GEORGE BROWN PRESS
JOURNALS, BOOKS & PROCEEDINGS

Journal of Computer, Signal, and System Research

Article

Research on Real time Decision Mechanism of Cloud Computing Driven Emergency Communication System Integrating Artificial Intelligence

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Abstract: In emergency response to sudden public incidents, the emergency communication system serves as one of the most critical basic support infrastructures, playing an indispensable role in command, dispatch, and rescue coordination. Its decision-making speed and accuracy directly affect the overall effectiveness of the emergency response. Traditional emergency communication systems exhibit significant disadvantages, including severe decision-making lag, poor adaptability to rapidly changing scenarios, static resource allocation, and persistent barriers to multi-party collaboration. Consequently, these legacy systems cannot adequately cope with the highly dynamic and complex environments encountered during extreme disasters. To address these critical shortcomings, the integration of the elastic computing power and distributed collaborative characteristics of cloud computing technology with the intelligent perception and real-time decision-making capabilities of artificial intelligence provides a transformative avenue for modernizing emergency communication networks. Starting from the core architecture of cloud computing-driven emergency communication systems, this article comprehensively summarizes the operational requirements and technical obstacles associated with real-time decision-making in severe emergency scenarios. Furthermore, it provides specific methodological frameworks and implementation plans for deploying artificial intelligence across various critical domains, such as advanced situational awareness, dynamic resource allocation, robust link support, and seamless collaborative decision-making. Finally, extensive simulation experiments are utilized to rigorously test and validate the operational effectiveness, latency reduction, and overall strategic advantages of this proposed intelligent decision-making method, demonstrating its potential to significantly enhance future disaster management and resilient communication protocols.

Keywords: artificial intelligence; cloud computing; emergency communication; real-time decision-making; cloud-edge collaboration

Received: 06 March 2026
Revised: 27 April 2026
Accepted: 07 May 2026
Published: 11 May 2026

1. Introduction

Due to the increasing frequency of natural disasters, accidents, public health incidents, and other emergencies in our country, the requirements for the response speed and disposal capability of the emergency support system are becoming increasingly stringent. The emergency communication system serves as the "brain" of emergency command, primarily responsible for on-site data transmission, command issuance, and collaborative work among various rescue teams. The stability of the emergency communication system's operation and the timeliness of decision-making directly influence the safety of people's lives and property. The traditional emergency communication system relies heavily on static resource allocation, manual command decision-making, and a fixed contingency plan system. In extreme situations such as earthquakes, floods, and forest fires, it demonstrates significant limitations [1, 2]. Firstly, communication lines in extreme environments are prone to damage, and traditional fault-handling programs respond slowly, often resulting in communication interruptions.

Secondly, the vast amount of heterogeneous data on-site cannot be quickly integrated and processed, and manual judgment is often too slow to keep pace with the evolving disaster scenarios. Thirdly, emergency communication resources are limited, and static configurations lead to simultaneous resource congestion and underutilization. Lastly, cross-departmental and interdisciplinary collaborative decision-making faces data barriers, preventing the formulation of optimal global disposal plans.

The development of cloud computing technology has provided emergency communication systems with elastic computing power, global data integration, and the ability to allocate distributed resources dynamically. Additionally, it has endowed the system with capabilities for autonomous perception, intelligent prediction, real-time decision-making, and continuous improvement. The integration of these technologies fundamentally addresses the decision-making challenges inherent in traditional emergency communication systems. This creates a real-time closed-loop decision-making system encompassing the entire process of "perception, prediction, decision-making, implementation, feedback, and improvement." Consequently, this article focuses on cloud computing-driven emergency communication systems as the research subject, exploring the integration and application of artificial intelligence technology within real-time decision-making mechanisms. It identifies the technical implementation pathways and validates the mechanism's actual performance through experimental analysis. This research aims to provide robust technical support for the intelligent upgrading of emergency communication systems, ensuring they are better equipped to handle the complexities and demands of modern emergency scenarios.

2. Core Architecture of Emergency Communication System Driven by Cloud Computing

The primary objective of an emergency communication system is to ensure uninterrupted communication, prompt data transmission, and precise command decisions during the entirety of an emergency response, even in highly complex and challenging environments. The architectural design of such a system must prioritize high availability, minimal latency, robust resilience, and seamless scalability. A cloud computing-driven emergency communication system adopts a three-tier structure comprising the cloud platform core layer, the edge computing layer, and the terminal access layer, arranged hierarchically from top to bottom. Additionally, it incorporates an emergency command application layer to facilitate the execution of decision-making tasks. Each layer is designed to function in a coordinated manner, ensuring the system operates efficiently and effectively. This multi-layered approach enables the system to adapt dynamically to varying demands, thereby enhancing its overall reliability and performance in critical scenarios (As shown in Figure 1).

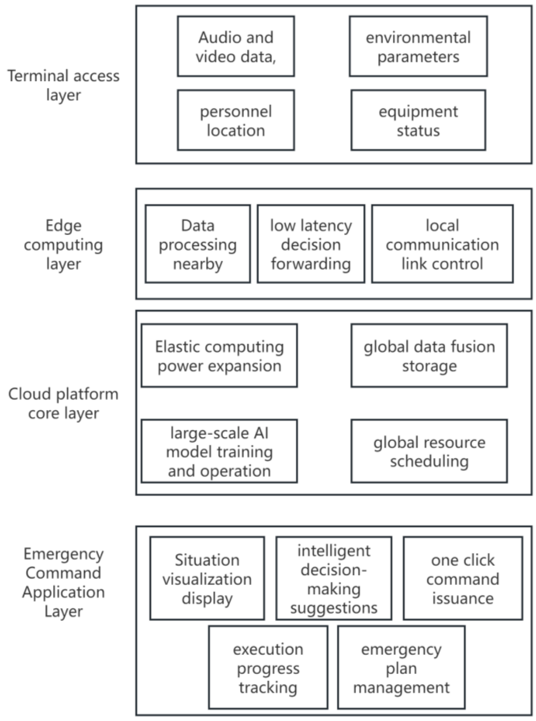

Figure 1. Core architecture of emergency communication system driven by cloud computing

3. Integrated Application of Artificial Intelligence in Real-Time Decision-Making Mechanism of Emergency Communication System

3.1. Real Time Perception and Feature Extraction of Emergency Scene Situation Based on Deep Learning

Situation awareness is a fundamental prerequisite for real-time decision-making in emergency communication systems. Only through accurate, timely, and comprehensive control of on-site disaster conditions, communication network status, and the spatial distribution of emergency resources can decision-makers formulate scientific, reasonable, and operational response strategies. In this study, a deep learning architecture integrating CNN and Transformer is adopted to enable rapid extraction of heterogeneous data features and real-time perception of emergency scenarios [3]. Compared with traditional feature extraction methods, this integrated model offers clear advantages in processing speed, robustness under interference, and adaptability to complex and dynamically changing environments. It can also improve the consistency of multi-source information interpretation, thereby enhancing the reliability of subsequent command and dispatch decisions.

In the data preprocessing stage, audio and video streams, sensor timing data, device status data, and geographic location data collected by terminal devices are processed in a unified manner to achieve spatiotemporal alignment, missing value filling, noise removal, and data normalization, thereby reducing the heterogeneity of multi-source data and providing standardized inputs for model training and inference. A 6-layer CNN model is employed for feature extraction from image and video data in the spatial dimension, with a specific structure consisting of 4 convolutional layers and 2 fully connected layers. Each convolutional layer is followed by a pooling layer and a batch normalization layer. ReLU is used as the activation function, and the convolution kernel size is set to 3×3 with a stride of 1. This configuration can effectively extract key features related to scene conditions, equipment status, and environmental changes in complex settings, while also reducing data volume and improving processing efficiency [4]. For data with temporal characteristics, a Transformer model is used for feature extraction, with 8 attention heads and a hidden layer dimension of 512. This model can effectively capture temporal correlation information in long-sequence data, identify dynamic trends in disaster evolution and communication link state changes, and improve the sensitivity of the system to sudden fluctuations and gradual deterioration. Through the coordinated processing of spatial and temporal features, the model establishes a more complete representation of the emergency scene and provides a stronger basis for subsequent risk assessment and resource scheduling.

At the same time, a bidirectional long short-term memory network (BiLSTM) is introduced, taking as input ten-dimensional time series data of the communication link, including packet loss rate, delay, jitter, and signal strength. During training, the Adam optimizer is adopted, and the learning rate is set to 0.0005-0.001. A Dropout layer with an inactivation rate of 0.2 is added to reduce the risk of overfitting and improve the generalization ability of the model under diverse emergency conditions. This network can effectively identify early abnormal states in the communication link, capture subtle variations before obvious failure occurs, and provide reliable support for subsequent fault prediction and preventive intervention. In practical deployment, the BiLSTM output can be fused with the CNN and Transformer feature outputs to form a multi-level situational awareness result, allowing the system to evaluate both current operating conditions and short-term development trends. Such a design is beneficial for improving the timeliness and accuracy of emergency command decisions, especially in scenarios characterized by high uncertainty, strong interference, and rapidly changing task demands [5, 6]. The main parameter configurations of the deep learning model for situational awareness are shown in Table 1.

Table 1. Situation Awareness Deep Learning Model and Core Parameter Configuration

Model Type	key parameters	Parameter Range/Settings	description
CNN	number of network layers	6 layers (4 convolutional layers, 2 fully connected layers)	Used for spatial feature extraction, convolutional layer followed by pooling layer and batch normalization layer
Transformer	number of attention heads	8	Capture long-range dependencies of time-series data, hidden layer dimension 512
BiLSTM	Number of hidden layer nodes	128	Bidirectional extraction of link timing features to identify abnormal states
General training parameters	learning rate	0.0005~0.001	Adam optimizer, balancing convergence speed and model stability
Model Type	Dropout deactivation rate	0.2	Reduce the risk of model overfitting and improve generalization ability

3.2. Dynamic Scheduling Decision of Emergency Communication Resources Based on Deep Reinforcement Learning

The dynamic optimal scheduling of emergency communication resources is a critical application scenario for real-time decision-making mechanisms. This study employs deep reinforcement learning (DRL) technology to develop a dynamic scheduling decision model for emergency communication resources. The model enables real-time allocation and scheduling of these resources, thereby maximizing the efficiency and ensuring the quality of communication systems [7]. By leveraging advanced computational techniques, the approach addresses the challenges of resource optimization in complex and rapidly changing environments.

To address the resource scheduling problem, it is modeled using a Markov Decision Process (MDP), which defines three fundamental elements: state space S, action space A, and reward function R. The state space S encompasses 20 state characteristics, such as the current bandwidth utilization rate of each communication link, the number of terminal accesses, signal strength, on-site disaster level, distribution of rescue points, and business priority. These characteristics collectively represent the system's operational status comprehensively. The action space A includes various scheduling measures, such as frequency band switching, bandwidth allocation, node routing adjustment, edge computing power offloading ratio, and access permission control. These measures enable comprehensive management of communication resources [8, 9]. The reward function R is primarily based on metrics such as end-to-end transmission delay, core business link connectivity, and overall resource utilization. The formula incorporates C for the connectivity rate of core business links, D for the average end-to-end transmission delay, D_{max} for the delay threshold, U for overall resource utilization, and ω_1、ω_2、ω_3 for the weight coefficients of each indicator. Additionally, $\omega_1+\omega_2+\omega_3=1$ is used to prioritize the connectivity of core command operations through appropriate weight settings.

$$R=\omega_1\times C+\omega_2\times\left(1-\frac{D}{D_{max}}\right)+\omega_3\times U$$

On this foundation, the Deep Q-Network (DQN) algorithm is utilized for model training and decision-making. The experience replay pool size is set to 10,000, and the target network is updated every 100 steps. The discount factor γ is configured at 0.95, while the learning rate is set to 0.001. The model's decision frequency is designed to perform state detection and strategy adjustments every 500 milliseconds. This configuration ensures that the scheduling decisions can adapt promptly to dynamic changes in the operational environment, thereby enhancing the system's responsiveness and reliability.

The integration of these methodologies ensures that the dynamic scheduling model can effectively respond to the complexities of emergency communication scenarios. By leveraging the DQN algorithm, the system achieves a balance between computational efficiency and decision accuracy. The frequent updates to the target network and the use of a well-structured reward function enable the model to prioritize critical communication tasks, such as maintaining core business link connectivity and minimizing transmission delays. This approach not only optimizes resource utilization but also ensures that the communication system remains robust and reliable under varying conditions, thereby meeting the stringent demands of emergency scenarios.

3.3. Machine Learning Based Link Fault Prediction and Adaptive Routing Decision Making

Using the logistic regression algorithm, a link fault prediction model is constructed. This algorithm is a classic binary classification method that efficiently categorizes and predicts the "normal/fault risk" status of a link [9]. The hypothesis function for this model is defined as:

$$h_\theta(x)=\frac{1}{1+e^{-\theta^T x}}$$

among which, θ^T represents the transposed parameter vector, x denotes the input feature vector, and $h_\theta(x)$ indicates the probability of a link experiencing a failure risk [10]. During the training phase of the model, the logarithmic loss function is employed as the cost function, with the formula expressed as:

$$J(\theta)=-\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log\left(h_\theta\left(x^{(i)}\right)\right)+\left(1-y^{(i)}\right)\log\left(1-h_\theta\left(x^{(i)}\right)\right)\right]$$

among which, m specifies the number of training samples, $y^{(i)}$ represents the actual label of the i-th sample, and $x^{(i)}$ corresponds to the feature vector of the i-th sample [11].

The gradient descent algorithm is utilized to iteratively optimize the parameters θ, with the updated formula being:

$$\theta_j := \theta_j - \alpha \frac{\partial J(\theta)}{\partial \theta_j}$$

among which, α sets the learning rate at 0.01, and the iterative process continues until the model converges, yielding the optimal parameters.

The model incorporates 12 core input features, including metrics such as average packet loss rate, end-to-end delay, jitter value, received signal strength, environmental interference strength, and remaining power of nodes over the past 10 seconds. The training dataset is derived from historical link failure data across diverse scenarios, and 5-fold cross-validation is applied to enhance the model's generalization capabilities. Following training and optimization, the model achieves fault prediction up to 3-5 seconds in advance, with an accuracy exceeding 94%. Upon predicting a link failure risk, the system promptly initiates adaptive routing decisions [12]. These decisions leverage an improved Dijkstra algorithm, integrating the link health weight output from the AI model to calculate and pre-establish alternative routes. This ensures seamless switching before an actual link failure occurs, effectively eliminating the communication interruptions associated with traditional routing protocols that rely on "re-routing after failure."

3.4. AI Driven Multi-Agent Collaborative Emergency Command Closed-Loop Decision-Making

The ultimate goal of emergency decision-making is to prioritize the effective execution of emergency response measures. This article develops an AI-driven multi-agent collaborative emergency command closed-loop decision-making mechanism, which encompasses the entire process of perception, decision-making, execution, feedback, and optimization. This mechanism addresses critical challenges such as barriers to cross-disciplinary collaboration and the disconnect between decision-making and execution, ensuring a seamless integration of all stages of emergency response.

Initially, a graph neural network (GNN) is employed to construct a multi-agent collaborative relationship graph. In this graph, emergency entities such as the command center, fire rescue teams, medical emergency units, transportation support services, and communication operation and maintenance teams are represented as nodes. The relationships between these entities, including their responsibilities, resource-sharing protocols, and command flow dynamics, are represented as edges, forming a comprehensive collaborative relationship graph. By leveraging graph feature learning, this approach facilitates the efficient flow of cross-disciplinary information and the sharing of decision-making intentions. It effectively eliminates data barriers among various entities and provides robust support for global collaborative decision-making processes.

Building on this foundation, the CART decision tree model is utilized to establish an emergency grading decision system. The decision tree is designed with a depth of 12 layers, where each node corresponds to a specific emergency response level and its associated disposal scenario. The system matches emergency plans based on critical information obtained from the situational awareness module, such as disaster severity, impact scope, and casualty figures. This automated process generates task orders and time node tables that can be directly issued and executed [11, 13]. Furthermore, a decision execution feedback improvement module is developed using a recurrent neural network (RNN). The model is configured with 128256 hidden layer nodes and a learning rate of 0.005. It processes real-time feedback on instruction execution from various entities, enabling rapid assessment of decision execution status. In cases of execution deviations, situational changes, or unsatisfactory disposal outcomes, the system promptly updates and adjusts decision-making parameters. This includes modifying command strategies and resource allocation plans, thereby establishing a comprehensive real-time decision-making loop. This ensures that emergency command decisions consistently align with the actual needs of on-site disposal operations.

4. Experiment and Verification

4.1. Experimental Design and Implementation

To validate the real-time decision-making mechanism of the artificial intelligence and cloud computing-driven emergency communication system proposed in this study, a distributed collaborative experimental environment encompassing cloud, edge, and terminal nodes was established. This environment was designed to simulate typical disaster emergency scenarios, enabling comparative testing experiments to assess system performance under various conditions. The experimental setup aimed to replicate real-world challenges encountered during disaster response, ensuring the system's applicability and reliability in practical scenarios [11, 14].

The experimental environment was structured with one cloud core node, eight edge computing nodes, and 30 emergency terminal nodes. The cloud node was equipped with 32-core CPUs, 128GB of memory, and four GPU graphics cards, utilizing a distributed cloud computing platform to compute the global decision model and store data. The edge computing nodes employed lightweight embedded devices with 8-core CPUs and 16GB of memory, deploying streamlined AI models to process on-site data and execute local decision-making tasks. Terminal nodes included diverse access points simulating portable base stations, satellite terminals, drones, sensors, video capture devices, and other disaster-site equipment. By simulating three common sudden disaster scenarios—earthquakes, floods, and forest fires—experiments were conducted in critical emergency situations such as link interruptions, sudden terminal access, and collaborative command among multiple entities. This comprehensive setup ensured the system's robustness and adaptability across a range of disaster conditions.

This study utilized PyTorch as the hosting platform to construct the architecture of a cloud- and edge-based global situational awareness and multi-agent collaborative decision-making system. Simulation experiments were conducted to verify the system's effectiveness. The experiments employed the 8T emergency communication history dataset, which contained labeled data for normal conditions, various link failure scenarios, and disaster evolution situations. The dataset provided a robust foundation for training and testing the system. The initial learning rate was set to 0.001, with a batch size of 64 samples, and the total number of training epochs was configured to 800. To prevent overfitting, the early stopping method was applied. This rigorous experimental design ensured that the system's performance metrics were thoroughly evaluated and optimized for real-world applications.

The core performance evaluation criteria for the experiments included fault prediction accuracy, average response delay, average resource scheduling delay, abnormal scenario link connectivity status, and system false alarm frequency. The target values were defined as follows: fault prediction accuracy of at least 94%, average response delay of no more than 1 second, average resource scheduling delay of no more than 500 milliseconds, link connectivity status of at least 99%, and system false alarm frequency of no more than 5%. A 10-fold cross-validation method was employed to assess the system's stability. Additionally, simulated extreme conditions, such as link interruptions, burst traffic, and electromagnetic interference, were introduced to test the system's robustness. The performance of the proposed system was then compared with traditional manual decision-making systems and static routing systems, highlighting its advantages in terms of accuracy, efficiency, and reliability under challenging conditions.

4.2. Analysis of Experimental Results

After conducting extensive rounds of testing across various scenarios, the performance indicators of the AI real-time decision-making system developed by our research institute have consistently met or exceeded the expected benchmarks in all evaluated aspects [3]. The primary data results for the system's performance indicators are detailed as follows: the accuracy of system link fault prediction reached 95.2%, surpassing the preset value of 94%; the average response time for decision-making was 0.72 seconds, well below the 1-second threshold; the average delay for resource scheduling was 380 milliseconds, significantly lower than the 500-millisecond real-time demand; and the system link connectivity rate in extreme scenarios exceeded 99.3%. Furthermore, the overall false alarm rate of the system was 3.8%, comfortably below the upper limit of 5%. Importantly, none of the indicators approached or fell below their respective lower limit thresholds, demonstrating the robustness and reliability of the system under diverse conditions.

The system described in this paper was compared with both traditional manual decision-making systems and conventional static routing systems, with the results presented in Table 2. The comparative data clearly illustrates the superior performance of the system proposed in this study. For instance, the average response time of the system was only 0.72 seconds, which is approximately one-third of the 510 seconds required for manual intervention in traditional human decision-making systems. From the perspective of link reliability, the system demonstrated the ability to predict line faults and proactively switch to alternative channels before the faulty line became non-functional. In contrast, traditional static routing systems lack any mechanism for early fault prediction, necessitating a complete restart of the routing process once a line fault occurs, which results in communication interruptions lasting approximately 2 to 3 seconds. Additionally, in terms of resource utilization, the dynamic scheduling approach employed by the system improved resource utilization efficiency to 89.2%, representing a 32.3% increase compared to the static allocation methods traditionally used. This enhancement ensures the system's ability to address emergency resource shortages and adapt to significant fluctuations in demand.

Table 2. Comparison of Performance Indicators for Different Decision Mechanisms

performance metrics	This article discusses AI+cloud computing decision system	Traditional manual decision-making system	Traditional static routing system
Average response time for decision-making	0.72s	5~10s	2-3 seconds (after malfunction)
Advance prediction of faults	3~5s	Nothing	Nothing
Extreme scenario link connectivity rate	99.3%	92.5%	90.6%
Average utilization rate of communication resources	89.2%	58.7%	56.9%
System false alarm rate	3.8%	8.5%	6.2%

This study also simulated scenarios involving aftershocks that caused partial damage to communication links. The system successfully identified the risk of main link failure 4.2 seconds in advance, enabling it to automatically establish a backup route and complete the switch without any interruptions to the communication process of core command operations. Conversely, the traditional static routing system only initiated the rerouting process after the link was completely disconnected, resulting in a core communication interruption lasting 2.3 seconds, which severely impacted the issuance of emergency command instructions. Furthermore, when multiple terminals attempted to connect simultaneously, the system utilized AI-driven dynamic scheduling of bandwidth resources to ensure all terminals were successfully connected [15, 16]. After activating the high-definition video feedback function, all terminals maintained normal communication status without any disruptions. In contrast, the traditional static bandwidth allocation method led to 11 terminal access failures and caused bandwidth blockages in core business operations, resulting in significant lag and inefficiencies.

5. Conclusion

This article proposes a comprehensive real-time decision-making solution tailored for emergency communication systems, leveraging the advanced capabilities of cloud computing. It addresses critical challenges inherent in traditional systems, including decision-making lag, limited adaptability to diverse scenarios, inefficient resource scheduling, and insufficient collaboration mechanisms. By utilizing the cloud-edge collaborative emergency communication system architecture, the study identifies key requirements and technical obstacles for achieving real-time decision-making in emergency scenarios. The proposed solution integrates a robust AI-driven decision-making framework encompassing situational awareness, resource scheduling, link assurance, and collaborative decision-making. This framework facilitates intelligent, real-time, and closed-loop decision-making processes throughout the emergency communication lifecycle. Simulation experiments demonstrate the efficacy of this mechanism, achieving second-level decision response times, precise fault prediction capabilities, and globally optimized resource allocation strategies. These advancements significantly enhance the support capacity and resilience of emergency communication systems. Future research could explore the scalability of this framework across varying emergency scenarios, assess its integration with emerging technologies such as 5G and IoT, and refine its adaptability to dynamic environmental conditions to further bolster system performance and reliability.

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