Journal of Computers Vol. 35 No. 6, December 2024, pp. 109-122
doi: 10.53106/199115992024123506009

Design and Implementation of Intelligent Oilfield Monitoring and Data Transmission System Based on Cloud-Edge Collaboration Technology

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Received 14 November 2024; Revised 2 December 2024; Accepted 3 December 2024

Abstract. With the rapid advancement of the Industrial Internet, technologies such as unmanned factories and smart factories have become increasingly pivotal for industrial transformation and upgrading. A key aspect of this transformation is the intelligent management of oilfield monitoring, which is vital for improving operational efficiency and reducing costs. This paper introduces a sophisticated intelligent platform designed for sensing, transmission, computation, and control within the oilfield monitoring sector, aligned with the Industrial Internet framework. Our platform is built on a cloud-edge integration architecture that integrates state-of-the-art data acquisition, communication technologies, and intelligent algorithms, enabling efficient data collection, secure transmission, and intelligent processing of oilfield data. We detail the platform's three-tier architecture, including the cloud server layer, Mobile Edge Computing (MEC) server layer, and Remote Terminal Unit (RTU) layer, and discuss the implementation of key technologies such as homomorphic encryption for secure data transmission and OFDM for efficient communication. We also present the computation offloading strategy based on the Markov Decision Process (MDP) and the CEC-WGD approach, which leverages gradient descent to optimize task offloading decisions dynamically. Experimental verification across various oilfield environments confirms the platform's significant potential to enhance monitoring efficiency, ensure production safety, and elevate operational intelligence. The findings demonstrate the platform's ability to meet the high demands for real-time performance and security in oilfield monitoring and data transmission systems, positioning it as a powerful tool for advancing smart industrial management.

Keywords: industrial internet, smart factory, cloud-edge integration, homomorphic encryption

1 Introduction

With the advent of Industry 4.0, Industrial Internet Technology has emerged as a central driving force behind the high-quality development of the manufacturing sector. This technology has not only advanced data acquisition and transmission capabilities but has also instigated revolutionary improvements in data processing and control systems. Smart Factories and Unmanned Factories, as pivotal applications of the Industrial Internet, impose unprecedented demands for real-time, secure, and intelligent data collection, transmission, processing, and control, particularly within complex production environments. In recent years, significant progress has been made in the construction of smart oilfields. Traditional data processing methods are increasingly inadequate to meet these rapidly evolving demands, highlighting the need for more efficient and intelligent solutions. The Smart Sensing, Transmission, Computation, and Control Platform proposed in this paper is specifically designed to tackle these challenges. In this context, the emergence of Industrial Internet technology has revolutionized the manufacturing industry. It not only improves productivity, but also injects new vitality into the sustainable development of the manufacturing industry. The rise of smart and unmanned factories requires a new level of real time, security and intelligence in data collection, transmission, processing and control. These requirements are the main driving force behind the widespread application of Industrial Internet technologies in these advanced factories. For example, Tian et al. [1] have thoroughly explored the development of offshore smart oilfields by combining computerized big data with IoT technologies, revealing the great potential of Industrial Internet technologies in smart oilfield management. Meanwhile, Liu et al. [2] further explored the development of smart oilfields and its far-reaching impact on the transformation of oil-dependent cities. The smart sensing, transmission, computation,

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and control platform proposed in this paper is carefully designed to meet these unprecedented requirements.

The platform facilitates comprehensive data perception and real-time transmission from industrial fields while employing advanced intelligent algorithms for in-depth analysis and processing. This enables precise control and decision support for industrial production. It features an innovative three-tier architecture comprising a Cloud Platform Layer, an Space-Air-Ground Integrated Network Layer, and a Factory Edge Layer, which ensures optimal performance at every stage, from data collection to control. Research by Oliveira et al. [3] also demonstrates that leveraging evolutionary intelligence technology can create an efficient smart oilfield management system, further validating the rationale and advanced design of the platform discussed in this paper.

At the cloud platform layer, a high-performance cloud computing environment is established to manage large data and perform complex intelligent decision tasks [4]. The system adopts a layered intelligence-driven architecture with multi-user collaboration on the cloud side for efficient task generation and decision offloading. In terms of communication model, the cloud platform uses vector quantization (VQ) technique before OFDM technique. This approach involves mapping oilfield data into a limited set of codebooks, which facilitates data compression while maintaining transmission efficiency, data integrity, and accuracy. Based on the communication model of OFDM technology and Shannon's theorem, the cloud platform uses a maximum data transmission rate calculation method to ensure efficient and reliable oilfield data transmission. In addition, the cloud platform formulates the computation offloading strategy as an optimization problem and transforms it into a Markov Decision Process (MDP), which enables it to dynamically adjust the task offloading strategy according to changes in the oilfield environment and resource availability. In addition, the cloud platform also adopts the efficient computational offloading strategy of CEC-WGD to solve the MDP problem, thus proving the higher performance of this strategy compared with the traditional single-point MEC offloading or random offloading algorithms, as evidenced by the simulation results.

At the edge of the factory, numerous sensors and edge computing nodes are deployed, and these devices are responsible for collecting and processing various types of data from the production floor. This data from the shop floor is processed and analyzed in real time. Through cloud-edge collaboration, when the system detects the need for more computing power, the platform can transfer specific data processing tasks to the cloud, thus further improving the efficiency and accuracy of data processing. At the same time, the edge nodes will also perform preliminary data filtering and preprocessing work, which can significantly reduce the amount of data to be transmitted, thereby reducing the cost of data transmission and related communications. Such a system not only significantly improves the response time of the system, but also improves the overall operational efficiency of the plant.

Through a series of empirical tests, we have found that the platform has demonstrated excellent performance in numerous industrial applications. Specifically, the platform has been successfully applied to real-time monitoring and data collection tasks of remote oil wells in Xinjiang oilfield operations. It is capable of transmitting well operation data in real time, ensuring that oilfield managers can grasp the production status of oil wells in a timely manner to make more accurate decisions. At Hebei Oilfield, the introduction of an efficient data analysis system supported by the platform has greatly improved the production decision-making process. This not only improves production efficiency, but also reduces operating costs.

In addition, the platform is able to transmit data in a stable and reliable manner despite the challenges of harsh weather conditions and remote locations in offshore oilfields. This provides strong technical support for the production management of offshore oilfields and ensures the continuity and safety of the production process.

The intelligent sensing, transmission, computation, and control platform developed in this paper significantly improves the intelligence and efficiency of industrial production. It provides a feasible solution for realizing comprehensive industrial production automation through real-time data acquisition, efficient data processing, and precise control algorithms. This platform not only has significant practical value, but also has a wide range of implementation potential, and can play a key role in various industrial fields to promote the digital transformation of industrial production.

The rest of this paper is organized as follows: Section II discusses related work; Section III presents the system model; Section IV discusses the implementation of key technologies including CEC-WGD methodology; Section V presents the experiments and analyses; and finally, Section VI outlines the future work.

2 Related Work

Ye et al. [5] put forth an intelligent resource scheduling method and system in response to the challenges posed by the advent of 5G and IoT technologies to cloud computing. The objective of the method is to reduce bandwidth costs, enhance quality of service (QoS), and mitigate network transmission delays through the real-time monitoring of bandwidth utilization and the dynamic reservation of MEC services. The study provides a detailed account of the mechanisms of resource scheduling, including the localization of MEC servers, client access monitoring, and bandwidth threshold-based MEC server leasing and resource caching policies. Furthermore, the article presents the architectural framework of the Cloud Edge Collaborative Resource Scheduling System, encompassing data extraction, real-time monitoring, dynamic decision-making, and co-scheduling modules. It underscores the significance of dynamically adjusting MEC server reservations by customer behavior. This research offers novel insights into enhancing resource utilization efficiency and data security in cloud computing.

Li et al. [6] explore the application of cloud edge collaboration technology in adjustable resource flexible control. The article first points out the limitations of existing resource monitoring and control devices, and proposes a new cloud edge collaborative control architecture that aims to improve the regulation of adjustable resources and the overall collaborative processing capability through the collaboration between the cloud and the edge. The study classifies the supply and use of energy resources in detail and designs an overall resource optimization and scheduling architecture. By constructing a simulated case system based on Cloudsim, the experimental results demonstrate the benefits of the cloud-edge collaborative architecture in improving the real-time and efficiency of data processing.

Tang et al. [7] investigate the problem of optimized composition for Internet of Things (IoT) services in the collaborative environment of edge computing and cloud computing [6]. The article proposes an innovative service composition mechanism that constructs an IoT service composition index by mining the prevalence of frequent functional interactions in the device-edge-cloud architecture and sets the priority of service requests and branching node preferences to maximize the service composition utility of multi-user requests. The mechanism leverages edge devices to offload IoT device tasks to support service execution and ensure service allocation utility and experimental results show that the approach outperforms other techniques in reducing overall energy consumption and facilitating service utility maximization.

Laili et al. [8] proposed a parallel group merge evolutionary algorithm (PGMEA) for the cloud-edge collaborative scheduling problem of large-scale tasks for industrial Internet of Things (IIoT) environments, which effectively reduces the communication overhead and energy consumption among the cloud, edge, and end devices by considering two cloud-edge collaboration modes, i.e., cloud-assisted edge computing and edge-assisted cloud computing. The algorithm achieves the allocation of cloud server and edge server resources for thousands of tasks in a few seconds by grouping tasks, applying evolutionary operators to find sub-solutions, and merging these sub-solutions for fine-tuning. The experimental results show that the approach significantly reduces the overall task computation time and energy consumption, thus improving the performance of cloud-edge cooperation.

Zhang et al. [9] proposed a method for searching entities in Internet of Things (IoT) environments by combining edge computing and cloud computing resources to achieve an efficient and privacy-preserving entity search approach. The approach specifically focuses on solving the problem of limited storage and computing power of IoT devices by outsourcing encrypted entity data to improve search efficiency and protect user privacy. The paper designs a secure search architecture and methodology to support users to perform real-time search and global search, and also proposes a technique to adaptively discriminate similar entities of interest by constructing attribute-differentiated encrypted indexes and query vector sets through attribute analysis and feature extraction to improve search efficiency and ensure fast index updates. In addition, the paper employs searchable encryption (SE) techniques, especially the ASPE algorithm, to allow searching in encrypted data domains while protecting data security. Through simulation experiments, the paper verifies that the proposed method can effectively improve the efficiency of IoT entity search while protecting privacy, demonstrating the potential and advantages of edge-cloud collaboration in entity search.

Rajesh et al. [10] aim to address data security issues in cloud computing, especially the protection of sensitive information. The paper proposes a novel encryption scheme based on multi-stage partial homomorphic encryption, which combines partial homomorphic encryption and multi-stage encryption techniques to realize secure and privacy-preserving data processing in cloud environments. The paper describes the implementation details of the RSA-based encryption scheme, including key generation, encryption, partial homomorphic multiplication, and decryption processes, and explores the potential of partial homomorphic encryption for applications in various domains. The article emphasizes the importance of the proposed multi-stage partial homomorphic encryption scheme for secure data processing in cloud computing and points out that future research directions include the analysis of potential threats and the evaluation of system performance.

Kavya et al. [11] explore the application of homomorphic encryption techniques in cloud computing and their importance in securing data. The paper first introduces the convenience and security challenges of cloud computing, followed by a detailed description of the basic concepts of homomorphic encryption, including its additive and multiplicative properties, and a comparison of the three types of partially homomorphic encryption, partially homomorphic encryption, and fully homomorphic encryption. By reviewing and analyzing the literature on existing homomorphic encryption research, the paper proposes a secure system for protecting medical data in the cloud using fully homomorphic encryption, aiming to improve the security and performance of data processing. The paper concludes by highlighting the potential of homomorphic encryption in cloud computing and points out that future research needs to address its performance issues to better protect online medical data using encryption systems such as EHES.

Research of Paroha et al. [12] describes a deep neural network (DNN)-based approach to real-time monitoring of oilfields that outperforms conventional monitoring techniques in terms of accuracy, detection speed, and responsiveness. Abhay Dutt Paroha, author of the article, notes that the DNN system is able to learn complex patterns and relationships in the data, significantly improving the ability to detect anomalies and adapt to changes in oilfield dynamics with 92.5% accuracy, 96.7% responsiveness, and a detection speed of 0.28 seconds. The paper also reviews related research, including real-time monitoring of hydrocarbon wells using network computing and neural network techniques, deep learning object recognition systems, and IoT data analytics. The proposed work includes data collection, feature extraction, DNN architecture design, training and learning, and real-time implementation. The results show that the method outperforms existing methods in several performance metrics, demonstrating the potential of deep learning techniques to improve decision making and operational efficiency in the petroleum industry.

Research of Xu et al. [13] discusses the methodology of smart oil field malfunction diagnosis using Internet of Things and big data analytics. The article is based on the analysis of a large amount of historical data from oil and water wells to monitor the changes in some important parameters in the wells and used for trend prediction and early warning system. The authors use the 6 Sigma algorithm to process the historical data and use big data trend analysis to diagnose six operating conditions, such as sand production and moisture anomalies, in combination with multiple parameters. The experimental results show that the algorithm is stable and reliable in practical applications, and is of great significance in ensuring normal oilfield production and improving oilfield management capabilities. The article also introduces the three-level structure of IoT in oilfield production: data acquisition and monitoring layer, data transmission layer, and data analysis and production management layer, and discusses in detail the relationship model between historical data trends and oilfield failures. Based on the 6 Sigma standard, the article determines the warning interval thresholds for each parameter and establishes an evaluation model for the 6 Sigma warning program. Finally, the stability and effectiveness of the algorithm is verified through experiments conducted on the actual database of Tianjin Dagang Oilfield, with an accuracy rate of more than 97%, which indicates that combining the theory of big data with the actual needs of oilfields has an important innovative and practical application value, and it helps technicians to easily operate and promotes the improvement of the oilfield management system.

Wazir et al. [14] present an innovative Internet of Things (IoT)-based architecture designed to provide the oil and gas industry with a reliable, efficient, and accurate monitoring solution for the oil and gas industry. Addressing the shortcomings of existing wireless sensor networks (WSNs) and supervisory control and data acquisition (SCADA) systems in the industry, such as system heterogeneity, high cost, and lack of flexibility and scalability, the paper's IoT architecture supports upstream, midstream, and downstream operations in the oil and gas value chain by streamlining the data collection process, enhancing communication orchestration, and reducing the complexity of device programming. The architecture consists of three core modules: smart objects, gateways, and control centers, each of which includes sensor, network, and application layers to enable effective monitoring and control of interconnected assets in the oilfield environment. The main contribution of the research is to propose an IoT architecture for oilfield environments, starting from the IoT sensing infrastructure, through the network domain, to the IoT applications. In addition, the architecture considers the design aspects of each layer and proposes techniques to support the reliability, efficiency and robustness characteristics of each layer. The paper also provides scenarios for applying this architecture in three areas of the oil and gas industry, including storage tanks, pipelines, and wellheads, with reduced reliance on labor through automation. Ultimately, the IoT architecture presented in this paper provides a new perspective on monitoring and operations in the oil and gas industry by enabling early identification and resolution of inefficiencies, saving time and money, and increasing business productivity.

3 System Architectures

We have developed a multi-user, cloud-edge collaborative, hierarchical OEC network architecture, as outlined in Fig. 1. This architecture is structured into three key layers: the cloud server layer, the Mobile Edge Computing (MEC) server layer, and the Remote Terminal Unit (RTU) layer [15]. In the oilfield, the RTU layer is comprised of l RTUs. The edge layer is formed by intelligent oil well production optimization platforms, which are equipped with edge servers and are situated around the cloud server. These platforms are designed to communicate primarily with RTUs within their communication range, with each RTU being able to link with only one platform during each time slot t. The system is also capable of task offloading to cloud servers, which can then interface with service providers to fulfill a broad spectrum of service needs. In the communication between MEC servers and cloud servers, employing the Paillier homomorphic encryption algorithm ensures secure transmission and computation of data in its encrypted state. This allows cloud servers to perform specific algebraic operations on ciphertext without decryption, and then securely transmit the results back to the MEC server for decryption, thereby achieving efficient data processing while protecting data privacy. This multi-user, cloud-edge collaborative, hierarchical OEC network architecture effectively allocates computing and storage resources, enhancing data security, reducing transmission costs, and improving data processing efficiency and system reliability. It enables rapid data processing near the source, minimizing latency while maintaining the security of data in an encrypted state, meeting the high demands for real-time performance and security in oilfield monitoring and data transmission systems. Furthermore, the flexibility and scalability of this architecture allow it to adapt to evolving business needs and support a variety of services, thereby enhancing the intelligent level of oilfield operations. The framework of cloud-edge collaboration network architecture is shown in Fig. 1.

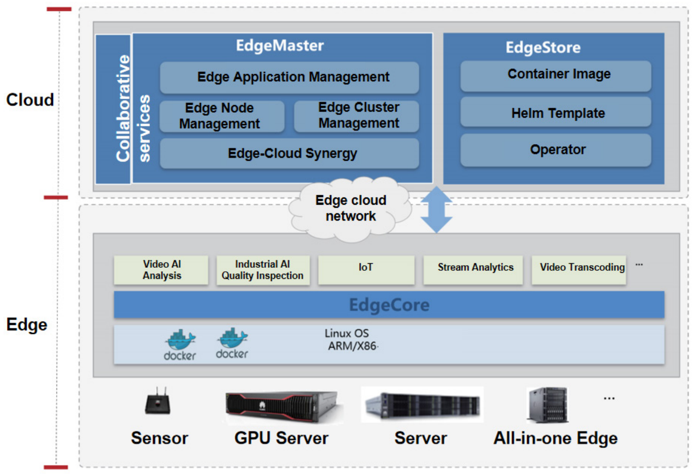

Fig. 1. Framework diagram of production monitoring cloud platform

3.1 Task Model

In the transmission model of the OEC, time is discretized to $\{1, 2, 3, \ldots, T\}$. Each time slot has a duration of length τ. At the commencement of each time slot, an RTU is capable of transmitting a computational task, denoted by n, i represents the number of RTUs, and $d_i(t)$, the size of the task data. The decision to offload tasks is denoted by $S_k^n = \{0,1\}$, where $k \in K$, $K = \{1,2\}$ correspond to the MEC server and cloud server, respectively. For any given computational task, only one offloading decision can be made [16].

3.2 Codebook-based Vector Quantization Modulation

At the transmitter, each active device first quantizes $d_i \in R^W$ and then modulates the quantized values onto a common modulation codebook. All active devices will transmit their simultaneously modulated codewords.

(1) Quantization Design: All devices use a single quantization codebook, denoted as $\boldsymbol{U} \in R^{Q \times N}$, where $N = 2^J$ represents a J-bit quantization with N quantization codewords, and $Q \geq 1 (Q \in N)$ denotes the length of each quantization codeword, i.e., $Q = 1$ and $Q > 1$ indicate scalar quantization and vector quantization (VQ), respectively. The vector at device $d_i \in R^W$ is divided into $D = W/Q$ blocks. Each block is then quantized independently using the codebook. Let the quantization be $\boldsymbol{b_k} \in [N]^D$, where the d-th element, $[\boldsymbol{b_k}]_d$, represents the quantization index of the corresponding block. Specifically, $[\boldsymbol{b_k}]_d$ is identified by finding the quantization codeword with the minimum Euclidean distance, which can be expressed as:

$$[b_k]_d = \arg\min_{i \in [N]} \left| [U]_{:,i} - [d_i]_{(d-1)Q+1:dQ} \right|_2 \qquad \textbf{(1)}$$

To determine the quantization codebook, any VQ method can be employed. By using VQ, the size of each partial model update can be reduced, thereby reducing the uplink (UL) communication overhead by a factor of Q. Additionally, a selection vector $x_k^d \in \{0,1\}^N$ is introduced, where $|x_k^d|_0 = 1$ and $[x_k^d]_{[bk]_d} = 1$. Thus, the quantized version of d_i can be represented as:

$$d_i = C(d_i) = (I_D \otimes U)[(x_k^1)^T, \ldots, (x_k^D)^T]^T \qquad \textbf{(2)}$$

(2) Codebook-based Modulation: This paper considers a common random access codebook shared by all devices, denoted as $P \in C^{L \times N}$, where each column of P is a codeword of length L, with a total of N codewords. In the proposed scheme, there is a one-to-one mapping between P and U. Specifically, if a device obtains a quantization value, the modulation codeword (or sequence) $[\mathbf{U}]_{:,n}$, with the same index n, $[\mathbf{P}]_{:,n}$ will be transmitted. Vector quantization combined with codebook-based modulation is particularly suited for the current wireless network environment due to its efficient data representation and transmission capabilities. This method maps signal vectors onto predefined codewords, optimizing the compression efficiency of signals while ensuring reliable and accurate communication within limited bandwidth. Consequently, it maintains data integrity, reduces transmission latency, and enhances spectrum utilization.

3.3 Communication and Computation Model

The RTUs use an advanced access technique, Orthogonal Frequency Division Multiplexing (OFDM), to communicate with the edge nodes of the OEC network. In this communication process, each RTU device occupies a separate channel for bidirectional transmission. The bandwidth of each channel is set to B. According to the famous Shannon's theorem, we can calculate the maximum data transmission rate that can be realized between the RTU device and the MEC server. Shannon's theorem states that the maximum data rate of a channel depends on the bandwidth of the channel and the signal-to-noise ratio. Using Shannon's formula, we can accurately calculate the maximum data transmission rate that can be realized between the RTU device and the MEC server under the given conditions of channel bandwidth and signal-to-noise ratio, as shown below:

$$R_n = B * \log_2\left(1 + \frac{P_i \cdot h_i}{N_O}\right) \qquad \textbf{(3)}$$

Here, P_i denotes the transmission power of the vehicular network user, h_i signifies the wireless channel gain, and N_O represents the power spectral density of the Gaussian noise. The probability of task transmission failure is denoted by p_n^{TRAN}.

For tasks offloaded to the MEC server, the transmission delay is defined as:

$$t_n^{MEC} = \frac{d_i}{R_n} \tag{4}$$

For tasks offloaded to the cloud server, the transmission delay is defined as:

$$t_n^{CS} = \frac{d_i}{R_{CS}} \tag{5}$$

where R_{CS} is the data transmission rate of the cloud server.

The computational delay for task n can be expressed as:

$$t_n^{COMP} = \frac{d_i b_i}{C_k^n} \tag{6}$$

Here, C_k^n represents the computational resources allocated by the server k to the task n.

Task offloading primarily encompasses three stages: task uploading, task execution, and result feedback. However, since the result data is typically much smaller than the RTU transmission data, this paper assumes that the delay for result feedback can be neglected [17]. The total processing delay T_n for task n can be calculated as follows:

$$T_n = t_n^{MEC} + S_k^n \cdot (t_n^{CS} + t_n^{HE}) + t_n^{COMP} \tag{7}$$

Here, t_n^{HE} represents homomorphic encryption latency.

The total energy consumption of a task can be defined as:

$$E_n = P_i \cdot t_n^{MEC} + p_2^k \tag{8}$$

When tasks are offloaded and require cloud server involvement, p_2^k indicates the computational energy consumption across different servers, and C_k represents the total computational resources of the server.

The transmission unreliability of a task is defined as:

$$R_n = p_n^{TRAN} + p_n^{COMP} - p_n^{TRAN} \cdot p_n^{COMP} \tag{9}$$

where p_n^{COMP} is the probability of task computation failure.

To account for users' preferences for delay, energy consumption, and quality of service in various scenarios, we consider incorporating a weighted factor indicator θ, here $\theta_1 + \theta_2 + \theta_3 = 1$. The cost function for this paper's model is constructed as follows:

$$G_n(t) = \theta_1 T_n(t) + \theta_2 E_n(t) + \theta_3 R_n(t) \tag{10}$$

3.4 Problem Formulation

The objective of this paper is to minimize the system's long-term total cost under constraints of latency, energy consumption, and service quality. We formulate the optimization problem as follows:

$$P1:\min_{S_k^n, C_k^n}\lim_{t\to\infty}\sum_{n=1}^{N}\sum_{k=1}^{k=2} S_k^n(t)\cdot G_n(t)$$

$$C1:\sum_{k=1}^{k=2} S_k^n(t)=1,\forall n\in N$$

$$C2:\sum_{n=1}^{N} S_k^n C_k^n \le 1,\forall k\in K$$

$$C3:0\le C_k^n \le C_k,\forall n\in N$$

$$C4:1-\prod_{n=1}^{N}(1-p_n^{TRAN})\le P^e$$

$$C5:T_n\le \tau,\forall n\in N$$

Constraints in the optimization problem are defined as: C1 denotes that each task can only be offloaded to a single location; C2 signifies that the total computational resources allocated to all tasks must not exceed the available resources; C3 represents the limitations on the computing and communication resources assigned by the server to the tasks; C4 stipulates that the probability of task offloading failure for all tasks should not exceed a certain threshold; C5 indicates the maximum delay limit for tasks [18].

4 Implementation of Key Technologies

Markov Decision Processes (MDPs) are a powerful mathematical framework that provides a systematic approach to solving complex decision problems characterized by stochastic and dynamic changes. This framework is particularly suited to optimization in environments of uncertainty, helping decision makers formulate the best course of action in the face of various possible future scenarios. Through the use of dynamic programming techniques and Bellman equations, MDPs are able to recursively compute the optimal strategy under different states to maximize long-term cumulative payoffs or minimize costs. The core strength of MDPs lies in their ability to simulate and analyze complex decision paths, providing quantitative solutions to decision problems that involve multiple stages and multiple choices. The ability of such frameworks to deal not only with deterministic factors, but also with stochastic variables, significantly improves the accuracy and reliability of simulations of real-world problems. The flexibility and robust modeling capabilities of MDPs have led to a wide range of applications in various fields, including, but not limited to, economics, engineering, computer science, and operations research, among others. In addition, MDPs have shown great potential in policy evaluation and strategic planning [19]. By combining theoretical analysis with practical applications, MDPs not only provide policy makers with a systematic approach to evaluation, but also enable them to validate the effectiveness of different strategies through simulation experiments. This process of simulation and validation strengthens the link between theory and practice and ensures the scientific and practical nature of the decision-making process. In this way, MDPs not only help policy makers better understand the behavior of complex systems, but also provide them with powerful tools to make informed decisions in the face of uncertainty and risk.

4.1 MDP Definition

Problem P1 is categorized as a mixed integer nonlinear programming (MINP) issue. To maintain its long-term stochastic optimization properties, we have reformulated P1 into a Markov Decision Process (MDP) framework, which encompasses the elements of State, Action [20]. To circumvent this challenge, this study employs an efficient strategy for computation offloading, drawing on the CEC-WGD (Weighted Gradient Descent) approach.

1. State: At time slot t , system state space can be defined as $s(t)=(d_t, b_t, f_{k=1}(t), f_{k=2}(t), B(t))$, where d_t is the size of task, b_t is the amount of computation required of task, $f_{k=1}(t), f_{k=2}(t)$ are the computational resources of the MEC and cloud server, respectively, and $B(t)$ is the bandwidth resource [21].
2. Action: The action space consists of the offloading decision variables, allocated computation resources, and communication resources for each task, respectively. Thus, the action can be defined as $x_k = \{S_k^1, S_k^2, ..., S_k^N, C_k^1, C_k^2, ..., C_k^N, B_1, B_2, ..., B_n\}$, where $\{S_k^1, S_k^2, ..., S_k^N\}$ represents the offloading decision in

OEC network, $\{C_k^1, C_k^2, ..., C_k^N\}$ represents the proportion of resources allocated, $\{B_1, B_2, ..., B_n\}$ represents the number of sub-channels assigned for each task.

3. We aim to minimize the weighted sum objective function $G_n(t)$. This can be achieved using gradient descent or other single-objective optimization algorithms. Taking gradient descent as an example, the update rule is:

$$x_{k+1} = x_k - \alpha \nabla G_n(x_k) \tag{11}$$

Where x_k is the vector of decision variables at the current iteration, α is the learning rate, $\nabla G_n(x_k)$ is the gradient of $G_n(t)$ at x_k.

4.2 CEC-WGD Approach

The essence of this method lies in employing the gradient descent algorithm to optimize a weighted sum objective function that encompasses multiple objectives. Through continuous iteration, the decision variables are progressively adjusted to approximate the optimal solution of the problem. During this process, weights can be assigned to reflect the relative importance of different objectives, ensuring a balance is struck in multi-objective decision-making. Moreover, the algorithm is equipped with clear termination conditions; once these conditions are met, such as reaching a certain number of iterations or achieving a solution quality that meets preset thresholds, the iteration process will be halted. This ensures both the efficiency of the algorithm and the feasibility of the solution. In this manner, we can identify a solution in multi-objective optimization problems that not only meets the requirements of each objective but also possesses practical operability.

$$\nabla G_n(x) = \lambda_1 \nabla T_n(x) + \lambda_2 \nabla Q_n(x) + \lambda_3 \nabla E_n(x) \tag{12}$$

$$x_{k+1} = x_k - \alpha(\lambda_1 \nabla T_n(x_k) + \lambda_2 \nabla Q_n(x_k) + \lambda_3 \nabla E_n(x_k)) \tag{13}$$

In contemporary oilfield management, the efficiency of real-time monitoring and data transmission is crucial. To enhance the security and efficiency of data transmission—particularly in the complex oilfield environments of Xinjiang and similar regions—an intelligent data transmission control system has been implemented. This system leverages cloud-edge collaboration and homomorphic encryption technology. The primary objective of this algorithm is to ensure the real-time, secure, and reliable transmission of monitoring data from oilfields by facilitating efficient data acquisition and transmission processes. The algorithm flow is illustrated in Table 1.

Table 1. Algorithm flow

Algorithm 1. Cloud-edge collaboration and weighted gradient descent strategy
1: Initialize system parameters: cloud platform layer, MEC server layer, and RTU layer. Initialize data acquisition and communication technology parameters.
2: while Time slot t from 1 to T:
3: for each RTU: Data collection from oilfield monitoring.
4: for each task: Compute offloading decision , select MEC server or cloud server.
5: if Task offloaded to MEC server: Calculate transmission and computation delay.
6: else if Task offloaded to cloud server: Calculate transmission and computation delay.
7: for each RTU: Use OFDM technology to transmit data to MEC or cloud server.
8: if Transmission fails: Update the probability of task transmission failure.
9:for each task: Execute computation on MEC or cloud server and update resource allocation.
10: if Result data is small: Ignore result feedback delay.
11: else: Calculate result feedback delay.

12: Solve the optimization problem using MDP and CEC-WGD method to update offloading strategy.

13: Update weights and gradient descent parameters.

$$x_{k+1} = x_k - \alpha \nabla G_n(x_k)$$

14: Check constraints: Task offloading failure probability, delay limits, and resource allocation.

15: if Constraints violated: Adjust offloading strategy.

16: end while

5 Simulation Experiments and Analysis

To validate the effectiveness of the intelligent oilfield data transmission control system, which integrates cloud-edge collaboration and homomorphic encryption technology, an experimental platform was established using Matlab. The Xinjiang Oilfield, known for its complex geographical environment and significant data transmission challenges, served as the case study. Various terminal devices and intelligent sensors were selected for data acquisition, simulating different operational scenarios.

As a major oil production base in China, the Xinjiang Oilfield faces unique challenges related to geographic terrain and data transmission. Therefore, it is crucial to build a robust network topology that enables efficient co-operation between edge nodes and core servers. To evaluate the control performance of the system and analyze its data transmission capability, emphasis is placed on evaluating the impact of different discount factors on convergence, the impact of computational power of MEC servers on total cost and mission arrival rate under different algorithms.

The processing power of the MEC server, aggregation server, and cloud server are set to =1.5*10^9 Hz, =2.5*10^10 Hz and =1.5*10^11 Hz respectively. the transmit power is = 2. 5 W, the wired data rate is == 15 Mbps, the Gaussian noise power spectral density is = -174 dBm/Hz, and the channel gain is = 127+ 30logd. The total system bandwidth is 20 MHz, and each subchannel has a bandwidth of 1 MHz. 30logd. The total system bandwidth is 20 MHz and the bandwidth of each subchannel is 1 MHz.

A comprehensive experimental analysis was conducted to evaluate the system’s performance in intelligent oilfield data transmission, and the results are presented in Table 2.

Table 2. Data result

Communication frame rate/fps	Sending period /ms	Sent data /byte	Received data /byte	Data accuracy/%	Average transmission delay /ms
2	1000	2250	2250	100.0	315
5	500	4500	4500	100.0	360
10	200	9000	9000	100.0	423
20	100	18000	17965	99.8	476
40	50	36000	35750	99.3	532
60	20	45000	44450	98.8	627
120	10	95000	93300	98.2	679
150	5	130000	127400	98.0	744

Based on Table 2, it can be seen that after implementing the designed system for smart oilfield data transmission, the maximum data accurate rate is 98%, and the average delay is 744 ms, which meets the basic data transmission requirements.

In addition, we also conduct many experiences under different situations, as is shown in the figures below.

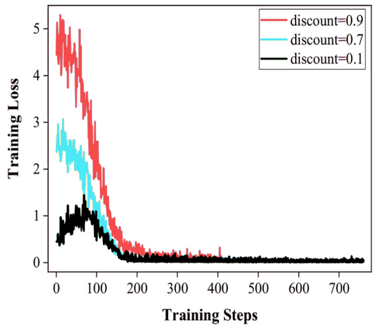

Fig. 2. Influence of discount factors on convergence

We first analyze the effect of different discount factors on convergence, as shown in Fig. 2. We set the discount factor to 0.9, 0.7 and 0.1. Fig. 2 shows that the training loss converges faster as the discount factor increases. This is because if the discount factor is set too small, the system can only reduce the total long-term cost of the system in the short term. If the discount factor is increased, the system gives more weight to future returns and the long-term return of the system is more guaranteed. To verify the performance of the CEC-WGD algorithm, three computational offloading methods, MEC Offloading (MO), Cloud Offloading (CO), and Random Offloading (RO), are compared with the CEC-WGD algorithm.

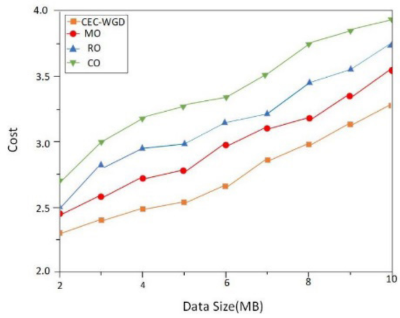

Fig. 3. Influence of data size of task on Cost G

Fig. 3 shows the effect of task data size on the total system cost for the different algorithms. The data size of each task varies between 2 and 10 MB. On average, the CEC-GD algorithm reduces the total system cost by 6%, 12%, and 21% compared to the CO, RO, and MO algorithms respectively.

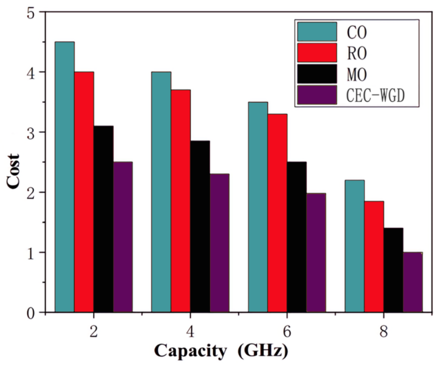

Fig. 4. Influence of computing capacity of MEC severs on Cost G

Fig. 4 shows the impact of MEC server processing power on the total cost of ownership for different algorithms. On average, the CEC-WGD algorithm reduces the total system cost by 6%, 14%, and 22% compared to the CO, RO, and MO algorithms respectively. This indicates that the computation of tasks is positively correlated with the computational power of the edge servers and that the CEC-WGD approach outperforms the baseline strategies in terms of energy consumption, latency control, and reliability in the network.

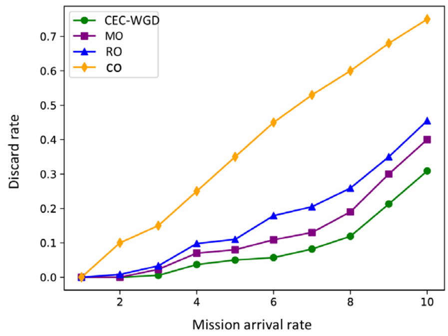

Fig. 5. Relationship between system reward and task arrival rate

However, as shown in Fig. 5, we can see that when the task arrival rate is too high, i.e., the inflow of tasks is too fast, the number of backlogged tasks in the UAV computation queue increases significantly. Due to the limited capacity of the queue, this leads to an increase in the task discard rate. In this case, it is difficult to increase the total number of tasks that the system can handle, and a bottleneck may even occur. As the number of tasks increases, the reward value of the system will slowly decrease and eventually converge to a relatively stable level. However, if the task arrival rate is too low, the number of tasks to be processed in the system is small and the queuing delay is almost negligible. In this case, the performance of the multiple dynamic offloading algorithms tends to match that of the local processing algorithms, so the system reward values are essentially the same. Overall, as the number of tasks increases, our proposed CEC-WGD algorithm shows a clear advantage in executing the offloading strategy, and compared to other algorithms, it is able to better cope with the changes in the task arrival rate, and thus achieves a higher system reward value.

6 Future Work

In the future, we will continue to explore the deep integration of cutting-edge technologies, including the Industrial Internet, IoT, big data, and artificial intelligence. Our goal is to build a more efficient, intelligent, and reliable platform for smart sensing, transmission, computing, and control, designed to meet the ever-evolving demands of the market and advancements in technology. To achieve this, we will prioritize innovative computing paradigms like edge and fog computing, examining their integration with the Industrial Internet. This integration aims to optimize data processing workflows, enhance system response times, and ultimately improve overall performance and user experience. We are committed to continuous efforts and innovation to ensure our platform adapts to future technological trends, providing advanced and reliable solutions across various industries.

With the widespread adoption of Industrial Internet technology, data security and system compliance will be key areas of our research focus. We will enhance the security mechanisms of our platform, incorporating data encryption, access control, intrusion detection, and more to ensure the secure transmission and storage of production data. We will explore various encryption algorithms, assessing their applicability in different scenarios to identify the most suitable technologies. Additionally, we will investigate access control policies to guarantee that only authorized users can access sensitive data, thereby preventing unauthorized access and potential data breaches. Moreover, we will develop and deploy advanced intrusion detection systems for real-time monitoring of network activities, enabling the prompt identification and response to potential security threats. We will keep pace with regulatory and policy developments to ensure our platform consistently meets industry standards and compliance requirements. Regular reviews and updates to our security strategies will align with evolving laws and regulations. Furthermore, we will maintain close collaboration with industry experts and regulatory bodies to ensure our security and compliance measures meet the latest industry standards. Through these initiatives, we aim to deliver a secure, reliable, and compliant Industrial Internet platform.

To enhance the practicality and market competitiveness of our smart sensing, transmission, computing, and control platform, we will actively expand its application scenarios and functionalities across key sectors. In the oil and gas industry, we will explore the platform’s potential for intelligent inspection, predictive maintenance, and energy efficiency management to improve operational efficiency and safety. For example, smart inspection systems will monitor the operational status of equipment in real-time, facilitating early problem detection and minimizing downtime, thereby increasing productivity. The predictive maintenance functionality will utilize data analysis to anticipate equipment failures, enabling proactive maintenance and reducing losses from unexpected breakdowns. In energy efficiency management, our platform will assist oil and gas companies in optimizing energy usage, reducing consumption, and promoting sustainable practices.

In the manufacturing sector, we will promote the platform’s application in smart manufacturing, supply chain collaboration, and quality control, enhancing the industry’s overall competitiveness. Smart manufacturing capabilities will automate and optimize production processes, improving productivity and product quality. Supply chain collaboration will enable seamless integration across the supply chain, enhancing responsiveness and flexibility. Quality control will leverage advanced data analytics to monitor quality indicators in real-time, facilitating timely identification and resolution of quality issues, ensuring stable and reliable product quality.

Additionally, we will expand the platform’s applications and functionalities in the energy transmission sector. In power transmission, our platform will support real-time grid monitoring and intelligent dispatching to enhance stability and reliability. In natural gas transmission, it will enable intelligent pipeline monitoring and leak detection, ensuring safe transmission. By continually expanding application scenarios and functionalities, we will enhance the vitality and broader application value of our smart sensing, transmission, computing, and control platform, enabling it to play a more significant role across sectors and drive digital transformation and intelligent upgrades in related industries.

To further promote the widespread adoption and healthy development of Industrial Internet technology within our platform, we are committed to actively participating in the formulation and implementation of relevant standards. We will forge close partnerships with industry standards organizations, research institutions, and businesses to collaboratively advance the standardization of Industrial Internet technology. By establishing unified technical standards and interface specifications, we aim to significantly enhance interoperability and portability among different platforms, thereby lowering the barriers and costs associated with technology adoption. This approach will facilitate the rapid dissemination and widespread application of technological advancements, accelerating the development of our smart sensing, transmission, computing, and control platform.

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