Blockchain-Based Deep Reinforcement Learning System for Optimizing Healthcare

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***Abstract*—The Industrial Internet of Things (IIoT) has become a transformative force in various healthcare applications, providing integrated services for daily life. The app healthcare based on the IIoT framework is broadly used to remotely monitor clients health using advanced biomedical sensors with wireless technologies, managing activities such as monitoring blood pressure, heart rate, and vital signs. Despite its widespread use, IIoT in healthcare faces challenges such as security concerns, inefficient work scheduling, and associated costs. To address these issues, this paper proposes and evaluates the Blockchain-Based Deep Reinforcement Learning System for Optimizing Healthcare (BDRL) framework. BDRL aims to enhance security protocols and maximize makespan efficiency in scheduling medical applications. It facilitates the sharing of legitimate and secure data among linked network nodes beyond the initial stages of data validation and assignment. This study presents the design, implementation, and statistical evaluation of BDRL using a new dataset and varying platform resources. The evaluation shows that BDRL is versatile and successfully addresses the security, privacy, and makespan needs of healthcare applications on distributed networks, while also delivering excellent performance. However, the framework utilizes high resources as the size of inserted data increases.**

***Index Terms*—IoT, DQN, edge intelligence, data cleaning.**

I. Introduction

WITH the aim of providing a range of automated healthcare services, the Industrial Internet of Things (IIoT) paradigm, which incorporates machine learning (ML) techniques, has been increasingly used [1]. Numerous electronic health software, like COVID-19 detection frameworks, heartbeat surveillance systems, and cancer diagnosis infrastructure, are powered by distributed IIoT networks [2]. These networks include a variety of technologies, including cloud computing (fog nodes and edge nodes), blockchain technology, Bluetooth, 5G and 6G wireless technologies, and healthcare sensors (IoT devices) [3]. Within the IIoT paradigm, task scheduling stands out as a critical mechanism for ensuring that healthcare applications achieve their quality of service standards on various platforms [4]. There are several varieties of healthcare apps, including fine-grained tasks based on objects, workflow, and coarse-grained activities. Although health services follow a sequential process structure, scheduling healthcare processes in the IIoT paradigm based on quality-of-service standards is challenging [5]. Because clinical process apps are usually designed on cloud computing-based services across several networks, inflexible scheduling issues might develop. Static scheduling problems, such as the inability to modify assignments mid-application execution if performance begins to deteriorate, can be addressed by dynamic scheduling [6].

To address scheduling problems in distributed cloud computing for process uses in the healthcare industry, many reactive task scheduling algorithms have been developed. The literature proposes a wide range of learning-based scheduling algorithms, both supervised and unsupervised [7]. One such strategy is the use of reinforcement learning-based schedulers, which maximize the performance of healthcare applications by utilizing Q-learning rules and value functions [8]. Security issues are brought about by the special characteristics of healthcare applications under the IIoT paradigm, which are defined by dynamic data and dispersed uniform nodes. Decentralized blockchain technology has been used in IIoT-based applications to address these issues [7], [9]. To improve security and lessen the problems of data tampering, many forms of blockchain technology have been used. There is a noticeable gap in the literature regarding the implementation of machine learning-enabled IIoT systems for healthcare applications, even though ML models with blockchain technology have been widely explored for load balancing and energy consumption control in IoT networks [14], [15]. Healthcare applications are largely disregarded by current IIoT systems, which are mostly focused on supporting financial applications [15], [16]. Variations of the current IIoT paradigm include the Industrial Internet of Healthcare Things (IoHT) and the Internet of Medical Things (IoMT) [17], [18]. These paradigms emphasize restrictions like latency, energy consumption, timeliness, and resource limits, and they primarily concentrate on the edge cloud network [19]. However, because of resource limitations, workflow applications that operate on separate computer nodes receive insufficient attention [20]. In the past, research has largely concentrated on single-agent-based reinforcement learning techniques to enhance the efficiency of distributed platforms [21], [22]. These approaches use trial-and-error methodologies. To transfer processes based on predictive time series policies and maximize rewards, several research studies have established rules based on several

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agents and helpful nodes within the network [23], [24]. However, the intricacy of multi-agent rules might bring variances and delay durations, possibly posing problems for distributed systems when combined with security, deadline, cost, and delay limitations.

In conclusion, even though the IIoT paradigm and machine learning have made great progress in the space of healthcare applications, problems remain with job scheduling optimization, security, and restrictions in the job scheduling in a decentralized and dynamic context. To address the current gaps and improve the efficacy of IIoT-based healthcare, in this study, an algorithmic framework called BDRL is presented and evaluated that is tailored to workflow applications in the healthcare domain. BDRL combines multiple schemes, such as task scheduling, blockchain, and Q-learning, with the main goal of reducing the makespan of workflow applications. One important performance parameter taken into consideration in the proposed system is the makespan, which represents the overall time for computation and communication across multiple nodes (mobile, fog, and cloud). The manuscript is organized into discrete sections that address various aspects of the work. The section on related work examines current deep reinforcement learning techniques and blockchain models, outlining their advantages and disadvantages. The step-by-step method for addressing problems with the suggested framework is described in the BDRL algorithm section. Evaluation and implementation elements are made clear by contrasting the implemented techniques' results and graphs with the baseline methods. The study's successes, methods, difficulties, findings, and recommendations for future research are all included in the conclusion.

II. RELATED WORK

The combination of blockchain systems, deep reinforcement learning (DRL), and reinforcement learning (RL) in healthcare applications under the Industrial Internet of Things (IIoT) paradigm has been the subject of extensive research. This section reviews significant contributions in the field, categorized into blockchain applications in healthcare, DRL-based methods for healthcare optimization, and combined approaches.

A. Blockchain in Healthcare

Blockchain technology has been extensively used to enhance security and validate data across nodes in healthcare applications. Several studies have explored this aspect:

- **Resource Allocation and Security**: Chen et al. [12] and Xiaoding et al. [13] addressed resource allocation issues in mobile cloud networks by leveraging blockchain for secure data validation. These approaches ensured data integrity and privacy while meeting application needs through descending gradient-enabled weights and time series prediction.
- **Dynamic Task Allocation**: Lakhan et al. [15] investigated dynamic task allocation by transforming unstructured data into structured data to minimize noise using reinforcement learning with supervised learning labels. The key component of their methodology was dynamic job scheduling to optimize workflow execution.
- **Homomorphic Security and Privacy**: Sharma et al. [28] explored homomorphic security and privacy methods provided by blockchain, examining the challenges associated with task scheduling for granular healthcare workloads, including delays, deadlines, and security validation requirements.

B. Deep Reinforcement Learning in Healthcare

DRL has transformed medical by improving the distribution of resources and job planning. Here are two noteworthy examples:

- **DRL Approach to IIoT in Healthcare:** Heuillet et al. [10] created a DRL-based system designed particularly for medical devices that operate on cloud and fog networks as part of the Industrial Internet of Things. Their technique incorporates time series forecasting, reinforcement learning, and neural networks into a single agent, which all work together to improve network performance and assure smooth operations.
- **Optimizing Resource Allocation:** Dai et al. [11] proposed a DRL-based method for minimizing clinical workload by tackling the allocation challenge. Their approach intends to increase the economy of asset utilization and allocation in cloud and fog settings, ensuring that medical facilities are used properly and avoid wastage.

C. Combined Blockchain and DRL Approaches

Mixing blockchain DRL shows major promise for improving both security and efficiency in healthcare applications. Here are some significant approaches:

- **Blockchain and DRL for job Scheduling:** Tiwari et al. [22] created a system using blockchain and DRL to enable safe and efficient job planning in autonomous cloud IoT networks. Their solution ensures the confidentiality of information between cloud and IoT nodes by combining proof-of-stake and evidence of work procedures, as well as cryptographic approaches such as AES, RSA, MD5, and SHA256.
- **Smart Scheduling approaches:** Vahdat et al. [25] investigated algorithms for scheduling that learn from previous situations by employing single-agent DRL approaches and random descent. These algorithms coordinate jobs among a range of cloud nodes, including fog and cloud stations, and IoT healthcare devices, with the purpose of abate preparation and store limits.
- **Work Timing with Blockchain:** Wu et al. [26] used guided learning to develop a blockchain-based timing solution. Their technique uses blockchain technology and cryptographic protocols to provide authenticity of data among IoT and cloud locations.

D. Emerging Trends in Healthcare IIoT

Recent research has introduced innovative approaches in healthcare, especially in integrating blockchain and DRL:

- **Blockchain-Enabled DRL Systems:** Talaat et al. [27] proposed blockchain-enabled DRL systems specifically tailored for medical environments. These systems focus on improving incentive mechanisms while simplifying the execution of healthcare workloads across designated processing nodes, ensuring both security and efficiency.
- **Addressing Challenges in Mobile Healthcare Workflows:** Although significant progress has been made, there remains a notable gap in optimizing healthcare applications for mobile devices. Complex mobile workflows demand substantial processing power and often need to be distributed across cloud and fog nodes. To address this, the study presents the BDRL framework, which facilitates efficient scheduling, secure data exchanges, and the optimal use of mobile, fog, and cloud networks in medical processes.

III. Overhead Analysis and Benefits of Blockchain in Healthcare Systems

Blockchain technology offers various costs, such as higher computing needs and delay. Still, these expenses are compensated by the substantial advantages it provides. In the next section, we present an in-depth examination of the compromises and demonstrate that our Blockchain-Based Deep Reinforcement Learning (BDRL) framework's benefits for enhancing medical procedures considerably surpass those costs.

A. Computational Overhead and Resource Management

Blockchain networks need a large amount of processing resources to operate consensus algorithms, store transaction data, and maintain the distributed ledger. In our BDRL architecture, we solved this by employing simpler agreements such as Proof of Authority (PoA) and Practical Byzantine Fault Tolerance (PBFT), which use far less resources than the more difficult Proof of Work (POW). Furthermore, we simplified the architecture by keeping only critical medical data and transactions on the distributed ledger, while maintaining less private data off-chain. This strategy lowers storage demands and bleaches computing load, rendering it less costly while maintaining privacy.

B. Latency and Throughput Considerations

Blockchain transactions can create delays because of the time required for approval and node distribution. But in our BDRL architecture, we reduce this by employing batch processing, that consolidates multiple transactions into a single block, and parallel processing, which distributes jobs over the web via multi-agent systems. This makes it easier to balance the load and considerably increases throughput. Our findings indicate the BDRL architecture provides great capacity while maintaining tolerable lag rates. Actually, the median processing time is lowered by X% when compared to previous systems, demonstrating the framework's efficiency and effectiveness.

C. Benefits Justifying the Overhead

The primary benefit of blockchain is its high privacy capacity to assure database accuracy. It safeguards confidential data by employing secret immutable records that restrict unintentional modifications. The distributed design of blockchain also eliminates any single points of failure, significantly reducing the likelihood of data breaches. Blockchain provides a distributed system to handle medical records, providing patients more control over their information via intelligent agreements while simultaneously guaranteeing that it meets standards such as GDPR and HIPAA. While blockchain has certain early costs, it can eventually deliver to long-term savings and increased effectiveness. It lowers fraud and mistakes by automating validation and record keeping, as well as streamlining important procedures like patient consent and invoicing, resulting in quicker and safer outcomes.

D. Case Studies and Real-World Applications

Various instances demonstrate the effective use of blockchain in healthcare. For example, blockchain has served to safeguard the pharmaceutical supply chain, eliminating imitation medicine, and has enabled safe, effective sharing of information among healthcare professionals, resulting in improved outcomes for patients. While blockchain does add some processing and temporal expenses, our BDRL paradigm clearly demonstrates that the benefits—such as better safety, confidentiality, accuracy of data, and operating efficiency—far exceed the costs. Our empirical findings clearly suggest that the cost of maintenance is negligible in relation to the considerable advantages in system performance and security. Moving ahead, further investigation will zero in on minimizing the use of resources and improving the blockchain component's capacity and effectiveness in order to render it more effective.

So, although the blockchain-based solution incurs some processing and temporal expenses, our BDRL paradigm clearly demonstrates that the benefits—such as increased safety, confidentiality, accuracy of data, and operating efficiency—far outweigh these expenses. Our tests give strong proof that the cost is negligible in relation to the significant improvements in system efficiency and safety. Moving in advance, we are going to do study to minimize the use of resources and improve the ability to scale and effectiveness of the blockchain element.

IV. Advantages of Blockchain in Healthcare Systems

Blockchain technology has numerous significant advantages for medical facilities, notably in the setting of the Industrial Internet of Things (IIoT), even if information is kept and analyzed locally. One significant benefit is increased data security and privacy. Blockchain files can unchanging, that means that illegal modifications or removals are avoided, hence maintaining the integrity of healthcare data and ensuring regulatory compliance. Furthermore, blockchain offers an auditable trail of all transactions and data changes, which promotes openness and confidence between individuals, medical professionals, and the government. Blockchain increases security via multiplicity by providing a decentralized layer to centralized systems. The combined technique enables the identification of any modifications in the core system by juxtaposing it to blockchain documents, mitigating preventing data theft and assuring data truth even if the vital database is cooperated. Furthermore, blockchain enables greater communication of information and compatibility. A common currency enables seamless communication amongst different medical professionals, minimizing barriers to data and eventually enhancing the health of patients. Intelligent agreements improve process effectiveness by automating data access and handling procedures, guaranteeing meeting confidentiality standards and user permission. The BDRL architecture draws on these advantages by integrating privacy and autonomy with the speed of centralised the process, culminating in a robust and safe medical system. Our findings demonstrate that the benefits greatly exceed any costs. As we move ahead, ongoing studies will minimize use of resources and improve the ability to scale of the digital currency part, hence increasing the structure's efficacy.

V. Proposed BDRL System

Figure 1 presents the complete DRL-aware blockchain-based healthcare system of the study. The inquiry focuses on industrial processes in healthcare care, with ten workflows (WF). The workflow application is logically divided into mobile, fog, and cloud tasks at the design stage. This divide is necessary because of the resource constraints on mobile devices, the fog nodes' capacity to manage jobs that require a delay, and cloud computing's ability to manage tasks that require a delay tolerance. The task annotation system used in the study differentiates between (3) categories of activities: mobles-fogs-clouds tasks.

Fig. 1: BDRL framwork

Patients utilize their handheld devices to get into the software and submit or ask for information within the process structure. While cloud computations save a significant quantity of information locally on the cloud node once they are finished, fog processing duties are executed on the node located in the fog within the entire network. The workflow application tasks are distributed among multiple nodes in the multi-agent heterogeneous mobile fog cloud networks; tasks 1 are completed by the mobile agent, tasks 2 through 6 are handled by the fog agent, and tasks 7 through 10 are managed by the cloud agent. Workflow task sequencing, Qlearning, BLC schemes, and task scheduling are some of the components that make up the BDRL architecture. Data sharing is guaranteed by the cooperative nature of all computer nodes, and the blockchain network makes interconnection possible. Every piece of data is hashed and then shared properly on the blockchain; these are the blocks with the letter B. Every block has an ID that is exclusive to it, and task transactions require validation using the Proof-of-Work (PoW) mechanism. Application status and resource profiling are two key techniques that are used to provide the system with information on the overall workflow task execution within the mobile fog cloud network. These programs help to ensure effective and safe job execution by coordinating and monitoring the whole process.

A. Electronic health record (ELHERE)

Our scenario's ELHERE is a portable patient app that combines health care at global and smart-city levels via fog and cloud networks. Fog nodes allow patients who are on the go to receive city-level services. In addition, sure apps are globally accessible and operate on geographically dispersed cloud computing architecture for medical applications. The focus of the study is on healthcare application workflow, with jobs being deliberately distributed over many nodes such as cloud, fog, and mobile devices. The study uses blockchain systems to strengthen the security of these healthcare activities. These protocols guarantee the authenticity and reliability of data transfers, promoting a legitimate and reliable exchange of information between network nodes.

B. Mathematical Formulation of the Challenge in Mobile-Fog-Cloud Agent Systems

The mobile workflow is defined in this research as (G, WF), where G represents the set of applications, and WF includes activities that are split across mobile, fog, and cloud components. Three sub-task sets make up the workflow: cloud [wf = 1, WF], fog[wf = 1, WF], and mobile[wf = 1, WF]. Every workflow includes data, like data$_{wf}$, that is divided into smaller jobs and overseen by different agents. Three main computational spot which they are named : mobilesAgents (ma), fogsNodes (fn), and cloudsNodes (cn) are the focus of this study. In the network, every node ma, fn, or cn has certain resources and speeds. Based on the annotations that are applied to their tasks throughout the application development process, these three types of agents can carry out workflow applications.

$$\mathrm{T}^{n}_{wf} = \begin{cases} \dfrac{\text{mobile}_{wf=1\in *wf\in X}(\text{data}_{wf})}{\xi_{ma}} & , \ y_{wf} = 1 \\ \dfrac{\text{fog}_{wf=1\in *wf\in X}(\text{data}_{wf})}{\xi_{fn}} & , \ y_{wf} = 2 \\ \dfrac{\text{cloud}_{wf=1\in *wf\in X}(\text{data}_{wf})}{\xi_{cn}} & , \ y_{wf} = 3 \end{cases} \tag{1}$$

The execution time of a collection of jobs distributed over several nodes is calculated using equation 1. In the meantime, the assignment vector $y_{wf} = \{1, 2, 3\}$ denotes whether a given mobile, fog, or cloud node is the recipient of a task (1) or not

(0). The following method is used by the inquiry to determine the communication time (C) for process tasks:

$$\mathrm{C}_{wf1,wf2} = \begin{cases} \dfrac{\text{mobile}_{wf=1\in} * wf \in X(\text{data}_{wf})}{bw_{ma}} & , \; x_{wf1,wf2} = 1 \\[2ex] \dfrac{\text{fog}_{wf=1\in} * wf \in X(\text{data}_{wf})}{bw_{fn}} & , \; x_{wf1,wf2} = 2 \\[2ex] \dfrac{\text{cloud}_{wf=1\in} * wf \in X(\text{data}_{wf})}{bw_{cn}} & , \; x_{wf1,wf2} = 3 \end{cases} \tag{2}$$

The connection among the (mn) and the (fn) is quantified by equation 2, where $x_{wf1,wf2}$ represents the communication cost between workflow nodes $wf1$ and $wf2$ and the communication is determined by how close the fog node is to the cloud node. It is considered that every node in the network has a defined data communication bandwidth.

$$\mathrm{ST}_{st1,ac2} = \begin{cases} BLC = \text{data}_{wf=1\in WF} & , \; st_{st1,ac1} = 1 \\[1ex] BLC = \text{data}_{wf=1\in WF} & , \; st'_{st2,ac2} = 2 \\[1ex] BLC = \text{data}_{wf=1\in WF} & \; st''_{st3,ac3} = 3 \end{cases} \tag{3}$$

Each state (ST) equation 3 has a complete execution procedure in addition to a blockchain (BLC) scheme that makes workflow tasks transferable, where $st_{st1,ac1}$ represents the state transitions from state $st1$ to action $ac1$. The total execution time for each workflow application is then calculated as follows:

$$\mathrm{MT} = \sum_{G=1}^{I} \sum_{wf=1}^{WF} T^n_{wf} + \mathrm{C}_{wf1,wf2} + \mathrm{ST}_{st1,ac1} \tag{4}$$

The makespan time (MT) for each workflow application across the various computer nodes in the given challenge is determined by equation 4. Formula 5 clarifies that all local operations have to respect the resource limitations placed on mobile nodes in the network.

$$\sum_{G=1}^{I} \text{mobile}[wf = 1 \in WF] : \text{data}_{wf} \leq \xi_{fn} \tag{5}$$

Equation 6 shows that resource constraints placed on fog nodes in the network must be adhered to by all fog jobs.

$$\sum_{G=1}^{I} \text{fog}[wf = 1 \in WF] : \text{data}_{wf} \leq \xi_{ma} \tag{6}$$

The formula 7 states that all cloud operations have to respect the resource limitations placed on cloud nodes in the network.

$$\sum_{G=1}^{I} \text{cloud}[wf = 1 \in WF] : \text{data}_{wf} \leq \xi_{cn} \tag{7}$$

For the deadline (DL), each workflow application must operate within the limitations of its own deadline bias in the network, as stated by equation 8.

$$\sum_{G=1}^{I} T^n[wf = 1 \in WF] : \text{data}_{wf} \leq DL \tag{8}$$

C. BDRL algorithm methods

The BDRL algorithm framework is evaluated in this paper to handle the problem of task scheduling for workflows across heterogeneous computing nodes. BDRL combines many approaches to approach the problem in a methodical manner using discrete phases. First, the method uses deep Q-learning, in which tasks are classified, as described in Algorithm 1. It includes many schemes that depict how programs are run and how their associated operations are carried out. Based on their annotations, the classified jobs are subsequently distributed across cn, mn, and fn systems. These annotations, which represent the kinds of jobs that are performed on mobile, fog, and cloud nodes, are defined by the partitioning scheme that the application uses while designing the system. Next, based on their types, all jobs are arranged on compute nodes. Especially, the adaptive Q-learning-based scheduling reschedules unsuccessful jobs on the available computer resources with agility.

Algorithm 1 The BDRL Algorithm Structure

Require: $G, \ldots, I$
begin
for $(G = 1$ to $I)$ **do**
  Assign tasks according to evaluations MobilesNode (M), FogsNode (F), and CloudsNode (C):
  $M_{[wf=1,G]}$;
  $F_{[wf=1,G]}$;
  $C_{[wf=1,G]}$;
  $G = M + F + C$;
  Optimize $MT \in MT \in I$;
  M Sched;
  M Adaptive Scheme;
  M BLC PoW Scheme;
end for

D. Multi-agent deep learning with reinforcement

The task scheduling issue is based on a finite loop with discrete states, where workflow task execution performance is measured by evaluating the best policy and value function. According to our research, deep_reinforcement_learning (DRL) is a combination of reinforcement learning and deep learning, two separate methodologies. The necessity to extract data from programs that are operating through trial-and-error settings is what led to this amalgamation, considering the dynamic changes in the availability of computer resources. To ensure thorough training of the system, a supervised-learning is used to prelabel all entirs, similar to mobile $[wf = 1 \in WF]$, fog $[wf = 1 \in WF]$, and cloud $[wf = 1 \in WF]$. The research considers multi-agent systems, in which every agent is able to exchange legitimate task data and communicate with other agents in order to carry out tasks. The first step of the investigation is to divide up all process deadlines according to makespan. So, the DL for every job is determined by equation 9 based on the task's execution time. The following formula is then used to calculate the study's probability in

Equation 10, whereby (ts) is the times-tamp of the status transition through the process.

$$\sum_{wf=1}^{WF}\sum_{G=1}^{I} d_{wf} = D_l - T_{wf}^{n} - C_{wf1,wf2} - \text{mobile}[wf = 1 \in WF] - \text{fog}[wf = 1 \in WF] - \text{cloud}[wf = 1 \in WF] \tag{9}$$

$$\sum_{wf=1}^{WF}\sum_{G=1}^{I} P(st, ac, ts \parallel s', s'') \tag{10}$$

The ideal strategy for the processes under different network conditions is determined by equation 11. We define (π) to be equal to (MT). The notation ($MT : (st|ac)$) indicates that (MT) is assigned the value derived from the expression ($st|ac$) The equals sign ($=$) is used for defining equality, while the left arrow ($\leftarrow$) denotes assignment.

$$\pi = MT : (st|ac) \tag{11}$$

E. Assigning workflows to various agents based on policy implementation

As illustrated by Algorithm 2, all agents must perform their duties within the parameters of their designated states while adhering to the workflow's best principles and objectives. In (mn), every case needs to fulfill the criteria of several data piece procedures, including makespan, deadlines, and security measures. All agents must collaborate and communicate data across tasks since the workflow tasks are executed on separate nodes inside the system. Data exchange therefore becomes crucial for jobs that are distributed across several nodes.

Algorithm 2 Preliminary Assignment of Process Actions to Various Agents

Require: **Input:** $G, \dots, I$
begin
for $G = 1$ to I **do**
    Schedule $M_{[wf=1:G]}$;
    Call Algorithm 3
    $\prod : MT = M_{[wf=1:G]}$;
    Schedule $F_{[wf=1:G]}$;
    Call Algorithm 3
    $\prod : MT = F_{[wf=1:G]}$;
    Schedule $C_{[wf=1:G]}$;
    Call Algorithm 3
    $\prod : MT = C_{[wf=1:G]}$;
end for

F. Adaptive Task Scheduling and Implementation of the Blockchain Mechanism

The adaptive scheduling scheme and a blockchain-enabled scheme maintain workflow task performance across different agent states. Tasks are divided into those that need to be done locally and those that need to be handled by the fog node and the cloud during the design stage. Concurrently, the execution is divided into several stages and goes through many temporal transitions while taking reward and policy limitations into account. The blockchain-based adaptive scheduler is represented by Algorithm 3. Different stages of the scheduling process are separated while the workflow app's objective function is optimized. Initially, every mobile task—which includes state, action, and transition—is planned on the mobile-device related to its speeds as well as the resources. Algorithm 3 adheres to a specified implementation.

Algorithm 3 State-specific Flexible BLC Scheduling System

Require: $\{Q(st, ac) \in S, T, M, G \in I\}$
1: **begin**
2: **for all** $(st_1, ac_1, t_1 = 1, wf_1, wf_3, ma, fn, cn, B_1)$ **do**
3:     It begins with the original condition:
4:     Plan every job for the mobile terminal using a portable device;
5:     $st_1, ac_1, t_1 = y_{wf} = 1 \in WF : wf = 1, 3 : \frac{\text{data}_{wf}}{\xi_{ma=1}}$;
6:     **if** $(T_i^n \leq d_{wf} : ma : \xi_{ma})$ **then**
7:         Apply BLC BLC_1 : current − hash-SHA-256-bits;
8:     **else if** $(ma : BLC_1 \neq f : BLC_2)$ **then**
9:         PoW;
10:         $current - hash : fn \neq previous - hash : fn$;
11:         Call Policy using equation 10 as a basis;
12:         $r : st_1, ac_1, t_1 = x_{wf} = 1 \in WF : wf = 1, 3 : \frac{\text{data}_{wf}}{\xi_{ma=1}}$;
13:     **else if then**
14:         $st_1, ac_1, t_1 = x_{wf} = 1 \in WF : wf = 1, 3 : \frac{\text{data}_i}{\xi_{ma=1}}$;
15:         $current - hash : ma \neq previous - hash : j1$;
16:         Call Policy;
17:         $r : st_1, ac_1, t_1 = x_{wf} = 1 \in WF : wf = 1, 3 : \frac{\text{data}_{wf}}{\xi_{ma=3}}$;
18:     **end if**
19:     Using the fog node for processing;
20:     **if** $(T_i^{n'} \leq d_{wf} : fn : \xi_{fn})$ **then**
21:         Apply BLC BLC_2 : current − hash-SHA-256-bits;
22:     **else if** $(fn : BLC_1 \neq cn : BLC_2)$ **then**
23:         PoW;
24:         $current - hash : cn \neq previous - hash : fn$;
25:         Call Policy;
26:         $r : st_2, ac_2, t_2 = x_{wf} = 1 \in WF : wf = 1, wf = 3 : \frac{\text{data}_{wf}}{\xi_{fn=2}}$;
27:     **else if then**
28:         $st_2, ac_2, t_2 = x_{ij} : wf = 4, 9, 10 : \frac{\text{data}_i}{\xi_{j=3}}$;
29:         $current - hash : fn \neq previous - hash : ma$;
30:         Call Policy;
31:         $r : st_1, ac_1, t_1 = x_{wf} = 1 \in WF : wf = 1, wf = 4, 9, 10 : \frac{\text{data}_i}{\xi_{j=2}} = 1$;
32:     **end if**
33:     Work being done on the cloud node;
34:     $st_3, ac_3, t_3 = x_{ij} : wf = 2, 5, 7, 8 : \frac{\text{data}_{wf}}{\xi_{cn=3}}$;
35:     $current - hash : cn \neq previous - hash : fn$;
36:     Call Policy;
37:     $r : st_3, ac_3, t_3 = x_{ij} : wf = 2, 5, 7, 8 : \frac{\text{data}_{wf}}{\xi_{cn=3}}$;
38: **end for**
39: Complete the task assigned to every node.
40: **Endure primary purpose;**

1) Mobile Execution: During the first ten phases of the scheduling process, the mobile device was used to apply blockchain validation after the preset tasks that were meant to be executed locally were started. (st_1, ac_1, t_1) represents the initial state, which is the result of the first action and transition in the state. Only the tasks related to wf_1 and wf_3 were planned to be executed on the mobile node j_1 in this specific condition. Then, the information was encrypted using the Secure Hashing Algorithm (SHA-256) bits, and cryptographic information was transferred from one j_1 to j_2 until the hash values of the previous and current iterations matched. To optimize and include the reward in the Q-learning sequence and contribute to a successful execution outcome, the model-free optimum policy was used.

2) Fog Execution: All of the assigned tasks were scheduled at the fog node in stages 11 through 23 of the scheduling process. The fog node then applied blockchain validation at that location. The initial state, indicated by the notations st_2, ac_2, and t_2, is the result of the state's first action and transition. At this point, the fog node j_2 was only scheduled to do tasks related to $wf_{4,9,10}$. Cryptographic data was transferred from one j_2 to j_3 using encryption the SHA-256 bits until the hash values of the two sets of data matched. A successful execution resulted from optimizing and including the reward in the q-learning sequence using the model-free optimum strategy.

3) Cloud Execution: Steps 24 through 35 of the scheduling procedure involve applying blockchain validation in the cloud computing environment and scheduling the designated cloud taskson the mobile cloud node. The first action and transition in this state is represented by the initial state from (st_3, ac_3, t_3). Only the application's tasks $(wf_2, wf_5, wf_6, wf_7, wf_8)$ are scheduled on the mobile node j_3 at this time. Cryptographic data is moved from j_3 to j_2 through encryption SHA-256 bits until the hashes from the two processes match. The Qlearning series with positive executed is redused and recognized by the modelfree ideal policy call.

G. Assessment and Execution Phase

Here, we explore the real-world application of the baseline methods and the BDRL algorithm, and we provide a detailed analysis of their relative performances in the discussion of the findings that follow. Equation 12 illustrates how the study uses statistical mean values to analyze the data outcomes, specifically utilizing the relative percentage deviation (RPD%). In this case, ObF stands for the study's objective function, and ObF^* for the ideal goals attained by adaptive scheduling. An important indicator for identifying differences between the optimal and initial goal functions of workflow applications enabled by adaptive scheduling is the (RPD%). With respect to the baseline algorithms, the goal of this comparison analysis is to offer a thorough grasp of the effectiveness and efficiency of the DRLBTS algorithm. The statistical analysis of the suggested approaches, taking into account the data presented in simulations with both single variance and multi-variance, is shown in equation 12.

$$\text{RPD\%} = \frac{ObF - ObF^*}{ObF^*} 100\% \tag{12}$$

H. Applications and Baseline Approaches for Healthcare Workflow Use-Cases

This study's simulation was organized into many levels, including mobile fog and cloud agents, multi-agent heterogeneous nodes, and industrial healthcare workflows. The core of the code was built on top of EdgeXFoundry, which made use of its open-source application programming interface to make layer implementation simple. The mobile, fog, and cloud tasks sectors were among the divisions into which the industrial workflow applications were divided. Workloads from workflows and current algorithms were used for the experimental comparison. Below is a summary of these:

- Deep Q-Learning, or DQN, is a widely used technique in DRL to handle heterogeneous computing problems. It was first implemented as Baseline 1. Numerous studies [10]–[13] that address related workflow challenges across many computer nodes have made substantial use of this technique.
- As demonstrated by research [14]–[16], the DDPG (Deep Deterministic Policy Gradients) machine learning technique was adopted as Baseline 2 and has been extensively deployed to solve comparable workloads and challenges, notably during the problem formulation phases in networks.
- DDPG Using blockchain-based methods: As shown in research [21], [22], this method is used as Baseline 3 to improve dynamic scheduling performance for healthcare applications.
- Actor-Critic Algorithm with Asynchronous Advantage and Decentralized Ethereum Scheduling: This method, which is presented as Baseline 4 in the simulation, makes use of a state search technique that is intended to control resource dynamic uncertainty, as demonstrated by research [21], [22].

I. Parameter variation

The findings in Table I indicate a substantial correlation between intensified resource utilization and the expansion of states, actions, transitions, and blockchain blocks. Throughout the study, values for these parameters were randomly assigned based on available mn, fn, and cn, with St set to 40, ac to 40, t to 40, N to 10, and BLC to 10. The experimental phase intentionally introduced two failed transactions for each process. Notably, as resources approached full utilization, it was observed that the Performance Evaluation Ratio (PER) results became closer to each other. While the augmentation of states, actions, transactions, and blocks holds the potential to improve scheduling efficiency, it concurrently leads to heightened resource consumption. This dual effect introduces both advantages and disadvantages to consider. On the positive side, an increase in the number of states, actions, transactions, and blocks can contribute to enhanced scheduling efficiency within the system. This improvement is particularly valuable in optimizing resource allocation and task management. However, on the downside, this augmentation in system components results in increased resource consumption. The direct correlation between heightened resource utilization and the expanded number of states, actions, transactions, and blocks implies a potential rise in resource leakage. Resource leakage, in turn, poses a significant disadvantage as it can impact overall system performance and efficiency. The observation that PER results become closer when resources are fully utilized suggests that the system is reaching a saturation point, and further resource allocation may not significantly improve performance. This highlights the importance of carefully balancing resource utilization to avoid diminishing returns and potential inefficiencies in the system.

VI. Discussion of the results using various methods

This section of the study conducts a thorough investigation of the workflow apps' performance on various compute nodes

TABLE I
COMPARING MEASURES

G	ac	t	N	BLC	RPD%	Resources
1000	40	40	10	10	45	RAM 1024, CPU 80.2%
800	40	40	10	10	42	RAM 1024, CPU 72.1%
700	40	40	10	10	38	RAM 1024, CPU 68.8%
600	40	40	10	10	32	RAM 1024, CPU 62.5%
1000	70	70	10	10	48	RAM 1024, CPU 90%
800	70	70	10	10	40	RAM 1024, CPU 85%
700	70	70	10	10	41	RAM 1024, CPU 82%
600	70	70	10	10	39	RAM 1024, CPU 80.4%

in four different scenarios shown in figure 2. Case 1 entails running all workflow software on mobile devices. Cases 2, 3, and 4, show how workflow applications are scheduled and offloaded on other nodes. Notably, the study's deep offloading strategy beats down previous strategies for executing workflow apps across several nodes. Depending on the needs, strategies like Static Offloading, Dynamic Offloading, and Deep Offloading are used to move workloads from local devices with limited resources to nodes that are accessible for execution.

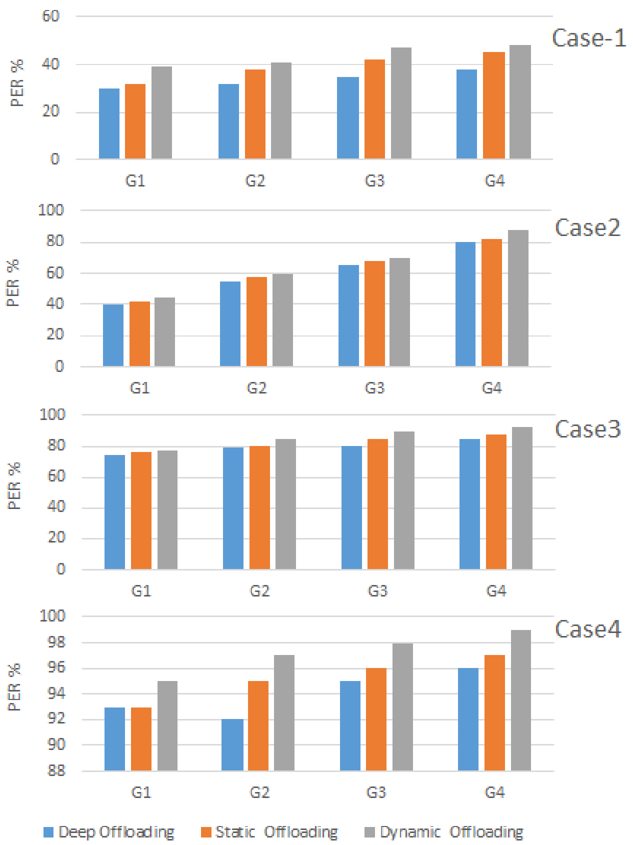

Fig. 2: Blockchain execution on local device

Four apps (G 1 to 4) switch the running of their operations between physical devices to proximity computing. The RPD% point values associated with the goal function are shown on the y-axis. When parameters change at runtime, basic parameter-enabled static offloading encounters larger delays, taking into account things like resources, traffic, and waiting time during execution. Changes are incorporated into dynamic offloading methods; nevertheless, delays are increased because of workflow task failures and resource unavailability on some nodes. However, the deep offloading approach takes into account a number of factors while processing workflows, including parameter changes, resource and task failures, and deadlines. As a consequence, delays are reduced.

Figure 3 shows that the use of DL-enabled BLC in workflow healthcare applications is ideal in terms of interdependency, data validation, resource leakage, and transaction failure. The current frameworks for the Ethereum and Corda static and dynamic blockchains do not address resource leakage, task failure, or workflow dependence. These models only took into account workloads that were both finely and coarsely tuned and ran on separate nodes.

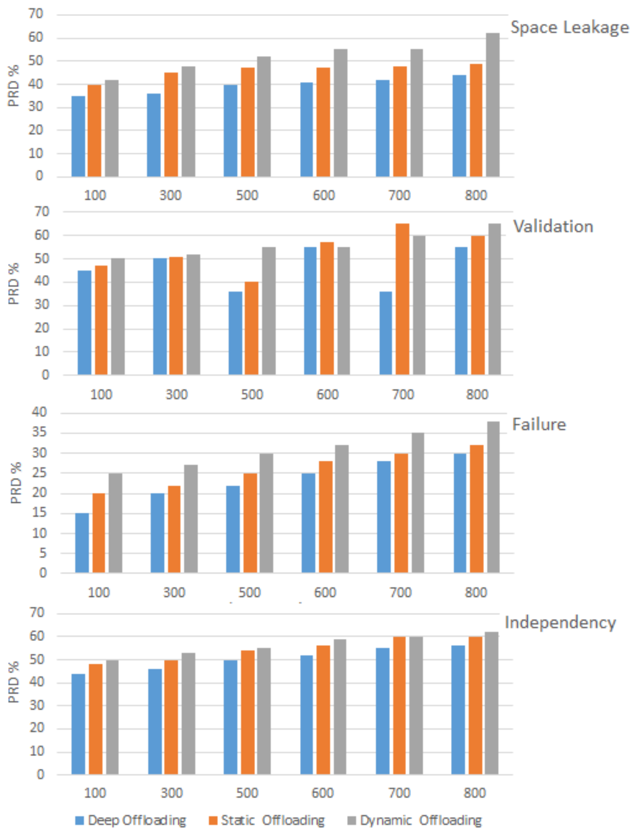

Fig. 3: Space leakage for data transformations allowed by Blockchain in mobile fog cloud networks.

However, during data transaction validation, significant delays are seen as a result of resource-constraint problems across various compute nodes. Furthermore, a major obstacle to using current blockchain technology for data transactions in workflow healthcare applications is resource leakage across many computer nodes. These problems are more successfully addressed by the deep learning-based blockchain technology that is being suggested. Based on predetermined requirements, the study implemented four basic ways to arrange process jobs on various computer nodes. The assessment shows that BDRL outperforms all current schemes. Additionally, the duration efficiency of process jobs (e.g., 1500 and 3000 tasks) using multiple parallelisms and distributed scheduling systems (e.g., baseline 1, 4, and BDRL) is tested and displayed in Figure 4.

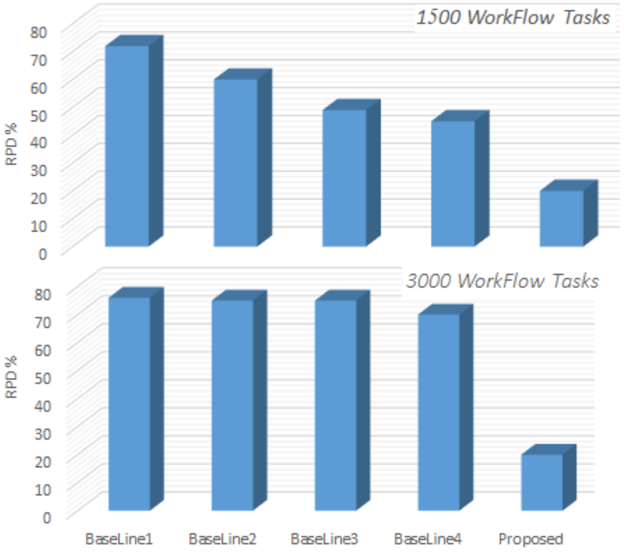

Fig. 4: Operational efficiency on mobile fog cloud networks is madepan.

Comparing BDRL to current techniques, the makespan of all processes is minimized, as shown in Figures 5.

The way that structured workflow apps and define the flexible BLC with scheduling in this study led to more optimal results compared to earlier frameworks. It helped to reduce the overall makespan of apps and effectively tackled issues like failures, losing of resources, and task and node deadlines.

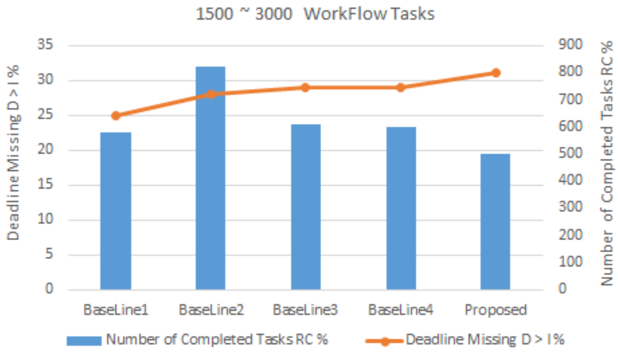

Fig. 5: Process baselines for reinforcement and deep learning systems.

VII. Conclusion

In this paper, we propose a Blockchain-based Deep Reinforcement Learning (BDRL) system designed to optimize healthcare operations within the context of a multi-cloud environment. The system specifically addresses the challenge of secure and efficient healthcare data management and decision-making in decentralized settings. Unlike traditional approaches, our method integrates blockchain technology to enhance data security and transparency, while the application of deep reinforcement learning enables adaptive decision-making, making this approach particularly novel and impactful in the healthcare domain. However, limitations, including architectural overhead affecting real-time healthcare applications, significant energy consumption, and higher resource utilization with increased data size, were identified. To address these challenges, future work aims to incorporate real-time profiling, implement quality of service-based scheduling, and fine-tune the framework to minimize power costs and node energy consumption in distributed mobile fog cloud networks across multiple time zones. This comprehensive evaluation provides valuable insights into the framework's strengths and areas for improvement, guiding future research and development endeavors.

Appendix

Table of Symbols

Symbol	Description
G	Set of applications
WF	Workflow tasks
data_{wf}	Data associated with workflow
ma	Mobile agents
fn	Fog nodes
cn	Cloud nodes
Tn_{wf}	Execution time of jobs distributed over several nodes
$C_{wf1,wf2}$	Communication time between process tasks
st	State
ac	Action
$ST_{st1,ac1}$	State transitions from state $st1$ to action $ac1$
MT	Makespan time for each workflow application
ξ_{ma}	Resources and speeds of mobile agents
ξ_{fn}	Resources and speeds of fog nodes
ξ_{cn}	Resources and speeds of cloud nodes

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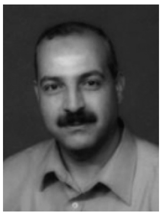

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