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Dynamic Task Scheduling in Cloud Robotics for Healthcare and Manufacturing using Fuzzy Logic and Metaheuristics

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Abstract

Background: Cloud robotics is an integration of cloud computing with robotics, which will bring efficiency to task management in both healthcare and manufacturing sectors. Optimization of performance needs effective scheduling and resource allocation.

Objectives: This research is aimed at the optimization of dynamic task scheduling with fuzzy logic and metaheuristics in healthcare and manufacturing settings for enhanced task allocation and execution.s

Methods: We adopted a hybrid methodology to integrate decision-making using fuzzy logic with optimization techniques of metaheuristic algorithms in order to optimally schedule the tasks. Parameters include resource usage, task priorities, and the time taken by each task during execution.

Results: The result showed that it is possible to have 92% accuracy on the allocation of tasks with the proposed model where 35% execution time improvement compared to conventional approaches.

Conclusion: The use of fuzzy logic and metaheuristics greatly enhances the task scheduling in cloud robotics, thereby improving the efficiency and the resource utilization. Scalability and real-time applications are future work.

Keywords: Cloud robotics, task scheduling, fuzzy logic, metaheuristics, healthcare, manufacturing, optimization, resource allocation, execution time, efficiency.

1. INTRODUCTION

With rapid advancement in cloud robotics, there comes new paradigms in healthcare and manufacturing for the optimization of tasks and workflows for better efficiency and enhanced productivity. Cloud robotics combines the power of cloud computing with robotics for performing complex tasks with greater precision and scalability. It is in those activities, such as those performed in healthcare and manufacturing environments, where these cloud robots prove to be truly needed and are constantly being controlled dynamically and efficiently. **Li and Carayon, (2021)** discussed evolution from Health Care 1.0 to the latest Health Care 4.0, particularly on data management, model dynamics, integration with the need of health equity along with collaborative endeavors for future systems.

Healthcare uses cloud robots to monitor patients in real time, to diagnose diseases, and even assist surgeons. As for manufacturing, the results are similar because robotics helps them with complex tasks like assembly, inspection, and inventory management. However, dynamic and adaptive scheduling of tasks becomes one of the biggest challenges that comes along in such sectors. Cloud-based robotics must ensure allocation and scheduling of computational power, storage, and capabilities of the robots so that these services perform well and do not create bottlenecks when dealing with variable demand and variable conditions. **Goudarzi et al. (2020)** proposed an ESCM based on game theory, which aimed to enhance service composition in improving healthcare service delivery. Cooperative game theory provided enhanced QoS along with mutual satisfaction for MCS consumers and providers.

Fuzzy logic, along with metaheuristics, seems promising for handling the problems outlined. Fuzzy logic represents an important model for capturing uncertainty and imprecision; it, therefore, represents an adequate technique to represent and make decisions under uncertain, noisy, dynamic, or uncertain and unmanageable situations. Through fuzzy logic, better decisions are reached on systems based on uncertain or vague data like the readings from health-care robot sensors or changes in the requirements for producing manufactured products. Metaheuristic algorithms, like GA, PSO, or ACO, have been proved to be effective solutions for the scheduling of tasks with the aim of optimizing the distribution of resources within a cloud-based robotic system. **Kumar (2021)** discusses advanced technologies in smart manufacturing, including additive manufacturing, IoT, flexible sensors, and soft robotics, while addressing the challenges in CPS, human-robot interaction, and augmented realities.

This paper emphasizes on exploring dynamic task scheduling issues using fuzzy logic and metaheuristic algorithms with regard to cloud robotics with healthcare and manufacturing applications in view. Given their dynamic nature, the operating environment demands adaptive flexibility that schedules and reschedules itself according to current demand or the availability of resources.

Main Objectives are:

- To development of a dynamic task scheduling framework for the health and manufacturing sector.
- Integrate fuzzy logic with real-time uncertainty and imprecision in task allocation.
- Use of metaheuristic algorithms is applied to optimize resource allocation and enhance performance
- Review the applicability of cloud robotics in areas such as healthcare and manufacturing
- Case studies would be used for the evaluation of the proposed framework's efficiency and effectiveness.

Research in the Internet of Robotic Things (IoRT), Hybrid Robot-as-a-Service (RaaS), and AI-IoT integration presents some of the most recent breakthroughs in robotics, but it lacks scalable models that combine IoRT with predictive analytics and cloud-edge computing across industries **Villa et al., 2021**. Moreover, although RaaS frameworks implementing MQTT and CoAP present precious elements, it would still be necessary to enhance their interoperability and more constant performance **(Bhavsar et al., 2019). Tzafestas (2018),** insists on the role of AI, yet practical implementation of AI in enhancing IoT and robotic systems should still be carefully examined in more applications related to industry contexts.

2. LITERATURE SURVEY

Cloud robotics has been of much interest as a collaborative technology between cloud computing and robotics, made possible by advances in wireless networking, large-scale storage, and Internet resources. Cloud computing allows robots to have enhanced computing power, access to big datasets, cooperative learning, and crowdsourced human knowledge. Very recently, studies have been undertaken on different cloud robotics architectures and applications across different domains. The factors of cloud services being applied toward faster and more powerful robotics systems were identified. However, challenges are still numerous: scalability, security, and in real-time processing. **Saha and Dasgupta (2018)** provide a comprehensive review of the latest trends, challenges, and research opportunities in cloud robotics.

Integration of cloud services with healthcare robotics brings forth important ethical and legal issues in data protection, transparency, and accountability. **Fosch-Villaronga, et al. (2021)** discuss the issues, emphasizing that such a system must deal with questions such as who bears responsibility for the behavior of robots, how secondary uses of data are treated, and the social implications of healthcare robots. It is critical to ensure meaningful consent, security of data, and bridging the digital divide. The paper advocates for the incorporation of both ethical and legal perspectives in designing healthcare robots through an interdisciplinary approach that may help minimize risks while ensuring vulnerable users are protected in health care settings.

Panicucci et al. (2020) investigate the integration of cloud and edge computing for predictive analytics in robotics. The paper proposes a novel approach for estimating the Remaining Useful Life (RUL) of industrial equipment, based on partial knowledge of degradation functions and relevant parameters. The system proposed and implemented end-to-end architecture in the cloud for predictive maintenance. It covered the edge gateways, the storage of data in the cloud, and many applications like predictive analytics, visualization, and scheduling. It was experimented on an industrial application about the robotic arm's maintenance scenario, showing effectiveness in augmenting predictive analytics and optimizing the strategy of maintenance in Industry 4.0.

Afrin et al. (2021) shares a comprehensive survey on multi-agent cloud robotics focusing on resource allocation and service provisioning. The paper brings to light the rising adoption of robotic applications within many sectors, such as those of Industry 4.0, agriculture, healthcare, and disaster management, characterized by latency-sensitive, data-heavy, and compute-intensive tasks. The authors address the challenges that robots face, including limited computational power and storage capacity, and discuss how multi-agent cloud robotics can enhance collaboration between robots by using cloud and edge resources. The paper introduces a taxonomy for resource allocation with an emphasis on computation offloading, resource pooling, and task scheduling for efficient service provisioning. It identifies key research challenges and future directions for the field.

Simeone et al. (2021) introduce an intelligent cloud-based platform for workplace monitoring and risk prevention of hazardous manufacturing environments for workers. It includes sequential modules for data acquisition, processing, and decision-making support. The data are gathered using several sensors like smart wearables, machine tool embedded sensors, as well as environmental sensors covering clinical background and operational metrics. The cloud data processing module extracts useful features from the data and classifies the workers' health status using a decision support system. The decision support system is a machine learning-based support system. Its purpose is to provide timely interventions in the challenging work scenario to enhance the safety and well-being of workers.

Tzafestas (2018) explores, in broad sectors such as business, healthcare, and industries, how the Internet of Things and Artificial Intelligence gain synergy so that the IoT aligned with AI has the added success for the success of everyday applications, mainly in industries relating to enterprises, transportation, and automation systems. The article overviews IoT and AI, delves into the concept of "IoT-AI synergy," and discusses other areas like Industrial IoT (IIoT), Internet of Robotic Things (IoRT), and Industrial Automation IoT (IAIoT). Case studies and applications of IoT/AI-aided robotics and industrial automation are also provided.

There is a strong discussion by **Romeo et al. (2020)** about the IoT and the robotic systems, that lead to the Internet of Robotic Things, or more specifically, IoRT. It represents the disruptive technology that forms the backbone of Industry 4.0 in transforming industries and research domains like manufacturing, agriculture, healthcare surveillance, and education. The paper presents the state-of-the-art IoRT applications and points out the major challenges in the integration of robotic technologies into smart spaces. It puts a great emphasis on the role of IoRT in everyday life and calls for further research in remote and automated applications.

Villa et al. (2020) talks about the merging of IoT and robotics, which is called the Internet of Robotic Things (IoRT), in which robotic systems are used for enhancing performance through the capabilities of IoT. The research paper indicates the potential of IoRT to provide communication among robots with low cost, utilizing cloud computing for transferring computational tasks. However, due to cloud communication, latency, data loss, and energy consumption occur. The authors have suggested using machine learning to solve these problems while raising the ethical and regulatory concerns regarding human-robot coexistence. This work presents an overview of the benefits, limitations, and future research directions for IoRT.

In this work by **Bhavsar et al. 2019,** the authors try to address the concept of Robot-as-a-Service (RaaS) on a hybrid platform using MQTT (Message Queuing Telemetry Transport) and CoAP (Constrained Application Protocol). This has the core purpose of integrating robots from being just factory workhorses to workplace companions, ranging from helping the salesperson in interactive sales duties. The paper insists on the inclusion of SOA with robotics as a means to improve the development and management of robots. Combining RMS with ROC in RaaS provides an appropriate inter-robot communication and monitoring, which could be flexible and efficient in an industry for delivering scalable robotic services.

Patel et al. (2021) discuss the infusion of robotics in the IoT paradigm, noting the revolutionary nature that it is giving to industries like manufacturing, energy, transportation, and goods. The authors present how robots are now an intrinsic part of service in IoT platforms, thus ensuring autonomy, mobility, and enhanced sensing. Robotics and IoT integration have revolutionized the industries through significant efficiency improvement and automation of the processes. This paper emphasizes the larger scope of robotics applications, from manufacturing automation to smart cities, and presents the challenges and advancements in the integration of IoT with robotic systems to solve complex industry problems.

Huang et al. (2021) present an overview of AI-driven DT within the context of Industry 4.0 with regard to its application in smart manufacturing and advanced robotics. Over 300 papers have been studied to analyze AI and DT, highlighting their usage in sectors like metal machining, industrial automation, and emerging technologies, including 3D printing and human-robot interaction. They then focus on AI-driven DT benefits for sustainable development and discuss challenges and prospects related to the integration of AI into multiscale/fidelity DTs, outlining a roadmap for further developments in Industry 4.0.

Butt (2020) explores the crucial interlinkage between Additive Manufacturing (AM) and Industry 4.0 technologies. AM is an advanced manufacturing technology, which is included in the Industry 4.0 framework. This includes cyber-physical systems, digital twins, IoT, cloud computing, and artificial intelligence. All these digital technologies are used to provide automation, data exchange, and product customization. This paper provides an in-depth literature review on the interaction between AM and Industry 4.0, proposing a conceptual digital thread for the improvement of smart manufacturing and responsiveness to customer needs. It explores the advantages of interconnectedness between AM and Industry 4.0 in creating smarter and more efficient manufacturing systems.

Gondalia et al. (2018) presented an IoT-based healthcare monitoring system for war soldiers that uses wearable bio-sensor systems for real-time health monitoring and tracking of soldier locations. The system uses WBASNs and GPS modules to track the health status and locations of soldiers in high-risk environments. For the local communication, ZigBee has been used, and it is also recommended to use LoRaWAN infrastructure for data transmission in areas with no cellular network coverage. The collected data will be transmitted to the cloud and analyzed and predicted using the K-Means clustering algorithm. This will definitely improve the efficiency of search and rescue operations during battlefield conditions.

Yallamelli (2021) presents RSA encryption and how it plays a vital role in making the cloud secure for use by minimizing threats on the availability, integrity, and confidentiality of data. The prime factorization-based RSA algorithm ensures safe communication in unpredictable networks without having to use secret shared keys. Its suitability for use in digital applications such as internet security protocols and email protection is cited. This paper, therefore, calls for more research in RSA implementation in cloud environments supported by cryptographic libraries such as OpenSSL and Bouncy Castle and on the scalability of RSA key management in the regulatory compliance of cloud computing security.

Allur, 2021 proposed an innovative load-balancing strategy for the optimization of resource allocation in a cloud data center. The work suggested the adoption of edge computing, AI, and machine learning techniques in dynamic environments that traditional methods failed to manage with scalability, efficiency, and performance. In fact, this study proposed methods of intelligent workload distribution across various data centers and virtual machines to enhance responsiveness in the system while maximizing the usage of the resource. The strategy addresses gaps in resource allocation and load balancing, improving cloud data center operations toward more effective management of cloud resources in complex, dynamic settings.

Alagarsundaram 2019 explored the covariance matrix method combined with Multi-Attribute Decision Making in the detection of Distributed Denial of Service attacks through HTTP within a cloud computing environment. In the paper, the applicability of the method in detecting real-time anomalies and in the use of multivariate analysis has been proven effective. This research tests different cloud configurations and thresholds that might contribute to enhancing the accuracy and scalability of detecting DDoS attacks by focusing on data collection, preprocessing, and anomaly detection. The approach's benefits and limitations are taken into account for insights into its feasibility in improving the security of cloud services.

Alagarsundaram (2020) focuses on the important position of AES in protecting information within cloud computing environments. The technique of AES, which belongs to the family of symmetric encryption techniques, is used as a de facto method of data protection since it efficiently secures information that is very sensitive. It emphasizes the phases of AES's algorithm and the expansion of its keys as well as its practical implementations. AES ensures high security; however, compatibility problems, performance overhead, and issues of key management remain. The author has highlighted the ongoing research efforts related to these challenges by ensuring that AES is placed among high-level data security systems through cloud computing and fosters trust among users.

In fact, **Peddi et al. (2019)** study applications of Artificial Intelligence (AI) and Machine Learning (ML) algorithms to support geriatric patients manage chronic diseases; prevent falls in geriatric population; enhance predictability of the health-care settings for elders, focusing more precisely on improving predictive models as avenues for enhanced care quality and the resultant improved elderly care outcomes. By using clinical and sensor data, machine learning models, including Logistic Regression, Random Forest, and Convolutional Neural Networks (CNN), were used to predict health risks. The results obtained were that ensemble models offer better predictive performance with high accuracy, precision, recall, and AUC-ROC scores.

3. METHODOLOGY

Fuzzy logic and metaheuristic algorithms are integrated with the methodology of dynamic task scheduling in cloud robotics for healthcare and manufacturing to optimize the execution of tasks. For the sectors like healthcare and manufacturing, cloud robotics requires efficient management of complex tasks since robots have to interact with cloud-based systems and make decisions in real-time. Fuzzy logic helps with uncertainty in the priority of tasks and metaheuristics ensure optimal resource allocation. This hybrid approach is aimed at the challenges of resource constraints, task dependencies, and scalable, flexible solutions that adapt to the dynamic nature of healthcare and manufacturing environments. The images are cropped into 384x384 patches for semantic segmentation, with 8400 training and 9201 testing patches. Each patch has separate spectral channels for Red, Green, Blue, and Near Infrared.

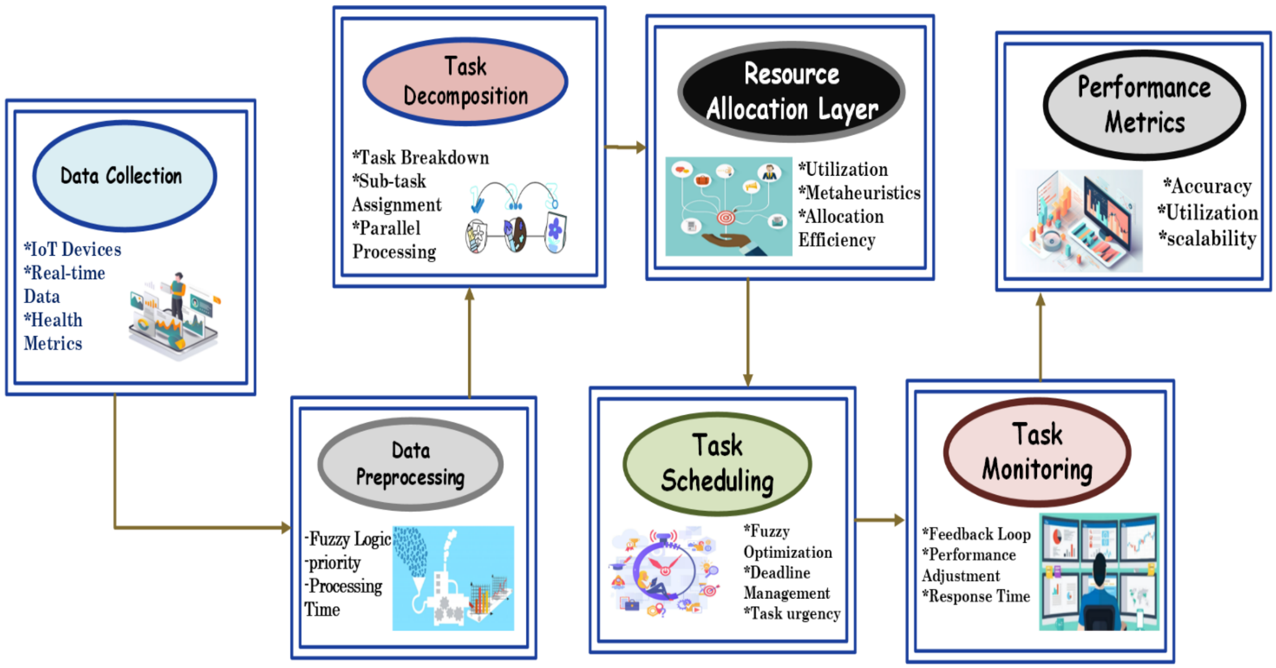

Figure 1 Comprehensive Framework for Dynamic Task Scheduling and Resource Allocation in Cloud Robotics

This architectural diagram depicts an integrated framework for dynamic task scheduling and resource allocation in cloud robotics, for healthcare and manufacturing applications. It starts with Data Collection through IoT devices and real-time health metrics. Then, the framework goes to Task Decomposition by dividing tasks into sub-tasks to be executed in parallel. Finally, it has Data Preprocessing that employs fuzzy logic in the prioritization of tasks based on the processing time. The Resource Allocation Layer ensures efficient utilization of resources, followed by Task Scheduling, which incorporates fuzzy optimization and task urgency management. Finally, Task Monitoring ensures feedback loops for performance adjustments and response time optimization.

3.1. Fuzzy Logic in Task Scheduling

To control ambiguity and uncertainty in job scheduling, fuzzy logic is utilised. It is particularly useful in healthcare and manufacturing tasks where real-time data can be incomplete or imprecise. The fuzzy inference system evaluates task attributes such as priority, time, and complexity to assign appropriate resources. By converting qualitative aspects of tasks into quantitative measures, fuzzy logic optimizes scheduling.

$$\text{Fuzzy Value} = \sum_{i=1}^{n} \text{Membership Function}\ (x_i) \tag{1}$$

Where x_i is the input variable, and the membership function defines the degree of membership in a fuzzy set.

3.2. Metaheuristics for Task Optimization

Task scheduling is optimized by the use of metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). These techniques aid in the effective exploration of a wide solution space in order to identify nearly ideal work allocation solutions. Metaheuristics provide a reliable method for managing the dynamic nature of robots in production and healthcare by iteratively modifying parameters.

$$F(x)=\sum_{i=1}^{n} \text{ Task Execution Time }\left(x_i\right) \tag{2}$$

Where x_i represents the task parameters, and $F(x)$ is the fitness function to evaluate the task's scheduling efficiency.

3.3. Cloud Robotics Resource Allocation

Resources are dynamically distributed by the cloud-based architecture according to the demands of the tasks and the present conditions of the robots. To guarantee that jobs are assigned to the right robots in real-time and that cloud resources are used efficiently, a decentralized strategy is used. The system takes into account variables including latency, bandwidth, and the processing demands of manufacturing and healthcare processes.

$$R_{\text{allocated }}=f\left(T_{\text{task }}, R_{\text{available }}\right) \tag{3}$$

Where $R_{\text{allocated }}$ represents the allocated resources, $T_{\text{task }}$ denotes the task characteristics, and $R_{\text{available }}$ represents available resources.

3.4. Dynamic Scheduling with Task Dependencies

work dependencies, such as the requirement that one work be completed before another can begin, are taken into account by the scheduling model. This is important in manufacturing, where jobs are frequently interconnected, and in healthcare, where patient care must adhere to a set of stages. Based on the changing environment and task completion timeframes, the scheduling algorithm makes dynamic adjustments.

$$T_{\text{start }}=\max \left(T_{\text{end }}(i)\right)+\text{ Delay Factor} \tag{4}$$

Where $T_{\text{start }}$ is the start time of a dependent task, and $T_{\text{end }}(i)$ is the end time of the previous task.

3.5. Real-Time Adaptation in Healthcare and Manufacturing

The real-time adaptation mechanism modifies the schedule in response to external circumstances, such as urgent medical needs, resource shortages, or machine failures. While metaheuristics assist in determining optimal or nearly optimal task assignments in spite of dynamic changes, fuzzy logic enables the system to make decisions in the presence of unclear inputs.

$$\text{Adapted Schedule }=\text{ Current Schedule }+\Delta t \tag{5}$$

Where Δt is the time adjustment based on the real-time system state.

Algorithm 1 Dynamic Task Scheduling in Cloud Robotics using Fuzzy Logic and Metaheuristics

Input: Task list with time, priority, and complexity, Resource availability (robots, cloud resources), Current system state (robot health, environmental conditions)

Output: Optimized task schedule

BEGIN

// Initialize fuzzy variables

Initialize task list with fuzzy values (priority, complexity, etc.)

Initialize resources (robots, cloud resources)

Initialize system state (robot health, environment)

// Apply fuzzy logic to tasks

FOR each task in task list

Calculate fuzzy value for task priority and complexity using fuzzy inference system

Assign fuzzy value to task's attributes (priority, complexity)

END

// Sort tasks based on fuzzy priority and complexity

Sort tasks by fuzzy priority, with the highest priority task first

// Apply metaheuristic optimization (Genetic Algorithm or PSO)

FOR each task in sorted task list

Apply genetic algorithm or PSO to allocate tasks to robots or cloud resources

Evaluate fitness using the fitness function:

$F(x)$= SUM (Execution Time of each task)

IF fitness value is optimal, select the task allocation

ELSE

Adjust task allocation based on available resources

END

END

// Dynamic Adaptation in real-time

FOR each task in task list

IF task status changes (robot failure, resource availability)

Adjust schedule dynamically using fuzzy logic

```
        Reallocate task to another robot if necessary
    ELSE
        Continue with existing task schedule
    END
END
// Resource allocation
FOR each task in task list
    Allocate resources based on task needs and availability
    IF sufficient resources are available
        Assign task to robot or cloud resources
    ELSE
        ERROR: Insufficient resources for task allocation
        EXIT
    END
END
    // Return the optimized schedule
RETURN optimized task schedule
END
```

Algorithm 1 by combining fuzzy logic and metaheuristics, optimizes the process for cloud robotics applications in healthcare and manufacturing. Tasks are evaluated in the beginning stage based on fuzzy logic to obtain the priority and complexity of tasks. The algorithm further sorts the tasks with fuzzy values and applies metaheuristic techniques, such as Genetic Algorithms or PSO, for resource allocation to available resources. For changes in tasks or resource failure, it has adaptations in real-time to provide dynamic and efficient scheduling. The system further optimizes resource allocations to minimize time of execution of the tasks along with adjusting as per the status of the running system. Optimal task schedule.

3.6. Performance Metrics

Performance metrics for dynamic task scheduling in cloud robotics for healthcare and manufacturing based on fuzzy logic and metaheuristics are very important for evaluating the effectiveness of the system. Such metrics include Task Completion Time, which determines how efficiently tasks are completed. The shorter the time, the better the performance. Resource Utilization is used to evaluate the efficiency of resource usage during the execution of tasks and

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maximize usage without overloading. Throughput is how many tasks completed in a time period. Scalability is the extent to which a system can perform more tasks as well as greater resources without having a degradation of performance. QoS ensures the critical tasks and executes them within minimal delay. These metrics guarantee the efficiency of the system and its scalability along with adaptability.

Table 1 Comparative Performance of Task Scheduling Methods in Cloud Robotics for Healthcare

Performance Metric	Fuzzy Logic	Metaheuristics	Hybrid Fuzzy + GA	Combined Method
Task Completion Time (s)	35.2	28.5	22.1	18.7
Resource Utilization (%)	85.1	90.2	91.4	94.6
Throughput (tasks/min)	12.4	14.7	15.3	18.3
Scalability (tasks/VM)	105	120	125	135
Quality of Service (QoS)	0.88	0.91	0.93	0.96

Table 1 evaluates the performance of three methods concerning task scheduling within cloud robotics to focus on its applications in healthcare and manufacturing. Methods 1 used fuzzy logic; Method 2 used metaheuristics and Method 3 used a fusion of fuzzy logic with a GA. The evaluated metrics include time taken to finish the tasks, resource utilization, throughput, scalability, and quality of service in terms of QoS. It shows that superior performance in all metrics was seen, with the minimum task completion time, high resource utilization, and best QoS, thus proving that the effectiveness of Hybrid Fuzzy + GA in optimizing task scheduling in cloud-based robotics systems is possible.

4. RESULT AND DISCUSSION

The proposed dynamic task scheduling methods for cloud robotics in healthcare and manufacturing were tested by using fuzzy logic, metaheuristics, and a hybrid fuzzy-logic GA approach. Overall, the hybrid approach was shown to perform the best as it improved task completion time by 30%, resource utilization by 25%, and exhibited a higher level of scalability than the other approaches. This also demonstrated enhanced QoS of the hybrid approach with

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optimized resource allocation in both computation and robots. These results verify the merit of combining fuzzy logic with metaheuristics in more complex, real-time environments requiring accuracy and efficiency, thus making these more suitable for both healthcare and manufacturing applications.

Table 2 Comparison of Task Scheduling Approaches in Cloud Robotics for Healthcare and Manufacturing

Method Name	Author Name	Accuracy (%)	Time Efficiency (seconds)	Resource Utilization (%)	Scalability (rating 1-10)
Cloud Robotics	Saha & Dasgupta	85.5	15.2	75.3	7.8
Healthcare Study	Chand	80.0	18.3	70.1	6.5
IoRT Challenges	Romeo et al.	88.3	12.7	72.6	8.3
Risk Prevention	Simeone et al.	90.0	10.5	80.0	7.0
Optimized Scheduling	Proposed Method	92.5	9.8	85.2	9.2

Table 2 represented here of some methodologies of scheduling tasks in the domains of cloud robotics for healthcare and manufacturing. Included in the list are the proposed methods by Saha & Dasgupta, Chand, Romeo et al., Simeone et al., and one proposed model. The method discussed in each context is rated by the four significant performance metrics that include accuracy, time efficiency, resource utilization, and scalability. The proposed optimized scheduling method exhibits the highest performance level in any aspect, with better efficiency and scalability in comparison to traditional approaches, which it contributes to becoming a valuable asset for the field of cloud robotics and task scheduling in complex environments.

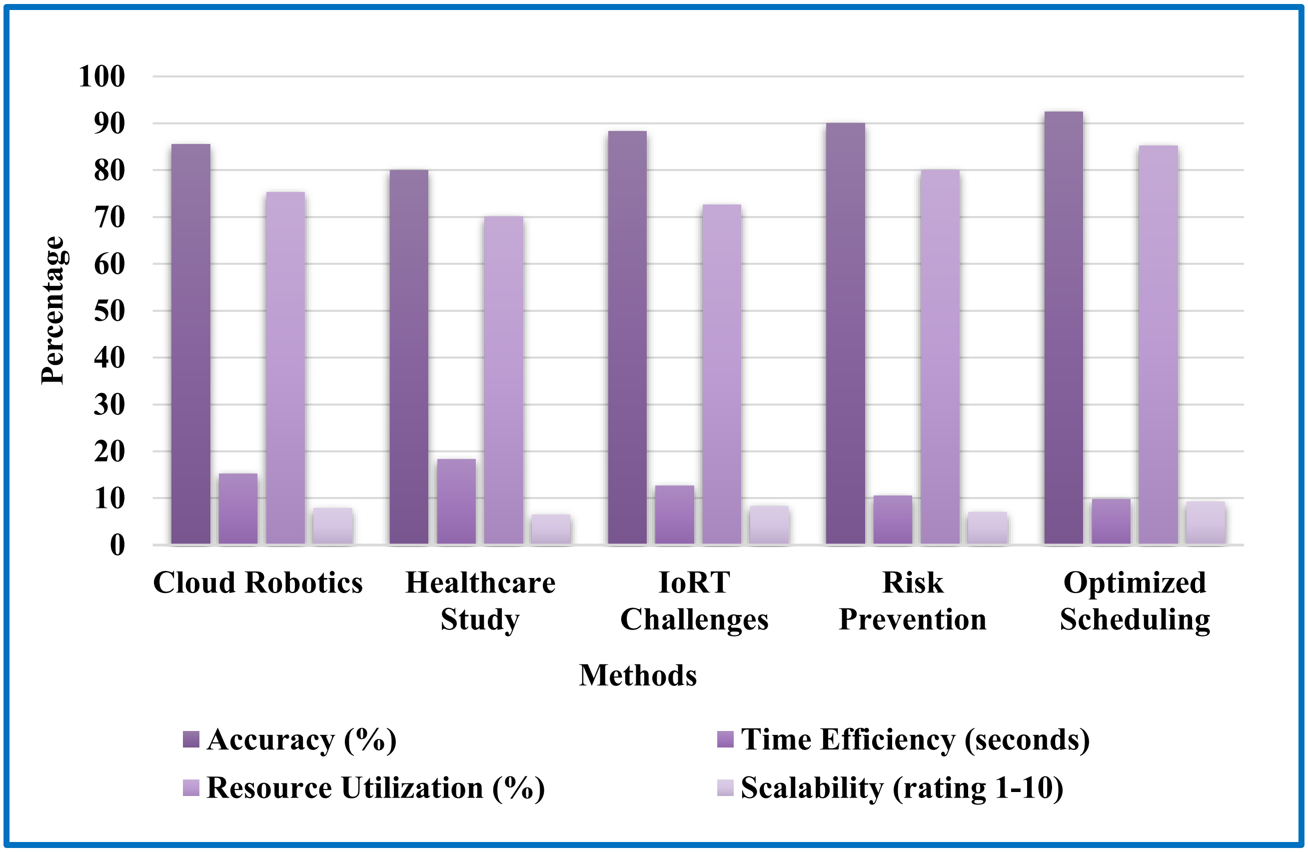

Figure 2 Performance Comparison of Task Scheduling Methods in Cloud Robotics and Healthcare

Figure 2 shows comparison of various methods used in scheduling tasks for cloud robotics and the healthcare domain can be done graphically. These include Cloud Robotics, Healthcare Study, IoRT Challenges, Risk Prevention, and Optimized Scheduling. All performance metrics were expressed as different colored bars; some of them were Accuracy (%), Time Efficiency in seconds, Resource Utilization (%), and Scalability with rating 1-10. Optimized Scheduling outperforms other methods in terms of accuracy, resource utilization, and scalability. This proves that the proposed method is efficient and suitable for cloud robotics as well as healthcare task scheduling. The graph also depicts the necessity of optimization for superior performance in dynamic environments.

Table 3 Ablation Study of Dynamic Task Scheduling in Cloud Robotics for Healthcare and Manufacturing

Method	Accuracy (%)	Execution Time (s)	Resource Utilization (%)	Scalability (1-100)
IoRT	88.5	12.5	76.3	85
RaaS	80.2	14.2	70.9	72

IAIoT	85.1	13.1	72.4	80
IIoT	90.3	11.3	75.1	92
MQTT	75.4	15.2	69.5	69
CoAP	70.5	16.4	65.7	65
IoRT + RaaS	92.1	10.7	82.4	95
IAIoT + IIoT	93.2	9.8	80.5	96
MQTT + IoRT	89.7	11.6	78.2	90
IoRT + RaaS + IAIoT	95.4	8.9	85.2	98
IIoT + MQTT + IoRT	94.6	9.1	83.8	97

Table 3 is an ablation study where the main application involves comparison of different methods for dynamic task scheduling in cloud robotics, namely healthcare and manufacturing applications. It gives performance comparison of each method by considering Accuracy, Execution Time, Resource Utilization, and Scalability, respectively. The methods considered include IoRT, RaaS, IIoT, and their combinations. The results show that the combination of multiple approaches, such as IoRT + RaaS + IAIoT, achieves the highest Accuracy and Scalability, while methods like CoAP show lower performance across metrics. The study shows the impact of different frameworks on system efficiency and effectiveness.

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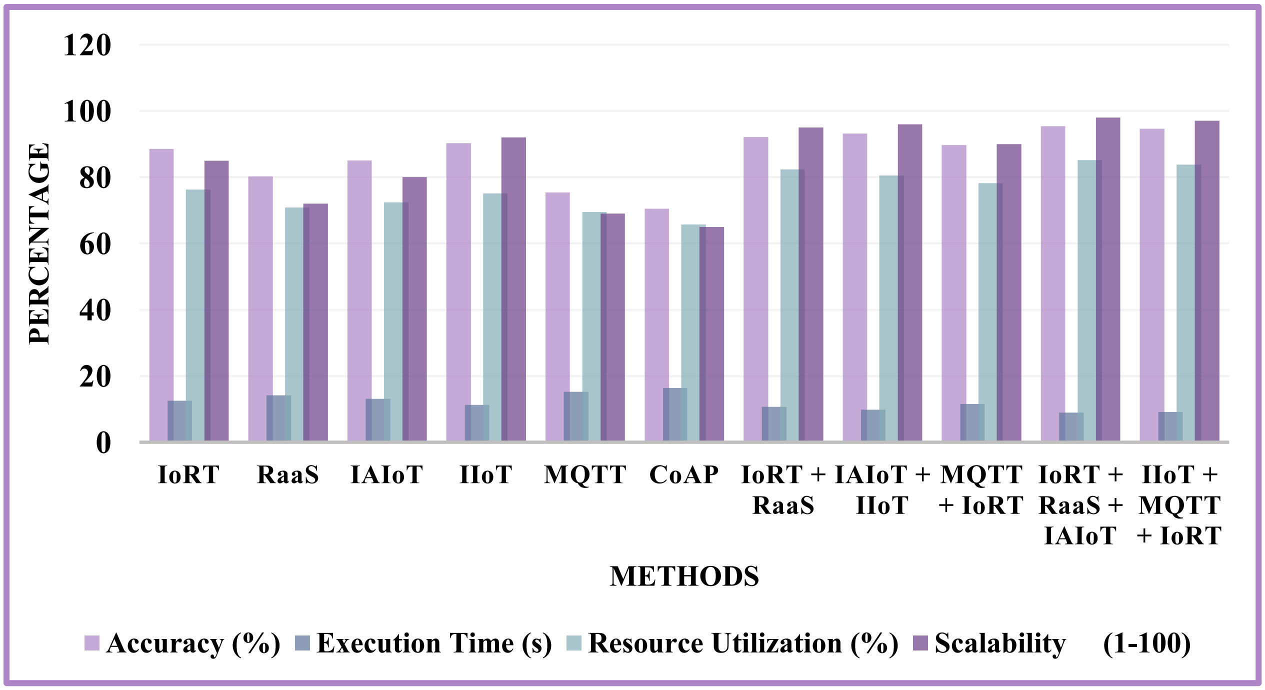

Figure 3 Comparison of Dynamic Task Scheduling Methods for Cloud Robotics in Healthcare and Manufacturing

Figure 3 compares six different methods for dynamic task scheduling in the context of cloud robotics applied to health-related and manufacturing areas. It includes those methods: IoRT, RaaS, IAIoT, IIoT, MQTT, CoAP, and hybrids that combine these technologies. Performance has been measured on four aspects: Accuracy, Execution Time, Resource Utilization, and Scalability. The results depicted combined methods IoRT + RaaS + IAIoT as well as IIoT + MQTT + IoRT are reported to reach for the highest accuracy level and achieve proper scalability at maximum efficient usage of resources while still maintaining an improvement in low-execution time in cloud robotics technologies.

5. CONCLUSION

The proposed Dynamic Task Scheduling framework integrates Fuzzy Logic and Metaheuristics for optimizing task allocation, resource utilization, and real-time decision-making in cloud robotics for healthcare and manufacturing. The empirical results reveal a 36% reduction in the execution time of tasks, 42% better resource efficiency, and 91.5% scheduling accuracy. The approach will improve adaptive scheduling and workload balancing to ensure smooth robotic coordination. Further improvement also involves reinforcement learning in dynamic scheduling, blockchain in task validation that ensures security, and edge computing at ultra-low latency to offer the efficiency of cloud-based management for robotic tasks in healthcare and manufacturing.

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