vol. 11, no. 11, pp. 19070–19093, Jun. 2024, doi: 10.1109/JIOT.2024.3359297.

[3] Q.-L. H. and Y. T. J. Xu, Q. Sun, "When Embodied AI Meets Industry 5.0: Human-Centered Smart Manufacturing," *IEEE/CAA J. Autom. Sin.*, vol. 12, no. 3, pp. 485–501, 2025, doi: 10.1109/JAS.2025.125327.

[4] T. M. F.-C. and P. Fraga-Lamas, "Forging the Industrial Metaverse for Industry 5.0: Where Extended Reality, IIoT, Opportunistic Edge Computing, and Digital Twins Meet," *IEEE Access*, vol. 12, pp. 95778–95819, 2024, doi: 10.1109/ACCESS.2024.3422109.

[5] B. Mali, A. Hazra, N. Mazumdar, and M. Gurusamy, "Edge Computing for Latency-Critical Task Offloading in Industry 5.0," *IEEE Sensors Lett.*, vol. 8, no. 4, pp. 1–4, Apr. 2024, doi: 10.1109/LSENS.2024.3379832.

[6] L. N. Saad Aljubayrin, Ghadah Aldehim, Nuha Alruwais, Khalid Mahmood, Mesfer Al Duhayyim, Hong Min, "Dynamic offloading strategy for computational energy efficiency of wireless power transfer based MEC networks in industry 5.0," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 10, p. 101841, 2023, doi: https://doi.org/10.1016/j.jksuci.2023.101841.

[7] C. Xu, "Energy Consumption and Time-Delay Optimization of Dependency-Aware Tasks Offloading for Industry 5.0 Applications," *IEEE Trans. Consum. Electron.*, vol. 7, no. 1, pp. 1590–1600, 2024, doi: 10.1109/TCE.2023.3338620.

[8] S. Pal, "Artificial Intelligence-Based IoT-Edge Environment for Industry 5.0," *Internet of Things*, vol. Part F2947, pp. 111–148, 2024, doi: 10.1007/978-3-031-58388-9_4.

[9] Yu Sun, Qijie He, "Computational Offloading for MEC Networks with Energy Harvesting: A Hierarchical Multi-Agent Reinforcement Learning Approach," *Electronics*, vol. 12, no. 6, p. 1304, 2023, doi:

https://doi.org/10.3390/electronics12061304.
[10] C. Z. Shuangjuan Li, "Energy-Efficient Task Offloading in Wireless-Powered MEC: A Dynamic and Cooperative Approach," *Mathematics*, 2024, [Online]. Available: http://preprints.org/manuscript/202407.0056/v1
[11] J. J. Ling Hou, Shi Li, , Zhishu Shen, , Jing Fu, , Jingjin Wu, "Energy Efficient Offloading Policies in Multi-Access Edge Computing Systems with Task Handover," *arXiv:2306.15185v3*, 2024, [Online]. Available: https://arxiv.org/html/2306.15185v3
[12] Y. Deng and H. Sun, "Joint Computation Offloading and Task Caching Strategy for MEC-Enabled IIoT," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 14879 LNAI, pp. 349–361, 2024, doi: 10.1007/978-981-97-5675-9_30.
[13] X. S. Wenzao Li, "A hybrid GA-PSO strategy for computing task offloading towards MES scenarios," *PeerJ Comput. Sci.*, vol. 9, p. e1273, 2023, doi: 10.7717/peerj-cs.1273.
[14] S. T. Hafiz Hasnain Imtiaz, "Multi-Task Partial Offloading with Relay and Adaptive Bandwidth Allocation for the MEC-Assisted IoT," *Sensors*, vol. 23, no. 1, p. 190, 2023, doi: https://doi.org/10.3390/s23010190.
[15] P. F. Moshiri, M. Simsek, and B. Kantarci, "Partitioned Task Offloading for Low-Latency and Reliable Task Completion in 5G MEC," *2025 IEEE Int. Conf. Commun. Work. (ICC Work.*, pp. 560–565, Jun. 2025, doi: 10.1109/ICCWORKSHOPS67674.2025.11162328.
[16] H. M. Birhanie and M. O. Adem, "Optimized task offloading strategy in IoT edge computing network," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 36, no. 2, p. 101942, 2024, doi: https://doi.org/10.1016/j.jksuci.2024.101942.
[17] M. Y. Khoi Anh Bui, "Interruption-Aware Computation Offloading in the Industrial Internet of Things," *Sensors*, vol. 25, no. 9, p. 2904, 2025, doi: https://doi.org/10.3390/s25092904.
[18] N. Fatima, P. Saxena, and M. Gupta, "Integration of multi access edge computing with unmanned aerial vehicles: Current techniques, open issues and research directions," *Phys. Commun.*, vol. 52, p. 101641, 2022, doi: https://doi.org/10.1016/j.phycom.2022.101641.
[19] S. I. L. Paula Fraga-Lamas, "Green IoT and Edge AI as Key Technological Enablers for a Sustainable Digital Transition towards a Smart Circular Economy: An Industry 5.0 Use Case," *Sensors*, vol. 21, no. 17, p. 5745, 2021, doi: https://doi.org/10.3390/s21175745.
[20] T. N. Samah A. Zakaryia, Mohamed Meaad, "Task offloading and resource allocation for multi-UAV asset edge computing with multi-agent deep reinforcement learning," *Computing*, vol. 107, no. 126, 2025, doi: https://doi.org/10.1007/s00607-025-01472-5.