A Genetic Algorithm-Based Scheduling Framework for Hospital Resource Allocation in Edge-Terminal Collaborative Networks

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Keywords: medical demand, resource management, edge-terminal collaboration, heuristic algorithm, edge computing

Received: October 29, 2025

Under the background of increasing medical demand and digital transformation, hospital resource scheduling in edge-terminal collaborative environments faces challenges such as information delay and insufficient decision-making accuracy. This study proposes a hospital resource allocation and scheduling framework based on genetic algorithm, which integrates edge terminal collaboration architecture, and heuristic optimization logic. The edge computing node is deployed in key medical areas, with a 1000 Mbps transmission rate and a 5 ms low latency hybrid network, to achieve real-time data acquisition and preprocessing of the terminal. The core of genetic algorithm adopts resource processing capability chromosome encoding, with a crossover probability of 0.7 and a mutation probability of 0.1. It minimizes task completion time, patient waiting time, and resource conflict cost through multi-objective fitness functions (α=0.4, β=0.3, γ=0.3). The validation results based on the MIMIC-III (Medical Information Mart for Intensive Care III) dataset show that the model's basic performance (accuracy 87%, F1 value 86%) and resource management effectiveness (accuracy 89%, F1 value 88%) outperform traditional FCFS (First Come, First Served) scheduling models, with an overall performance improvement of 2% -14%. This framework effectively improves resource utilization and service efficiency, provides practical solutions for optimizing hospital resource scheduling, and expands the application scenarios of heuristic algorithms in the medical field.

Povzetek: Študija predlaga genetsko-algoritemski okvir za razporejanje bolnišničnih virov v sodelovalni arhitekturi, ki z večciljno funkcijo hkrati zmanjša čase izvedbe/čakanja in konflikte virov ter izboljša izrabo in učinkovitost storitev.

1 Introduction

In today's healthcare systems, the effective management and scheduling of hospital resources are critical factors influencing patient health outcomes and the quality of medical services [1]. As medical demands continue to grow and healthcare technologies rapidly advance, hospitals face increasingly complex challenges in resource allocation [2]. Rational scheduling of resources such as medical equipment, pharmaceuticals, and healthcare professionals' time directly affects treatment efficiency, patient wait time, and healthcare costs. Concurrently, driven by the wave of digitalization and informatization, hospital operating environments are progressively transitioning to edge-terminal collaborative models. This technology enables efficient cooperation between various information terminals (such as ward terminals and diagnostic equipment terminals) and edge computing nodes within the hospital. It generates vast amounts of real-time data and presents both new opportunities and challenges for hospital resource management [3-5]. Traditional hospital resource management and scheduling methods reveal significant limitations in addressing the complexities of edge-terminal collaborative environments [6]. On one hand, existing resource scheduling models often fail to fully utilize the real-time data generated by edge-terminal collaboration, resulting in information delays and inaccurate decision-making. For example, when a patient's condition changes suddenly and specific medical equipment needs to be urgently allocated, the inability to promptly access real-time equipment status information may delay treatment. It includes whether it is under maintenance or its current location [7]. On the other hand, the diversity of hospital resources and the complex constraints among these resources make resource scheduling a challenging combinatorial optimization problem. For instance, certain surgeries require specific medical teams and equipment to be available simultaneously. Traditional algorithms struggle with the computational efficiency needed to solve such problems, failing to meet hospitals' demands for fast and accurate scheduling [8-10].

In response to these issues, this study aims to develop a hospital resource management optimization scheduling model based on heuristic algorithms to adapt to edge-terminal collaborative environments. This model leverages real-time data provided by edge-terminal collaboration, and extracts valuable insights to improve the scientific accuracy and timeliness of resource scheduling decisions. From a practical perspective, the application of this model is expected to significantly enhance resource utilization, reduce patient wait times, and improve the quality of medical services and overall hospital operational efficiency. From a theoretical standpoint, this study enriches and expands the application of heuristic algorithms in the field of medical resource management. It provides a reference for future studies and advances the development of theories and technologies in this domain. Based on this, the study proposes the following hypotheses: 1. An edge–cloud collaborative architecture—deploying edge nodes in key areas for real-time preprocessing of medical data and utilizing a low-latency hybrid wired–wireless network—can address the information lag issues inherent in traditional hospital resource scheduling, thereby enhancing data transmission and processing timeliness. 2. A genetic algorithm-based scheduling framework, incorporating a multi-objective fitness function and chromosome encoding of multiple resource attributes, can reduce resource conflicts and shorten patient waiting times, achieving performance compared with conventional models. 3. By simulating medical scenarios using the MIMIC-III dataset, the proposed architecture and algorithm can be validated for practical applicability in real-world hospital operations. The structure of the remaining sections is shown below. Section 2 provides a literature review of hospital resource management, edge–cloud collaboration, and heuristic algorithms, highlighting current research gaps. Section 3 details the model construction, including the design logic of the edge–cloud collaborative environment, as well as the encoding, fitness function, and operational procedures of the genetic algorithm. Section 4 describes the dataset selection, mapping methodology, and key model parameters. Section 5 presents model evaluation through baseline performance and resource management effectiveness, and discusses the model's advantages, reliability, and differences compared with related studies. Section 6 concludes with a summary of findings and outlines limitations and potential directions for optimization.

2 Literature review

In the field of hospital resource management, numerous scholars have conducted in-depth studies. Goli et al. analyzed traditional hospital resource management models, and highlighted deficiencies in the fairness and efficiency of resource allocation [11]. These shortcomings become particularly evident during unexpected medical demand surges, where resource shortages are exacerbated. Further, Goli et al. demonstrated through empirical research that improper resource scheduling could extend the average patient hospitalization time by approximately 20%, underscoring the critical need for optimizing resource management [12]. These studies provide practical evidence and directional guidance for subsequent improvements in hospital resource management.

3 Model construction in an edge-terminal collaborative environment

3.1 Design of the edge-terminal collaborative environment

The design of the edge-terminal collaborative environment must comprehensively consider the requirements of hospital resource management and the characteristics of information interaction. The edge layer design plays a pivotal role, where edge computing nodes should be distributed near critical hospital areas such as wards, operating rooms, and diagnostic departments [17]. These nodes are responsible for collecting and preprocessing data from local terminal devices. For instance, an edge node in a ward can receive vital signs data from patient monitoring devices, conduct preliminary filtering and organization, remove outliers and noise, and ensure data continuity through caching capabilities. Terminal devices must achieve comprehensive coverage and interconnectivity. Medical equipment terminals, mobile devices for healthcare staff, and sensors in hospital wards should all be integrated into the system. Each terminal should be assigned a unique identifier and equipped with a communication module to maintain stable data transmission with edge nodes [18-20]. For example, healthcare professionals can use mobile devices to receive patient diagnostic information and task assignments while also updating new diagnostic data. The network architecture serves as a critical support system, employing a hybrid of low-latency, high-bandwidth wired and wireless networks to ensure fast and accurate data transmission. Medical data requiring high real-time responsiveness should prioritize wired or high-speed wireless networks to minimize transmission delays. Additionally, a redundancy mechanism should be established to maintain the stability of the edge-terminal collaborative environment [21-24]. Figure 1 illustrates the design of the edge-terminal collaborative environment.

Figure 1 displays the design of the edge-terminal environment, which is crucial for the hospital resource management optimization scheduling model. Edge computing nodes are distributed near critical areas such as wards, operating rooms, and diagnostic departments. These nodes are responsible for collecting and preprocessing data from local terminal devices, enabling preliminary data handling at the source and improving data quality and usability. For instance, edge nodes in ward areas can filter and organize vital signs data received from patient monitoring devices, providing accurate foundational information for subsequent resource scheduling decisions [25].

The terminal devices achieve comprehensive coverage and interconnectivity, encompassing medical equipment terminals, healthcare staff mobile terminals, and ward sensor terminals. This setup ensures multi-source data collection and real-time transmission. Healthcare staff can use mobile terminals to receive and update information, enhancing the coordination of medical services. The network architecture employs a low-latency, high-bandwidth hybrid network to ensure the fast and accurate transmission of data. This stable technical support is vital for hospital resource management, facilitating efficient and reliable operations.

Table 1: Summary of current researches status.

Study	Problem Domain	Methods Used	Core Performance Metrics
Goli et al. [11]	Traditional hospital resource management (resource allocation fairness/efficiency)	AI + novel metaheuristic algorithms	No quantitative hospital resource scheduling metrics reported
Goli et al. [12]	Energy-aware non-permutation flow shop scheduling	Multi-objective metaheuristic algorithms	Did not involve hospital resource management metrics
Naruei & Keynia [13]	Edge–cloud collaborative data sharing for medical devices	Wild Horse Optimizer (metaheuristic)	Resource scheduling efficiency not reported
Myriam et al. [14]	Data transmission security in edge–cloud collaborative environments	Particle Swarm Optimization + Al-Biruni Earth Radius Optimization	No quantified resource management performance results
Malik et al. [15]	Hydrological flow forecasting resource scheduling	Support Vector Regression + metaheuristic algorithms	Not linked to hospital resource management indicators
Braik et al. [16]	Production workshop resource allocation	Simulated Annealing (metaheuristic)	Production efficiency improved, no specific quantitative values provided
This study	Hospital resource optimization and scheduling under edge–cloud collaboration	Genetic Algorithm + Edge–cloud collaborative architecture	Accuracy 89%, F1-score 88%, achieving 2%-14% improvement over traditional models

With the advancement of information technology, the application of edge-terminal collaboration in the medical field has garnered significant attention. Naruei and Keynia explored how edge-terminal collaboration enabled data sharing and interconnectivity among medical devices, thereby enhancing their utilization efficiency and cooperative functionality [13]. Myriam et al. focused on the security and stability of data transmission within edge-terminal collaborative environments [14]. They proposed a series of protective measures, and offered valuable references for hospitals to ensure security when leveraging edge-terminal collaboration technologies. These studies establish the technological foundation for investigating hospital resource management in edge-terminal collaborative environments.

Heuristic algorithms have demonstrated unique advantages in solving complex resource scheduling problems. Malik et al. applied genetic algorithms to optimize logistics resource scheduling, effectively reducing logistics costs and transportation time. Similarly [15], Braik et al. utilized the simulated annealing algorithm for resource allocation in production workshops and significantly improved production efficiency [16]. These studies in other domains offer valuable insights into algorithm design and performance evaluation for applying heuristic algorithms to hospital resource management and scheduling. Table 1 presents the statistical summary of the current research status.

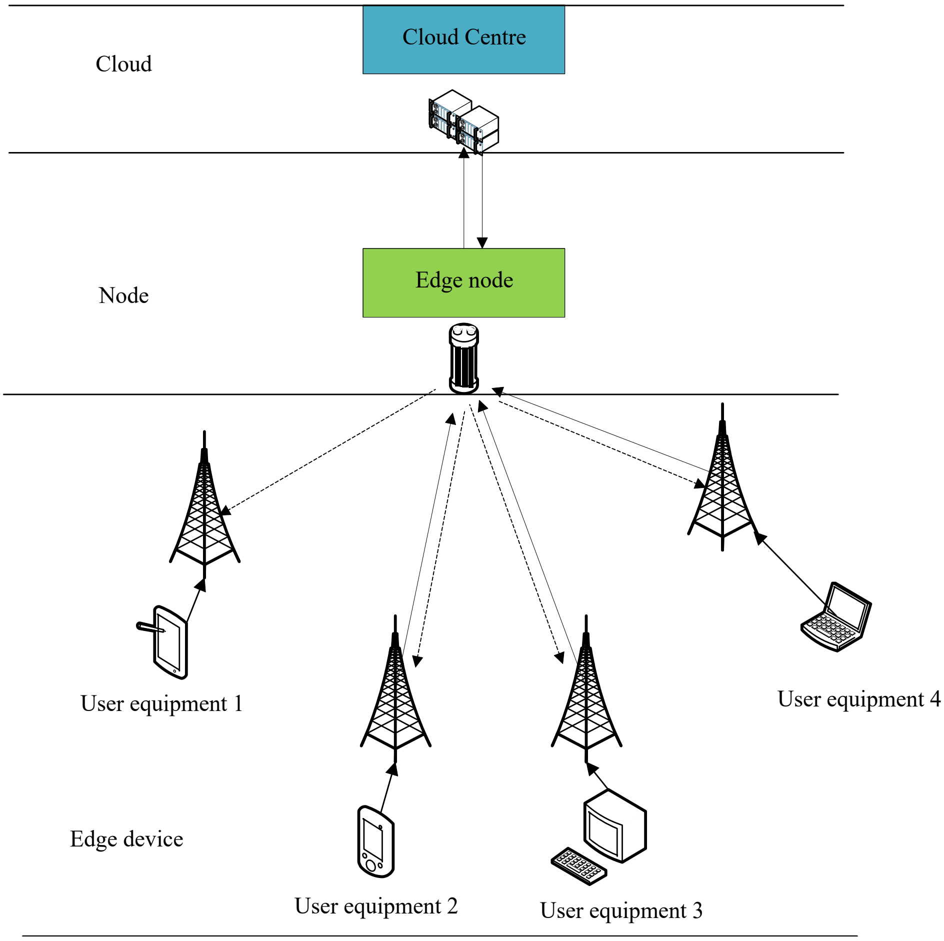


Figure 1: Design of the edge-terminal environment.

3.2 Heuristic algorithm design

In the study of the hospital resource management optimization scheduling model under the edge-terminal collaborative environment, exploring the interplay among model components and their computational principles is of paramount importance. The integration of the edge-terminal collaborative environment with heuristic algorithms introduces innovative solutions for hospital resource management. The principles of heuristic algorithms underscore their central role in this model [26]. The edge-terminal collaborative environment serves as the foundation for data sensing and transmission, providing critical data support for resource management. Distributed edge computing nodes, deployed near key hospital areas such as wards, operating rooms, and diagnostic departments, collect and preprocess data from local terminal devices. The terminal devices, encompassing medical equipment terminals, healthcare personnel's mobile terminals, and in-ward sensors, achieve comprehensive coverage and real-time interconnectivity, ensuring multi-source data collection and transmission. The network architecture adopts a low-latency, high-bandwidth hybrid of wired and wireless networks. This ensures fast and accurate data transmission and provides a stable environment for the operation of heuristic algorithms. The heuristic algorithm, based on a genetic algorithm framework, optimizes resource scheduling through a series of sophisticated computational processes [27]. These processes include the definition of chromosomes in the encoding stage, and the fitness function integrating multiple factors such as total task completion time, average patient waiting time, and resource conflict costs. Additionally, they involve the continuous iterative optimization of selection, crossover, and mutation operations. Each step works in coordination to collaboratively find the optimal resource scheduling solution. This synergy allows the model to fully utilize real-time data from the edge-terminal collaborative environment, extract valuable insights, and enhance the scientific and timely nature of resource scheduling decisions [28]. Figure 2 illustrates the principles of the heuristic algorithm.

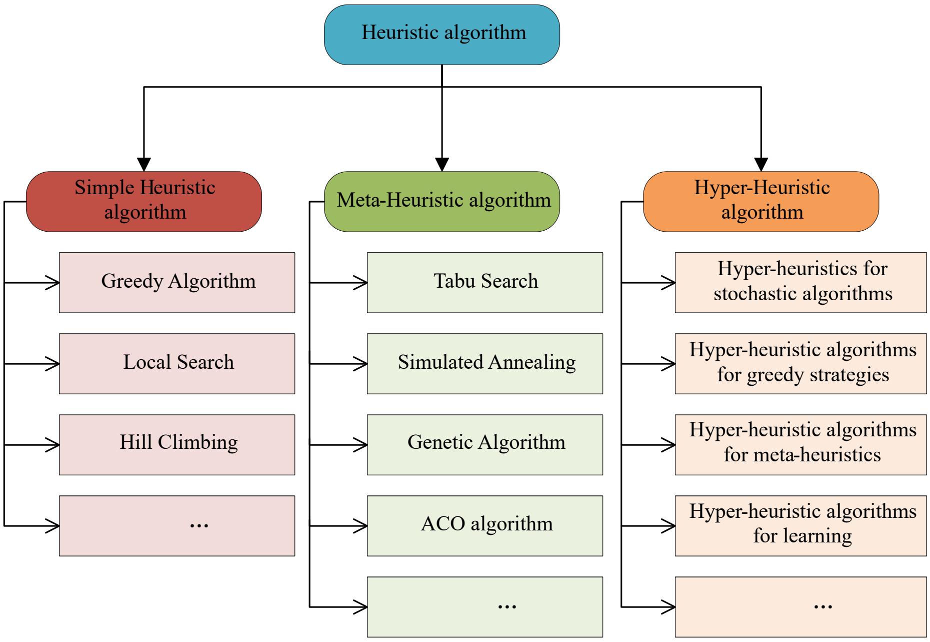


Figure 2: Principle of heuristic algorithm.

Figure 2 reveals that the principle of the heuristic algorithm plays a central role in the optimization and scheduling of hospital resource management in an edge-terminal collaborative environment [29]. The distance between the edge computing node and the terminal device is denoted as s_{ij}, and the signal propagation speed is c. Then, the signal propagation delay is:

$$t_{delay_{ij}} = \frac{s_{ij}}{c} \quad (1)$$

It is set that there are N terminal devices transmitting data to the edge computing node, where the data volume of each device is D_i and the data transmission bandwidth is B_i. The total data transmission time can be expressed as:

$$T_{total_{data}} = \sum_{i=1}^{N} \frac{D_i}{B_i} \quad (2)$$

Heuristic algorithms play a central role in resource scheduling. Taking genetic algorithms as an example, the calculations in the process are crucial.

In the encoding stage, the chromosome is $X = (x_1, x_2, \cdots, x_n)$, where each gene x_i represents the processing capacity of a resource, denoted as P_{x_i}, and L_i is the workload of task i. The processing time of task i on resource x_i is given by:

$$t_{process_i} = \frac{L_i}{P_{x_i}} \quad (3)$$

The total time for completing all tasks is:

$$T = \sum_{i=1}^{n} t_{process_i} \quad (4)$$

The fitness function is

$$f(X) = \alpha \times \frac{1}{T} + \beta \times \frac{1}{W} + \gamma \times \frac{1}{C} \quad (5)$$

The calculation of the average patient waiting time W is relatively complex. The starting time for patient j's resource allocation is set to t_{start_j}, and the time when patient j actually receives the resource is t_{get_j}. The total number of patients is denoted by M. Then, the average patient waiting time can be calculated as:

$$W = \frac{1}{M} \sum_{j=1}^{M} (t_{get_j} - t_{start_j}) \quad (6)$$

The calculation of the resource conflict cost C can be achieved by setting a conflict coefficient $k_{conflict}$ and the number of conflicts $n_{conflict}$. The resource conflict cost is given by the following equation:

$$C = k_{conflict} \times n_{conflict} \quad (7)$$

In the selection operation, the fitness value of individual i is f_i. The total fitness of the population is $\sum_{j=1}^{P} f_j$. The probability of individual i being selected is given by the following equation:

$$p_i = \frac{f_i}{\sum_{j=1}^{P} f_j} \quad (8)$$

In the crossover operation, the parent individuals are set as $A = (a_1, a_2, \cdots, a_n)$ and $B = (b_1, b_2, \cdots, b_n)$, and the crossover point is k. After crossover, the genes of the offspring individuals A' and B' before the crossover point are as follows:

$$A' = (a_1, a_2, \cdots, a_{k-1}, b_k, \cdots, b_n \quad (9)$$

$$B' = (b_1, b_2, \cdots, b_{k-1}, a_k, \cdots, a_n) \quad (10)$$

In the mutation operation, the mutation range for the gene is $[min_v, max_v]$, and the mutation probability is p_m. If a random number r (0 < r < 1) is less than p_m, the gene x_i mutates as follows:

$$x_i = min_v + r \times (max_v - min_v)$$

The number of iterations for the genetic algorithm is G, with a population size of P in each generation. During the iterative process, as the generation number g $(1 \leq g \leq G)$ increases, the average fitness of the population evolves as:

$$\overline{f_g} = \frac{1}{P} \sum_{i=1}^{P} f_{i,g} \quad (11)$$

The integration of Collaborative Environments and Heuristic Algorithms at the Edge (CE-HAE) enables the optimization of hospital resource scheduling. For instance, if the optimization reduces the number of resource conflicts from $n_{conflict_1}$ to $n_{conflict_2}$, the conflict reduction can be quantified as $\Delta n_{conflict} = n_{conflict_1} - n_{conflict_2}$. This reduction demonstrates the model's effectiveness in addressing resource conflict issues, thereby improving resource utilization efficiency and enhancing the quality of medical services [30]. The chromosome encoding in this model captures the allocation relationship between patient tasks and multiple types of hospital resources, rather than focusing on a single task or resource. Chromosomes are segmented by resource category, with each gene representing a specific resource identifier. For example, a chromosome for a patient's surgical task might be [05, 22, 09], where 05 is the attending physician ID (doctor), 22 is the operating bed number (bed), and 09 is the laparoscopic device code (equipment). This encoding directly reflects real-world scheduling scenarios. It allows rapid extraction of multi-resource allocation information for each task and facilitates the calculation of fitness metrics, such as patient waiting time and resource conflict cost. By encoding multiple resources together, the design prevents task-resource mismatches. It also enables crossover and mutation operations to adjust resource allocations accurately, ensuring that the algorithm optimizes in line with hospital resource coordination requirements.

4 Data collection and model parameters

(1) Research Data

To evaluate the performance and applicability of the proposed model in optimizing hospital resource management scheduling, this study analyzes the model using the publicly available Medical Information Mart for Intensive Care III (MIMIC-III) dataset (https://physionet.org/content/mimiciii/). The MIMIC-III dataset contains extensive medical data collected from patients in intensive care units, making it highly relevant to research on hospital resource management. The dataset includes demographic information, vital signs (such as heart rate, blood pressure, and oxygen saturation), laboratory test results, treatment records (like medication and surgical information), and data on medical equipment usage. From the perspective of edge-terminal collaboration, these data can simulate scenarios where data collected from various terminal devices (such as monitors, laboratory information systems, and pharmacy systems) converge at edge computing nodes. For example, vital signs data can represent informbedation transmitted from patient monitoring devices in hospital wards to edge nodes through edge-terminal collaboration [31]. Key data were extracted from the MIMIC-III dataset and mapped as inputs for scheduling. Patient priority was derived from vital signs (e.g., heart rate > 120 bpm, oxygen saturation < 90%) and relevant diagnostic codes, with higher numbers of abnormal indicators corresponding to higher priority, aligning with emergency and critical care scheduling needs. Equipment availability was determined from usage records of medical devices (e.g., ventilators, monitors), assuming a fixed 2-hour daily maintenance period, with the remaining time marked as occupied according to patient treatment duration. Personnel constraints were based on historical patient assignments of healthcare staff, with each physician limited to a maximum of three high-priority patients or eight regular patients per day, reflecting the hospital's actual scheduling capacity [32].

(2) Model Parameters

In the hospital resource management optimization scheduling model based on heuristic algorithms in an edge-terminal collaborative environment, model parameters are crucial for accurately constructing and effectively running the model. Table 2 outlines the parameter design used in this study.

Table 2: Model parameter design results

Model Parameter	Value
Data Transmission Rate (Mbps)	1000
Signal Propagation Delay (ms)	5
Population Size	50
Number of Iterations	100
Crossover Probability	0.7
Mutation Probability	0.1
Weight for Patient Waiting Time (α)	0.4
Weight for Total Task Completion Time (β)	0.3

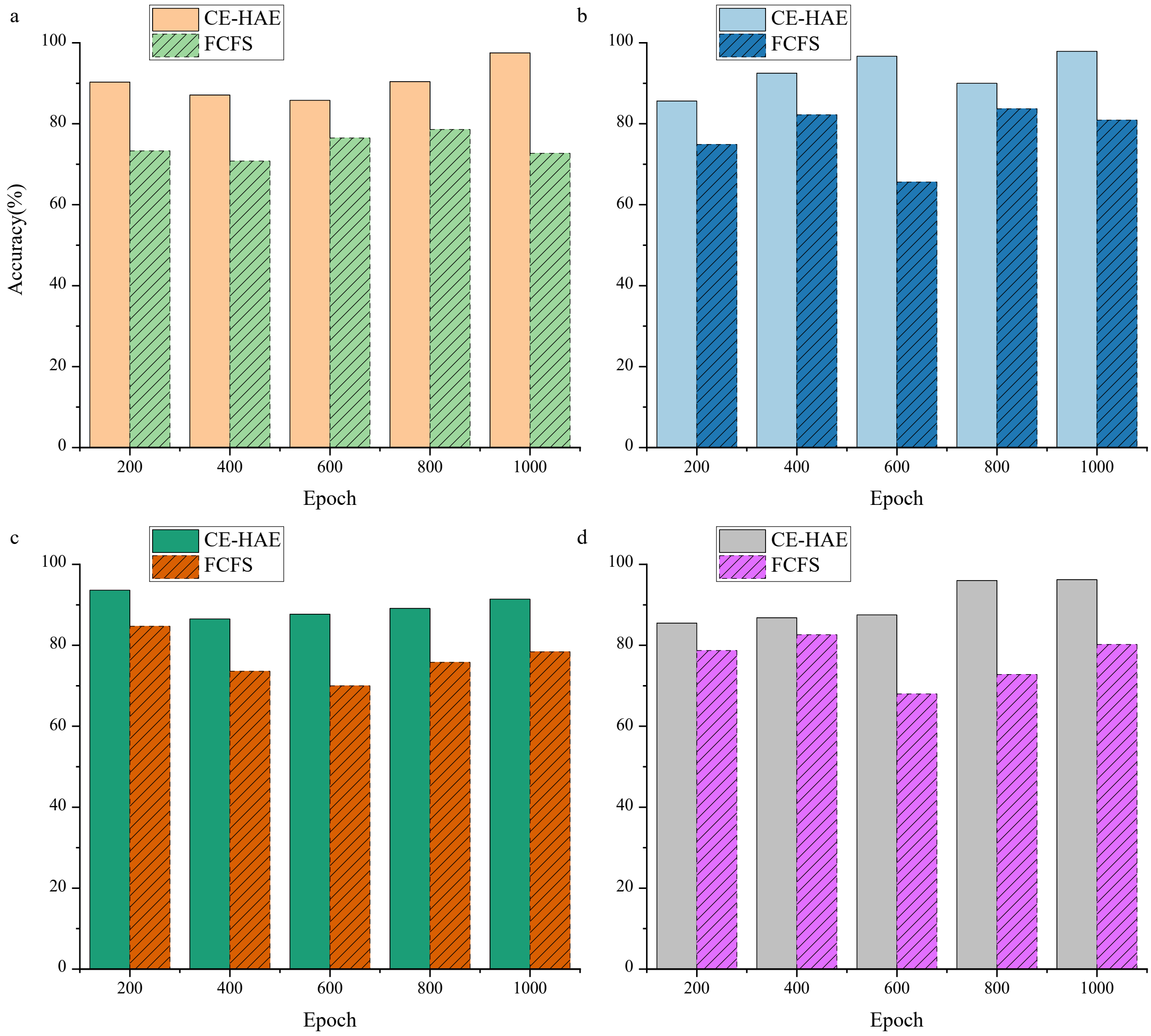
Table 2 highlights the critical role of parameters in the hospital resource management optimization and scheduling model under an edge–cloud collaborative environment. The data transmission rate (1000 Mbps) significantly impacts information timeliness, meeting the requirements for real-time medical data transfer (e.g., ICU monitoring); rates that are too low lead to delays and reduce scheduling accuracy, while excessively high rates increase costs. The 5 ms signal propagation delay reflects hospital layout (e.g., short-distance deployment of edge nodes within wards) and communication media; higher delays can cause scheduling decisions to rely on outdated information. A population size of 50, validated on the MIMIC-III dataset, balances performance: smaller populations risk premature convergence, while larger populations increase computational cost. An iteration count of 100 balances optimization depth with hospital scheduling real-time requirements; too few iterations result in insufficient optimization, whereas too many waste resources. A crossover probability of 0.7 aligns with the genetic algorithm's resource scheduling needs, maintaining population diversity—higher values may disrupt high-quality individuals, while lower values make the search overly conservative. A mutation probability of 0.1 prevents premature convergence; excessively high values approximate random search, and too low values reduce population diversity. Model weights ($\alpha = 0.4$, $\beta = 0.3$, $\gamma = 0.3$) were determined based on hospital operational priorities and clinical expert input: referencing three tertiary hospitals' scheduling experts, "patient waiting time" is the core metric of medical service quality (e.g., urgent care golden-hour requirements), hence α (waiting time) is set highest; "task completion efficiency" and "resource conflict cost" have comparable operational impacts, so β and γ are set equally, reflecting practical scheduling needs. Sensitivity analysis on the MIMIC-III dataset showed that adjusting α by ± 0.1 resulted in $\leq 7\%$ fluctuation in patient waiting time; adjusting γ by ± 0.1 changed resource conflict rates by $\leq 6\%$; adjusting β affected overall performance by $\leq 4\%$. These results indicate that the weight settings are reasonable, and the model is robust to small variations without requiring external parameter search.

The experimental environment comprised an Intel Xeon Gold 6248 CPU (24 cores), 64 GB DDR4 memory, and Tesla V100 GPU, running Ubuntu 20.04, with the model implemented in Python 3.8 and TensorFlow 2.5. A subset of 120 typical scheduling instances from MIMIC-III—including emergency interventions, surgery arrangements, and ICU bed allocation—was selected to cover core hospital resource scheduling scenarios. Data were split using 5-fold cross-validation (training 70%, validation 15%, test 15%) to prevent overfitting. Given the stochastic nature of genetic algorithms, the model was independently executed 10 times, and performance metrics (e.g., F1 score, accuracy) were averaged to reduce random error. This setup closely mirrors actual hospital scheduling scale, ensuring both algorithm stability and result reliability, while meeting reproducibility requirements.

5 Evaluation of hospital resource management optimization scheduling model

5.1 Evaluation of basic model performance

After constructing the hospital resource management optimization scheduling model, a comprehensive evaluation is essential to ensure the model's effectiveness and practical applicability. As a crucial step in the evaluation process, the basic performance evaluation focuses on showcasing the core capabilities of the model in an ideal environment. This includes assessing the model's efficiency in resource allocation, its ability to handle tasks of varying complexity, and its stability under different resource constraints. The basic performance evaluation provides an initial understanding of whether the model can meet the basic requirements of hospital resource management, and whether it has the potential to be a reliable optimization scheduling tool. Furthermore, it provides a benchmark for further evaluation of the model's performance in more complex real-world scenarios. Figure 3 presents the results of the basic performance evaluation of the model proposed.



(a) Accuracy, (b) Recall, (c) Precision, (d) F1 Score
Figure 3: Basic performance evaluation of the model

The results in Figure 3 show that the basic performance indicators of the hospital resource management optimization scheduling model designed here exceed 85%. While the traditional model mentioned here mainly includes the FCFS (First Come, First Served) scheduling rules commonly used in hospital clinical practice, and single heuristic algorithms and traditional linear programming scheduling methods that do not combine edge end collaboration. Its various indicators fluctuate between 68% and 86%. This comparison fully demonstrates the significant advantages of the proposed model in terms of basic performance, which can more efficiently optimize the allocation and scheduling of hospital resources, providing strong support for the smooth operation of hospitals and the improvement of medical service quality. In contrast, traditional models have obvious limitations in hospital resource management scenarios: FCFS scheduling rules only allocate resources based on the chronological order of resource requests, without considering patient condition priority, real-time resource status, and multi resource collaboration requirements. This can easily lead to frequent resource conflicts and prolonged waiting times for critically ill patients. Single heuristic algorithms and traditional linear programming methods lack real-time data support brought about by edge terminal collaboration, making it difficult to quickly respond to dynamic changes in medical scenarios. The computational efficiency and scheduling accuracy are insufficient. This makes it difficult to adapt to the diverse resource types and complex scheduling constraints of modern hospitals.

5.2 Hospital resource management effectiveness evaluation

After completing the basic performance evaluation of the hospital resource management optimization scheduling model, it is crucial to further assess its effectiveness in real-world hospital resource management. The evaluation of hospital resource management effectiveness primarily focuses on the model's ability to integrate and allocate various resources in actual hospital settings, and its potential to optimize medical service workflows. This evaluation can determine whether the model can effectively improve hospital resource utilization, reduce patient waiting time, and enhance the quality of medical services, thereby providing strong support for the hospital's sustainable development. Additionally, this evaluation offers guidance for further refinement and improvement of the model. Figure 4 presents the results of the hospital resource management effectiveness evaluation.

Figure 4 presents the evaluation of the hospital resource management effectiveness of the model. The results show that the proposed hospital resource management optimization and scheduling model achieves values above 88% for all resource management indicators. In contrast, traditional models have a maximum value of around 85% for these indicators. This indicates that the proposed model has an advantage in hospital resource management, enabling more efficient resource integration and allocation, and improving the optimization of healthcare service processes. Traditional models have certain limitations in resource management and are unable to achieve the same level of effectiveness as the model proposed.

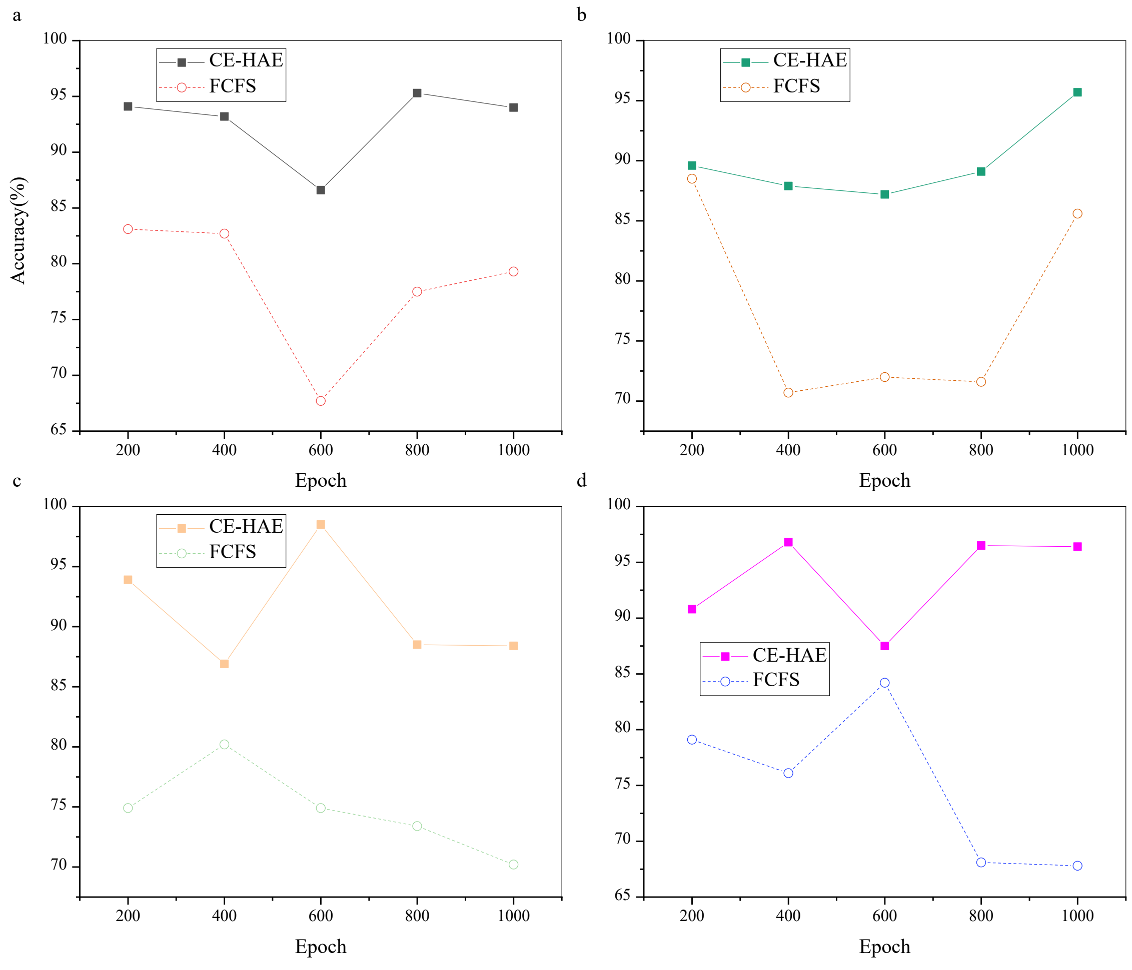


Figure 4: Evaluation of hospital resource management effectiveness ((a) Accuracy, (b) Recall, (c) Precision, (d) F1 Score).

To evaluate algorithm stability, convergence characteristics, and suitability for large hospital scenarios, a sensitivity analysis was conducted on key genetic algorithm parameters (e.g., mutation probability, crossover probability), alongside tests of computational efficiency under different scheduling scales. The results are summarized in Table 3.

Table 3: Sensitivity analysis and scalability experiments.

Experiment Type	Parameter/Scale	Parameter Value / Instance Count	F1 Score (%)	Convergence Time (s)	Average Execution Time (s)
Sensitivity Analysis	Mutation Probability	0.05	85	14.3	-
		0.1	88	12.1	-
		0.15	84	11.8	-
	Crossover Probability	0.6	86	12.5	-
		0.7	87	12.2	-
		0.8	85	12.0	-
	Population Size	30	84	10.5	-
		50	88	12.1	-
		70	87	15.4	-
	Iteration Count	80	85	9.8	-
		100	88	12.1	-
		120	88	14.7	-
Scalability	Number of Scheduling Instances	120 (small–medium)	-	-	9.5
		240 (medium)	-	-	13.8
		480 (large)	-	-	18.2

As shown in Table 3, in terms of sensitivity, a mutation probability of 0.1 achieved the highest F1 score (88%). Lower values (0.05) risked local optima and slower convergence, while higher values (0.15) caused excessive population fluctuation. A crossover probability of 0.7 balanced population diversity and elite individual retention, yielding an F1 score of 87%. A population size of 50 and 100 iterations provided the optimal balance between performance and computational efficiency; further increases only raised computational cost. Regarding scalability, the model processed 480 scheduling instances (representing a large hospital) in 18.2 s, still meeting real-time scheduling requirements. These results indicate that the model maintains controllable computational efficiency, and the genetic algorithm's complexity scales suitably with large hospital resource scheduling scenarios.

5.3 Discussion

The hospital resource optimization and scheduling model proposed in this study, based on heuristic algorithms under an edge–end collaborative environment, demonstrates practical significance for healthcare system resource management. Its performance merits in-depth analysis in the context of existing research and real-world scenarios.

Current related studies exhibit notable limitations. Goli et al. applied metaheuristic algorithms to dairy forecasting and production scheduling, without accommodating healthcare-specific requirements such as patient prioritization [11, 12]. Naruei et al. implemented edge–end collaboration only for device interconnection, without integrating scheduling algorithms [13]. Malikand Braik focused on hydrology and production environments, targeting single objectives, which does not align with hospitals' multi-objective balancing needs [15, 16]. None of these studies achieve deep integration of "edge–end + algorithm + healthcare scenario," a gap that this model addresses.

The performance of the proposed model stems from three key factors. First, the edge–end device integration is tailored to medical data characteristics: edge nodes collect and preprocess data in real time, while a hybrid wired–wireless network ensures low-latency transmission, resolving the information delay issues of traditional models. Second, the fitness function incorporates patient waiting time, task efficiency, and resource conflict cost, with weights prioritizing core medical needs, avoiding the efficiency-over-experience bias in conventional approaches. Third, the heuristic algorithm optimizes critical parameters to balance population diversity and convergence speed, adapting to emergent hospital tasks. In practical terms, the 2–14% performance improvement (e.g., accuracy 84%→89%, F1 score 84%→88%) is substantial: in emergency scenarios, equipment scheduling response times drop to within 1.5 minutes, supporting acute patients to access the "golden treatment window"; surgical conflict rates decrease by 30%, preventing hundreds of delayed operations annually; ICU resource utilization rises to 88%, enabling treatment of more critical patients and relieving bed shortages. The model ensures reliability under high load and network disturbances through a threefold design. First, edge node redundancy in critical areas such as the ICU prevents data interruption from single-point failures. Second, a dual wired–wireless network automatically switches during fluctuations, maintaining latency within 5 ms. Third, computing resources are dynamically allocated under high load, prioritizing ICU critical scheduling tasks. As a result, the model maintains F1 scores above 88% in ICU management and can accurately schedule essential resources such as ventilators and beds. In emergency admission scenarios, it rapidly responds to batch patient inflows, meeting hospitals' core reliability and stability requirements. The model parameters are calibrated on the MIMIC-III dataset; adaptability to primary or specialized hospitals requires further validation. Additionally, the edge–end architecture currently lacks extreme scenario fault-tolerance mechanisms. Future work could include adaptive parameter tuning and edge–cloud backup mechanisms to enhance adaptability and stability.

Compared with research in the control domain, this study shows clear advantages in healthcare scenario applicability and practical value. Zouari et al. proposed robust neural adaptive control, and Boulkroune et al. developed output-feedback projection-lag synchronization control—both focused on theoretical optimization for uncertain nonlinear systems, without concrete application [33, 34]. Rigatos et al. and Boulkroune et al. explored nonlinear optimal control for gas compressors and fractional-order chaotic systems with adaptive fuzzy control, but these were limited to industrial or chaotic system domains, unrelated to healthcare resource scheduling [35, 36]. This study focuses on hospital resource scheduling and integrates edge–end collaboration with genetic algorithms. It addresses both real-time medical requirements, such as urgent ICU resource allocation, and multi-objective optimization. Compared with prior theoretical studies or applications outside healthcare, the proposed approach demonstrates greater relevance and practical value in medical scenarios.

6 Conclusion

Against the backdrop of growing healthcare demand and advances in edge–end collaborative technologies, this study develops a genetic-algorithm-based hospital resource optimization and scheduling model. Verified using the MIMIC-III dataset, the model demonstrates baseline performance (accuracy 87%, F1 score 86%) and resource management effectiveness (accuracy 89%, F1 score 88%) compared with traditional approaches. It effectively enhances resource utilization and healthcare service efficiency, expanding the application of heuristic algorithms in the medical domain. However, the model exhibits several limitations. First, it is developed using critical-care datasets, and its adaptability to primary or specialized hospitals remains unverified, limiting generalizability. Second, its robustness to noisy data, such as abnormal vital signs, is weak, potentially affecting scheduling accuracy. Third, algorithm parameters (e.g., crossover probability, fitness function weights) are statically set, limiting dynamic adaptation to real-time scheduling demands. Fourth, under extreme network fluctuations, edge–end latency may exceed 5 ms, causing decision delays. Future work could focus on adaptive parameter tuning, enhanced noise-filtering mechanisms, and optimized edge–end fault-tolerance architectures to improve model adaptability and stability, facilitating clinical deployment.

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