**Genetic algorithm-based optimization of patient flow and scheduling in outpatient medical institutions**

Nursultan Sagidullaev1, 2, a), Abat Muratov 3, Raushan Usnatdinova3, Muzaffar Sayidov4

1 Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Uzbekistan

2 Nukus State Technical University, Uzbekistan

3 Karakalpak State University, Uzbekistan

4Navoi State University of Mining and Technologies, Navoiy, Uzbekistan

a) Corresponding author: [*nursultansagidullaev@gmail.com*](mailto:nursultansagidullaev@gmail.com)

**Abstract.** Efficient patient flow management is a critical challenge for modern outpatient medical institutions due to high patient demand, limited resources, and uneven physician workload. This paper proposes a genetic algorithm–based optimization model for patient scheduling and patient-to-doctor assignment. The model integrates queueing theory with evolutionary optimization to minimize patient waiting time and balance physician workload. The proposed approach is evaluated using discrete-event simulation under realistic outpatient clinic conditions. Experimental results show that the genetic algorithm significantly reduces average waiting time and workload variance compared to traditional scheduling methods, demonstrating its effectiveness for improving healthcare service efficiency.

**INTRODUCTION**

Healthcare systems worldwide are undergoing rapid transformation driven by demographic changes, technological advancements, and increasing demand for medical services. Outpatient medical institutions, such as polyclinics and specialized consultation centers, face particularly acute challenges related to patient flow management. High patient arrival intensity, limited number of physicians, and strict time constraints lead to congestion, long queues, and excessive waiting times [1, 2].

Patient waiting time is a critical indicator of healthcare service quality. Numerous empirical studies indicate that prolonged waiting not only reduces patient satisfaction but also negatively affects treatment outcomes and the overall efficiency of medical institutions. Therefore, optimizing patient flow and scheduling processes has become a key objective for healthcare administrators and policymakers [3, 4].

Traditionally, patient service processes in medical institutions have been modeled using queueing theory. In such models, patients are considered as incoming requests, physicians as service channels, and waiting areas as queues. Multi-channel queueing systems with waiting provide valuable insights into system behavior, including expected waiting time, queue length, and server utilization. However, classical queueing models typically rely on simplifying assumptions regarding arrival and service distributions and do not incorporate adaptive control mechanisms [5,6]. Research on patient flow optimization has a long history rooted in queueing theory and operations research. Early studies modeled healthcare facilities as single-channel or multi-channel queueing systems to estimate waiting times and service capacity requirements. These models provided a theoretical basis for understanding congestion phenomena in medical institutions [7].

Recent research highlights the limitations of static scheduling and rule-based approaches in dynamic healthcare environments. Patient arrival patterns often vary throughout the day, physician availability changes due to breaks or emergencies, and service times differ significantly depending on the nature of medical consultations. Under such conditions, static schedules quickly become inefficient [8].

To address these challenges, intelligent optimization methods have been increasingly applied in healthcare operations management. Metaheuristic algorithms, particularly genetic algorithms, are well suited for solving complex scheduling and resource allocation problems characterized by nonlinearity, multiple objectives, and large solution spaces. Genetic algorithms imitate natural evolutionary processes and iteratively improve candidate solutions through selection, crossover, and mutation. Genetic algorithms have been widely applied to scheduling problems in various domains, including manufacturing, transportation, and healthcare. In healthcare, GA-based approaches have been used for nurse rostering, operating room scheduling, and appointment planning. These studies confirm that genetic algorithms can efficiently handle multi-objective optimization and complex constraints [8, 9].

This study aims to develop a genetic algorithm-based model for optimizing patient flow and appointment scheduling in outpatient medical institutions. Unlike traditional approaches, the proposed model dynamically adapts to changes in system state and optimizes multiple performance criteria simultaneously. The integration of queueing theory with evolutionary optimization provides a hybrid framework capable of addressing real-world healthcare management problems.

Subsequent studies extended classical models by incorporating priorities, multiple service stages, and patient classification. For example, priority queueing models were used to differentiate emergency patients from routine consultations. Multi-stage models captured the sequential nature of medical examinations and diagnostic procedures. Despite their analytical value, these models often assume stationary arrival rates and exponential service time distributions, limiting their applicability in practice.

With the advent of medical information systems, researchers began exploring simulation-based approaches. Discrete-event simulation enables detailed modeling of patient pathways, resource constraints, and operational policies. Simulation studies demonstrated that dynamic scheduling and load balancing could significantly reduce waiting times. However, simulation alone does not provide optimal decision rules and typically requires integration with optimization algorithms [10].

In related optimization research outside the healthcare domain, dynamic mathematical models combined with optimization theory have demonstrated strong effectiveness in managing complex resource distribution systems. For example, a recent study proposed a dynamic optimization framework for minimizing transmission costs in electricity distribution networks by formulating a primal problem and solving its corresponding dual using optimality conditions and duality theorems. Numerical experiments confirmed that integrating analytical modeling with optimization algorithms significantly improves system efficiency and decision-making quality. Although the application domain differs, the methodological principles of combining system modeling with optimization techniques are directly relevant to patient flow management problems in healthcare systems [11, 12].

Nevertheless, existing GA-based healthcare scheduling models often focus on isolated subsystems and do not explicitly incorporate queueing-theoretic workload indicators. The lack of integration between analytical queueing models and evolutionary optimization limits their effectiveness in outpatient patient flow management.

This paper addresses this gap by combining queueing system workload metrics with genetic algorithm optimization to develop an adaptive patient flow management model.

**PROBLEM STATEMENT AND MATHEMATICAL MODEL**

An outpatient medical institution can be formally represented as a multi-channel service system in which patients arrive randomly and require medical consultations of varying duration. Let the incoming patient flow be characterized by an arrival intensity , which may vary over time due to daily and weekly patterns. Physicians act as service channels, and the total number of available doctors is denoted by .

Each physician provides service with an average rate , which depends on professional specialization, experience, and type of consultation. The service process is inherently stochastic, as consultation times vary significantly across patients. Therefore, the outpatient clinic can be approximated by a multi-channel queueing model of the M/M/m type with waiting (1).

The system load is defined as:

(1)

where is the average service rate across all physicians. When , the system becomes unstable, leading to unlimited queue growth and unacceptable waiting times.

However, classical queueing models assume homogeneous service channels and static scheduling policies. In real medical institutions, physicians exhibit heterogeneous workloads, and patient service times are highly variable. As a result, static assignment rules fail to ensure balanced workload distribution.

Let be the set of patients arriving during a planning horizon, and let be the set of physicians. Each patient has an estimated consultation duration , derived from historical medical data. Each physician has a current workload level , calculated as the ratio of scheduled service time to available working time.

The scheduling problem consists of assigning each patient to exactly one physician such that the following objectives are achieved:

1. Minimize the average patient waiting time.
2. Minimize workload imbalance among physicians.
3. Prevent overload situations where exceeds a predefined threshold.

Formally, this constitutes a multi-objective optimization problem with combinatorial complexity. Analytical solutions are infeasible for realistic problem sizes, necessitating the use of heuristic or metaheuristic optimization methods.

**GENETIC ALGORITHM–BASED OPTIMIZATION MODEL**

### 1. Genetic Representation

In the proposed genetic algorithm, a candidate solution is represented as a chromosome encoding patient-to-physician assignments. Each chromosome is a vector (2):

(2)

where indicates the physician assigned to patient . This representation ensures feasibility by construction, as each patient is assigned to a single physician.

### 2. Initial Population Generation

The initial population is generated using a hybrid approach. A portion of chromosomes is created randomly to ensure population diversity, while the remaining chromosomes are generated using heuristic rules, such as assigning patients to the least-loaded physicians. This hybrid initialization accelerates convergence without sacrificing exploration capability.

### 3. Fitness Function Design

The fitness function integrates multiple performance indicators into a single scalar objective (3):

(3)

where:

* is the average waiting time across all patients,
* is the variance of physician workloads,
* is an overload penalty term,
* are weighting coefficients reflecting institutional priorities.

The overload penalty is defined as:

(4)

where is the maximum allowable workload threshold.

### 4. Genetic Operators

**Selection.** Tournament selection is employed to choose parent chromosomes based on fitness ranking, promoting high-quality solutions while maintaining genetic diversity.

**Crossover.** Single-point crossover is applied with probability , exchanging segments of parent chromosomes to generate offspring solutions.

**Mutation.** Mutation randomly reassigns a small number of patients to different physicians with probability , preventing premature convergence.

**Elitism.** The best-performing chromosomes are preserved across generations to ensure solution quality does not degrade.

### 5. Termination Criteria

The algorithm terminates when either a maximum number of generations is reached or when improvements in fitness value fall below a predefined threshold, indicating convergence.

**EXPERIMENTAL** **RESULTS**

To evaluate the effectiveness of the proposed approach, a discrete-event simulation environment was developed to emulate outpatient clinic operations. The simulation incorporates stochastic patient arrivals, variable service times, and real-world scheduling constraints.

### 1. Experimental Parameters

The main input parameters used in the simulation model are summarized in Table 1. These parameters reflect realistic outpatient clinic conditions, including daily patient arrival volume, physician availability, consultation duration, and peak demand periods.

**TABLE 1.** Simulation input parameters

|  |  |
| --- | --- |
| Parameter | Value |
| Daily patient arrivals | 450–700 patients |
| Number of physicians | 12–18 |
| Average consultation time | 10–25 minutes |
| Peak arrival period | 09:00–12:00 |

Three scheduling strategies were compared:

1. First-come, first-served (FCFS)
2. Load-based heuristic scheduling
3. Proposed genetic algorithm-based optimization

### 2. Performance Metrics

The effectiveness of each scheduling strategy was assessed using the performance metrics listed in Table 2. These indicators capture both operational efficiency and patient-centered service quality.

**TABLE 2**. Performance metrics used for evaluation

|  |  |
| --- | --- |
| Metric | Description |
| Average patient waiting time | Mean time patients spend waiting before service |
| Maximum queue length | Maximum number of patients waiting simultaneously |
| Physician workload variance | Measure of workload balance among physicians |
| System utilization rate | Proportion of physician working time utilized |
| Patient satisfaction index | Composite indicator of patient service quality |

### 3. Results Analysis

The comparative performance of traditional scheduling and the proposed GA-based optimization approach is summarized in Table 3. The results indicate a substantial improvement across all key performance metrics, including patient waiting time, queue length, physician workload balance, and patient satisfaction.

**TABLE 3.** Performance comparison of scheduling approaches

|  |  |  |
| --- | --- | --- |
| Metric | Traditional scheduling | GA-based scheduling |
| Average waiting time (min) | 28 | 13 |
| Maximum queue length (patients) | 37 | 14 |
| Physician workload variance | 0.22 | 0.07 |
| Patient satisfaction (%) | 68 | 89 |

The comparative results presented in Figure 1 provide a comprehensive evaluation of the proposed GA-based scheduling approach. As shown in Figure 1:a and Figure 1:b, significant reductions in patient waiting time and queue length are achieved compared to the traditional scheduling strategy. Furthermore, Figure 1:c demonstrates improved workload balance among physicians, while Figure 1:d confirms a notable increase in patient satisfaction. These results collectively indicate the effectiveness of the proposed optimization model in enhancing outpatient clinic performance.

The results presented in Figure 1 confirm that the proposed GA-based optimization approach consistently outperforms traditional scheduling methods. Reductions in waiting time and queue length, combined with improved workload balance, lead to higher patient satisfaction and overall system efficiency. Average waiting time was reduced by more than 50%, while workload variance among physicians decreased by approximately 60%. Importantly, overload situations were effectively eliminated during peak hours.

These improvements are attributed to the algorithm’s ability to adaptively redistribute patients in response to real-time workload changes.

The results confirm that integrating genetic algorithms with queueing-based workload models offers significant advantages over static scheduling approaches. Unlike rule-based systems, the proposed method dynamically balances competing objectives and adapts to fluctuating demand.

|  |  |
| --- | --- |
|  |  |
|  |  |

**FIGURE 1.** Comparative performance analysis of traditional and GA-based scheduling approaches.

One notable advantage of the genetic algorithm is its robustness to uncertainty. The model does not rely on strict assumptions regarding arrival or service time distributions, making it suitable for real-world deployment. Additionally, the modular design allows seamless integration with existing medical information systems.

Potential limitations include computational overhead for large-scale systems and the need for accurate estimation of consultation durations. However, these challenges can be mitigated through parallel computation and machine learning–based time prediction models.

**CONCLUSION**

This study presents a comprehensive genetic algorithm-based framework for optimizing patient flow and appointment scheduling in outpatient medical institutions. By extending classical queueing theory with evolutionary optimization, the proposed approach addresses key operational challenges, including long waiting times and uneven physician workloads.

Simulation results demonstrate substantial improvements in service efficiency, patient satisfaction, and system stability. The proposed model is flexible, scalable, and applicable to both public and private healthcare institutions.

Future research will focus on real-time optimization, integration with electronic health records, and the development of hybrid models combining genetic algorithms with reinforcement learning techniques.

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