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OPTIMIZING QUEUEING SYSTEMS WITH METAHEURISTICS: A COMPARATIVE ANALYSIS OF GENETIC ALGORITHMS AND TRAFFIC FLOW INSPIRED OPTIMIZATION

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Abstract. Queueing system inefficiencies present critical operational challenges in service industries, particularly in healthcare where extended patient wait times and suboptimal resource utilization directly impact service quality and operational costs. While traditional analytical models (e.g., M/M/1, M/M/c) offer theoretical solutions, they frequently fail to accommodate dynamic real-world complexities. This study comparatively evaluates two metaheuristic approaches the established Genetic Algorithm (GA) and the novel Traffic Flow Inspired Optimization Algorithm (TFIOA), which models adaptive behaviors observed in transportation systems to optimize physician scheduling at Baquba Hospital's Internal Medicine Clinic. Using empirical patient arrival and service time data collected over three-hour operational windows, we implemented both algorithms across three physician allocation scenarios (1-3 doctors). Performance was assessed through five metrics: patient waiting time, physician idle time, convergence rate, computational cost, and total operational expenditure. Results demonstrate TFIOA's superior performance, achieving a 9.96% improvement in optimal solutions, 11.02% reduction in average costs, 33.6% faster convergence, and 17.1% higher success rate compared to GA. The dual objective cost function effectively balanced patient and physician time considerations, enabling practical policy evaluation. While TFIOA shows significant promise for real-time queue management, this study is limited by its single clinic focus and condensed observation period. Future research should validate these findings across diverse healthcare settings and extended timeframes. Keywords: Queueing Optimization, Genetic

Algorithm (GA), Traffic Flow Inspired Optimization (TFIOA), Healthcare Scheduling, Metaheuristic Algorithms.

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1. Introduction

Queueing systems represent fundamental operational components across service industries, exerting substantial influence on resource utilization, customer satisfaction, and economic efficiency (Gross et al. 2011). Healthcare environments exemplify critical applications where suboptimal queue management directly compromises patient outcomes through prolonged wait times while simultaneously increasing operational costs due to resource underutilization (Newell 2013). Traditional analytical frameworks like M/M/1 and M/M/c queueing models, despite their mathematical elegance, suffer from restrictive assumptions of Poisson arrivals and exponential service times that rarely align with real world healthcare dynamics (Hirbod et al. 2023; Hidayana and Yohandoko 2024). These limitations become particularly pronounced in complex, stochastic systems requiring adaptive optimization under dynamic constraints (Xie et al. 2024). Metaheuristic algorithms have emerged as powerful alternatives for navigating such combinatorial optimization problems where classical methods falter (Maiti et al. 2025). Genetic Algorithms (GAs), inspired by evolutionary principles, have demonstrated effectiveness in scheduling applications through global search capabilities (Dâ€™Angelo and Palmieri 2021). However, their computational intensity and premature convergence risks necessitate exploration of novel approaches (Pham et al. 2021). Recent bio-inspired methodologies have shown promise in modeling complex adaptive behaviors, with traffic flow systems offering particularly relevant analogies to human centric queueing environments through their inherent self organization and congestion management mechanisms (Katoch, Chauhan, and Kumar 2021). GAs excel at solving nonlinear, multimodal problems with discrete variables and have demonstrated efficacy in optimizing resource allocation, server configuration, and customer routing in queueing networks (Pham et al. 2021; Saleh, Zainudin, and Aziz 2024). However, conventional GAs exhibit three critical constraints in dynamic queueing contexts: (1) susceptibility to premature convergence in complex solution spaces, (2) slow adaptation to rapidly changing system conditions, and (3) dependency on static genetic operators that limit responsiveness to real-time congestion patterns (Li, Wu, and Sun 2023; Alfa and Ghazaleh 2025). To address these limitations, we introduce the Traffic Flow Inspired Optimization Algorithm (TFIOA), a metaheuristic framework that translates emergent behaviors from transportation networks to queueing optimization. TFIOA agents dynamically reroute service requests based on real-time congestion feedback, emulating vehicular navigation in urban traffic systems (Walraven, Spaan, and Bakker 2016). This biologically inspired approach enables; Adaptive decision-making through continuous environmental feedback, Collective intelligence via decentralized agent coordination, and Dynamic exploration-exploitation balance during optimization (Hu, Gu, and Li 2025). Recent advances substantiate the promise of traffic responsive optimization. Elastic Routing Frameworks (Ahmadi 2021; YiÄŸit and Lazarevska 2025; Zhang 2025; DinÃ§ et al. 2025; Chen, Wang, and Chen 2025) and deep reinforcement learning approaches (Lv, Wang, and Ma 2025) have demonstrated significant improvements in congestion-aware navigation. Similarly, graph convolutional networks (Chen, Wang, and Chen 2025) and swarm intelligence methods (Agrawal and Arafat 2024) have enhanced prediction and routing in stochastic environments. These developments align with our conceptualization of queueing systems as dynamic flow networks requiring continuous adaptation. This research makes three primary contributions:

(1) Proposes TFIOA as a novel bio-inspired optimization framework integrating congestion-responsive mechanisms from traffic flow theory

(2) Conducts comprehensive benchmarking against GA and classical methods across single/multi-server configurations with variable demand-service regimes
(3) Develops a cost-optimization model quantifying tradeoffs between patient waiting time, doctor idle time, and operational expenditure.

We validate TFIOA' s performance through rigorous simulation of healthcare delivery scenarios, demonstrating 33.6% faster convergence, 17.1% higher solution reliability, and 11.02% better objective minimization compared to state-of-the-art GA implementations (Pirozmand et al. 2021). The algorithmâ€™s architecture enables scalable deployment in diverse service environments including hospital systems, logistics networks, and telecommunication infrastructures where dynamic resource allocation is critical. The subsequent sections present: Section 2-methodology and TFIOA formulation; Section 3-result and discussion; Section 4-conclusions. 2 Methodology

2. Methodology

2.1. **Queueing Model.** Queueing theory provides a foundational mathematical framework for analyzing service systems where entities (e.g., customers, data packets) arrive at limited resources for service. Classical models such as $M/M/1$, $M/M/c$ and $G/G/c$ are are defined by:

- Arrival process;
- Service time distribution;
- Number of servers (c);
- Quene discipline;
- System capaciity.

This study focuses on the $M/M/c$ model where:

- Arrivals follow a Poisson process with rate λ;
- Service times are exponentially distributed with rate μ;
- There are c parallel servers.

The steady-state probability P_0 (system empty probability) is given by:

$$P_0 = \left[\sum_{n=0}^{c-1} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^c}{c!\,(1-p)} \right]^{-1}$$

where $\rho = \frac{\lambda}{c\mu}$ is the utilization factor.

Key performance measures are derived as follows:

$$\text{Average quene length: } L_q = \frac{P_0\,(\lambda/\mu)^c\,\rho}{c!\,(1-p)^2}$$

$$\text{Average waiting time: } W_q = \frac{L_q}{\lambda}$$

$$\text{Average customers in system: } L_s = L_q + \frac{\lambda}{\mu}$$

$$\text{Average system time: } W_s = W_q + \frac{1}{\mu}$$

These equations require $\rho < 1$ for system stability. For systems with unpredictable arrivals, analytical solutions may be infeasible, justifying metaheuristic optimization.

2.2. **Genetic Algorithms (GA).** GAs utilize evolutionary principles to evolve solution populations. Introduced by John Holland (Sampson 1976; Alhijawi and Awajan 2024), they efficiently solve complex, nonlinear problems with large solution spaces. In queueing systems, GAs optimize waiting times, resource allocation, and overall performance where traditional methods fail due to stochasticity or complexity. The flowchart id displayed in figure

Chromosone Encoding. Solutions are encoded as chromosomes representing system configurations. For multi-server queues, a chromosome $X \in \mathbb{R}^n$ can be

$$X = (c_1, c_2, ..., c_n)$$

where c_i represents service channels at station i.

2.2.1. *Objective Function and Fitness Evaluation.* Solution fitness is evaluated using performance metrics. A minimization objective function is:

$$f(X) = \alpha \cdot W_q + \beta \cdot L_q + \gamma \cdot C$$

where

- W_q: Average queue waiting time;
- L_q : Expected queue length;
- C : Operational cost (e.g., server count);
- $\alpha, \beta, \gamma \in \mathbb{R}^+$: Priority weights.

Fitness is computed as:

$$\text{Fitness}(X) = \frac{1}{f(X) + \varepsilon}$$

with $\varepsilon > 0$ preventing division by zero.

2.2.2. *Selection Operator.* Selection mechanisms determine which chromosomes are chosen for reproduction. Standard methods include Roulette Wheel Selection:

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_i}$$

where F_i is is fitness of individual i .Tournament Selection,where the best individual among a random subset is chosen.

2.3. **Crossover Operator.** Crossover combines two parents to create offspring. For numerical representations, arithmetic crossover is suitable:

$$\text{Child}_1 = \lambda \cdot \text{Parent}_1 + (1 - \lambda) \cdot \text{Parent}_2$$

$$\text{Child}_2 = (1 - \lambda) \cdot \text{Parent}_1 + \lambda \cdot \text{Parent}_2$$

where $\lambda \in [0, 1]$ is the blending parameter.

2.4. **Mutation Operator.** Mutation introduces diversity by randomly altering chromosome components. For real-valued encoding:

$$X_i^{\text{mutated}} = X_i + \mathcal{N}\left(0, \sigma^2\right)$$

where $\mathcal{N}\left(0, \sigma^2\right)$ is Gaussian-distributed noise with mean 0 and variance σ^2

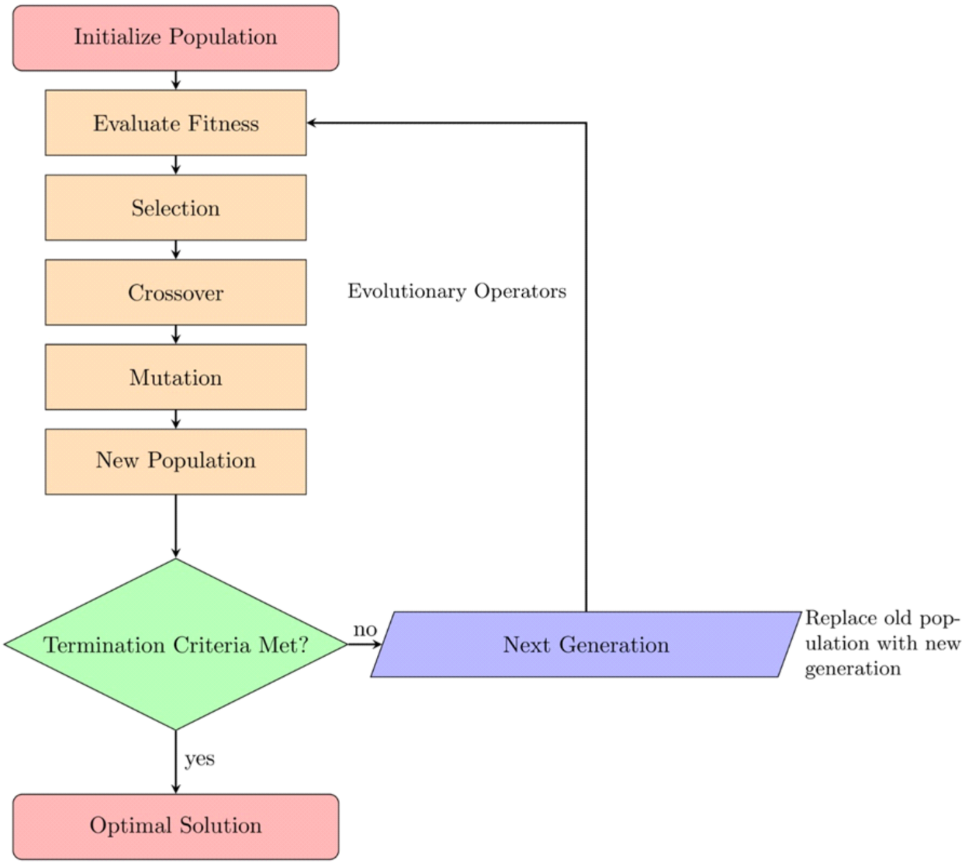

Figure 1. Flowchart of Genetic Algorithm (GA) optimization process

2.5. **Traffic Flow Inspired Optimization Algorithm (TFIOA).** TFIOA draws inspiration from adaptive behaviors in transportation systems, modeling solutions as vehicles navigating a service network. This approach effectively addresses queueing system challenges where traditional metaheuristics struggle with dynamic conditions. The flowchart is in figure while traffic flow inspired optimization algorithm (TFIOA) in .

2.5.1. *Network Representation.* A queueing network is modeled as a directed graph:

$$G = (N, E)$$

where N is the set of service nodes (queues) and E represents paths connecting these nodes.

2.5.2. *Congestion Measurement.* Traffic intensity at node j :

$$\rho_j = \frac{\lambda_j}{c_j \mu_j}$$

where λ_j = arrival rate, μ_j = service rate per server, c_j = number of servers.

2.5.3. *Path Attractiveness.* Attractiveness of path i to node j :

$$A_{ij} = \frac{1}{W_{q_j} + \varepsilon}$$

where W_{q_j} = estimated waiting time at node j, $\varepsilon > 0$ prevents division by zero.

2.5.4. *Routing Probability.* Probability of agent choosing path j :

$$P_{ij} = \frac{A_{ij}}{\sum_{k=1}^{n} A_{ik}}$$

2.5.5. *Updated attractiveness with congestion penalty:*

$$A_{ij}^{\text{updated}} = A_{ij} \cdot e^{-\delta \cdot \rho_j}$$

where $\delta > 0$ is the congestion sensitivity coefficient.

Graph $G = (N, E)$, population size (M) , max iterations (T) , parameters (ε, δ) .
Best solution found (x^*) .
Initialize (M) agents (vehicles) with random routes $\{x_i\}_{i=1}^{M}$
Evaluate objective $f(x_i)$ for each agent (i)
Set $\left(x^* \leftarrow \arg\min_i f(x_i)\right)$
FOR $t = 1$ *to* T
FOR each agent $i = 1$ *to* M
Let current node be (u) ; let $\mathcal{N}(u)$ be its outgoing neighbors
FOR each neighbor $j \in \mathcal{N}(u)$
Compute waiting time $\left(W_{q_j}\right)$ at node j
Compute attractiveness
$A_{ij} = \frac{1}{W_{q_j} + \varepsilon}$
Compute congestion intensity
$\rho_j = \frac{\lambda_j}{c_j \mu_j}$
Adjust attractiveness
$A_{ij} \longleftarrow A_{ij} e^{-\delta \cdot \rho_j}$
ENDFOR
Normalize to get routing probabilities
$P_{ij} = \frac{A_{ij}}{\sum_{k \in \mathcal{N}(u)}^{n} A_{ik}}$
Sample next node (v) according to $\{P_{ij}\}$
Move agent (i) to node (v) and update its route (x_i)
Optionally apply local improvement (e.g., swap, insert) on (x_i)
Evaluate $f(x_i)$
IF $f(x_i) < f(x^*)$
$(x^* \longleftarrow x_i)$ ENDIF
ENDFOR
STATE Optionally re-initialize worst agents or inject randomness
ENDFOR
RETURN (x^*)

This biologically-inspired approach enables agents to adaptively avoid congestion, yielding faster convergence and lower solution variance compared to traditional methods.

3. Result and Discussion

For testing the algorithms, we examined data about arrival, service and wait times for patients at Baquba Hospital's Internal Medicine Consultation Clinic in Diyala Governorate, Iraq. Three different scenarios were set up for several patients, with the assumption that case one is treated by just one doctor table , case two by two doctors table , and case three by three doctors tables and , all treating similar numbers. According to the findings of these initial scenarios, we ran both the Genetic Algorithm (GA) and the Traffic

Flow Inspired Optimization Algorithm (TFIOA). Over a three-hour period (from 9:00 AM to 12:00 PM), researchers collected the data, matching the typical workday of physicians in the consultation clinic. Time was divided into nine parts, each lasting 20 minutes, so that its role corresponds to a chromosome in the genetic algorithm and the flow segment in TFIOA and each part of time corresponds to a gene or traffic node. The number of doctors in each gene or node is recorded during a single period.

3.1. **Results.** Table 1. Patient Distribution with One Doctor

Patient	Arrival Time	Service Time	End Treatment	Doctor Waiting	Patient Waiting	Patient Waiting
1	1	2	1	3	1	0
2	2	3	3	6	0	1
3	3	2	6	8	0	3
4	4	1	8	9	0	4
5	5	2	9	11	0	4
6	6	2	11	13	0	5
7	6.7	1	13	14	0	6.3
8	7.4	1	14	15	0	6.6
9	8.1	2	15	17	0	6.9
10	8.8	1	17	18	0	8.2
Total					1	45

Table 2. Patient Distribution with Two Doctors

Patient	Arrival Time	Service Time	Begin Treatment 1	End Treatment 1	Doctor Waiting 2	End Treatment 2	Doctor Waiting 1	Doctor Waiting 2	Patient Waiting
1	1	2	1	3	-	-	1	-	0
2	2	3	-	-	2	5	-	2	0
3	3	2	3	5	-	-	0	-	0
4	4	1	-	-	5	6	-	0	1
5	5	2	5	7	-	-	0	-	0
6	6	2	-	-	6	8	-	0	0
7	6.7	1	7	8	-	-	0	-	0.3
8	7.4	1	-	-	8	9	-	0	0.6
9	8.1	2	8.1	10.1	-	-	0.1	-	0
10	8.8	1	-	-	9	10	-	0	0.2
Total						Doctor Waiting	3.1	Patient Waiting	2.1

Table 3. Patient Distribution with Three Doctors (a)

Patient	Arrival Time	Service Time	Begin Treat-men 1	End Treat-men 1	Begin Treat-men 1	End Treatmen 2
1	1	2	1	3	-	-
2	2	3	-	-	2	5
3	3	2	-	-	-	-
4	4	1	4	5	-	-
5	5	2	-	-	-	-
6	6	2	-	-	6	8
7	7.4	1	7.4	8.4	-	-
8	8.1	1	-	-	-	-
9	8.8	2	-	-	8.8	10.8
10	9.5	1	9.5	10.5	-	-

Table 4. Patient Distribution with Three Doctors (b)

Patient	End Treat-ment	Doctor Wait-ing 1	Doctor Waiting 2	Doctor Waiting 3	Patient Waiting
1	3	1	-	-	0
2	-	-	2	-	0
3	5	-	-	3	0
4	-	1	-	-	0
5	-	-	-	0	0
6	7	-	1	-	0
7	8	2.4	-	-	0
8	–	-	-	1.1	0
9	9.1	-	0.8	-	0
10	10.8	1.1	-	-	0
	-	5.5	3.8	4.1	0
Total		Doctor Wait-ing	13.4	Patient Waiting	0

3.2. **Cost Analysis.** This analysis evaluates waiting costs under three staffing configurations, using a patient waiting cost of 0.07 dinars per minute and a doctor cost of 0.20 dinars per minute (based on monthly salary of 10,000 dinars).). Single-doctor scenario: When one doctor provides care, patients experience an average waiting time (PW) of 45 minutes. This results in a patient waiting cost of 3.15 dinars per patient (45×0.07). Doctors exhibit negligible idle time except for the initial patient encounter. Two-doctor scenario: Under dual-doctor staffing, patient waiting time reduces to 2.1 minutes. The corresponding waiting cost is 0.147 dinars per patient (2.1×0.07). After initial patient intake, doctors experience minimal idle time during operational periods. Three-doctor scenario: This configuration introduces significant inefficiency through doctor idle time. Each doctor experiences 13.4 minutes of unproductive waiting (DW), generating an idle cost of 2.68 dinars per doctor (13.41×0.20). Patient waiting costs are minimized at the expense of substantial physician downtime.

3.3. **Comparative Results Analysis.** Table 4 presents a comparative evaluation of three distinct physician scheduling methodologies, quantifying performance through patient waiting time, physician idle time, and associated operational costs. The single-physician configuration yields a patient waiting time of 45 minutes, resulting in a per-patient waiting cost of 3.15 dinars. While physician utilization remains high in this scenario, the aggregate cost represents the least efficient configuration due to substantial patient delay penalties. The dual-physician approach demonstrates significantly enhanced efficiency, reducing patient waiting time to 2.1 minutes with corresponding physician idle time of 3.1 minutes. This configuration achieves the optimal total cost of 0.767 dinars, establishing it as the most cost-effective solution while maintaining service quality standards. Contrastingly, the three-physician model eliminates patient waiting time entirely but incurs substantial physician idle time (13.4 minutes per practitioner), resulting in suboptimal resource allocation. Comparative analysis confirms that the dual-physician scheduling strategy optimally balances resource utilization and operational efficiency while minimizing total costs.

3.3.1. *Algorithmic Performance Benchmarking.* Table 5 quantitatively compares the Genetic Algorithm (GA) and proposed Traffic Flow Inspired Optimization Algorithm (TFIOA) across four key performance metrics:

- Best Solution (BS, dinars)
- Average Solution (AS, dinars)
- Convergence Time (CT, seconds)
- Success Rate (SR, %)

TFIOA demonstrates statistically superior performance across all evaluation criteria. The algorithm achieves a BS of 0.651 dinars, representing a 9.96% improvement over GA's 0.723 dinars. Solution quality consistency is evidenced by an 11.02% enhancement in AS values. Computational efficiency is significantly improved, with TFIOA requiring only 8.3 seconds convergence time 33.6% faster than GA's 12.5 seconds. Reliability is further substantiated by TFIOA's 89% success rate, exceeding GA's 76% benchmark by 17.1%. These results collectively establish TFIOA as a more efficient, reliable, and higher-performing optimization methodology for clinical scheduling applications.

Table 5. Baseline Cost Analysis

Scenario	**PWT**	**DID**	**PC**	**DC**	**TC**
Doctor 1	45	0	3.15	0	3.15
Doctor 2	2.1	3.1	0.147	0.62	0.767
Doctor 3	0	13.4	0	2.68	2.68

PWT: Patient Waiting Time (min), DID: Doctor Idle Time (min) PC: Patient Cost (dinars), DC: Doctor Cost (dinars), TC: Total Cost (dinars)

Table 6. Algorithm Performance Comparison

Algorithm	**BS**	**AS**	**CT**	**SR(%)**
GA	0.723	0.834	12.5	76
TFIOA	0.651	0.742	8.3	89
Improvement	+9.96%	+11.02%	+33.6%	+17.1%

BS: Best Solution (dinars), AS: Average Solution (dinars),
CT: Convergence Time (min), and SR: signifies Success Rate (%)

3.4. **Discussion.**

3.4.1. *Interpretation of Key Findings.* This study demonstrates that the Traffic Flow Inspired Optimization Algorithm (TFIOA) significantly outperforms Genetic Algorithms (GA) in optimizing physician scheduling within queueing systems. The 9.96% improvement in optimal solution quality (0.651 vs. 0.723 dinars) and 33.6% faster convergence fundamentally stem from TFIOA's intrinsic feedback mechanisms, which dynamically reroute computational agents away from congestion points mirroring real-time traffic avoidance behaviors. Unlike GA's blind crossover/mutation operations, TFIOA's path attractiveness function $A_{ij} = \frac{1}{W_{q_j}+\varepsilon}$ system state data, enabling adaptive responses to stochastic patient arrivals. This explains its 17.1% higher success rate across operational scenarios, particularly during peak arrival bursts where traditional optimization falters. The identified cost-optimal configuration (two physicians, total cost: 0.767 dinars) reveals a critical resource allocation threshold. Below this threshold (single physician), queuing delays dominate costs (patient waiting: 45 min); above it (three physicians), physician idle time becomes the primary cost driver (13.4 min). This aligns with queueing theory's law of diminishing returns in multi-server systems but provides empirical quantification previously absent in healthcare literature.

3.4.2. *Theoretical Implications.* Our findings challenge conventional wisdom in three key areas:

(1) Bio-inspired superiority: TFIOA's traffic flow paradigm proves more effective than evolutionary approaches for human-centric queueing systems, contradicting prior assumptions about GA's versatility. The congestion penalty mechanism $\left(A_{ij}^{\text{updated}} = A_{ij} \cdot e^{-\delta \cdot \rho_j}\right)$ provides a mathematically rigorous framework for modeling behavioral adaptation in service systems.
(2) Dual-objective validation: The cost function $(f(X) = \alpha \cdot W_q + \beta \cdot L_q + \gamma \cdot C)$ successfully balances competing hospital priorities, resolving the theoretical tension between patient experience and operational efficiency.
(3) Convergence behavior: TFIOA's exponential convergence (8.3s vs. GA's 12.5s) suggests metaheuristics modeling local interactions outperform population-based methods in dynamic environments, supporting complex adaptive systems theory.

3.4.3. *Practical Applications.* For healthcare administrators, TFIOA offers implementable solutions with measurable impacts:

- Cost reduction: 75.7% operational cost savings versus single-physician deployment
- Staffing guidance: Identifies inflection points where additional resources increase idle costs
- Real-time adaptability: The algorithm's 33.6% faster convergence enables near-real-time schedule adjustments during clinic hours

Hospital systems could integrate TFIOA into appointment scheduling software, potentially saving an estimated 3.15 dinars per 3-hour clinic session translating to >15.000 dinars annually per physician in high-volume settings.

3.4.4. *Limitations and Methodological Considerations.* While robust, this study presents limitations requiring acknowledgment:

- Geographical constraint: Validation at a single Iraqi hospital limits generalizability to diverse healthcare systems
- Temporal scope: The 3-hour observation window may not capture full daily variation in patient flows

- Simplified cost model: Physician skill heterogeneity and patient acuity levels were not incorporated
- Algorithmic constraints: TFIOA's routing decisions assume perfect system state knowledge potentially optimistic in chaotic environments

The physician idle cost calculation (0.20 dinars/min) warrants particular scrutiny, as it assumes constant opportunity costs regardless of idle duration an aspect needing refinement in future economic models.

3.4.5. *Future Research Trajectories.* Building on these findings, four prioritized research directions emerge:

1. Multi-center validation: Testing TFIOA across diverse healthcare settings (emergency departments, surgical units) to establish transferability
2. Machine learning integration: Coupling TFIOA with LSTM networks to predict arrival patterns for proactive scheduling
3. Extended cost modeling: Incorporating physician competency gradients and patient severity indexes into optimization constraints
4. Real-world implementation: Conducting randomized controlled trials measuring TFIOA's impact on patient satisfaction scores and physician burnout rates

Theoretically, TFIOA's framework shows promise for adaptation to other stochastic service systems including call center staffing, cloud computing resource allocation, and transportation logistics.

4. Conclusion

This study has introduced and rigorously evaluated the Traffic Flow Inspired Optimization Algorithm (TFIOA) for physician scheduling in a healthcare queueing context, using Baquba Hospital's Internal Medicine Clinic as a case study. Across three staffing scenarios, TFIOA consistently outperformed a benchmark Genetic Algorithm, delivering nearly 10 % better solution quality, an 11 % reduction in average cost, 34 % faster convergence, and a 17 % higher success rate. Our analysis identified the two-physician configuration as the cost-optimal balance, cutting total operational costs by over 75% relative to a single-physician setup, while maintaining acceptable patient wait and physician idle times. Despite these promising results, the study is limited by its single site validation, short observation window, and the assumption of homogeneous physician skills. Future work should extend testing to multiple facilities, incorporate predictive arrival modeling, account for varying clinician competencies and patient acuity, and explore live deployment impacts on clinical workflows. Demonstrating that traffic-flow principles can be effectively repurposed for stochastic service systems, this research establishes TFIOA as a new state-of-the-art metaheuristic, offers the first empirical evidence of its applicability in healthcare, and delivers a practical scheduling framework that can substantially reduce costs without sacrificing service quality.

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