

Multi-objective optimization for emergency healthcare resource allocation

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Abstract

Emergency healthcare systems are faced with the challenging problems of distributing scarce resources quickly, fairly and economically and balancing limited resources with unpredictable demand. This study aims to present a multi-objective optimization methodology for ambulance allocation, healthcare manpower deployment, beds, equipments and emergency supplies to healthcare facilities. The model concurrently seeks to minimize response time, cost of operation, resource limitations and risk to the patient and maximize the scope of coverage and the utilization of resources. Forecasts of demand, facility levels, transportation limitations and priorities are included in the decision process. Balanced allocation alternatives of conflicting objectives are identified using Pareto based optimization. Simulation results show that better results in emergency coverage, waiting time, allocation cost and resource available have been achieved than that of traditional single objective approaches. The framework can be used to guide emergency healthcare planning in case of a routine crisis and/or a large-scale disaster that is responsive, transparent, and based on evidence.

Subject Classification: 65K10.

Keywords: Emergency healthcare, Resource allocation, Multi-objective optimization, Pareto optimization, Response-time minimization, Healthcare planning.

I. Introduction

To manage emergency healthcare systems, they are faced with the challenges of limited capacity, changing priorities, unclear patient flow and time constraints. There is significant evidence of the increased death toll, congestion,

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and operational costs associated with delays in the provision of ambulances, beds, clinicians, medicines, blood units and diagnostic equipment [1, 2]. The traditional allocation methods tend to focus on a specific criterion such as cost or response time, without considering fairness, service coverage, resource use and severity of patients. Emergency planning thus must be seen as a problem of achieving several conflicting goals, all of which must be balanced [3, 4, 5]. Such a problem can be formulated mathematically as a multi-objective optimization problem, which gives rise to a set of efficient allocation alternatives, instead of one solution that is optimized for a single objective. It allows decision makers to consider the various trade-offs between response time, treatment accessibility, operating costs, workload balancing, risk of shortage, and clinical outcomes [6, 7]. Comparable solution identification with Pareto-based techniques can help in making decisions in a transparent and context-sensitive manner, when there are solutions that can improve one objective but degrade another. The aim of this study is to create a multi-objective framework for allocation of healthcare resources in emergency in interconnected facilities and service areas [8, 9]. The model embodies the resource availability, projected demand, facility capacity, travel time, patient priority and logistical limitations by means of decision variables and objective functions. It aims at reducing response time, allocation expenses, shortage and inequality of allocation along with increasing coverage and utilization [10, 11]. Comparative experiments are conducted to compare the approach to the conventional allocation strategies, in cases of demand scenarios. The resulting framework provides support for decision making during routine emergencies, mass-casualty incidents and disaster preparedness, thus helping to increase the system's resilience and enhance patient support [12, 13].

II. Mathematical Optimization in Healthcare

Healthcare constraints are converted to decisions in mathematical optimization models, which optimize capacity planning, scheduling, allocation and service delivery in facilities without excessive costs, delays, shortages and inefficiencies [14].

$$\text{Minimize } Z_1 = \sum_{i=1}^H \sum_{j=1}^P c_{ij} x_{ij} \quad (1)$$

The total operating cost (1) is obtained by adding up the unit allocation costs for the different regions of demand and health care facilities, which allows for the economically efficient allocation of resources during emergency situations, consistently.

$$\text{Minimize } Z_2 = \frac{\left[\sum_{i=1}^H \sum_{j=1}^P t_{ij} x_{ij} \right]}{\left[\sum_{i=1}^H \sum_{j=1}^P x_{ij} \right]} \quad (2)$$

The average emergency response time, which is calculated as the accumulated travel-time allocations divided by the total assigned resources, is estimated by Equation (2) and is useful for making decisions about clinical interventions in a timely manner to provide rapid response services.

$$\text{Minimize } Z_3 = \sum_{j=1}^P \max[0, d_j - \sum_{i=1}^H x_{ij}] \quad (3)$$

Equation (3) is used to minimize the amount of shortfalls, by calculating only the positive value of the difference between regional need and the resources allocated, this equation would reduce the number of shortfalls and make the facilities more prepared to deal with emergency patients.

$$\text{Maximize } Z_4 = \frac{[\sum_{j=1}^P \min(d_j, \sum_{i=1}^H x_{ij})]}{[\sum_{j=1}^P d_j]} \quad (4)$$

By comparing the regional demand that is met with the overall demand for healthcare services, as shown in Equation (4), maximum service coverage is obtained by distributing limited emergency resources to the maximum number of patients, fairly.

$$\sum_{j=1}^P x_{ij} \leq C_i, \text{ for all } i \quad (5)$$

$$\sum_{i=1}^H x_{ij} + s_j \geq d_j, \text{ for all } j \quad (6)$$

Equation (5) ensures that the resources allocated to each facility do not exceed its capacity, keeping the resource use within limits, preserving stability in operations and ensuring that the distribution of resources in case of a crisis is feasible in the healthcare network. The minimum regional demands of the allocated resources and shortage variables are preserved with the help of Equation (6), which guarantees that all the required emergency service requirements are met while making it possible for the optimization model to determine the shortages.

$$E_{RMS} = \sqrt{\left\{ \left(\frac{1}{P} \right) \sum_{j=1}^P [d_j - \sum_{i=1}^H x_{ij}]^2 \right\}} \quad (7)$$

The root mean square allocation error (as in equation (7)) measures allocation deviations between required and supplied resources, and is a measure of overall performance in the provision of healthcare that is accurate, balanced, and demand responsive, with a smaller value representing more accurate, balanced, and demand responsive allocations of resources overall.

$$\text{Minimize } Z = \sqrt{w_1 Z_1^2 + w_2 Z_2^2 + w_3 Z_3^2 + w_4 (1 - Z_4)} \quad (8)$$

Equation (8) has the ability to balance the four objectives (cost, response time, shortages and uncovered demand) by using weighted squared objectives, and results in an efficient overall selection of emergency allocation solutions.

III. Multi-Objective Optimization Techniques

Multi-objective methods consider conflicting healthcare objectives that are compared in terms of Pareto fronts, weighted sums, evolutionary algorithms and goal programming with the aim of devising solutions that balance multiple objectives while producing efficient and equitable allocations of healthcare resources.

$$\text{Minimize } F(x) = \sum_{k=1}^K w_k f_k(x) \quad (9)$$

In this case, several health care objectives are used together in a single scalar objective function via assigned weights, to rapidly determine the efficient resource allocation in emergency situations that satisfy all health care goals.

$$\text{Minimize } F_{N(x)} = \sum_{k=1}^K w_k \left[\frac{(f_{k(x)} - f_k^{\min})}{(f_k^{\max} - f_k^{\min})} \right] \quad (10)$$

This is because objectives measured in different scales can be normalized in the equation (10) so that proportionately, without numerical bias, all of them contribute to the optimization of these objectives.

$$f_{k(x)} \leq \varepsilon_k, k = 2, 3, \dots, K \quad (11)$$

The optimization of primary objective while keeping remaining objective values within the pre-defined epsilon limits in (11) helps to perform systematic trade-off analysis between emergency healthcare allocation goals and constraints effectively.

$$\text{Minimize } Z = \sum_{k=1}^K (w_k^- d_k^- + w_k^+ d_k^+) \quad (12)$$

By minimizing both the positive and negative deviations from desired healthcare targets, weighted by the importance of the achievement, Equation (12) enables decision makers to reach the desired performance levels for the resources, cost, response, coverage, and equity at the same time.

$$D(x) = \sqrt{\left\{ \sum_{k=1}^K \left[\frac{(f_{k(x)} - f_k^*)}{(f_k^{\max} - f_k^{\min})} \right]^2 \right\}} \quad (13)$$

The smallest distance in the equation (13) is the most desired and balanced healthcare allocation alternative which is the most desirable and closest to ideal objective values among all candidate solutions.

$$CD_i = \sum_{k=1}^K \left[\frac{(f_k^{i+1} - f_k^{i-1})}{(f_k^{\max} - f_k^{\min})} \right] \quad (14)$$

The crowding distance calculation as given in equation (14) is used to prevent the use of same solutions by neighboring individuals in the population, maintaining population diversity and exploring widely distributed alternatives of resource-allocation solutions in the objective space efficiently and effectively with consistency.

$$x^* = \arg \min_{x \in \Omega} \sqrt{\left\{ \sum_{k=1}^K w_k [f_{k(x)} - f_k^*]^2 \right\}} \quad (15)$$

Equation (15) chooses the compromise solution that is closest to the ideal solution sets of the objective values, which offers a viable tradeoff between cost, timeliness, coverage, shortages and utilization.

IV. Emergency Healthcare System Description

The emergency healthcare system is composed of patient, ambulance, hospital, medical team, beds, equipment and supply networks that are coordinated to provide timely healthcare in the face of variable demand and crises.

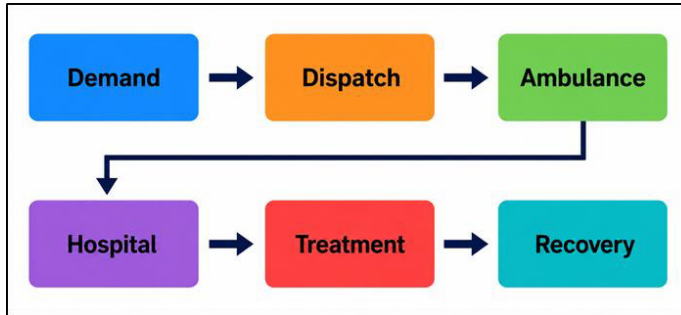


Figure 1
Emergency Healthcare Service Delivery Framework

As shown in Figure 1, the progression of emergency healthcare starts with identifying the need for emergency care, dispatching it, transporting by an ambulance, receiving treatment and recovery at the hospital in a coordinated manner.

$$A_{j(t)} = A_{0j} + \alpha_j \sin(\omega_j t) + \varepsilon_{j(t)} \quad (16)$$

In this model (in equation (16)), arrival rates of emergency patients reflect baseline demand, periodic variations and random disturbances, reflecting realistic temporal variations in the demand for healthcare resources.

$$\frac{dD_{j(t)}}{dt} = A_{j(t)} - S_{j(t)} - \mu_j D_{j(t)} \quad (17)$$

$$S_{i(t)} = \sum_{r=1}^R \eta_{ir} u_{ir(t)} \quad (18)$$

$$T_{ij} = \frac{L_{ij}}{v_{ij}} + \tau_i + \delta_{ij} \quad (19)$$

The changes over time in regional emergency caseloads (patient-demand evolution) are captured by equation (17) as the difference between arrivals and completed services and natural departures. To determine the capacity of hospital services, equation (18) computes the level of efficiency of various resources and their active amounts, to indicate the level of treatment that can be achieved during an emergency. Equation (19) provides an approximation of the time it will take the ambulance to reach the patient from travel distance, vehicle speed, dispatch wait time and unexpected delays, which will enable correct emergency transportation planning decisions to be made.

$$L_{ij} = \sqrt{[(p_i - p_j)^2 + (q_i - q_j)^2]} \quad (20)$$

This equation (20) calculates the straight-line distance between a healthcare facility and an incident, and is a basic measure for routing ambulances and for choosing the nearest healthcare facility for an incident.

$$\rho_{i(t)} = \frac{\lambda_{i(t)}}{m_i \mu_i} \quad (21)$$

The level of the facility workload is the ratio of patients that arrive to the total capacity of the facility (Equation 21), which means that it is a measure of the congestion risk and operational pressure levels.

$$W_i = \frac{\rho_i}{[\mu_i(1 - \rho_i)]} \quad (22)$$

The patient queueing time is estimated by equation (22) which illustrates the strong dependence of the queueing time on the level of the facility utilization with service rate, as load levels approach saturation.

$$B(t) = \sqrt{\left\{ \sum_{j=1}^P \left[\alpha D_j^{2(t)} + \beta W_j^{2(t)} + \gamma T_j^{2(t)} \right] \right\}} \quad (23)$$

This was achieved by combining patient demand, waiting time and response time in a burden measure based on the root of the three variables as shown in equation (23), which allows for the assessment of overall burden of an emergency system and its allocation urgency.

V. Resources, Demand, and Decision Variables

The resources are the number of personnel, vehicles, beds, medicines and equipment; the demand is the number of patients' needs; the decision variables are the quantities, facilities location, assignments and prioritisation of scheduling, optimally across facilities.

$$\sum_{j=1}^P q_{ijr} \leq R_{ir}, \text{ for all } i \text{ and } r \quad (24)$$

Effectively, Equation (24) restricts the amount of each resource used in different demand regions to its respective facilities' availability keeping the infeasible assignments, over-allocation and lack of resource operation during emergencies at bay.

$$\sum_{i=1}^H q_{ijr} + u_{jr} \geq D_{jr}, \text{ for all } j \text{ and } r \quad (25)$$

$$D_{jr}^w = \sum_{p=1}^L \pi_p D_{jrp} \quad (26)$$

Allocated resources plus recorded unmet demand are equal to or greater than regional requirements (25) which enables the model to meet the demands while accurately and consistently identifying the unmet demands as they are unavoidable. Effective and clinically useful resource demand calculations for emergency resource allocation decisions with limited capacity are made with Equation (26) which calculates the weighted demand across patient categories, with higher weight given to the critical patient categories.

$$R_{ir}^{rem} = R_{ir} - \sum_{j=1}^P q_{ijr} \quad (27)$$

Residual availability is calculated using equation (27) in order to keep track of inventory stocks even as they are being allocated and to plan for re-

distributing and re-stocking at the right time during an emergency across regions.

$$U_{ir} = \left[\frac{\sum_{j=1}^P q_{ijr}}{R_{ir}} \right] \times 100 \quad (28)$$

The value of the allocated quantities in equation (28) describes as a percentage of available resources, the operational efficiency and indicates a facility that is under utilising, in balance, or over putting pressure on the resources during an emergency.

$$\sigma_D = \sqrt{\left\{ \left(\frac{1}{PR} \right) \sum_{j=1}^P \sum_{r=1}^R (D_{jr} - D_{bar})^2 \right\}} \quad (29)$$

The RMSE of the demand from the data of equation (29) measures the dispersion of demand, which is useful when dealing with a geographically unequal emergency situation in different areas of the service region and providing robust allocation.

$$E = 1 - \sqrt{\left\{ \left(\frac{1}{P} \right) \sum_{j=1}^P \left[\left(\frac{\sum_{i=1}^H \sum_{r=1}^R q_{ijr}}{D_j} \right) - U_{bar} \right]^2 \right\}} \quad (30)$$

The equation (30) computes the allocation fairness of the demand adjusted provision of emergency healthcare across regions: the higher the value of the index, the better the overall performance of allocation of emergency healthcare across regions is.

VI. Result and Discussion

The results show that the multi-objective allocation leads to significant reductions in response time, shortages, operating cost and workload imbalance, and increases in coverage, utilization, equity and accessibility of emergency treatment of regions.

Table 1
Comparative Performance of Healthcare Resource-Allocation Methods

Allocation Method	Average Response Time (min)	Operational Cost (\$×10 ³)	Resource Utilization (%)	Demand Coverage (%)	Unmet Demand (%)
Conventional Allocation	24.8	186.4	71.3	78.6	21.4
Single-Objective Optimization	19.6	162.8	79.5	84.2	15.8
Weighted-Sum Optimization	16.7	154.3	85.1	89.7	10.3
NSGA-II Optimization	14.2	149.6	89.4	93.5	6.5

Table 1 illustrates improved performance of emergency health services in allocating care, as measured by the improvement that occurred over time. The

longest response time, highest operation cost, lowest utilization and maximum unmet demand are achieved by conventional allocation. Moderate gains can be achieved with single objective and weighted summarization methods. The allocation methods by response, cost, utilization and coverage are compared in Figure 2.

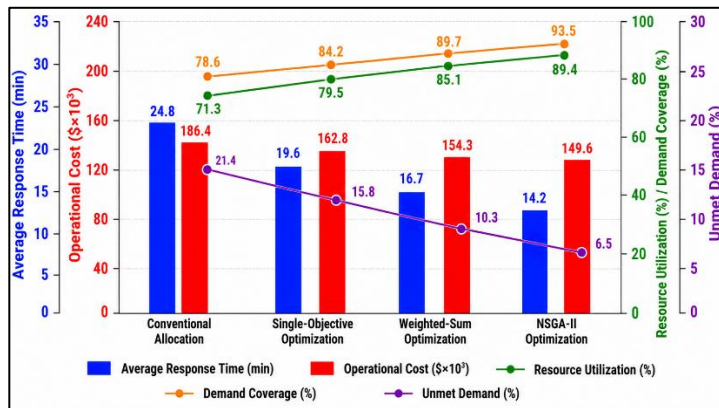


Figure 2
Comparative Performance Analysis of Emergency Healthcare Resource Allocation Methods

The combination of NSGA-II yields the best results: a response time of 14.2 Minutes, a cost of \$149.6 thousand, an 89.4% utilization and a 93.5% demand coverage and a total unmet demand of 6.5%.

Table 2
Resource-Allocation Results Under Emergency-Demand Scenarios

Demand Scenario	Patient Demand	Ambulances Allocated	Beds Allocated	Fulfilment Rate (%)
Low Demand	250	18	165	98.4
Moderate Demand	500	31	308	96.8
High Demand	750	43	446	94.1
Critical Demand	1,000	56	571	90.6

The number of emergency resources allocated increases with emergency demand, as shown in Table 2. Patient demand is boosted from 250 to 1,000, meaning that the ambulances have to be raised from 18 to 56, beds from 165 to 571. The Figure 3 below shows how resources are allocated based on the various emergency demand levels.

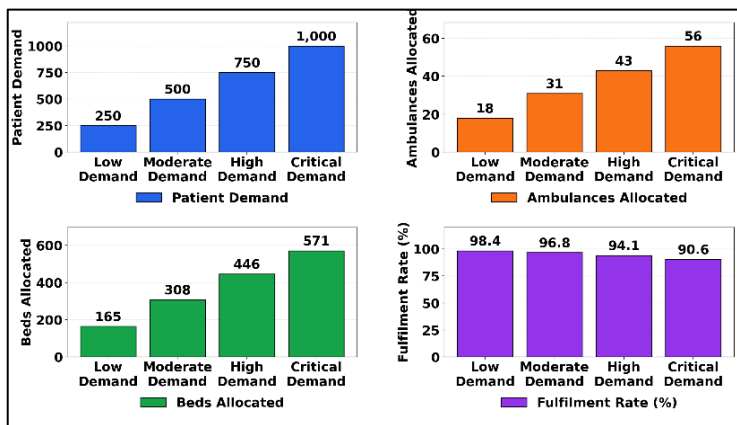


Figure 3
Emergency Healthcare Resource Allocation across Demand Scenarios

While all these expansions are made, the fulfilment rate is not getting better but rather it is decreasing a little each day when the demand is low but drops significantly when the demand is critical, from 98.4% to 90.6% of the time. This decrease suggests increasing capacity pressures and a capacity adaptation approach along with reserve resources.

VII. Conclusion

This research provided a multi-objective optimization solution for emergency health care resources allocation in the case of limited capacity and uncertain demand. It balances the response time, cost, shortages, coverage, equity and resource utilisation to deliver balanced solutions for ambulances, beds, people, medicines and medical equipment. The Pareto-based analysis helps decision-makers to consider trade-offs and make choices based on clinical priorities and operational constraints. This shows that the results are obtained with lower delays, better service coverage, lower resource deficits and a more balanced workload distribution compared to the traditional single-objective based approaches. The model thus enhances the ability to be prepared for emergencies and helps to take timely decisions, based on evidence. The implications for future research are to incorporate real-time demand forecasting, dynamic routing, stochastic disruptions and hospital data to make the system more adaptable, scalable, and applicable.

References

- [1] F. Baesler, O. Cornejo, C. Obreque, E. Forcael, and R. Carrasco, "A multi-objective simulation-optimization framework for emergency

- department efficiency using RSM and goal programming,” *Systems*, vol. 13, no. 10, Art. no. 912 (2025), doi: 10.3390/systems13100912.
- [2] M. Liu, L. Liu, F. Liang, and G. Wang, “Research on multi-objective optimization model and algorithm for reliability location of emergency facilities,” *Appl. Sci.*, vol. 16, no. 6, Art. no. 3105 (2026), doi: 10.3390/app16063105.
- [3] A. A. Abu-Ein, A. R. El-Saeed, O. M. Al-Hazaimeh, H. Ardah, G. Hassan, M. Tawfik, and I. S. Fathi, “Symmetry-driven multi-objective dream optimization for intelligent healthcare resource management and emergency response,” *Symmetry*, vol. 18, no. 3, Art. no. 530 (2026), doi: 10.3390/sym18030530.
- [4] J. C. Arias, J. J. Cubillas, and M. I. Ramos, “Optimising health emergency resource management from multi-model databases,” *Electronics*, vol. 11, no. 21, Art. no. 3602 (2022), doi: 10.3390/electronics11213602.
- [5] A. Sapatnekar, D. Sharma, R. Thakare, A. Dombale, V. Nandgaonkar, and S. Radhakrishnan, “Enhancing RSA algorithm security through advanced combinatorial $n!$ permutations in cryptographic protocols,” *J. Discrete Math. Sci. Cryptogr.*, vol. 29, no. 2-A, pp. 445–452 (2025), doi: 10.47974/JDMSC-2476.
- [6] E. N. Kapukaya and S. I. Satoglu, “A multi-objective dynamic resource allocation model for search and rescue and first aid tasks in disaster response by employing volunteers,” *Logistics*, vol. 9, no. 1, Art. no. 41 (2025), doi: 10.3390/logistics9010041.
- [7] W. Wang, J. Fan, W. Zhu, Y. Cai, Y. Yang, X. Zhang, Y. Yao, and X. Chang, “When demand uncertainty occurs in emergency supplies allocation: A robust DRL approach,” *Appl. Sci.*, vol. 16, no. 2, Art. no. 581 (2026), doi: 10.3390/app16020581.
- [8] F. E. Almuhaifith, T. Hussain, H. S. Bakouch, H. H. El-Damrawy, and S. M. Aljeddani, “A characterizable probability model: Properties and flood data application,” *J. Stat. Manag. Syst.*, vol. 29, no. 3, pp. 301–329 (2025), doi: 10.47974/JSMS-1493.
- [9] C. Sun, H. Chen, X. Zhang, P. Zhang, and J. Ma, “Multi-objective emergency facility locations considering point-flow integration under rainstorm environments,” *Systems*, vol. 14, no. 5, Art. no. 454 (2026), doi: 10.3390/systems14050454.

- [10] J. Yuan and B. Sun, "Multi-objective optimization model for emergency evacuation based on adaptive ant colony algorithm," *AI*, vol. 6, no. 9, Art. no. 203 (2025), doi: 10.3390/ai6090203.
- [11] J.-C. Huang, K. H.-C. Chen, and Y.-H. Liao, "Resource allocation in multi-objective epidemic management: An axiomatic analysis," *Mathematics*, vol. 13, no. 13, Art. no. 2182 (2025), doi: 10.3390/math13132182.
- [12] Y. Wang and X. Zhu, "A multi-regional collaborative optimization model of emergency medical materials for responding to COVID-19," *Processes*, vol. 10, no. 8, Art. no. 1488 (2022), doi: 10.3390/pr10081488.
- [13] A. M. AbdelAziz, L. Alarabi, S. Basalamah, and A. Hendawi, "A multi-objective optimization method for hospital admission problem—A case study on COVID-19 patients," *Algorithms*, vol. 14, no. 2, Art. no. 38 (2021), doi: 10.3390/a14020038.
- [14] R. Ma, F. Meng, and H. Du, "Research on intelligent emergency resource allocation mechanism for public health emergencies: A case study on the prevention and control of COVID-19 in China," *Systems*, vol. 11, no. 6, Art. no. 300 (2023), doi: 10.3390/systems11060300.

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