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A New Scheduling Challenge for Real-World Human-Robot Collaboration in Internet of Things Applications

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ABSTRACT

Cloud computing, robotics, the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) are some of the technologies that make up the Internet of Robotic Things (IoRT). Transportation, industry, healthcare, and security all heavily rely on IoRT. IoRT has the potential to significantly accelerate human growth. Robots can send and receive data to and from other people and devices thanks to IoRT. This study reviews IoRT in terms of comparable architectures, methodologies, and capabilities. The associated research difficulties are so outlined. When creating robotic systems and objects, IoRT architectures are crucial. Human-robot cooperation, or HRC, is quickly emerging as a crucial element of smart manufacturing, healthcare, and service sectors due to the rapid integration of Internet of Things technology. However, real-world implementation of such systems poses challenging scheduling challenges due to the dynamic, diverse, and resource-constrained nature of IoT contexts. This paper presents a novel scheduling problem for real-world human–robot collaboration in Internet of Things applications, which aims to balance communication disruptions, computation demands, and safety-critical interactions. In contrast to traditional scheduling methods, which primarily deal with deterministic scenarios, the proposed perspective emphasizes flexibility in response to erratic human behavior, changing network conditions, and diverse device capabilities. The challenge is increased by the need to guarantee energy efficiency, real-time responsiveness, and secure data exchange across scattered IoT nodes. This scheduling problem needs to be fixed to improve system productivity and human safety, reduce job execution latency, and accomplish seamless coordination. This work lays the foundation for exploring new scheduling models that bridge the gap between theoretical frameworks and the practical requirements of IoT-enabled human–robot collaboration.

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1. INTRODUCTION

More independent, flexible, and adaptable production systems are needed for industrial innovation as Industry 4.0 (also known as Connected Industry) grows [1]. Among other enabling technologies, Digital Twins, IIoT (Industrial Internet of Things), and CPS (Cyber-Physical Systems) can help create autonomous and adaptable industrial production systems. However, the lack of producer flexibility is highlighted by the limited ability to adjust to unforeseen circumstances or production flaws. Combining shop floor personnel and robots in production lines is suggested as a viable way to address this problem and enable flexible output in industrial settings. Technologies like collaborative robots, or cobots, are becoming more and more important in this situation where humans and robots coexist in order to ensure the safety of floor workers. Manufacturing facilities see financial, spatial, and productivity advantages as a result of the cobots' safe design, adaptability, and reduced costs. The absence of safety barriers or spatial reconfiguration while deploying one or more cobots is how these advantages are seen in industrial processes. Installing cobots rather than standard industrial robots in these shared locations is crucial since worker safety is the primary consideration in collaborative circumstances. As a result, a completely fence-free area can be established, enabling cooperative working modes between the cobots and shopfloor operators. In this situation, HRI makes perfect sense in order to create a suitable method for facilitating and enabling safe human-robot interaction. In this way, the HRI can also be viewed as a tool that enables the execution of tasks in industrial settings that call for the amalgamation of human and robot talents.

However, safe interaction options and a fence-free area are not enough to create an industrial collaboration situation. In order to ensure shopfloor safety in any circumstance, the entire application must be impervious to damage. Therefore, any risk source, such as tool shape or load characteristics must be monitored in real industrial collaborative scenarios. According to the literature, it is becoming more and more crucial to guarantee shopfloor safety in industrial settings without a protective fence in order to properly implement a collaborative approach. Robotics and the IoT have combined to generate previously unheard-of possibilities for intelligent, networked, and cooperative systems. Among these developments, HRC has become a paradigm shift that allows robots to collaborate with people in the fields of manufacturing [2], healthcare, logistics, and services. Unlike traditional industrial robots, which operated in isolated environments, collaborative robots—or cobots—are designed to interact safely and efficiently with humans, complementing human dexterity, adaptability, and decision-making capabilities with robotic precision, strength, and endurance [3]. The evolution of IoT has further enhanced this collaboration by providing seamless connectivity between humans, robots, and distributed devices, thereby enabling real-time sensing, communication, and task coordination. However, there are new and complicated issues brought about by the increasing use of IoT-enabled HRC systems, especially when it comes to scheduling jobs to balance resource restrictions, safety, and efficiency.

In real-world environments, scheduling plays a critical role in determining how tasks are allocated, executed, and coordinated between humans and robots. Traditional scheduling methods, which often assume static task execution environments and predictable workloads, are insufficient for IoT-driven HRC scenarios. Human actions are inherently uncertain, robots operate under hardware constraints, and IoT devices introduce variability in terms of network latency, data availability, and computational resources. As a result, task scheduling in such environments must go beyond classical optimization approaches, incorporating adaptability, context-awareness, and real-time decision-making. For example, in a smart manufacturing setting, a human worker may deviate from a predefined sequence, requiring the robot and IoT infrastructure to adjust its schedule instantly to avoid delays, maintain safety, and ensure productivity. This interplay between humans, robots, and IoT systems creates a scheduling challenge that is both dynamic and multidimensional.

It is imperative to resolve this scheduling issue due to the growing reliance on HRC across various disciplines. In the medical field, collaborative robots assist surgeons, nurses, and elderly patients; their actions and human objectives need to be carefully synced [4]. Cobots and human workers work together to optimize logistics and warehousing processes such as sorting, distribution, and selection, which requires ongoing job reallocation according on the situation at hand. Industrial IoT robots with smart sensors need to collaborate with human operators to maintain equipment, monitor production quality, and adapt to shifting demand. In each of these scenarios, efficient scheduling is required to balance real-time responsiveness, energy savings, overall system performance, and human security [5].

The IoT context, which includes dispersed networks, a variety of devices, and varying workloads, makes this issue more challenging. Sensors, actuators, and edge devices provide massive data streams that need to be processed locally or transferred to the cloud, depending on latency and energy constraints. It is difficult to guarantee that jobs are finished on time due to unpredictable delays, bandwidth limitations, and network disruptions. Additionally [6], edge devices, which often operate under strict power limits, require energy-conscious scheduling algorithms that optimize computation and communication workloads. Security and privacy concerns also become important since sensitive data from human-robot interactions must be treated in ways that preserve confidentiality while promoting real-time collaboration. When taken as a whole, these components highlight the limitations of existing scheduling techniques and the need for creative frameworks created especially for HRC scenarios made possible by IoT.

Recent research has explored different scheduling strategies, such as heuristic-based optimization, reinforcement learning, and priority-driven task allocation, to address partial aspects of this problem. While these methods have demonstrated effectiveness in controlled or simulated environments, they often fail to capture the unpredictability of real-world human–robot collaboration. For example, reinforcement learning can adapt to dynamic changes, but its training overhead and computational requirements may not align with the limited resources of edge devices. Similarly, heuristic approaches can optimize specific objectives, such as minimizing latency, but may overlook critical aspects such as human safety or energy efficiency. The motivation behind this research is to bridge the gap between theoretical scheduling models and the practical requirements of IoT-enabled HRC systems [7]. A new scheduling challenge is defined not merely by efficiency metrics but also by the need to integrate human behavior, real-time environmental feedback, and heterogeneous IoT infrastructure into the scheduling process. Such a perspective calls for interdisciplinary approaches that combine insights from computer science, robotics, human factors engineering, and communication networks. By framing scheduling as a multifaceted challenge, this work aims to contribute toward the design of intelligent, context-aware scheduling strategies that can adapt to uncertainties while ensuring seamless coordination between humans and robots.

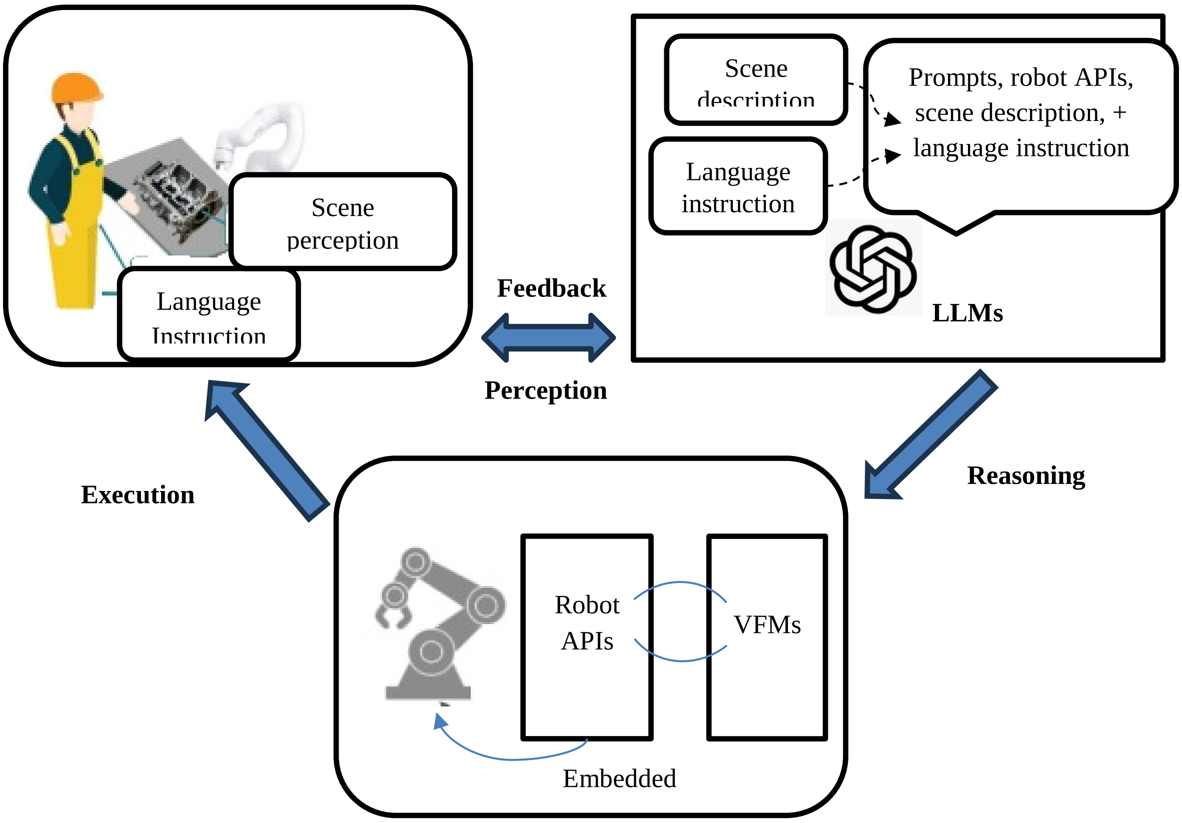

Figure 1. The FMs-based HRC method's rationale

Figure 1 depicts the architecture of the FMs-based HRC technique, which consists of three modules: perception, reasoning, and execution. The HRC system's workflow for carrying out manufacturing tasks is as follows. First, the voice recognition model receives real-time human language commands from its perception module, which translate them into textual explanations [8]. The robot status and object locations are among the exterior descriptions that are updated at specific intervals. Second, LLMs receive textual instructions and physical descriptions. Based on the HRC prompt, they deduce robot control algorithms that adhere to environmental restrictions and human instructions.

The remainder of the paper's structure are an outline of IoRT methods, architecture, and capabilities are provided in Section 3. The recent literature survey is summarized in Section 2. In Section 4, the emphasis is on security and the classification of security risks. The work is concluded in Section 5, which also outlines the future scope and emphasizes key open research issues in this vibrant field of study.

2. RELATED WORKS

Numerous advantages highlight the need for sophisticated scheduling systems, including increased productivity through streamlined processes and decreased downtime; lower operating expenses through optimal resource use and decreased waste; better resource management through efficient task and resource allocation; and real-time adaptability capabilities that enable adjustments to changing circumstances and demands. The topic of task scheduling optimization in flexible job shop (FJS) environments—which are essential to Industry 4.0—where several non-identical robots work in parallel while being constrained by blocking and buffering is the focus of this research [9]. This work addresses the particular difficulties of multi-robot assignment and parallel tasking within FJS, in contrast to earlier research that frequently oversimplify the issue by concentrating just on transfers or single-type robot configurations. In order to handle a variety of product kinds and shifting production needs, these environments bring about a high degree of variability and necessitate flexible scheduling. Managing work distribution across several non-identical robots, allocating resources to avoid delays brought on by constrained buffer space and blocking situations, and timing optimization to prevent downtime are the main difficulties in this topic.

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Due to the uncertainty of end-of-life products, nearly all EOL products must be disassembled in order to realize the potential value of recycling them. As a result, the human–robot cooperation disassembly strategy must dynamically optimize in real-time disassembly processes or sequences [11]. A computational framework was introduced to evaluate the best disassembly sequence by examining the partial disassembly sequence in the age distribution of EOL products. This was done in order to establish a correlation among the aging distribution and the quality of the EOL products and the impact of uncertain EOL goods reliability and the most beneficial disassembly sequences. The quality uncertainty of EOL products presents numerous obstacles to the creation of an optimal disassemble process planning system. The disassembly process can be optimized to mitigate the uncertainty.

3. METHODS AND MATERIALS

3.1. IoRT Definitions and Concept

The IoRT is an intelligent ecosystem that combines robotics, AI, and the IoT. While robots are autonomous machines, they are also interconnected entities that can perceive, reason, act, and learn in distributed environments [12]. IoRT expands on the idea of IoT by incorporating robotic platforms that can perform physical tasks in conjunction with humans and other smart devices, interpret data, and make context-aware decisions. IoT focuses on connecting sensors, devices, and systems via the internet to facilitate data collection and exchange.

Several researchers and standardization bodies have attempted to define IoRT [13] in ways that emphasize its unique position at the intersection of IoT and robotics:

- **IoRT as an ecosystem:** It can be defined as a network of intelligent robotic devices that sense, process, and communicate data through IoT infrastructures while performing coordinated physical actions in the real world.
- **IoRT as an extension of IoT [14]:** From another perspective, IoRT represents the evolution of IoT into cyber-physical systems, where connected robots replace passive devices and sensors with autonomous agents that actively interact with humans, objects, and environments.
- **IoRT as a collaborative framework:** In the context of human–robot collaboration, IoRT enables seamless task scheduling, adaptive decision-making and real-time communication, thus ensuring that both humans and robots operate as part of a cooperative and adaptive network.

The **concept of IoRT** rests on four fundamental pillars:

1. **Sensing and Perception**: IoRT systems are equipped with advanced sensors (vision, proximity, tactile, thermal, and environmental sensors) that gather real-time information about human activities, object states, and environmental conditions [15]. This sensory data is shared across IoT platforms, enabling robots to interpret their surroundings accurately.
2. **Communication and Connectivity**: Through IoT protocols such as MQTT, CoAP, 5G, and edge computing infrastructures, IoRT enables seamless communication between robots, humans, and distributed devices. This connectivity ensures low-latency interactions, critical for time-sensitive applications like healthcare or industrial automation.
3. **Computation and Intelligence**: Unlike traditional IoT nodes, IoRT integrates robotic intelligence and machine learning algorithms that allow autonomous decision-making. Robots can process information locally at the edge, or collaboratively in the cloud, to adapt to dynamic scenarios such as changing human tasks or unpredictable environments.
4. **Action and Collaboration**: IoRT emphasizes the ability of robots not only to sense and process but also to act physically in coordination with humans and machines. Collaborative robots (cobots), drones, and mobile platforms within IoRT systems execute tasks such as assembly, inspection, medical assistance, and logistics while ensuring human safety and system efficiency.

IoRT is important because it can turn passive IoT networks into intelligent, adaptable, and active systems. IoRT, for instance, allows robots in smart manufacturing to recognize human motions and instantly modify their operations. IoRT robots in healthcare use IoT sensors to track patient vitals and provide prompt interventions. IoT-enabled warehouses and networked robotic fleets interact in logistics to dynamically improve delivery schedules. The next generation of human–robot interaction in IoT-enabled environments is thus made possible by the idea of IoRT [16], which embodies the combination of connectivity, autonomy, and collaboration. IoRT goes beyond conventional automation to construct adaptive, context-aware, and human-centric robotic ecosystems by tying perception, intellect, and action over distributed networks.

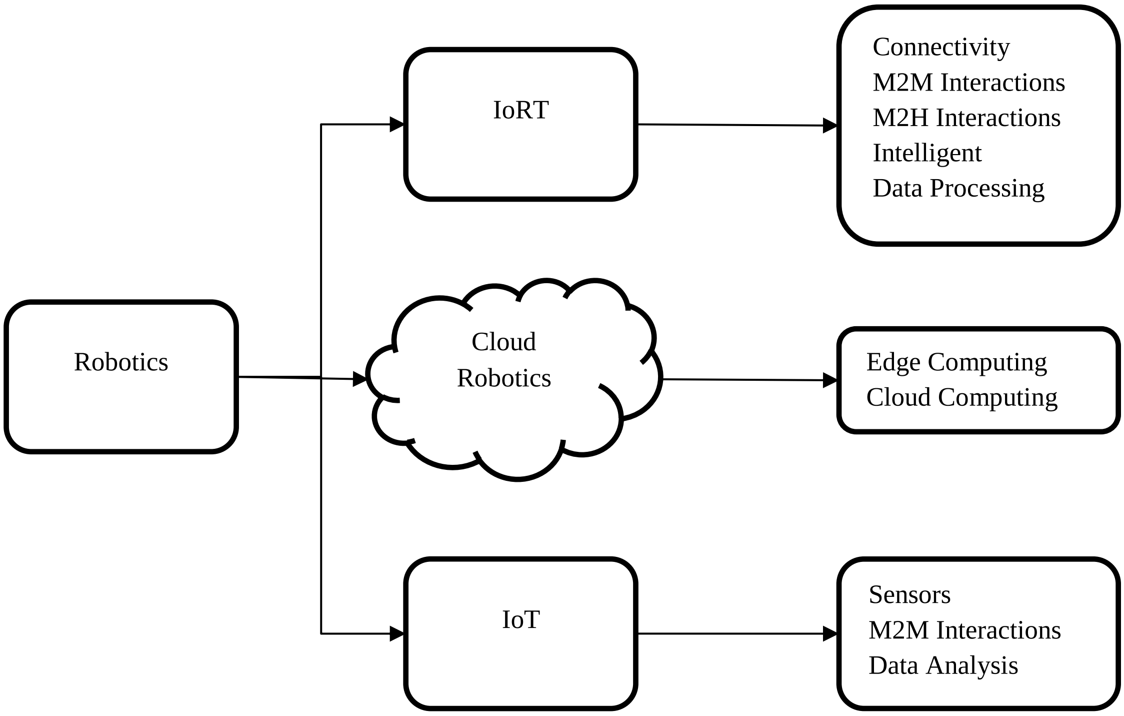

Figure 2. Robotics and its functionalities represented diagrammatically

A practical illustration of robotics that emphasizes its essential elements: perception and sensing, control and decision-making, actuation, and communication. The figure 2 shows how robots engage with people and IoT devices in collaborative settings by integrating sensor data, processing information using control systems and AI algorithms, and performing physical actions.

3.2. How Does IoRT Communication Happen?

The key mechanism that permits intelligent coordination between robots, people, sensors, and Internet of Robotic Things (IoRT) devices is communication. IoRT creates a distributed communications framework where data flows smoothly across perception, networking, and application levels, in contrast to traditional robotics systems, which frequently rely on localized and segregated control. Robots and IoT-enabled sensors start the process by gathering contextual and environmental data, like system states, object locations, and human motions. High-speed, low-latency networks like 5G and Wi-Fi 6 then offer lightweight communication protocols like MQTT, CoAP, or REST to transport this sensory data. A large portion of the data is pre-processed at the edge to decrease latency and ease the strain on centralized cloud systems, enabling real-time decision-making at the robot or gateway level. After processing, the data is converted into commands that may be used to control robotic behavior. This allows robots to immediately adjust to changes in human behavior or environmental circumstances.

Multiple dimensions of communication take place in IoRT environments: humans communicate with robots via voice, gesture, or wearable interfaces; robots communicate with other machines and IoT devices on their own; and cloud-based services integrate with edge nodes to strike a balance between real-time responsiveness and heavy computation. In addition to ensuring effective work scheduling, this multidirectional information flow keeps robots safe by allowing them to anticipate and adjust to human activity.Security is essential to this communication process because, in order to prevent misuse or unauthorized access, sensitive interaction data must be sent via secure, encrypted channels. All things considered, IoRT communications is an ongoing, flexible, and smart process that turns discrete robotic systems into networked ecosystems where humans, machines, and smart devices collaborate and make decisions in real time.

3.3. IoRT Communication Challenges

- Despite the smooth integration that the IoRT provides between people, robots, and IoT devices, a number of issues with its communication framework impact effectiveness, dependability, and safety in practical applications. Since real-time collaboration necessitates incredibly quick data flow, latency is one of the biggest obstacles. The safety of human-robot contact or the performance of coordinated tasks can be jeopardized by even a fraction of a second of delay. Maintaining reliable low-delay communication over diverse networks is still a significant challenge, even as technologies like 5G and edge computing lower latency. Since IoRT settings frequently produce enormous streams of sensory information from vision systems, touch sensors, and IoT devices, bandwidth constraint is another important problem. Congestion and packet loss may result from sending and processing such massive amounts of data at once, especially in large-scale industrial or medical applications.
- As IoRT systems incorporate many robots, sensors, and IoT platforms that may function under various standards, data formats, and communication protocols, a second difficulty is the heterogeneity of devices and protocols. Standardized frameworks are necessary to achieve smooth interaction between these disparate systems, and they are still developing. Scalability is also an issue since it becomes exponentially more difficult to schedule jobs, manage communication, and guarantee real-time response as the number of connected devices rises. This is especially important in dynamic settings where human activity and robotic processes are extremely variable, like logistics warehouses or smart factories.
- In IoRT communication, security and privacy are major issues in addition to technical difficulties. Sensitive information, such as biometric data, health indicators, or manufacturing details, is frequently included in human–robot interactions. If intercepted or altered, this information could have serious repercussions. Advanced authentication procedures, encryption techniques, and even blockchain-based frameworks are needed to provide secure communication. It's a fine balance to put these security layers in place without sacrificing latency or energy efficiency. Moreover, energy limitations frequently affect IoRT devices, particularly those at the edge, making it challenging to maintain constant high-performance communication without depleting resources.
- Lastly, it is impossible to ignore the problem of fault tolerance and dependability. Communication can be hampered in real-world applications by hardware issues, network outages, or environmental disruptions. Therefore, an IoRT system needs to be able to dynamically adjust, reroute communication channels, and continue to function even in the event of partial system failures. Realizing the full potential of IoRT requires overcoming these interpersonal obstacles since only strong, secure, and low-latency interaction architecture can guarantee safe, effective, and human-centered cooperation between robots and IoT-enabled objects.

3.4. IoRT's capabilities

Sensing, intelligence, and action are all combined into a single, interconnected framework by the IoRT, which is a revolutionary paradigm rather than just an extension of the IoT. Its capabilities extend beyond basic data gathering and processing, allowing robots to function as independent, flexible, and cooperative agents in intelligent settings. Perception and context awareness are two of IoRT's core competencies. IoRT systems are able to sense the physical world in great detail by merging IoT-enabled devices like wearables and environmental monitors with robotic sensors like cameras, LiDAR, and tactile sensors. Robots are able to respond effectively to dynamic and unpredictable situations because of their sensory integration, which enables them to follow item movement, detect human gestures, and comprehend environmental changes.

Real-time coordination and communication is another essential IoRT capability. Low-latency data interchange between robots, humans, and dispersed objects is made possible by IoRT through IoT connectivity protocols and cutting-edge networks like 5G and edge computing. In delicate applications like surgery, collaborative production, or disaster response, this guarantees that robotic actions stay in sync with human activities. Swarm robotics and multi-agent task execution are made possible by IoRT systems, which also promote high levels of collaboration among several robots by ensuring smooth communication.

Additionally, the IoRT framework demonstrates the capacity for independent learning and decision-making. IoRT uses artificial intelligence and machine learning at the edge, enabling robots to evaluate data locally and make quick choices without relying on distant servers, in contrast to standard IoT systems that mostly rely on cloud-based computation. IoRT-enabled robots can adjust to unforeseen circumstances; such human error, equipment malfunctions, or shifts in work priorities, thanks to their autonomy. Furthermore, IoRT systems have the ability to continuously learn from encounters, which will help them become more dependable partners over time.

The ability to do tasks and take physical action is equally significant and sets IoRT apart from exclusively digital IoT devices. In addition to processing data, IoRT robots also carry out physical duties like patient aid, assembly, transportation, and inspection. IoRT is transformed from a passive monitoring network into an active ecosystem that solves problems thanks to this action-oriented capability. Furthermore, IoRT exhibits safety and flexibility because collaborative robots are made to detect human presence and modify their behavior to avoid mishaps. Predictive analytics and fail-safe procedures are combined to guarantee that IoRT systems can operate dependably in situations where vital resources and human lives are at risk.

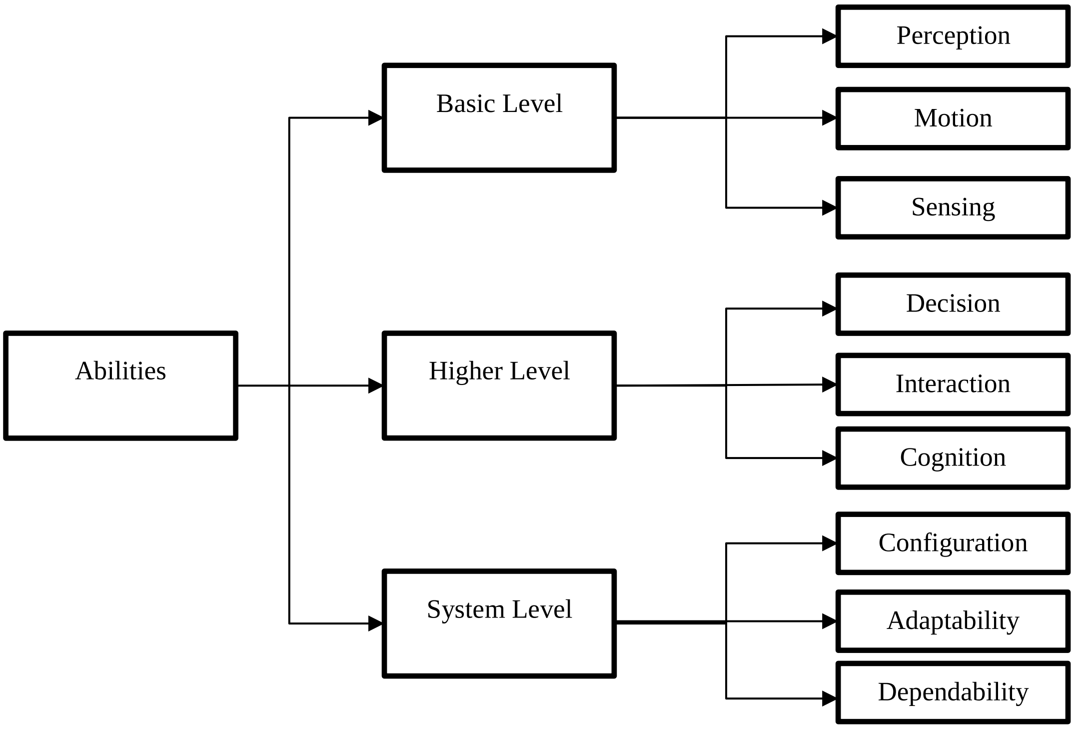

Figure 3. An analysis of the traits of robotic objects

Robotic objects are not merely mechanical systems; they are intelligent, autonomous, and interactive entities that combine hardware, software, and networked intelligence to perform tasks in dynamic environments. Analyzing their traits is essential for understanding how robots can be integrated into the Internet of Robotic Things (IoRT) ecosystem, where collaboration, adaptability, and efficiency are critical. The traits of robotic objects can be examined in terms of functionality, intelligence, adaptability, and interaction.

Autonomy, or the capacity to carry out activities without constant human supervision, is one of the most basic characteristics of robotic objects. Levels of autonomy range from robots that obey preset commands to sophisticated systems that can learn and correct themselves. The quality of intelligence, made possible by AI and ML algorithms, is closely related to autonomy. Robotic things with intelligence are able to interpret sensory data, identify patterns, and make decisions based on context. In IoRT contexts, where robots must adjust to unpredictable human behaviors, fluctuation information from IoT devices, and shifting ambient circumstances, this is especially crucial.

Adaptability is another important quality. It is becoming more and more common for robotic things to function in unstructured settings where established guidelines might not always be applicable. Robots with flexibility can react to unforeseen situations by changing their course in reaction to real-time sensor data, avoiding collisions, or rescheduling duties. Scalability or a robot's ability to blend in with bigger IoRT systems and coexist with other robots, IoT devices, and people without requiring significant reconfiguration, further enhances this quality.

Characteristics of robotic things are also determined by their actuation capabilities and physical embodiment. Actuators, grippers, or mobility systems provide robots the ability to move around, manipulate items, and engage in physical contact with people. Perception and sensing skills complement these physical characteristics, allowing robots to use cameras, LiDAR, tactile sensors, and Internet of Things-based data flows to comprehend their surroundings. The effectiveness of robotic decision-making and interaction is directly impacted by the precision and accuracy of these sensors. Equally crucial is the trait of engagement and collaboration. In IoRT, robotic objects are cooperative agents that communicate with humans and other machines rather than being standalone robots. The characteristics that make robotic devices appropriate for real-world human–robot collaboration include safe collaborative behaviors, natural interfaces like gestures or voice instructions, and effective communication. As a result, safety becomes a fundamental characteristic, guaranteeing that robots can work alongside people without endangering them. Failure-safe procedures, compliance monitoring, and human behavior prediction are used to accomplish this [17].

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The server used for the simulated assessment of the system demo has a 12 core CPU, 8GB of RAM, an 18-core GPU with dynamic caching and hardware-accelerated ray tracing, and 512GB of SSD storage. Using Python Interpreter, edge nodes were simulated on the testbed to mimic a real-world federation edge scenario. The Flower framework was utilized in the demo's DHT-based configuration. A decentralized network was simulated by each node instantiating numerous Docker containers, each of which operated as a separate federated client. The assessment made use of the Human and Robot Approaching Behaviors Database, which included about 38 robot approach group trials and 380 human-centered group trials. A baseline configuration was used for comparison, utilizing a Jupyter Notebook small-scale federated learning environment.

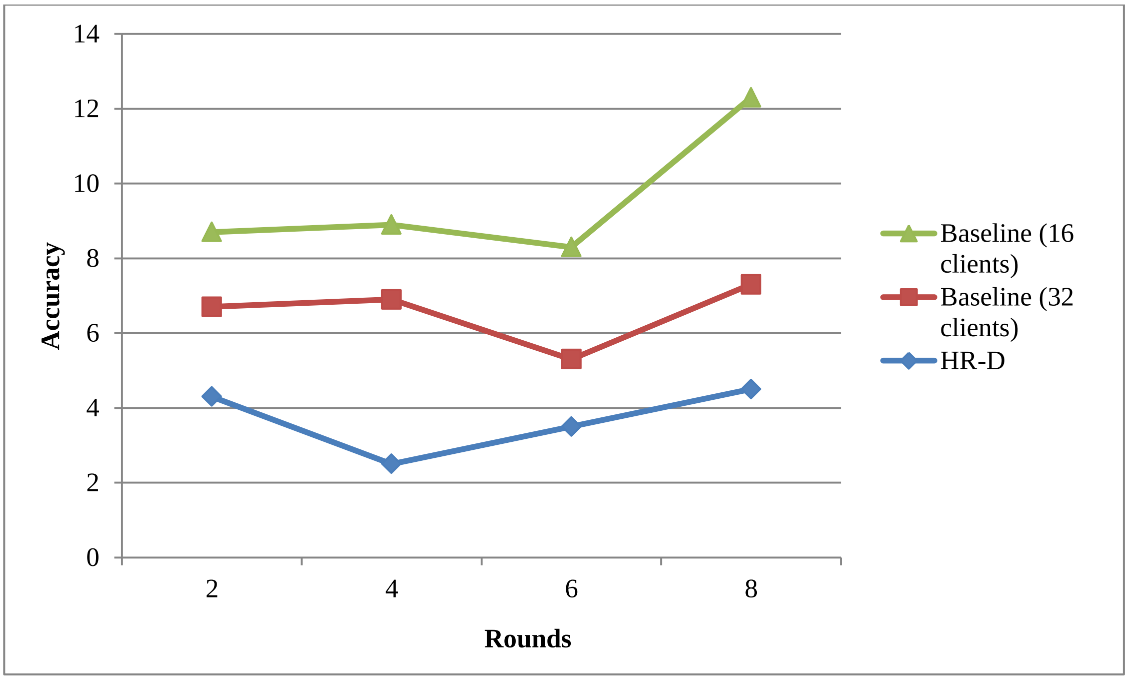

Figure 4. Performance assessment of the federation model, encompassing HR-D client recuperation

As seen in Figure 4 [18], the tests concentrated on the trained model's accuracy, the trend of loss reduction throughout training, the creation time of clients and boxes, and the client restoration performance. The durability of HR-D's Consolidated Hash and peer-to-peer overlay in handling model updates is demonstrated by the figure, which shows that the loss remains at a low value close to the original baseline model. The capacity of HR-D to facilitate effective training for HRI applications is demonstrated by its quick convergence to a low loss. The accuracy numbers indicate that the representation in containers DHT stabilizes for the majority of iterations and attains nearly the same accuracy as the default federation model, demonstrating the platform's capacity to sustain excellent model quality.

In addition, the setup time demonstrates that the DHT overlay has a small effect on the runtime cost compared to the baseline containerized setup without DHT implementations. Lastly, the analysis of client recovery delay demonstrates that containerized clients may be recovered in a matter of seconds, underscoring the platform's strong dependability and capacity to sustain efficient runtime performance under changing circumstances.

5. CONCLUSION

When integrating human-robot collaboration, the IoT ecosystem poses significant scheduling challenges that go beyond traditional computer models. Real-world scheduling must account for the variety of IoT devices, the fluidity of human activity, and the strict timing limitations of robotic systems. In addition to being flexible and energy-efficient, frameworks that can provide safety, reliability, and scalability are required to address this new scheduling issue.

The analysis of scheduling in human-robot collaboration makes it evident that existing methods cannot meet the demands of highly networked Internet of Things environments. Because robots must coordinate their task performance with unpredictable human behavior, shifting network conditions, and many data sources, real-time scheduling is both essential and difficult. To tackle this challenge, distributed decision-making, context-aware computing, and artificial intelligence must be used to build scheduling systems that can dynamically adjust to change while maintaining resilience and efficiency.

Ultimately, the future of human-robot collaboration in Internet of Things applications depends on reconsidering scheduling strategies that take intelligence, flexibility, and teamwork into consideration. By advancing these scheduling techniques, researchers and developers may enable robots function as smooth, safe, and productive partners with humans in a range of application domains, such as manufacturing, healthcare, smart cities, and service industries. This study therefore emphasizes the importance of creative scheduling strategies as a basis for creating the IoRT and realizing its transformative potential in real-world applications.

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