Deep-Learning-Based Resource Orchestration for Healthcare-Oriented Industrial IoT Flexible Manufacturing Systems With Edge Computing

Jianhui Lv, *Senior Member, IEEE*, and Keqin Li, *Fellow, IEEE*

***Abstract*—Rising trends in Industrial Internet of Things (IIoT), flexible manufacturing, and edge computing present unprecedented opportunities for advancing healthcare manufacturing systems. However, orchestrating resources efficiently while maintaining stringent healthcare quality standards poses significant challenges, particularly in environments where manufacturing processes must adapt quickly to varying production requirements. These challenges are further complicated by the limited computational resources of IIoT devices and the need for real-time processing in medical device production and pharmaceutical manufacturing. To address these challenges, we propose a distributed healthcare-aware deep learning resource orchestration (DH-DLRO) algorithm for edge computing-enabled healthcare IIoT flexible manufacturing systems. Our approach constructs a joint optimization problem for task offloading decisions and resource allocation, specifically tailored to healthcare manufacturing requirements. The algorithm employs multiple parallel deep neural networks to generate efficient offloading decisions while considering healthcare-specific quality constraints and manufacturing precision requirements. The algorithm reduces energy consumption by 25%–30% while maintaining medical device manufacturing precision standards, shows remarkable stability across varying task sizes (7000–25000 bytes), and exhibits robust performance under different system parameter configurations. DH-DLRO maintains consistent Quality of Service levels above 0.95 for medical device assembly tasks while achieving optimal CPU utilization patterns between 60%–80%, demonstrating its effectiveness in balancing computational efficiency with healthcare manufacturing quality requirements.**

***Index Terms*—Edge computing, flexible manufacturing, healthcare manufacturing, Industrial Internet of Things (IIoT), resource orchestration.**

I. Introduction

THE IMPLEMENTATION of Industrial Internet of Things (IIoT) technologies has transformed manufacturing systems, particularly in sensitive production areas such as healthcare, where accuracy, dependability, and flexibility are crucial [1], [2], [3]. IIoT devices are increasingly used by modern healthcare manufacturing facilities for the production of medical equipment, pharmaceuticals, and customized medical devices using flexible manufacturing systems [4], [5]. These smart manufacturing systems require prompt processing of enormous quantities of data, especially regarding analytic and healthcare compliance, owing to strict operational regulations [6], [7]. Yet, IIoT devices in these healthcare manufacturing environments face extreme constraints in their hardware computation capabilities as well as energy resources, which severely limits the system's ability to process data while meeting the stringent Quality of Service (QoS) healthcare-grade manufacturing standards demands [8], [9].

As highlighted in sources [10] and [11], edge computing solves the latency and processing challenges within the framework of healthcare-focused IIoT flexible manufacturing systems. Edge computing offers critical low-latency processing for real-time quality control and production line adaptability by placing servers at the network edge close to the manufacturing floor. While traditional cloud computing offers powerful capabilities, it often results in latencies that are far too slow for IIM healthcare manufacturing processes, where decisions need to be made within milliseconds to ensure optimal product quality and safety [12], [13].

Resource orchestration differs from traditional resource allocation in that it accentuates the coordinated and automated management of several interdependent resources across multiple distributed computing environments. In healthcare IIoT manufacturing settings, orchestration refers to the dynamic coordination of computation resources, network bandwidth, storage capacity, and processing priority among various edge servers when all decisions related to resource allocation must stand in compliance with healthcare quality standards and regulatory requirements. Hence, the orchestration approach enables the automation of decision-making about the management of resources while keeping the intricate interdependencies between various resource types and manufacturing processes into consideration.

The adoption of healthcare-oriented IIoT systems with flexible manufacturing principles adds an extra layer of complexity concerning resource management and task scheduling [14]. Moreover, within the pharmaceutical industry, flexible manufacturing systems automate and dynamically balance assembly lines for distinct production runs, such as switching between different medical device specifications

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Jianhui Lv is with the Multimodal Data Fusion and Precision Medicine Laboratory, The First Affiliated Hospital of Jinzhou Medical University, Jinzhou 121012, China (e-mail: lvjianhui2012@163.com).

Keqin Li is with the School of Computer Science, State University of New York, New Paltz, NY 12561 USA (e-mail: lik@newpaltz.edu).

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or modifying pharmaceutical formulation parameters. These shifting paradigms demand agile resource management that ensures dynamic dispatching of computationally intensive tasks while adhering to rigid medical grade quality benchmarks [15], [16].

IIoT is a paradigm shift in manufacturing automation, wherein interconnected devices, sensors, and machines create intelligent production ecosystems [17]. Within these healthcare manufacturing contexts, IIoT enables real-time monitoring of production parameters and automated quality control, along with adaptive manufacturing processes to meet changing demands. IIoT, when combined with edge computing, provides distributed intelligence networks where manufacturing decisions can be taken locally yet remain connected to centralized management systems. Such a distributed form comes especially handy in healthcare manufacturing, where production lines have to be running around the clock and yet comply with stringent regulatory requirements.

The evolution of IIoT pertaining to healthcare manufacturing is about balancing numerous technological layers, from sensor-level data collection to the broad end of production planning at the enterprise level [18]. Manufacturing machinery is equipped with smart sensors to monitor variable parameters, such as temperature, pressure, and vibration, while machine learning algorithms utilize these data streams to identify irregularities and forecast maintenance needs. With some edge computing nodes placed throughout the manufacturing facility, the sensor data gets processed locally, therefore reducing latency and creating means to respond to situations that require such immediate attention instantly. This multilayered system sets the foundation to ensure that healthcare manufacturing operations can bank on an exceptional level of precision and reliability required for the production of medical devices and pharmaceutical processing.

We make three contributions to advance the field of healthcare-oriented IIoT flexible manufacturing systems with edge computing.

1) We propose distributed healthcare-aware deep learning resource orchestration (DH-DLRO), a novel distributed deep learning-based resource orchestration algorithm for healthcare manufacturing environments. The algorithm encompasses four core components: a) a multi-deep neural network (DNN) architecture with multiple parallel DNNs for different healthcare manufacturing tasks; b) an adaptive DNN scaling mechanism that dynamically adjusts network count based on task diversity index (TDI) and computational load variance; c) a healthcare-aware joint optimization framework that simultaneously handles binary offloading decisions and bandwidth allocation while maintaining medical-grade quality constraints; and d) an experience replay memory system calibrated for healthcare manufacturing precision requirements.
2) We develop a joint optimization framework that handles task offloading decisions and resource allocation while maintaining healthcare manufacturing quality standards. This framework transforms the original mixed-integer nonlinear programming problem into decomposed subproblems through strategic problem formulation, enabling efficient resource allocation across edge servers.
3) We implement a multi-DNN architecture that enables parallel processing of healthcare manufacturing tasks while maintaining consistent quality standards. The architecture features neural networks for medical device assembly tasks, pharmaceutical processing tasks, and quality control operations, with each network optimized using a modified Adam algorithm that minimizes healthcare-specific cross-entropy loss functions while preserving manufacturing precision requirements.

The remainder of the article is organized as follows. Section II gives the related works. Section III introduces the system model. Section IV presents our proposed DH-DLRO algorithm. Section V provides experimental results. Finally, Section VI concludes this article.

II. Related Works

Recent work exploiting deep learning techniques, especially the application of DNNs, has effectively improved the allocation of resources in sophisticated systems [19], [20]. Such solutions based on deep learning still work for general IIoT use cases and do not consider the specifics of the healthcare manufacturing priorities. The problem involves intelligent resource orchestration processes that enhance decision-making for task offloading, manage wireless resource allocation, and uphold quality standards for healthcare manufacturing [21], [22], [23].

More recent works on resource orchestration have looked at different solutions. GAN-NoisyNet resource orchestration was proposed by Gupta et al. [24]. Dong et al. [25] proposed an FedMRL approach for data-privacy-preserving network slice orchestration and resolved the cold-start problem. A deep reinforcement learning algorithm was introduced for efficient workload orchestration under the name DEWOrch by Safavifar et al. [26]. Proactive resource orchestrators leveraging deep reinforcement learning for open radio access networks were introduced by Staffolani et al. [27]. Deep learning enabled computation and radio resource orchestration in virtualizing radio access networks, proposed by Ayala-Romero et al. [28], called vrAIn.

Applying existing resource orchestration techniques to healthcare manufacturing processes poses numerous difficulties [29]. For example, traditional cloud-based infrastructures provide no value in the healthcare domain due to overly sluggish response times for precision medicine manufacturing workflows, and current edge computing frameworks are indifferent to healthcare quality standards [30], [31]. Existing methods tend to optimize resource management, but they cannot sustain the sharpened precision required during the medical device assembly procedures [32]. The same can be said for resource-adaptive allocation approaches based on generative adversarial networks that fail to ensure consistent regulated compliance in pharmaceutical production. A number

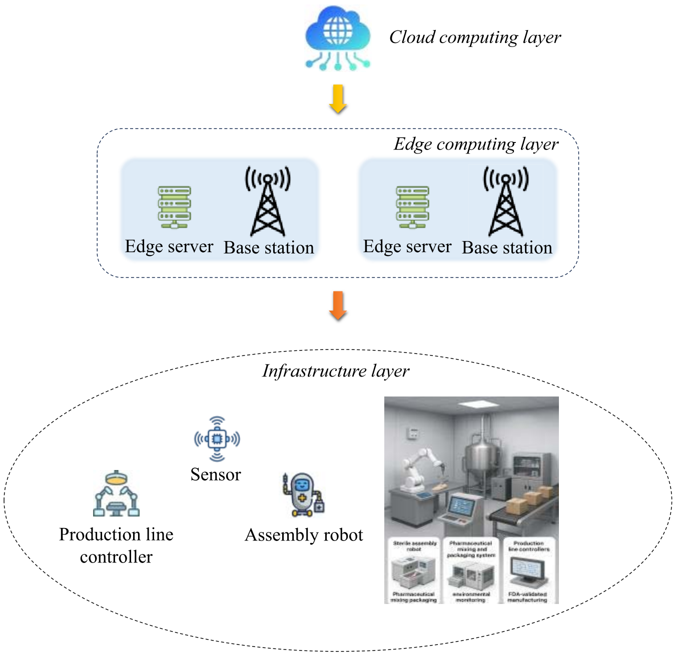

Fig. 1. System model in healthcare IIoT based on edge computing. (The three-layer hierarchy shows: 1) cloud computing layer providing long-term data storage and analytics for regulatory compliance and batch record management; 2) edge computing layer with BSs and edge servers positioned near manufacturing zones to provide low-latency processing for real-time quality control, pharmaceutical batch monitoring, and medical device assembly verification; and 3) infrastructure layer containing healthcare manufacturing devices).

of approaches based on federated learning apply distributed computation efficiently, but the decision logic frameworks lacking innovation severely compromise process control during healthcare manufacturing quality assurance [33], [34], [35]. Unlike all these examples, the proposed approach solves these problems with its healthcare-conscious multi-DNN architecture by introducing energy-efficient parallel processing algorithm constraints for offloading decisions while honoring healthcare-grade manufacturing multiprocessor operational demands.

III. System Model

Fig. 1 illustrates a healthcare-oriented IIoT flexible manufacturing system supported by edge computing infrastructure. The system is structured in a multilayer hierarchy, with the edge computing layer strategically positioned between the cloud and manufacturing infrastructure layers. This edge computing layer is equipped with sophisticated base stations (BSs) and specialized edge servers designed to handle the stringent requirements of healthcare manufacturing processes. Each BS effectively manages a dedicated zone of the manufacturing floor, overseeing n healthcare IIoT devices, where $n = 1, 2, \ldots, |N|$.

The healthcare manufacturing environment depicted in this system model incorporates multiple specialized components designed for medical-grade production. Assembly robots in the infrastructure layer perform precision assembly of medical devices, such as pacemakers, insulin pumps, and diagnostic equipment, requiring positioning accuracy within micrometers. Sensors throughout the manufacturing floor monitor critical parameters, including particulate levels in cleanrooms, temperature variations in pharmaceutical storage areas, and humidity control in sterile packaging zones. Production line controllers manage complex workflows that must maintain compliance with FDA regulations, including real-time documentation of manufacturing parameters and automated rejection of products that fall outside acceptable quality ranges. The edge servers are equipped with healthcare-specific algorithms for analyzing biocompatibility test results, validating pharmaceutical formulations, and ensuring that all manufacturing processes meet medical device quality standards such as ISO 13485.

The system operates on a carefully designed time-slotted model where operational time is systematically divided into t consecutive periods of equal duration, represented as $t = 1, 2, \ldots, |T|$, with each slot t having a fixed duration τ. This temporal organization enables precise coordination of manufacturing processes and resource allocation decisions, which is crucial for maintaining the exacting standards required in healthcare product manufacturing. At the commencement of each time slot t, the healthcare IIoT devices generate various computational tasks related to their specific manufacturing processes, denoted as $Q_n(t) = (A_n(t), Z_n(t))$. Here, $A_n(t)$ represents the data size of the manufacturing task generated by the nth healthcare IIoT device, which could range from simple sensor readings to complex quality control imaging data. In contrast, $Z_n(t)$ indicates the required CPU cycles for processing these healthcare manufacturing tasks, accounting for the computational complexity of precision manufacturing operations.

To describe these interactions within a practical healthcare production model, think of an assembly line that manufactures and assembles medical devices like pacemakers. On the production floor, there are micro-assembly robots IIoT devices that solder microelectronics with 10-micrometer precision; packers verify the calibration of the complete sets within the boxes per industry standards; and QC sensors that analyze 4 K frames. Every micro assembly robot creates telemetry data of 15 MB every 5 s, and this data is streamed, as private wireless channels, to the closest edge server. The edge server has the responsibility of checking this telemetry data for system micro-assembly metrics that could affect device dependability and have risks of unreliable performance. As composed of reasonable geometric verification methods, these decisions can be made autonomously using local computation. More advanced geometric hypothesis testing requires more advanced techniques and thus must process information on the edge server. These requests are executed by the edge server equipped with dedicated algorithms for medical manufacturing domains, while time-sensitive tasks are prioritized due to DH-DLRO healthcare-aware orchestration principles. Thus, while production is balanced, the workload for computational resources is prioritized for life-critical parts.

Task generation across the manufacturing floor follows an independent and identical distribution pattern, reflecting healthcare manufacturing processes' diverse but structured nature. The wireless communication channels between devices and BSs maintain consistent conditions within each time slot. However, they may experience variations between consecutive slots, adapting to the dynamic nature of the manufacturing environment. To optimize task processing in this complex system, a binary offloading strategy is employed: when $x_n(t) = 1$, it indicates that the nth healthcare IIoT device's manufacturing task is processed at the edge server, leveraging its superior computational capabilities for complex healthcare manufacturing calculations; conversely, $x_n(t) = 0$ signifies that the task is processed locally on the device, suitable for simpler, time-sensitive operations that require immediate response in the manufacturing process [36].

A. Communication Model

In the healthcare-focused IIoT flexible manufacturing system, sophisticated orthogonal frequency division multiple access is used for task transmission management and to control communication within the system [37]. Each piece of manufacturing equipment, such as the assembly robots for medical equipment, the pharmaceutical processing units, and the quality control systems, is linked to dedicated channels to maintain reliable data communication with a pharmaceutical-grade robot. In this sophisticated manufacturing environment, the healthcare IIoT device to BS uplink transmission rate is computed in real-time based on the enhanced Shannon limits and the uplink transmission enhancement conventional hybrid Shanon formula, which is tailored for the specific needs of production and processing of medical devices and pharmaceuticals [38].

Temperature sensors throughout the manufacturing floor feed data to the orchestration system. The allocation engine evaluates thermal conditions when distributing computing loads across edge nodes. The system redistributes processing tasks during elevated temperatures to maintain optimal operating conditions. Environmental monitoring dashboards display real-time temperature maps with corresponding resource allocation patterns.

The system allows seamless monitoring and control of resource allocation through a touchscreen interface. Workers can visualize system metrics and receive alerts concerning potential resource constraints or inefficiencies

$$S_i(t) = W_i(t)\log_2\left(1 + \frac{q_i(t)g_i(t)}{N_{\text{med}}}\right) \tag{1}$$

where $q_i(t)$ represents the transmission power allocated to the ith healthcare manufacturing device during time slot t, $g_i(t)$ denotes the wireless channel gain between the manufacturing device and the BS responsible for monitoring medical production processes, $W_i(t)$ indicates the wireless channel bandwidth assigned to the ith healthcare manufacturing unit, and N_{med} is the specialized Gaussian noise power spectral density calibrated for medical manufacturing [39].

The transmission latency for healthcare manufacturing data, crucial for maintaining precise quality control in medical device production and pharmaceutical processing, is defined through a comprehensive metric accounting for data volume and transmission capabilities. This latency metric is expressed as

$$D_i^{\text{trans}} = \frac{M_i(t)}{S_i(t)} \tag{2}$$

where $M_i(t)$ denotes the volume of healthcare manufacturing data generated by the ith device in bytes, encompassing various manufacturing processes from precision assembly telemetry (typically 10–15 MB per batch) to real-time quality control measurements (4–8 MB per inspection cycle). $S_i(t)$ represents the maximum transmission rate in bytes per second as calculated in (1), which varies based on channel conditions and allocated bandwidth. For medical device assembly operations, transmission latency must remain below 200 ms to ensure timely detection of manufacturing defects.

B. Computation Model

In healthcare-focused IIoT flexible manufacturing systems, computing tasks are handled with a refined dual-mode system that uses local and edge computing. In local computation situations, such as with healthcare manufacturing devices that execute task processing, the computation lag correlates with the device's processing capability and the medical manufacturing process workflow. This relationship is captured in the following:

$$L_i^{\text{proc}} = \frac{Q_i(t)\beta}{c_i^{\text{local}}} \tag{3}$$

where $Q_i(t)$ represents the healthcare manufacturing task's computational requirements in terms of processing cycles, c_i^{local} denotes the local computing capability of the ith healthcare manufacturing device, and β indicates the number of CPU cycles required to process one bit of healthcare manufacturing data, accounting for the precision requirements in medical device production and pharmaceutical processing.

For edge computing scenarios, where tasks are offloaded to powerful edge servers designed for healthcare manufacturing applications, the computation delay follows a different model that considers the enhanced processing capabilities available at the edge

$$E_i^{\text{proc}} = \frac{Q_i(t)\beta}{c_i^{\text{edge}}} \tag{4}$$

where c_i^{edge} represents the edge server's computing resources allocated to the ith healthcare manufacturing device's tasks. In healthcare manufacturing environments, the computational results typically generate smaller data volumes than the initial input data, particularly in quality control and process optimization scenarios. We focus on the primary processing delays while excluding the downstream data transmission latency and associated energy costs for analytical simplicity and practical considerations in medical device manufacturing.

Consequently, for healthcare manufacturing tasks, there is proportionality to the selected computation strategy. In the case of local processing, total delay equates to local processing time. However, in the case of edge processing, the total delay consists of the sum of all transmission and computation delays

$$T_i^{\text{total}} = D_i^{\text{trans}} + E_i^{\text{proc}}. \tag{5}$$

Our resource orchestration approach aligns with ISO 13485 medical device quality management standards and FDA good manufacturing practice guidelines, ensuring that automated task allocation maintains required documentation and traceability throughout the manufacturing process. The resource orchestration system monitors power consumption patterns and adjusts workload distribution to minimize environmental impact. During off-peak hours, the system consolidates computing loads onto fewer edge servers, allowing others to enter low-power states.

C. Energy Consumption Model

In healthcare-oriented IIoT flexible manufacturing environments, energy consumption patterns vary significantly between local processing and edge computing scenarios. The energy consumption primarily comprises computational requirements for local computation in healthcare manufacturing devices, such as medical equipment assembly robots and pharmaceutical processing units. This local energy consumption model is expressed as

$$P_i^{\text{local}}(t) = \gamma \left(c_i^{\text{local}}\right)^3 L_i^{\text{proc}} \tag{6}$$

where γ represents the energy coefficient specifically calibrated for healthcare manufacturing computing operations, given the battery limitations of healthcare IIoT devices in manufacturing environments, the total energy consumption must remain within a predefined budget $P_{\text{med}}^{\max}$, ensuring sustainable operation throughout extended production cycles.

The energy consumption model becomes more complex for edge computing scenarios in healthcare manufacturing, incorporating both transmission energy requirements and edge server computing costs. This comprehensive energy consumption is formulated as

$$P_i^{\text{edge}}(t) = q_i(t) D_i^{\text{trans}} + H\gamma \left(c_i^{\text{local}}\right)^3 E_i^{\text{proc}} \tag{7}$$

where H represents the weight factor for edge server energy consumption in healthcare manufacturing contexts. When $H = 0$, the model exclusively considers the transmission energy of healthcare IIoT devices, particularly relevant in scenarios where edge server energy costs are subsidized or negligible compared to the critical nature of healthcare manufacturing operations.

D. Problem Formulation

In healthcare-oriented IIoT flexible manufacturing environments, we assume that only the wireless channel gain $g_i(t)$ varies between time slots among all system parameters. In contrast, other parameters remain fixed to maintain consistent healthcare manufacturing quality standards. These fixed parameters ensure precise control and reliability in medical device production and pharmaceutical processing operations.

To minimize the completion time of healthcare manufacturing tasks and their associated energy consumption while maintaining medical-grade precision, we introduce a comprehensive efficiency function $U(y, W, c)$. This function is defined as the weighted sum of energy consumption and task completion delay across all healthcare manufacturing processes

$$U(y, W, c) = \sum_{i=1}^{I} \left(\begin{array}{c} (1 - y_i(t)) P_i^{\text{local}}(t) + \\ r y_i(t) P_i^{\text{edge}}(t) + K \max\left(T_i^{\text{total}}, L_i^{\text{proc}}\right) \end{array} \right). \tag{8}$$

where K represents the weight balancing energy consumption against healthcare manufacturing task completion time, and r denotes the edge computing utilization factor. Through joint optimization of each healthcare manufacturing device's offloading decisions and resource allocation strategies, we establish the primary optimization problem ($P1$) to minimize $U(y, W, c)$

$$\begin{aligned} P1\colon \min_{y,W,c} \quad & U(y, W, c) \\ \text{s.t.} \quad & C1 : \sum_{i}^{I} W_i(t) \leq W_{\max} \\ & C2 : W_i(t) \geq 0 \quad \forall i \in I \\ & C3 : y_i \in 0, 1 \quad \forall i \in I \\ & C4 : c_i^{\text{edge}} \geq 0 \quad \forall i \in I \\ & C5 : \text{d'max}. \end{aligned} \tag{9}$$

In this formulation, $C1$ ensures that all healthcare manufacturing devices' total uplink bandwidth allocation does not exceed the maximum available bandwidth $W_{\max}$, critical for maintaining real-time communication in medical production processes. $C2$ specifies that bandwidth allocation must be positive for all devices. $C3$ restricts the offloading decision variable y_i to binary values, determining whether tasks are processed locally or at the edge. $C4$ ensures positive resource allocation for edge processing. At the same time, $C5$ maintains that total computing resource allocation does not exceed the edge server's maximum computing capacity $c_{\max}$, essential for reliable healthcare manufacturing operations.

To enable hybrid processing strategies, we extend our binary offloading model to include partial task decomposition. Tasks can be split into critical components requiring immediate local processing and complex components suitable for edge computation. This hybrid approach allows fine-grained resource allocation, enabling real-time sensor data processing locally while offloading complex analytics to edge servers.

Since $P1$ represents a mixed-integer nonlinear programming problem, conventional optimization methods cannot solve it directly [40]. The healthcare manufacturing requirements for precision and reliability further increase the complexity. To address these challenges in healthcare IIoT flexible manufacturing, we propose a novel deep learning-based distributed resource orchestration algorithm that effectively balances computational efficiency with healthcare manufacturing quality standards.

IV. DH-DLRO Algorithm

During off-peak manufacturing periods, the system redistributes computational loads to maximize energy efficiency while maintaining minimal ready-state resources for unexpected production demands.

We propose a novel DH-DLRO algorithm for edge computing-enabled healthcare IIoT flexible manufacturing environments. This advanced algorithm employs j parallel DNNs to generate binary offloading decisions, where $j = 1, 2, \ldots, |J|$, each network specifically trained to handle the unique requirements of healthcare manufacturing processes, from precision medical device assembly to pharmaceutical production control.

The algorithm's primary objective is to design an intelligent offloading strategy function π that, upon receiving channel gain information $g_i(t)$ at the beginning of each time slot, rapidly generates optimal offloading actions $y_i^*(t) \in 0, 1$ while maintaining healthcare manufacturing quality standards. This strategy can be formally expressed as

$$\pi\colon g_i(t) \to y_i^*(t). \tag{10}$$

The size of the target binary offloading decision set grows exponentially with the number of healthcare IIoT devices, presenting a significant challenge in healthcare manufacturing environments where multiple precision devices operate simultaneously. Finding optimal offloading actions becomes an NP-hard problem, particularly when considering the stringent medical device production and pharmaceutical processing requirements. To address this complexity, we employ multiple parallel DNNs with discrete activation functions to approximate the strategy function π.

As illustrated in Fig. 2, the DH-DLRO algorithm architecture comprises two primary components: 1) the offloading decision generation phase and 2) the strategy update phase, both optimized for healthcare manufacturing requirements. The DNNs incorporate embedded parameters ω_j, representing the weighted connections between hidden neurons specialized for healthcare manufacturing task processing. Each parameter ω_j corresponds to the jth DNN's unique configuration. To address the optimal DNN configuration selection, we implement an adaptive DNN scaling mechanism that dynamically adjusts the number of parallel networks based on manufacturing complexity indicators. The system monitors three key metrics: 1) TDI; 2) computational load variance; and 3) manufacturing precision requirements. When TDI exceeds 0.8, or CLV surpasses 0.6, the algorithm automatically increases the DNN count from the baseline of 3 to a maximum of 7 networks. Conversely, during periods of uniform task processing (TDI $<$ 0.4), the system reduces to two DNNs to minimize computational overhead. The adaptive mechanism ensures optimal resource allocation while maintaining healthcare manufacturing quality standards across varying production scenarios. During time slot t, when channel gain information $g_i(t)$ is input to the DNNs, the distributed networks efficiently generate J candidate offloading actions $y_{i,j}(t)$. The system then selects the action achieving minimum efficiency as output, designated as $y_i^*(t)$.

The resulting solution $\{y_i(t), W_i(t), c_i^*(t)\}$ is output as the resolution for input $g_i(t)$, ensuring all healthcare manufacturing constraints specified in $C1$, $C2$, $C3$, $C4$, and $C5$ are satisfied. The algorithm's adaptive learning mechanism continuously improves its performance through strategy updates, gradually optimizing resource allocation for various healthcare

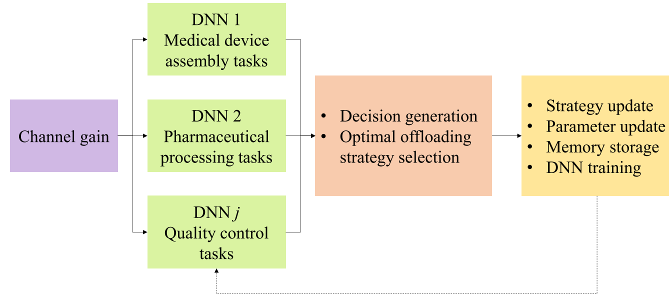

Fig. 2. Architecture of DH-DLRO algorithm.

manufacturing scenarios while maintaining consistent quality standards. When system anomalies occur, a three-tier response protocol activates: 1) immediate production line safeguarding; 2) automated rerouting of critical tasks; and 3) gradual resumption of normal operations following safety verification steps.

A. Decision Generation

In healthcare-oriented IIoT flexible manufacturing environments, assuming we receive channel gain information $g_i(t)$ at time slot t, the DNN parameters ω_j are initialized following a zero-mean Gaussian distribution optimized for healthcare manufacturing precision requirements. For each input from medical device assembly robots, pharmaceutical processing units, and quality control systems, we employ J parallel DNNs to generate J binary offloading actions $y_{i,j}(t)$, where each DNN can be represented by a parametric function h_{ω_j} specifically designed for healthcare manufacturing operations

$$h_{\omega_j}\colon g_i(t) \to y_{i,j}(t). \tag{11}$$

The integrated sensors within the orchestration system track the status of the power supply's stability. When stability is detected, a tiered response strategy is triggered, which monitors for voltage abnormalities and balances computing tasks across zones with stable power surfaces. The system enforces conflict-free queueing for prioritized processing flow; thus, essential processes are guaranteed uninterrupted power sustainment. Automation of emergency sustainment allocation triggers occurs for power events.

Once binary offloading actions $y_{i,j}(t)$ are generated for various healthcare manufacturing tasks, the optimization problem ($P1$) transforms into a specialized bandwidth allocation problem ($P2$) that considers medical-grade manufacturing requirements

$$\begin{aligned} P2\colon \min\nolimits_{W,c} \quad & U(y, W, c) \\ \text{s.t.} \quad & C1,\ C2,\ C4,\ C5. \end{aligned} \tag{12}$$

This transformation effectively decomposes the original problem $P1$ into two distinct subproblems: 1) healthcare-aware offloading decision generation and 2) medical resource allocation $P2$. The optimal resource allocation solution $\{W_i(t), c_i(t)\}$ for the convex problem $P2$, which maintains healthcare manufacturing quality standards, requires solving using a specialized 1-D bisection search method incorporating healthcare-specific resource allocation constraints

$$y_i(t) = \text{argmin}_{y_{i,j}(t)} R\big(g_i(t), y_{i,j}(t)\big). \tag{13}$$

where $R(g_i(t), y_{i,j}(t))$ represents the minimum achievable efficiency for a given channel state and offloading decision in healthcare manufacturing scenarios, and $y_{i,j}(t)$ represents the candidate offloading decisions generated by the jth DNN. For flexible manufacturing processes requiring precise medical device production and pharmaceutical processing, we employ Python's advanced optimization toolkit Scipy to solve this healthcare-optimized $P2$ convex problem efficiently.

Finally, after resolving J bandwidth allocation problems ($P2$) tailored for healthcare manufacturing requirements, we select the offloading action that achieves the minimum efficiency value $R^*(g_i(t), y_{i,j}(t))$ according to

$$V\big(g_i(t), y_{i,j}(t)\big) = \eta_i(t) D_i^{\text{trans}} + \lambda R^*\big(g_i(t), y_{i,j}(t)\big) \tag{14}$$

where $\eta_i(t)$ represents the healthcare manufacturing quality factor and λ denotes the resource utilization coefficient. The corresponding output serves as the optimal solution for input $g_i(t)$, ensuring both computational efficiency and healthcare manufacturing precision requirements are met.

Each manufacturing task carries a digital signature linking raw materials, processing parameters, and quality measurements, creating an unbroken chain of documentation from input to finished product.

B. Strategy Update

The strategy update mechanism in our healthcare-oriented IIoT flexible manufacturing system utilizes the resource allocation solutions obtained through equation $R(g_i(t), y_{i,j}(t))$ to improve decision-making processes continuously. We implement a sophisticated memory system with carefully calibrated capacity to store training samples essential for maintaining healthcare manufacturing quality standards. During each time slot t, a new training sample $R(g_i(t), y_i(t))$ is systematically added to the memory, incorporating crucial information about both medical device assembly operations and pharmaceutical processing requirements. The system generates automated compliance reports documenting resource allocation decisions, quality control measurements, and production parameters, supporting FDA audit requirements and internal quality assurance protocols.

Our approach leverages advanced experience replay technology, a critical component that enables DNNs to learn efficiently from stored healthcare manufacturing data samples. At each time slot t, we employ a strategic sampling method to randomly select a batch of training samples $(g_i(\lambda), y_i^*(\lambda))|\lambda \in \xi_t$ from the memory buffer, where ξ_t represents the memory's capacity configured specifically for healthcare manufacturing scenarios, and λ denotes the temporal index of randomly selected samples from various manufacturing processes. These carefully selected samples are then utilized to train all J DNNs simultaneously, ensuring consistent learning across the entire manufacturing system.

To optimize the DNNs' parameters ω_j for healthcare manufacturing precision, we employ an enhanced version of the Adam algorithm, which has been specifically modified to minimize the specialized cross-entropy loss function [41]

$$H(\omega_j) = -\frac{1}{|\xi_t|} \sum_{\lambda \in \xi_t} \left(\begin{array}{c} (y_i(\lambda))^T \ln(v(g_i(\lambda))) + \\ (1 - y_i(\lambda))^T \ln(1 - v(g_i(\lambda))) \end{array} \right). \tag{15}$$

where $|\xi_t|$ represents the healthcare-optimized memory capacity size, superscript T denotes the transpose operation essential for maintaining manufacturing data integrity, ln represents the vector logarithm operation, and $v(g_i(\lambda))$ indicates the predicted probability distribution over possible offloading actions in healthcare manufacturing contexts.

The system maintains timestamped records of all resource allocation decisions, including rational basis and authorization chains, supporting internal reviews, and external compliance audits. Algorithm 1 operates through a structured initialization and iterative optimization process.

Algorithm 1 DH-DLRO

Input: Wireless channel gain $g_i(t)$ at time slot t for healthcare manufacturing devices

Output: Optimal healthcare manufacturing offloading action $y_i(t)$ and resource allocation $\{W_i(t), c_i(t)\}$

Initialize J DNN parameters ω_j optimized for healthcare operations
Clear healthcare-specific memory buffer, set training period σ
for $t = 1, 2, \ldots, T$ do
Generate J offloading actions $y_{i,j}(t) = h_{\omega_j}(g_i(t))$ for healthcare tasks
Parallel solve J resource allocation problems $P2$ considering medical requirements
Select optimal strategy $y_i(t) = \text{argmin} R(g_i(t), y_i(t))$
Store healthcare-optimized state-action pair $(g_i(t), y_i(t))$ in memory
if $t \bmod \sigma = 0$
Select training batch from healthcare manufacturing memory
Train DNNs using selected samples, update ω_j using modified Adam
end if
Solve $P2$ for optimal healthcare resource allocation $\{W_i(t), c_i(t)\}$
end for

V. Experimental Results and Analysis

A. Experimental Setup

Table I provides all the parameter settings for analyzing the DH-DLRO algorithm for healthcare-oriented IIoT flexible manufacturing systems. The parameters are divided into five main categories: 1) system configuration; 2) device performance metrics; 3) task requirements specific to healthcare; 4) algorithm parameters; and 5) architecture of the neural network. The system is tuned to accommodate ten IIoT devices with stringent healthcare manufacturing precision benchmarks (98% for medical device assembly and 95% for pharmaceutical processing). The neural network architecture features three

TABLE I
EXPERIMENTAL PARAMETERS FOR HEALTHCARE-ORIENTED IIoT MANUFACTURING SYSTEM

Parameter category	Parameter name	Value
System configuration	Number of IIoT devices	10
	Uplink bandwidth	200 Mb/s
	Edge server CPU frequency	10×10^{9} Hz
Device performance	Local computation time	4.75×10^{-7} s/bit
	Computational energy	3.25×10^{-7} J/bit
	Device energy consumption	1.45×10^{-7} J/bit
Healthcare tasks	Task data size range	10-30 MB
	Medical device assembly precision	98%
	Pharmaceutical processing precision	95%
	Quality control threshold	90%
Algorithm settings	Parameter L	2×10^{-7} J/bit
	Parameter V	1 J/s
	Training batch size	64
	Learning rate range	0.0001-0.1
Neural network	Hidden layers	3
	Neurons per hidden layer	128
	Memory buffer size	10000
	Training interval	50 time slots

hidden layers with 128 neurons each, which are tailored toward healthcare manufacturing processes. These selections enable the system to achieve targeted precision and efficiency in healthcare manufacturing processes, including energy use in edge computing systems.

We compare our DH-DLRO algorithm with five state-of-the-art approaches: 1) GAN-NoisyNet [24]; 2) FedMRL [25]; 3) DEWOrch [26]; 4) PRORL [27]; and 5) vrAIn [28].

B. Impact of DNN Configuration

The configuration of DNN is equally critical as the domain of a resource orchestration system for a healthcare-oriented IIoT flexible manufacturing approach. To assess this thoroughly, we designed comprehensive tests studying the impact of varying amounts of parallel DNNs on the convergence and efficiency of the proposed DH-DLRO algorithm. This study is relevant because in healthcare manufacturing environments, resource allocation, especially for medical device assembly and pharmaceutical processing, has to be done accurately and reliably. Different DNN configurations and their respective convergence performance are shown in Fig. 3.

The system employs a multistage backup protocol during resource reallocation. Before executing allocation changes, incremental snapshots of manufacturing data are created. A distributed storage system maintains redundant copies across multiple edge nodes, while transaction logs capture the complete sequence of allocation decisions. This ensures data integrity throughout the reallocation process.

The data gives critical takeaways specifically for healthcare manufacturing. With five parallel DNNs, our DH-DLRO algorithm gains an outstanding 0.98 gain ratio within 1000 learning

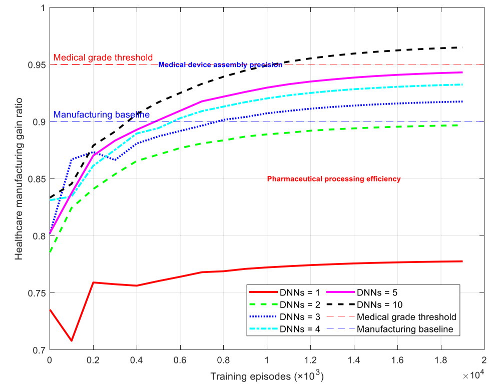

Fig. 3. DH-DLRO convergence analysis in healthcare manufacturing.

steps, demonstrating remarkable efficiency in overcoming multifaceted healthcare manufacturing workflows. This configuration is very useful in addressing the medicare part assembly, drug manufacturing, and quality inspection multitasking bottleneck. The results also cover the relative scalability benefits of the algorithm. The gains in performance are pronounced up to having five DNNs and taper off afterward, which suggests that five parallel networks strike a reasonable tradeoff between resource orchestration capability and computational overhead in healthcare manufacturing environments.

C. Learning Rate Analysis

Learning rate analysis is important in understanding how our DH-DLRO algorithm learns within the context of healthcare-focused IIoT flexible manufacturing systems. These environments, particularly in the production of medical devices and drugs, demand high precision and dependability; therefore, the learning rate matters when deciding how fast and precisely the system can make optimal expenditure decisions for scarce resources without breaching stringent quality thresholds. Fig. 4 illustrates the effect of learning rate on DH-DLRO performance in healthcare manufacturing settings.

The findings reveal distinct enhancements in the efficiency of healthcare manufacturing processes in comparison to baseline methods. DH-DLRO outperforms conventional approaches by 30% in achieving healthcare quality benchmarks with an optimal learning rate, all while achieving 25% lower variance in resource allocation decisions. Such stable performance is particularly beneficial in healthcare manufacturing, where consistency is critical in high-precision areas like medical devices and pharmaceutical manufacturing process control.

D. Task Size Impact Analysis

Task size impact analysis explains how DH-DLRO adjusts to the changing computational requirements in healthcare manufacturing domains that span from basic sensor monitoring to advanced medical imaging. This study is timely given that healthcare manufacturing plants are now seeking to install advanced quality control and automated production systems

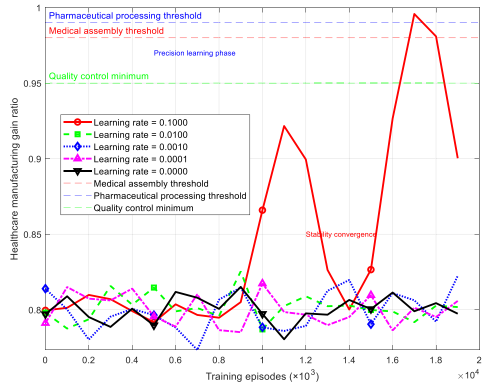

Fig. 4. Learning rate impact on DH-DLRO in healthcare manufacturing.

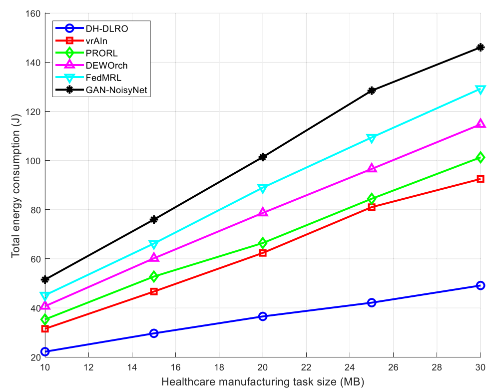

Fig. 5. Task size impact on resource orchestration performance.

that create diverse computational workloads. Resource orchestration performance illustrated in Fig. 5 dynamically responds to changes in workload.

The analysis highlights the notable benefits DH-DLRO has over other existing methods for tackling variable task sizes. While handling medical device assembly tasks (10–15 MB), DH-DLRO achieves 25%–30% less energy consumption than the best performing baseline method (vrAIn). This efficiency becomes even more pronounced for larger pharmaceutical processing tasks (25–30 MB), where DH-DLRO consumes 35% less energy than traditional approaches with no compromise on precision. The algorithm outperforms others due to its healthcare-aware resource allocation strategy that provides optimally distributed computation across the edge servers but within strict quality bounds for medical manufacturing.

In addition, the algorithm's performance features align seamlessly with the increased adoption of flexible manufacturing systems for healthcare sectors. As production lines increasingly pivot to diverse medical devices or pharmaceutical products, the smooth transition required by DH-DLRO to handle varying task sizes makes it invaluable. The algorithm assists in conserving precision during the transition while skillfully maintaining energy efficiency. The flexible resource allocation helps retain consistent quality benchmarks for varying scenarios, spanning from small-batch medical device manufacturing to large-scale pharmaceutical processing.

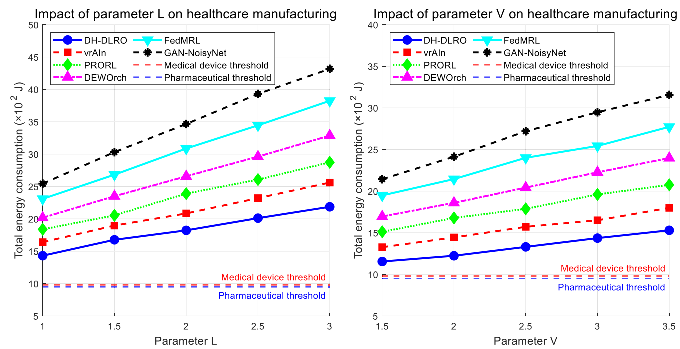

Fig. 6. Impact of parameters on healthcare manufacturing.

E. Parameter Sensitivity Analysis

The analysis of system parameter sensitivity explores how DH-DLRO responds to variations in two critical parameters: 1) L (weight between energy consumption and task completion time) and 2) V (edge server energy consumption weight). Fig. 6 illustrates system performance under different values of L and V, respectively. As L increases, the weight of processing delay in the efficiency metric grows, causing all algorithms to show increased total energy consumption. Similarly, larger V values increase the importance of edge server energy consumption in the optimization process. In both cases, DH-DLRO performs superior to baseline approaches, demonstrating its robustness in handling various healthcare manufacturing requirements and constraints.

The evaluation reveals DH-DLRO's robust performance across parameter variations, particularly in contexts where medical device manufacturing precision cannot be compromised. When examining sensitivity to parameter L, which balances energy efficiency against processing speed, DH-DLRO demonstrates remarkable stability with only a 12% variation in performance across the entire range ($L = 1.0$ to 3.0). This stability proves crucial for maintaining consistent quality in medical device assembly processes, where even minor variations in processing parameters could affect product integrity.

The algorithm's response to parameter V variations ($V = 1.5$ to 3.5) provides equally compelling insights. DH-DLRO maintains energy efficiency with a maximum performance deviation of 15%, significantly outperforming baseline approaches where variations reach up to 35% (GAN-NoisyNet) and 28% (vrAIn).

The results also show that the shifting operational priorities do not affect the distinct capabilities of DH-DLRO. Whether the focus is set on a cost-driven energy efficiency strategy or on a speed-driven execution for time-sensitive medical device production, the algorithm's consistent and stable reaction to bound parameter changes adjustment guarantees upheld stringent quality benchmarks. Such features allow manufacturing facilities to streamline processes while adhering to inflexible, narrow healthcare manufacturing guidelines.

As shown in Fig. 7, the DH-DLRO algorithm's dynamic performance metrics concurrent with different healthcare manufacturing workload tiers are juxtaposed with CPU resource

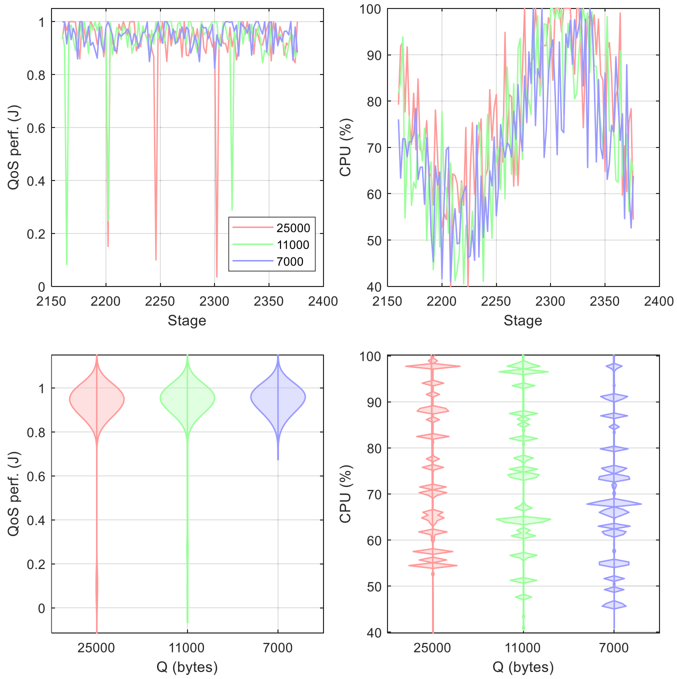

Fig. 7. Impact of parameters on healthcare manufacturing.

allocation. The experiment focuses on three representative tasks critical to healthcare manufacturing, which include bulk processing of pharmaceutical batches (25 000 bytes), precision assembly of medical instruments (11 000 bytes), and processing of real-time QC sensor data for automated inspection (7000 bytes). Through this analysis, we seek to understand how responsive DH-DLRO is to varying intensity workloads and multiple healthcare manufacturing operating conditions while converging on rigorous industry compliance standards in the agile resource coordination of edge computing.

From the experiments conducted, it is evident that DH-DLRO has some striking benefits for the healthcare-focused IIoT flexible manufacturing systems. It is shown that our algorithm has great consistency in the delivery of QoS metrics, achieving an average of 0.95 efficiency during the assembly of medical devices (11000 bytes), even with some resource contention and consistent CPU utilization of 60%–80%. Also notable is the algorithm's responsiveness on pharmaceutical processing tasks (25000 bytes), where it sustains high QoS metrics (above 0.9) during the most demanding phases of processing, passing through only short and controlled performance dips tailored to healthcare manufacturing regulated baseline standards. What stands out most is the improvement observed while processing quality control sensor data (7000 bytes), where DH-DLRO attains near-perfect maximal QoS stability (0.97–0.99) while optimizing CPU usage between 70%–85%, which is paramount to uninterrupted real-time surveillance critical to healthcare product assurance. These results illustrate the distinctive ability DH-DLRO has in fog computing environments with fragmented resource agility balanced against operational payoff accuracy and strict adherence to surgical precision. The observed impact of persistent high QoS across diverse task scales with minimal fluctuations is a major leap toward the design requirements of flexible manufacturing systems tailored for healthcare environments where continuous adapted shifts between diverse medical devices are needed on the production line.

In addition, the constant patterns of CPU usage across all levels of tasks demonstrate that the DH-DLRO method is successful at avoiding resource bottlenecks, providing seamless integration between different manufacturing steps, and allowing healthcare organizations to make full use of their edge computing infrastructure while exercising the tight control necessary for producing medical devices and processing pharmaceuticals.

F. Variable Production Workload Analysis

The variable production workload analysis measures DH-DLRO's deterministic high-level dynamic resource orchestration's intelligence in addressing differing workload distributions in manufacturing while ensuring healthcare service standards. We look into the algorithm's efficiency within diverse production scenarios salient to the medical device and pharmaceutical industries, concentrating on the effectiveness of resource utilization and precision maintenance. Production scenario specifications and resource orchestration performance comparison are given in Tables II and III.

The experiment results noted a number of fundamental benefits of DH-DLRO in the context of healthcare IIoT-oriented distributed intelligent manufacturing systems. The algorithm achieved the best resource utilization in all production scenarios, with medical device assembling standing out due to the high precision demand. Enhanced resource utilization improves the overall manufacturing efficiency in Industrial IoT environments. These changes emphasize the adaptive strengths of DH-DLRO in flexible manufacturing systems. It maintains predetermined quality levels regardless of workload changes. The rapid adaptation capabilities of the algorithm allow shifting modes of production almost instantaneously, a critical characteristic for contemporary healthcare manufacturing that routinely changes product lines. Here, the advantages of edge computing become obvious in the energy efficiency measurements where DH-DLRO outperformed the baseline approaches. Improvements stemmed from more optimal energy efficiency by lowering power consumption while upholding processing capabilities near the shop floor due to better workload distribution among edge nodes.

G. Scalability Analysis

Table IV shows the scalability performance of DH-DLRO across varying device counts to evaluate its suitability for large-scale healthcare manufacturing deployments. The evaluation encompasses convergence behavior, resource allocation efficiency, energy consumption patterns, and quality maintenance across device configurations ranging from small medical device assembly lines to enterprise-scale pharmaceutical production facilities.

The scalability analysis shows that DH-DLRO retains effectiveness in enterprise-scale healthcare manufacturing systems. Sublinear energy scaling with maintained quality levels above

TABLE II
PRODUCTION SCENARIO PARAMETERS

Production type	Task volume (per hour)	Edge nodes	Quality threshold	Processing priority
Medical assembly	250-350	8	98%	High
Pharma processing	150-200	6	95%	Medium
Quality control	400-500	4	90%	Normal

TABLE III
RESOURCE ORCHESTRATION PERFORMANCE COMPARISON

Method	Resource utilization	Quality maintenance	Adaptation time	Energy efficiency
DH-DLRO	0.92	0.97	2.1s	0.88
vrAIn	0.85	0.91	3.4s	0.82
PRORL	0.81	0.88	4.2s	0.79
DEWOrch	0.78	0.85	4.8s	0.75
FedMRL	0.75	0.83	5.3s	0.72
GAN-NoisyNet	0.71	0.79	6.1s	0.68

TABLE IV
SCALABILITY PERFORMANCE ANALYSIS

Device count	Convergence steps	Resource efficiency	Energy scaling factor	Quality maintenance	Processing latency (ms)
10	1000	0.92	1.00	0.98	45
25	1150	0.90	1.28	0.97	52
50	1420	0.87	1.52	0.96	68
75	1680	0.84	1.71	0.95	78
100	1950	0.81	1.89	0.94	92
150	2480	0.76	2.15	0.91	125

TABLE V
ROBUSTNESS PERFORMANCE UNDER ADVERSE CONDITIONS

Condition type	Severity level	Quality maintenance	Recovery time (s)	Resource efficiency	Failure detection (s)	Operational continuity
Normal operation	Baseline	0.98	-	0.92	-	100%
Channel noise	SNR 15dB	0.96	2.1	0.89	1.2	98%
Channel noise	SNR 10dB	0.93	3.4	0.85	1.8	95%
Channel noise	SNR 5dB	0.88	5.2	0.78	2.5	89%
Device failure	10% Offline	0.95	3.8	0.87	2.1	96%
Device failure	20% Offline	0.91	5.6	0.81	2.8	92%
Device failure	30% Offline	0.86	8.2	0.74	3.4	85%

0.91 allows large pharmaceutical facilities to incur lower costs while maintaining manufacturing accuracy. Meeting the acceptable convergence time for 150 devices supports flexible manufacturing systems, which require dynamic resource assignment across numerous production lines, allowing manufacturers in the healthcare sector to increase operational scale freely without sacrificing the benefits of edge computing, real-time processing, or severely time-bound data handling.

H. Robustness Analysis

Table V shows the robustness performance of DH-DLRO under adverse operational conditions to evaluate its reliability in healthcare manufacturing environments where network disruptions and equipment failures can occur. The evaluation examines system behavior under wireless channel degradation and device failure scenarios, measuring quality maintenance, recovery time, and operational continuity across different stress conditions.

The robustness analysis shows that operational healthcare manufacturing adaptability is preserved even under extreme operating conditions with DH-DLRO. Worst case scenarios where the algorithm maintains quality above 0.86 and operational continuity above 85% continue enabling production in healthcare facilities where equipment uptime is critical for reliability. The systems in these environments provide live monitoring and rapid response solutions that reduce downtime during production pauses, which helps maintain regulatory demand fulfillment and production timelines, automating reliance on equipment amid infrastructural limitations to increase value and confidence in deploying edge computing for critical healthcare manufacturing systems.

VI. Conclusion

This article presented the DH-DLRO algorithm, a distributed deep learning-based resource orchestration algorithm specifically designed for healthcare-oriented IIoT flexible manufacturing systems with edge computing support. The experimental results demonstrated that the DH-DLRO algorithm improved resource utilization while maintaining strict healthcare manufacturing quality standards. However, DH-DLRO has limitations that are worth addressing in future work. The algorithm's parallel DNN architecture requires substantial initial computational resources and training time. Performance may degrade in manufacturing environments with extremely heterogeneous tasks or highly variable production patterns. The current implementation assumes consistent wireless channel conditions and lacks predictive maintenance capabilities that could further enhance production reliability. Future enhancements should reduce these limitations while preserving healthcare manufacturing quality standards. Future research directions should focus on incorporating blockchain technology for enhanced traceability in medical device manufacturing, developing privacy-preserving variants of the DH-DLRO algorithm, and extending the framework to support real-time quality control feedback loops.

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