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Research Article

Optimizing Hospital Operational Efficiency Using AI: A Multi-Objective NSGA-II Model for Real-World Medical Data in Syria

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ABSTRACT

This study presents an AI-driven multi-objective optimization approach using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to enhance hospital operational efficiency in Syria. Using real-world data from the Tishreen University Hospital over a 60-day period, the research addresses three conflicting objectives: minimizing average patient waiting time, reducing daily operational costs, and maximizing the number of patients treated. Six key operational variables were selected to build the optimization model, including bed availability, physician count, and daily admissions. The NSGA-II algorithm successfully generated a set of Pareto-optimal solutions, each reflecting different trade-offs among the objectives. Statistical analysis and visualizations confirmed the complexity and nonlinearity of hospital operations, showing that increases in resources or costs do not always lead to improved outcomes. The results offer decision-makers a range of efficient operational configurations tailored to various institutional priorities. This model provides a valuable decision-support tool, especially in resource-constrained healthcare environments like Syria. Future research will focus on integrating real-time data, expanding operational variables, and validating the model across different institutions to support broader policy implementation and operational standardization.

1. INTRODUCTION

Artificial intelligence has earned significant milestones in growing healthcare services by analyzing large amounts of data, conducting predictions, and making decisions [1-5]. Healthcare operations in Syria struggle with multiple difficulties due to increasing service requirements and scarce resources and performance shortcomings in medical care. Operating difficulties at Tishreen University Hospital Department remain severe because the institution needs to find a balance between its operational efficiency and cost-effectiveness and healthcare quality standards. Healthcare management problems which challenge complex healthcare settings now receive promising solutions through recent developments of artificial intelligence (AI) and multi-objective optimization methods [6][7]. The research investigates hospital operational optimization through NSGA-II as a strong multi-objective optimization tool to reduce waiting times and operational expenses simultaneously while enhancing patient flow. Operations research and healthcare management literature form the foundation of this study since they reveal how AI-driven models enhance decision-making under resource restrictive situations [8][9]. Through analysis of Tishreen University Hospital real data, the study selects average waiting time and daily patient admissions and available beds and physician count and operational costs and treated patients as essential variables for building their multi-objective structure. NSGA-II effectively produces Pareto-optimal solution sets because the conflicting multiple objectives require such generation methods. Stakeholders then access these trade-offs independent of weighting assignments [10][11]. This research enhances healthcare operations optimization studies by offering practical strategies based on Syrian hospital needs. This research supports worldwide AI applications in healthcare [12] while also giving specific methods to enhance hospital performance [12]. Through the study, the team used both descriptive statistics and Pareto-front analysis to show that their solutions worked properly as described [13]. The research results assist healthcare leaders and government officials who aim to improve public services while growing healthcare needs and limited funding.

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2. LITERATURE REVIEW

Significant interest has developed during recent decades regarding operations research (OR) and artificial intelligence (AI) integration in healthcare management because organizations need optimized resource utilization combined with cost reductions and better patient health outcomes. OR serves as an essential instrument for healthcare systems optimization in situations where resources are limited according to the work of [14]. Through research conducted by Xie and Lawley [6] scientists extended previous work by demonstrating how OR approaches enhance crucial hospital operational performance indicators related to patient journey optimization and service rendering periods. Multi-objective optimization frameworks developed further healthcare management by allowing administrators to optimize cost reduction against service quality elevation [7]. The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) stands as a vital evolutionary algorithm which addresses intricate healthcare optimization problems. NSGA-II became an industrial standard because it generates Pareto-optimal solutions efficiently for trade-off problems where weights are not needed [10]. NSGA-II demonstrates remarkable capabilities for non-linear and high-dimensional datasets according to Zhang et al. [11] and offers valuable benefits for healthcare applications working with variables like patient admissions and bed capacity and staffing levels. The algorithm proved best-in-class in practical implementation while demonstrating capabilities that exceeded hospital requirements for developing regions as shown by [13]. Modern healthcare research focuses on data-driven decision systems which enhance healthcare operational processes. The collaboration between big data analytics techniques with OR models allow researchers to detect unseen operational issues while simultaneously forecasting demand patterns according to [12]. The approach works exactly for the Tishreen University Hospital because they possess historical performance data about waiting times and operational costs along with patient throughput metrics. Research conducted by Saghafian et al. [8] together with Dai and Tayur [9] presented concrete examples about how AI-OR applications transform emergency casualty treatment and big healthcare organizations. These research works demonstrate optimizing hospital operations demands leading computational tools as well as profound knowledge of regional constraints and stakeholder requirements. The existing literature provides a robust theoretical and methodological foundation for this study, bridging gaps between OR, AI, and healthcare management. By leveraging NSGA-II and real-world data, this research extends prior work to address the unique operational challenges of Syrian healthcare institutions, offering a replicable framework for similar settings globally [15-17].

3. METHODOLOGY

3.1. Data collection

This study relies on six key variables, selected based on their importance in evaluating the performance of healthcare institutions and their ability to represent the operational, financial, and service aspects of the healthcare system. These variables include: (1) average waiting time per patient, which reflects the speed of service provision; (2) the number of patients admitted daily, as an indicator of demand; (3) the number of available beds, to measure capacity; (4) the number of available physicians, as a measure of human resources; (5) daily operating costs, to measure the financial burden; and (6) the number of patients treated, as an indicator of the system's efficiency in providing care. These variables represent key inputs and outputs within the multi-objective programming model and are used to analyze and improve the balance between operational efficiency, service quality, and cost. Public health institutions in Syria are experiencing increasing pressures due to population growth, increasing demand for healthcare services, and a shortage of human and material resources. At the Tishreen University Hospital, the operational challenge is centered on the inability to achieve an effective balance between speed of service delivery, cost, and quality. High average waiting times, limited bed capacity, and insufficient human resources lead to a decline in the overall performance efficiency of the institution. The objective of the model is to analyze these factors and propose operational solutions that achieve the optimal balance between efficiency, cost, and quality of service. Six operational variables were identified based on their importance in measuring performance:

TABLE I. DESCRIPTION OF STUDY VARIABLES

Symbol	Variable	Type	Description
X_1	Average waiting time per patient	Minimization objective	Reflects service delivery efficiency and speed
X_2	Daily patient admissions	Input	Indicator of daily demand volume
X_3	Available beds	Input	Measure of capacity
X_4	Available physicians	Input	Indicator of human resources
X_5	Daily operational cost	Minimization objective	Measure of daily financial burden
X_6	Number of treated patients	Maximization objective	Meas

Based on the previous variables, three main objectives were formulated:

- Reduce the average waiting time per patient $min X_1$
- Reduce the daily operating cost $min X_5$
- Increase the number of patients treated $max X_6$

These objectives often conflict, requiring trade-offs through multi-objective mathematical modeling.
A 60-day data collection was conducted from the records of the Tishreen University Hospital, including:

TABLE II. DAILY OPERATING DATA FOR THE TISHREEN UNIVERSITY HOSPITAL DURING THE PERIOD FROM 1/1/2025 TO 2/29/2025.

Date	Average waiting time per patient (minutes)	Daily patient admissions	Available beds	Available physicians	Daily operational cost (dinars)	Number of treated patients
01/01/2025	46.22	159	150	34	961988.8	83
02/01/2025	86.55	188	154	28	1072056	152
03/01/2025	71.24	161	239	39	888640.6	172
04/01/2025	61.91	190	163	36	870755.4	105
05/01/2025	30.92	132	176	36	669296.6	112
06/01/2025	30.92	103	158	39	565171.9	154
07/01/2025	24.07	105	228	31	1128051	158
08/01/2025	80.63	168	164	26	1130293	119
09/01/2025	62.08	139	239	21	943171	156
10/01/2025	69.57	188	191	22	737320.9	175
11/01/2025	21.44	120	226	36	744446.7	122
12/01/2025	87.89	108	200	24	1008169	144
13/01/2025	78.27	94	212	36	1127977	91
14/01/2025	34.86	124	245	36	1120961	146
15/01/2025	32.73	144	201	36	1045913	92
16/01/2025	32.84	168	245	21	949422.2	126
17/01/2025	41.3	150	153	21	558898	77
18/01/2025	56.73	88	243	24	613140.1	84
19/01/2025	50.24	167	172	20	1128988	165
20/01/2025	40.39	80	164	20	924500.3	154
21/01/2025	62.83	187	192	38	506437.9	113
22/01/2025	29.76	87	178	21	571030.1	117
23/01/2025	40.45	167	185	31	964451.2	126
24/01/2025	45.65	142	162	25	503543.1	163
25/01/2025	51.92	90	181	23	612565.6	105
26/01/2025	74.96	194	220	30	884113.7	83
27/01/2025	33.98	160	208	36	984326.6	173
28/01/2025	56	87	235	25	956372.9	91
29/01/2025	61.47	114	177	24	656988.5	106
30/01/2025	23.25	114	215	39	998525.5	145
31/01/2025	62.53	112	191	21	666074.4	82
01/02/2025	31.94	84	194	25	727779.8	125
02/02/2025	24.55	185	211	30	1022544	86
03/02/2025	86.42	182	206	35	954743	165
04/02/2025	87.59	120	155	35	1094456	61
05/02/2025	76.59	107	177	20	960329	149
06/02/2025	41.32	86	177	28	897816	76
07/02/2025	26.84	152	193	25	565572.3	163
08/02/2025	67.9	151	233	35	757401.1	92
09/02/2025	50.81	91	179	22	685641.7	68
10/02/2025	28.54	113	211	39	670792.8	102
11/02/2025	54.66	112	224	23	1181107	177
12/02/2025	22.41	127	241	38	775168.4	107
13/02/2025	83.65	198	238	22	1124433	98
14/02/2025	38.11	102	211	38	941797	152
15/02/2025	66.38	141	246	39	1056368	101
16/02/2025	41.82	167	150	26	851846	178
17/02/2025	56.4	116	176	39	903832.7	85
18/02/2025	58.27	178	211	28	844762.4	158
19/02/2025	32.94	123	226	20	636670.1	109
20/02/2025	87.87	183	152	27	1005716	84
21/02/2025	74.26	165	219	26	696540.7	83
22/02/2025	85.76	170	221	37	517021.2	72

23/02/2025	82.64	114	176	27	951830.6	119
24/02/2025	61.85	144	158	20	623977.5	66
25/02/2025	84.53	178	211	30	1158321	116
26/02/2025	26.19	180	186	37	1167750	95
27/02/2025	33.72	126	246	29	1140405	104
28/02/2025	23.17	157	200	22	759111.1	79
29/02/2025	42.77	82	193	26	510819.6	124

3.2. Statistics framework

The optimization problem in healthcare operations involves multiple conflicting objectives that must be balanced. The general formulation is:

$$\min \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x})]$$
$$g_i(\mathbf{x}) \le 0, i = 1,2,\dots,m$$
$$h_j(\mathbf{x}) = 0, j = 1,2,\dots,p$$
$$\mathbf{x} \in \mathbb{R}^n$$

where: $f(\mathbf{x})$ is the vector of objective functions, $g_i(\mathbf{x})$ and $h_j(\mathbf{x})$ are inequality and equality constraints, respectively. A solution $\mathbf{x}^*$ is *Pareto optimal* if no other solution $\mathbf{x}$ exists such that:

$$f_i(\mathbf{x}) \le f_i(\mathbf{x}^*) \ \forall i \in \{1,2,\dots,k\}$$

and at least one objective is strictly improved:

$$f_j(\mathbf{x}) < f_j(\mathbf{x}^*) \ \text{ for at least one } j$$

The set of all Pareto-optimal solutions forms the *Pareto front* (Deb et al., 2002). The Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) is an evolutionary multi-objective optimization technique that efficiently approximates the Pareto front. Its key components are:

Non-Dominated Sorting

Solutions are ranked into *fronts* based on dominance:

- **Front 1**: Non-dominated solutions.
- **Front 2**: Solutions dominated only by Front 1.

Crowding Distance

To maintain diversity, NSGA-II uses a crowding distance metric:

$$CD_i = \sum_{j=1}^{k} \frac{f_j(i+1) - f_j(i-1)}{f_j^{\max} - f_j^{\min}}$$

where: $f_j(i)$ is the *j*-th objective value of the *i*-th solution. $f_j^{\max}, f_j^{\min}$ are the max and min values of the *j*-th objective. Tournament selection prefers solutions with better ranks and higher crowding distances and Crossover & mutation generate new candidate solutions.

The model is based on integrating three conflicting operational objectives within a multi-objective programming framework. The goal is to achieve a balance between reducing waiting time and operational costs on the one hand, and increasing the number of patients treated on the other. Three main objective functions are defined, and constraints are derived from statistical and functional relationships between resources and actual outputs, using coefficients based on historical data or empirical estimates. Where:

The variables X_2, X_3, X_4 serve as operational constraints (capabilities and demands), and the objectives represent conflicting objective functions. The model is as follows:

$$\min f_1(X1) = X_1 \qquad \text{(Minimize average waiting time)}$$
$$\min \quad f_2(X) = X_5 \qquad \text{(Minimize operating cost)}$$
$$\max \quad f_3(X) = X_6 \qquad \text{(Maximize number of patients treated)}$$

Constraints:

$$X_6 \leq \alpha_1 X_4 + \alpha_2 X_3$$
$$X_5 = \beta_1 X_4 + \beta_2 X_3 + \beta_3 X_2$$
$$X_1 = \gamma_1 \cdot \frac{X_2}{X_4} + \gamma_2 \cdot \frac{X_2}{X_3}$$
$$X_i \geq 0 \ \forall i \in \{1,2,3,4,5,6\}$$
$$X_2, X_3, X_4 \in \mathbb{N}$$

The parameters γ_i α_i β_i are extracted from recorded historical data. The first constraint relates the number of patients that can be treated to the number of doctors and beds. The second constraint calculates the daily operating cost as the sum of the costs of human and material resources and demand. The third constraint reflects a direct relationship between waiting time and demand intensity compared to the number of resources. This model is solved using the AI - NSGA-II algorithm in Python to generate a set of Pareto-optimal solutions, which balance conflicting objectives without imposing prior weights. AI - NSGA-II (Non-Dominated Sorting Genetic Algorithm II) algorithm was chosen for the following reasons:

- Its efficiency in handling multi-objective models
- Its ability to find Pareto-efficient solutions
- It's executable in Python using open libraries such as DEAP and Platypus.

4. RESULTS

Last part of this research shows how NSGA-II was used to analyze operational data from Tishreen University Hospital. A descriptive statistical approach provides initial information about the variations and distributions of operational indicators such as average waiting time operational costs and patient throughput numbers. After establishing statistical foundations, the procedure proceeds with detecting Pareto-optimal solutions that reflect the trade-offs among studied conflicting objectives. Hospital performance correlations with resource distribution can be evaluated through visual display techniques that incorporate bivariate graphs and three-dimensional graphical representations. These research findings deliver an entire assessment regarding how artificial intelligence-based multi-objective optimization approaches can support healthcare operations strategic decision systems.

TABLE III. DESCRIPTIVE STATISTICS OF OPERATIONAL DATA FOR THE STUDY PERIOD

Indicator	Waiting Time (minutes)	Admitted Patients	Available Beds	Available Physicians	Cost (SYP)	Treated Patients
count	60	60	60	60	60	60
mean	52.72	137.73	198.13	29.12	861,302.4	118.08
std	21.38	35.36	29.73	6.68	206,168.1	33.91
min	21.44	80	150	20	503,543.1	61
25%	32.92	111	176	23	670,418.7	89.75
50%	51.36	140	197	28	900,824.4	112.5
75%	69.99	167.25	221.75	36	1,011,763	152
max	87.89	198	246	39	1,181,107	178

The descriptive statistics presented in Table 2 provide a comprehensive overview of the operational data collected over the 60-day study period at the Tishreen University Hospital Department. The results reveal significant variability across key performance indicators. The average waiting time per patient was 52.72 minutes, with a standard deviation of 21.38 minutes, indicating considerable fluctuations in service delivery efficiency. The minimum and maximum waiting times ranged from 21.44 to 87.89 minutes, highlighting periods of both optimal performance and notable inefficiency. Daily patient admissions averaged 137.73, with a standard deviation of 35.36, reflecting fluctuating demand. The department operated with an average of 198.13 available beds and 29.12 physicians, though these resources exhibited variability (SD = 29.73 and 6.68, respectively). Operational costs averaged 861,302.4 Syrian dinars (SYP) per day, with a wide range from 503,543.1 to 1,181,107 SYP, suggesting disparities in daily expenditures. The number of treated patients averaged 118.08 daily, with a standard deviation of 33.91, underscoring inconsistencies in throughput. The quartile analysis further elucidates these trends. For instance, 25% of days had waiting times below 32.92 minutes, while 75% fell below 69.99 minutes, demonstrating that a significant proportion of days experienced moderate to high delays. Similarly, the median values for admitted patients (140), beds (197), and physicians (28) align closely with the means, suggesting a relatively symmetric distribution for these variables. However, the cost and treated patient's metrics show skewness, as evidenced by the disparity between median and mean values.

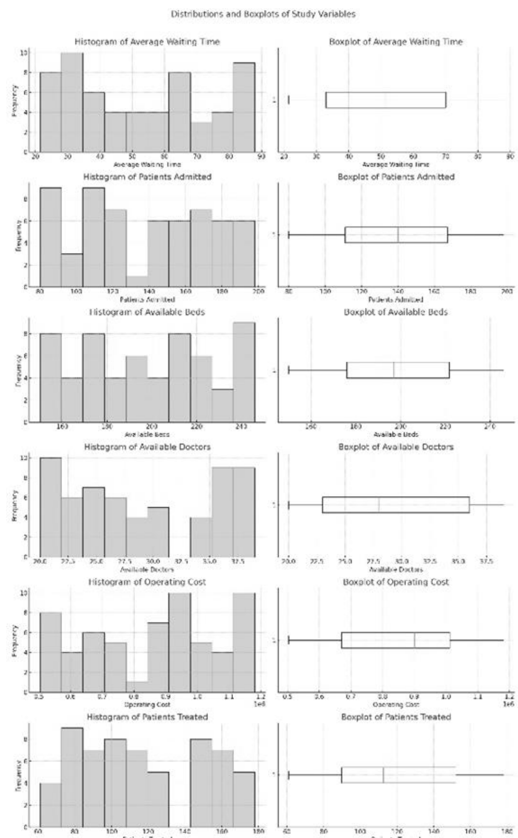

Fig. 1. Distribution Analysis of Key Operational Variables

The distribution analysis of operational variables exists in Figure 1 for the 60-day study period from Tishreen University Hospital. The figure demonstrates the characteristics of each variable through three visualization methods which include box plots with histogram foundations and density curve features for understanding average waiting time per patient (minutes), daily patient admissions, available beds, available physicians, daily operational costs (SYP), and number of treated patients. A central line in each box points to the median while box edges demonstrate interquartile ranges (IQR) to evaluate both data variability and distribution symmetry. Average waiting times demonstrate a right-skewed pattern because extra-long durations exceeding 80 minutes exist along with a median of 51.36 minutes. The data distribution analysis through density plots and density curves shows multimodal patterns in daily patient arrival rates and treated patient totals because these variables exhibit varying demand patterns. The illustration emphasizes that available resources (including beds and physicians) do not correspond with operational results (such as waiting times and treated patients). The limited range of available physicians from 20 to 39 affects both waiting times and treatment facility capacity through the indicated inverse relationships. The graphical analysis supports the findings shown in Table 4 showing that multiple objectives must optimize these linked factors. The figure functions as an essential diagnostic method by showing operational challenges so it can guide the following NSGA-II modeling framework.

TABLE IV. Top 10 Pareto-Optimal Solutions Using AI - NSGA-II Algorithm

Solution #	Avg. Waiting Time (min)	Operating Cost (SYP)	Patients Treated	Patients Admitted	Beds Available	Physicians Available
10	21.44	744,446.7	122	120	226	36
42	22.41	775,168.4	107	127	241	38
58	23.17	759,111.1	79	157	200	22
29	23.25	998,525.5	145	114	215	39
6	24.07	1,128,051	158	105	228	31
32	24.55	1,022,544	86	185	211	30
56	26.19	1,167,750	95	180	186	37
37	26.84	565,572.3	163	152	193	25
40	28.54	670,792.8	102	113	211	39
21	29.76	571,030.1	117	87	178	21

Table 4 presents the top 10 Pareto-optimal solutions derived from the NSGA-II algorithm, each representing a distinct trade-off between the conflicting objectives of minimizing average waiting time, reducing operational costs, and maximizing the number of patients treated. These solutions exemplify the principle of Pareto efficiency, where no single objective can be improved without compromising another. The data reveals several critical insights. First, the solution with the lowest average waiting time (21.44 minutes, Solution #10) achieves this efficiency at a moderate operational cost (744,447 SYP) and a balanced patient throughput (122 treated). Conversely, solutions prioritizing cost minimization (e.g., Solution #21 at 571,030 SYP) exhibit higher waiting times (29.76 minutes) and lower physician availability (21), underscoring the inherent trade-offs between resource allocation and service speed. Notably, Solution #6 demonstrates that higher costs (1,128,051 SYP) can yield superior patient throughput (158 treated) but require optimized bed and physician ratios (228 beds, 31 physicians). The variability in physician availability (21–39) and bed capacity (178–246) across solutions highlights the nonlinear relationship between resources and outcomes. For instance, Solutions #29 and #40, both with 39 physicians, differ in cost and waiting time, suggesting that mere increases in staff do not guarantee efficiency without strategic alignment with other variables. The Pareto front thus provides actionable configurations, enabling policymakers to select solutions tailored to specific institutional priorities—whether cost containment, patient satisfaction, or treatment capacity.

The NSGA-II algorithm produces Pareto-optimal solutions which are visualized through three-dimensional scatter data concerning actual operational data from Tishreen University Hospital in Figure 2. The figure demonstrates how three opposing objectives relate to each other through their display of average waiting time (in minutes) on the X-axis while using daily operating cost in Syrian Dinar (SYP) on the Y-axis and patient numbers on the Z-axis. The points in this chart show various solutions where different trade-offs find equilibrium while neglecting any specific criterion. The intensity of color scheme communicates the patient treatment numbers which aids in identifying solutions with superior performance. The movement pattern of points exhibits discernible trade-off relationships. Solutions in the bottom front part of the graph achieve good patient throughput at the expense of reduced waiting times and operating costs. Multiple factors determine the Z-dimension placement of points with higher positions indicating enhanced treatment capacity although these configurations demand investment costs or prolonged wait periods. Hospital operational points are distributed across the assessment graph as an indication of the complex non-linear nature of hospital operations that create trade-offs between different measurement points. Visual data representation plays a fundamental role when administrators from hospitals want to assess their operational approaches within practical conditions. The decision tool provides decision support through a range of non-inferior options that match various healthcare priorities between cost-effectiveness and service delivery speed and local capacity.

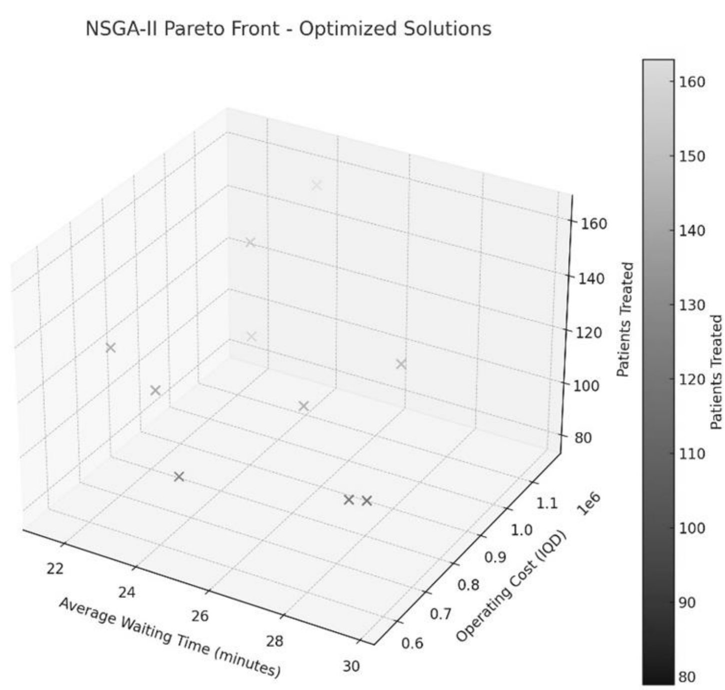

Fig. 2. 3D Visualization of Pareto Front Solutions Using AI - NSGA-II Algorithm

Fig. 3. Bivariate Relationship Between Average Waiting Time and Number of Treated Patients

The graphical presentation in Figure 3 shows the relationship between waiting time and the number of treated patients based on solutions generated by NSGA-II algorithm from Pareto-optimal values. The line chart displays how optimized configurations affect both service speed and treatment volume among possible options. The graphical representation includes the waiting time duration in minutes on the x-axis alongside the number of daily patients on the y-axis. Hospital operational dynamics create a complex nonlinear pattern because there is no step-by-step monotonic relationship between waiting times and patient numbers. The combination of short waiting times (around 24 minutes) enables treatment centers to process more than 160 patients, yet there are also points with comparable or even slightly longer waiting times that result in considerably lower patient volumes. Available resources along with system capacity constraints act as the mediators that affect the speed-throughput connection in hospital services. Operational variables generate fine changes in data points because their sensitivity controls outcome performance. A minor extension of patient waiting times does not necessarily improve operational capacity because the effect may sometimes produce decreased system performance. The figure shows that operational configurations need individual assessment since decision-makers cannot depend on linear patterns here. Healthcare strategies that require NSGA-II optimization frameworks remain essential due to their ability to identify realistic solutions under operational limitations.

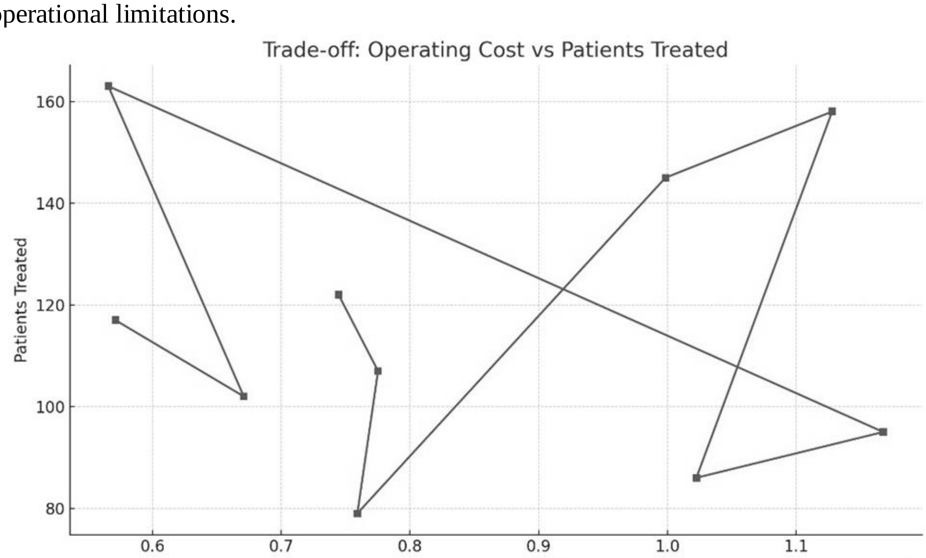

Fig. 4. Operational Cost-Efficiency Frontier: Treatment Capacity vs. Daily Expenditure

Figure 4 showcases the two-dimensional presentation that demonstrates operating cost against patient treatment numbers based on NSGA-II optimized solutions. The Syrian Dinar operating costs for daily expenses appear on the horizontal x-axis and the patient treatment numbers are shown on the vertical y-axis. The graph displays multiple feasible solutions which demonstrate proper allocation between health service capacity and financial expenses. The datapoints demonstrate irregularity because there is no simple linear or monotonic correlation. Treatment solutions under 700,000 SYP demonstrate cost-efficient operation by providing medical care to over 160 patients. The patient's throughput capacity from high-cost configurations (over 1,100,000 SYP) remains limited, which indicates wasted resources or poor allocation of funding. Results demonstrate that when resource expenses rise it does not guarantee superior performance because of this non-linear relationship between financing and results. Blocking centers identify multiple critical financial levels which create dramatic impact zones on the ability to treat patients. The NSGA-II model presents solutions in clusters at different cost points because it maintains flexibility in finding various operational approaches with identical budget limitations. Hospital administrators can use this figure to make decisions through its practical functionality which demonstrates patient treatment enhancement versus cost-effective operational configurations. The necessary elements for healthcare resource allocation in limited environments include both performance benchmarking techniques and cost-benefit analysis methods.

5. CONCLUSION

This study demonstrated the effectiveness of integrating AI-based multi-objective optimization, specifically the NSGA-II algorithm, to improve operational efficiency in a large Syrian hospital using real-world data. The results confirmed that balancing waiting time, cost, and patient throughput can be achieved through Pareto-optimal configurations, offering decision-makers flexibility without imposing rigid prioritizations. The generated solution space provides actionable alternatives for resource allocation, capacity planning, and performance benchmarking. Future work will focus on enhancing the model's predictive capability by incorporating dynamic, real-time hospital data and expanding the variable set to include emergency cases, surgery types, and seasonal demand fluctuations. Moreover, hybrid models combining NSGA-II with machine learning techniques such as neural networks or reinforcement learning could further improve adaptability and responsiveness in high-uncertainty environments. Finally, validation across multiple healthcare facilities will assess the model's generalizability and support nationwide scalability.

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Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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References

[1] A. Bohr and K. Memarzadeh, "The rise of artificial intelligence in healthcare applications," *Artificial Intelligence in Healthcare*, pp.25-60, 2020. https://doi.org/10.1016/B978-0-12-818438-7.00002-2

[2] S. Aminizadeh, A. Heidari, M. Dehghan, S. Toumaj, M. Rezaei, et al., "Opportunities and challenges of artificial intelligence and distributed systems to improve the quality of healthcare service," *Artificial Intelligence in Medicine*, vol.149, pp.102779, March 2024. https://doi.org/10.1016/j.artmed.2024.102779

[3] M. M. Mijwil, "Smart Architectures: Computerized Classification of Brain Tumors from MRI Images Utilizing Deep Learning Approaches," *Multimedia Tools and Applications*, vol.84, no.5, pp. 2261-2292, October 2024. https://doi.org/10.1007/s11042-024-20349-x

[4] E. Stamate, A-I. Piraianu, O. R. Ciobotaru, R. Crassas, O. Duca, et al.," Revolutionizing Cardiology through Artificial Intelligence—Big Data from Proactive Prevention to Precise Diagnostics and Cutting-Edge Treatment—A Comprehensive Review of the Past 5 Years," *Diagnostics*, vol.14, no.11, pp.1103, May 2024. https://doi.org/10.3390/diagnostics14111103

[5] M. Barakat, N. A. Salim, and M. Sallam, "University Educators Perspectives on ChatGPT: A Technology Acceptance Model-Based Study," *Open Praxis*, vol.17, no.1, pp. 129–144, 2025. https://doi.org/10.55982/openpraxis.17.1.718

[6] X. Xie and M. A. Lawley, "Operations research in healthcare," *International Journal of Production Research*, vol.35, no.24, pp.7173-7176, December 2015. https://doi.org/10.1080/00207543.2015.1102356

[7] M. Capan, A. Khojandi, B. T. Denton, K. D. Williams, T. Ayer, J. Chhatwal, et al., "From Data to Improved Decisions: Operations Research in Healthcare Delivery," *Medical Decision Making*, vol.37, no.8, pp.849-859, April 2017. https://doi.org/10.1177/0272989X17705636

[8] S. Saghafian, G. Austin, and S. J. Traub, “Operations research/management contributions to emergency department patient flow optimization: Review and research prospects,” *IIE Transactions on Healthcare Systems Engineering*, vol.5, no.2 pp.101-123, June 2015. https://doi.org/10.1080/19488300.2015.1017676

[9] T. Dai and S. Tayur, “OM Forum—Healthcare Operations Management: A Snapshot of Emerging Research,” Manufacturing & service operations management, vol.22, no.5, pp.869-887, October 2020. https://doi.org/10.1287/msom.2019.0778

[10] S. Verma, M. Pant, and V. Snasel, “A Comprehensive Review on NSGA-II for Multi-Objective Combinatorial Optimization Problems,” *IEEE Access*, vol.9, pp.57757 - 57791, April 2021. https://doi.org/10.1109/ACCESS.2021.3070634

[11] P. Zhang, Y. Qian, and Q. Qian, “Multi-objective optimization for materials design with improved NSGA-II,” *Materials today communications*, vol.28, pp.102709, 2021. https://doi.org/10.1016/j.mtcomm.2021.102709

[12] S. Guha and S. Kumar, “Emergence of big data research in operations management, information systems, and healthcare: Past contributions and future roadmap,” *Production and Operations Management*, vol.27, no.9, pp.1724-1735, December 2017. https://doi.org/10.1111/poms.12833

[13] H. Ma, Y. Zhang, S. Sun, T. Liu, and Y. Shan, “A comprehensive survey on NSGA-II for multi-objective optimization and applications,” *Artificial Intelligence Review*, vol.56, no.12, pp.15217-15270, June 2023. https://doi.org/10.1007/s10462-023-10526-z

[14] W. P. Pierskalla, “Operations research - A valuable resource for improving quality, costs, access and satisfaction in health care delivery,” In Engineering the System of Healthcare Delivery, vol.153, pp. 241 - 276, 2010. https://doi.org/10.3233/978-1-60750-533-4-241

[15] S. Shetaban, M. M. S. Esfahani, A. Saghaei, and A. Ahmadi, “Operations research and health systems: A literature review,” *Journal of Industrial Engineering and Management Studies*, vol.7, no.2, pp.240-260, August 2020. https://doi.org/10.22116/jiems.2020.231406.1360

[16] M. Heydari, K. K. Lai, Y. Fan, and X. Li, “A Review of Emergency and Disaster Management in the Process of Healthcare Operation Management for Improving Hospital Surgical Intake Capacity,” *Mathematics*, vol.10, no.15, pp.2784, August 2022. https://doi.org/10.3390/math10152784

[17] P. Gao, H. Wang, S. A. Cushman, C. Cheng, C. Song, and S. Ye, “Sustainable land-use optimization using NSGA-II: theoretical and experimental comparisons of improved algorithms,” *Landscape Ecology*, vol.36, pp.1877-1892, June 2020. https://doi.org/10.1007/s10980-020-01051-3