

Internet of things-enabled fuzzy goal programming for healthcare resource allocation

Zainab M. Ali¹, Saad Adnan Zabin², Iraq T. Abbas³

¹Department of Water Resources Engineering, College of Engineering, University of Baghdad, Baghdad, Iraq

²Ministry of Education General Directorate of Education of Baghdad/Al-Karkh Firs-Asim Bin Thabit Intermediate School for Boys, Baghdad, Iraq

³Department of Mathematics, College of Science, University of Baghdad, Baghdad, Iraq

Article Info

Article history:

Received Apr 6, 2026

Revised Jun 3, 2026

Accepted Jul 18, 2026

Keywords:

Fuzzy goal programming
Healthcare resource allocation
IoT-enabled healthcare systems
Multi-criteria decision-making
Reconfigurable decision support
Uncertainty modeling

ABSTRACT

Resource allocation of medical services under uncertainty (from COVID-19) is crucial for resilient healthcare service provision during pandemics, emergency surges and resource shortages. In this study, an internet of things (IoT)-assisted fuzzy goal programming (FGP) framework is developed for the allocation of healthcare resources in a network of five regional hospitals. The considered model combines fuzzy aspiration levels and priority weights with operational constraints to simultaneously optimize the portion of patients served, the overall resource utilization and the total cost-these three conflicting objectives all related to intensive care unit (ICU) beds, ventilators, and medical staff. It is modeled using mixed-integer linear programming (MILP) model and solved through LINGO and Python. Experimental results demonstrate that the proposed FGP framework outperforms classical linear programming (LP), enabling expanding patient service coverage from 83.4% to 93.7%, while improving healthcare resource allocation regarding crack utilization of critical healthcare resources. Sensitivity analysis under low, moderate and high uncertainty levels also indicates that the model remains above 90% coverage regardless of demand side and supply shocks. These results illustrate that the proposed framework represents a flexible, resilient and adaptive decision-support framework for healthcare resource allocation under uncertain operational contexts.

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Corresponding Author:

Iraq T. Abbas

Department of Mathematics, College of Science, University of Baghdad

Baghdad, Iraq

Email: iraq.t@sc.uobaghdad.edu.iq

1. INTRODUCTION

Effective healthcare resource allocation is considered one of the hottest challenges in contemporary health care systems, especially during pandemics, emergency outbreaks or other similar situations like seasonal epidemics, and mass-casualty incidents. Hospital systems often have a lack of intensive care unit (ICU) beds, ventilators, healthcare, human resources, and money while trying to provide quality medical care. Traditional deterministic optimization methods are insufficient to handle many real-world healthcare decision-making problems faced and the solution suffered from lack of a foundation with rising uncertainty in both patient demand and operational conditions [1], [2].

With the emergence of internet of things (IoT-enabled) medical infrastructures, healthcare resource monitoring and management in modern day (and even some not-so-distant past) healthcare environments have been transformed. Smart sensors and wearable medical devices, as well as monitoring systems alongside hospital information systems continuously generate real-time data pertaining to patient conditions, bed utilization, ventilator usage and availability of staff. Recent studies further demonstrate that IoT-enabled healthcare systems can support intelligent allocation and scheduling of limited medical resources while balancing operational efficiency, cost, and quality of care [3]. Fog-cloud architectures have also been investigated for efficient allocation of computational resources in IoT-driven smart healthcare applications, particularly when heterogeneous healthcare tasks require adaptive and timely resource management [4]. Intelligent decision-support mechanisms that can dynamically reallocate scarce resources to various parts of such complex, embedded and reconfigurable healthcare systems will need to be developed in the context of uncertainty. Thus, the confluence of fuzzy goal programming (FGP) with IoT driven healthcare ecosystems present a feasible and more elastic universal posture for real-time decision making whereby operational conditions may widely vary over time due to emergency situations or impending epidemics or varying degree of patient acquired demand that change frequently in wide variables [1], [5]. Furthermore, edge-computing-based IoT healthcare systems can improve the efficiency of resource allocation and task offloading while reducing energy consumption and satisfying delay-sensitive healthcare requirements [6]. Within this frame of reference, the proposed framework can be interpreted as a dynamic healthcare resource allocation system that is adaptable enough to vary its allocations according to current conditions in each area. Recent studies have also demonstrated that deadline-aware resource allocation in IoT-enabled healthcare environments can improve resource utilization and support the timely execution of critical healthcare tasks under constrained computing resources [7]. A recent breakthrough in IoT-based healthcare infrastructures and embedded monitoring systems enabled by smart medical devices, patient-monitoring systems, wearable sensors, and hospital information systems has revolutionized the management of health care delivery platforms able to generate operational data in real-time. Such technologies enable dynamic and reconfigurable healthcare environments with time varying resource availability and patient demand. Thus, healthcare decision-support models need to be sufficiently adaptive and robust while ensuring computational efficiency to support on-the-fly feasibility under uncertainty [8]–[12]. Moreover, intelligent resource-allocation mechanisms based on IoT communication infrastructures have demonstrated the ability to improve resource utilization, energy efficiency, scalability, and reliable healthcare data transmission in smart healthcare environments [13]. Introduction multiple studies have analyzed the optimization of healthcare system through various methods, including mathematical programming and fuzzy optimization as well as multi-criteria decision-making techniques. In healthcare scheduling and resource allocation, classical linear programming (LP) and integer programming methods are developed; spotting that such functions have full observable parameter values, as well as fixed objective value. To overcome the uncertainty, researchers proposed FGP which represents aspiration levels and objective functions with fuzzy sets along with a tolerance limit where goals can be achieved partially [12], [14]–[17]. Fuzzy optimization methods have been recently used to enhance the flexibility and robustness of healthcare planning under uncertain operating conditions [18]–[21].

Despite these advances, however, significant limitations still exist. To begin with, there are numerous healthcare optimization methods that use deterministic assumptions as well as highly reduced fuzzy representations (as spatial logistics modeling) which do not appropriately anticipate the operational uncertainty associated with dynamic nature of operations. Coverage, resource use and operational cost were optimized independently in most previous studies rather than balancing together as trade-off within an overall multi-objective framework. Lastly, the literature on trading FGP models with IoT-enabled and reconfigurable healthcare environments where decision variables are dynamically changed in accordance with ongoing operational conditions has been scarce.

To mitigate these challenges, this research presents an IoT based FGP framework for optimized multi-criteria allocation of healthcare resources under uncertainty. In this study, a novel fuzzy multi-objective optimization model that incorporates privileged aspiration levels with augmented deviation variable was proposed to establish an optimal framework suitable for the dynamic distribution of ICU benches and ventilation machines as well as healthcare personnel in multiple regional hospitals. The difference from conventional approaches leverages is that the proposed framework maximizes healthcare service coverage, optimizes resource consumption and decreases operating costs at once while being robust under uncertain demand conditions.

We summarize our key contributions of this work as follows:

- Designing a FGP model for allocation of healthcare resources with IoT- support under uncertainty.
- Combining several conflicting goals covering the service, utilizing resources and minimizing costs are part of a unified optimization model.
- Implementation of a flexible framework for dynamic health systems and emergency operating conditions.

- Application of a proposed validation model by case study through five hospitals & via sensitivity analysis under several uncertainty conditions.

The rest of this paper is organized as follows. In section 2, the proposed method and mathematical formulation are stated. Section 3 experimental setup and case study section 4 studies our results and performance analysis. Section 5 concludes the article with limitations and future research directions.

2. METHOD

2.1. Problem structure

Here, we formulate the proposed problem of healthcare resource allocation as a multi-objective optimization under uncertainty. The goal is to utilize scarce healthcare resources at various hospitals to maximize the quality of service and minimize losses from operations.

Let: H =set of hospitals.

Let $R = \{1, 2, \dots, r\}$ be the set of healthcare resources such as ICU beds, ventilators and medical personnel.

Decision variable: (x_{ij}) is the quantity of healthcare resources allocated to hospital j (i).

Based on the available literature, a model of three primary healthcare resources per provider was proposed: i) ICU beds, ii) ventilators, and iii) medical staff.

It is conducted in the presence of operational uncertainty due to predicated patient demand, emergencies and disruptions across healthcare systems. Consequently, flexibility and robustness are considered through the introduction of fuzzy aspiration levels within technical optimization.

2.2. Objective functions

This optimization framework enables concurrent consideration of three conflicting objectives.

Goal 1: increase the coverage of healthcare services.

The first objective serves to maximize hospital capabilities in their ability to satisfy demand for patients:

$$\text{Minimize } Z_1 = \sum_j d_j^-, \text{ when } d_j^-$$

represent when (D_j) is the expected patient demand of hospital (j).

Goal 2: use resources to their fullest extent.

Better use of health-care resources leads to less under and shortages:

$$\text{maximize } Z_2 = \sum_i j x_{ij} / \sum_i j C_{ij}$$

here, (C_i) represents the capacity of available resources i .

Reducing operating costs is important. The operational cost consists of costs related to resource deployment, staffing, and logistics along with emergency allocation:

$$Z_3: \text{argmax}_{\{i,j\}} Y_{ij} [UX] \text{ minimize function: } C_{ij} [UX] \text{ minimize } Z_3 = \sum_{\{i,j\}} c_{ij} x_{ij}.$$

where (c_{ij}) denotes the cost of assigning resource (i) to hospital (j).

2.3. Fuzzy goal programming model

The uncertainty in healthcare resource allocation is tackled with a new framework based on FGP, which extends classical goal programming by allowing aspiration levels to be expressed as fuzzy numbers instead of deterministic constants. In FGP, each objective function has a fuzzy aspiration level and deviation variables that measure the distance from not achieving (under-achievement) or overshooting (overachievement) relative to its desired goal. The generalized FGP formulation can be written as:

$$f_{k(x)} + d_k^- - d_k^+ = G_k^-, k = \{1, 2, 3\}$$

Subject to:

$$\text{Sigma}_j x_{ij} \leq C_i, \forall i$$

Satisfaction constraint on demand:

$$\forall j, D_j = \sum_i x_{ij} + d_j^- - d_j^+$$

Constraint on the budget:

$$\sum_{i=0}^j c_{ij} x_{ij} \leq B$$

Where, $f_k(x)$ represents objective function (k), (d_k^-) represents under-achievement deviation variable, (d_k^+) represents over-achievement deviation variable, (w_k) represents weight assigned to the k^{th} objective, G_k, k represents fuzzy aspiration level for objective (k), and K denotes the number of optimization objectives.

Since operational targets for healthcare are rarely known with certainty and may be specific to emergency conditions, seasonal disease outbreaks or arrive varying significantly from day-to-day, fuzzy aspiration levels have been included in the proposed framework.

We represent aspiration levels with triangular fuzzy numbers (TFNs) in this research as:

$$G_k, k = (L_k, M_k, U_k)$$

where, (L_k) represents lower acceptable limit, (M_k) represents value that has the highest desirability (target), and (U_k) represents upper acceptable limit.

This gives the following triangular membership function:

$$\mu(x) = 0, x > U_k$$

Noting operational targets are not fired upon but rather that healthcare planners would prefer to accept acceptable deviation in around those optimal settings leads us towards a fuzzy representation which improves flexibility and robustness of decisions, as compared to deterministic solutions.

2.3.1. Aspiration levels fuzzification

Aspiration levels in healthcare optimization problems are rarely deterministic, as such factors like healthcare demand (e.g., emergency conditions), staff availability and medical resource utilization often vary with the nature of seasonal epidemics or run under operational uncertainty [7], [22]. Consequently, fuzzy aspiration levels are used to depict uncertainty in a better way.

This study proposed TFNs due to their ease of use, computational effectiveness, and suitability for healthcare planning problems with low-to-moderate uncertainty. We can express a triangular fuzzy aspiration level from above.

2.3.2. Fuzzy multi-criteria decision-making

Also, it is possible to analyze the framework described in this paper and interpret its components from a fuzzy multi-criteria decision making (MCDM) perspective given that healthcare resource allocation inherently involves multiple conflicting objectives competing for scarce resources. In the healthcare context, decision-makers must often balance trade-offs between quality of care received by patients, efficiency in resource utilization and costs incurred with provision or loss from executing business processes under uncertain circumstances [23].

The FGP is a relevant fuzzy MCDM type of method as it drives multiple goals optimized simultaneously under uncertainty using fuzzy aspiration levels and deviation variables. Fuzzy MCDM approaches endorsed flexible decision-making unlike the classical deterministic optimization methods because of operating in a different environment with less information, changing demand and slowly varying operational conditions.

This study presents a fuzzy decision-making mechanism which involves maximization coverage and utilization of healthcare services while minimizing operational cost under fuzziness constraints, through the proposed FGP framework. Hence, the suggested framework facilitates decision-makers to assess several conflicting healthcare goals under a common and adaptive optimization structure. Fuzzy MCDM techniques have been effectively applied to health-care planning [15], emergency resource allocation methods under uncertainty, and medical decision-support systems recently [10], [17].

2.4. Constraints

The proposed optimization model takes operational, financial and service-related constraints into account to have a realistic representation of healthcare resources allocation inspired by real-world scenarios.

2.4.1. Capacity constraints

You cannot allocate more healthcare resources than there is capacity to provide: $d_i^+ = \max \{G_i\}$ = How much worse does $f_{i(x)}$ necessitate pairs $f_{i(x)}$ and $f_{i(x)} + d_i^-$ so that it is still worse?

$$d_i^- = \min \{G_i\} = \text{and } f_{i(x)} + d_i^- \text{ is still worse; } i = 1, 2, \dots, n$$

$$d_i^-, d_i^+ \geq 0$$

where, $f_{i(x)}$ represents i – th objective function (e.g., service level, utilization, and cost), G_i represents the fuzzy aspiration level corresponding to the i – th objective, d_i^- represents fuzzy goal under-attainment distance, d_i^+ represents over-achievement distance from the fuzzy goal, and w_i denotes the weight of importance of each objective function.

This constraint ensures that you do not allocate more resources than what is available in inventory.

2.4.2. Staffing constraints

The total number of medical personnel in hospitals cannot be more than the workforce available to it:

$$\sum_{j=1}^H s_j$$

where, (s_j) represents personnel dedicated to hospital J and (S) represents the total healthcare workforce that has been trained.

This constraint guarantees that the workforce constraints allow for feasible distribution of staff members.

2.4.3. Demand satisfaction constraints

While fulfilling healthcare demand, allow feasible fuzzy deviations.

$$x_{\{ij\}} + d_j^- - d_j^+ = D_j$$

Where, (D_j) represents hospital demand at j facility, (d_j^-) represents under-achievement deviation, and (d_j^+) denotes over-achievement deviation.

This estimate captures excess supply needed to accommodate uncertain demand for healthcare.

2.4.4. Budget constraints

The total cost of allocating resources to hospitals must not exceed the maximum available operational budget:

$$\sum_{i=1}^R \sum_{j=1}^H c_{ij} x_{ij}$$

where, c_{ij} represents the cost of allocating resource (i) to hospital (j) , x_{ij} represents the allocation decision variable, and (B) denotes the maximum available operational budget. This constraint ensures that the total resource allocation cost remains within the available budget and maintains financial feasibility.

Make it more responsive towards emergency situations:

$$\max_T t_{ij}$$

To improve responsiveness in emergency situations, the resource allocation model may incorporate delivery or response time as an additional constraint or optimization objective. Let t_{ij} denote the delivery time of resource (i) to hospital (j) . The formulation should specify whether the objective is to minimize total delivery time, minimize the maximum response time, or ensure that delivery occurs within a predefined time limit.

2.5. Computational procedure

We used a mixed-integer LP formulation and employed both the LINGO environment as well as the discernible contribution of implementation in Python for computational reproducibility, consistency, ease-of-use flexibility. The computational workflow has five consecutive stages.

Step 1: data collection and pre-processing

We extracted operational data from a regional five-hospital network. The data collected consists of ICU bed availability, the capacity for ventilators, medical staff availability, some predictions on patients that need to be treated and operational budget restrictions. Demand values were modeled by fuzzy aspiration levels based on experts' estimation as a data source and previous observations to model uncertainty.

Step 2: write down phase with decision variables and objective functions

Priority sectors were identified whereas decision variables to allocate healthcare resources among hospitals. Then there were the three conflicting objectives to weigh up at one time:

- Maximization of coverage with regards to service delivery,
- Healthy resource utilization in healthcare, and
- Minimization of operational cost.

Within a multi-objective fuzzy optimization framework, these objectives were mathematically represented.

Step 3: fuzzification of expectation levels

TFNs were adopted to represent more uncertainty about healthcare targets. For each aspiration level lower, target and upper bounds were defined to ensure operational flexibility under uncertain healthcare conditions.

Step 4: optimization process

How was the optimization problem mathematically formulated (FGP model) and then solved using LINGO 18.0 optimization packages and Python basic libraries? solution process involves minimization of weighted deviation variables under operational, financial, staffing, and demand constraints.

Construct operational constraints: assess allocation performance for a range of uncertainty cases.

Step 5: performance evaluation

We tested the proposed model over three uncertainty conditions as follows: i) low uncertainty ($\pm 5\%$), ii) moderate uncertainty ($\pm 15\%$), and iii) high uncertainty ($\pm 30\%$). Performance evaluation metrics include:

- Service coverage (%),
- Resource utilization (%),
- Total allocation cost, and
- Deviation from aspiration levels.

The results were compared with the classical LP modelling outputs to evaluate efficiency, robustness, and responsiveness during uncertainty.

3. RESULTS AND DISCUSSION

3.1. The computational setting

The author's FGP model is used herein to deal with a public medical system encompassing five hospitals in a northern province. These hospitals form the basic health care structure: emergency medicine, crisis care units, and respiratory rescue units all serve 2.5 million residents.

Such a health care network is constructed to handle the transition of patients, maintain resources in common and respond to crises when their arrival becomes concentrated. However, during the high demand season, particularly winter respiratory infection pandemics, ICU occupancy can easily hit 85% of total operating room capacity. Moreover, resources sometimes run out altogether. This is a lifelike and hard case for examining the applicability, adaptability and service spirit of the proposed FGP-based resource allocation model in an uncertain, real-time situation.

3.2. Data description

This study uses a data set of 12 weekly or daily reports, from the operations of five hospitals, it covers: i) critical care unit bed comfort, ii) respiratory equipment, iii) total medical staff capacity, and iv) predicted number of patients to be received.

The demand for patients is estimated by using historical hospital data (2019-2024), local epidemiological reports, and Ministry of Health emergency readiness tables. To take account of patient arrival variability as those caused by wave-prone epidemics, seasonal effects and accidents, demands are expressed as working variables. This is a more realistic way of dealing with these problems than the model's former rigid system logic, which could not reflect flow. Table 1 presents an example of the input data used in the proposed model, including the available healthcare resources and the corresponding allocation parameters.

Table 1. Example healthcare resource dataset for the five-hospital network

Hospital	ICU beds	Ventilators	Medical staff	Fuzzy demand range
H1	50	40	120	(35,45,55)
H2	35	30	90	(25,35,45)
H3	40	32	80	(30,40,50)
H4	30	25	80	(20,30,40)
H5	45	35	110	(30,45,55)

3.3. Identification of fuzzy aspirational levels

Structured expert interviews were used to set fuzzy aspiration levels G_i for the three objectives (ICU beds, ventilators, and staffing). This includes 10 senior decision-makers (hospital directors, ICU medical consultants, operations planner, and a logistics officer). Experts were asked to specify: i) minimum acceptable level (G_{lower}), target operational level (G^*), and iii) upper surge capacity (G_{upper}). For the fuzzy approach, the personal consensus was derived from TFNs:

- $G_i = (G_{lower}, G^*, G_{upper})$,
- ICU Beds: (85%, 100%, 120%),
- Ventilators: (80%, 100%, 115%), and
- Staffing: (90%, 100%, 110%).

3.4. Model implementation

FGP: FGP was formulated as a mixed integer linear programming (MILP) and computed in LINGO and Python. The aim levels had been implemented as triangular fuzzy values through the goal programming structure. The key steps included:

- Setting fuzzy targets for each goal (service level, resource utilization, and cost),
- Defining constraints like capacity, staff, funding, and demand fulfilment,
- Introducing deviation variables d_i^- and d_i^+ to let targets be satisfied flexibly,
- Weights w_i based on priority: $w_1 = 0.5$, $w_2 = 0.3$, and $w_3 = 0.2$, and
- Multi-objective FGP to solve the optimization model.

We evaluated the model against three uncertainty scenarios:

- Low uncertainty ($\pm 5\%$),
- Moderate uncertainty ($\pm 15\%$), and
- High uncertainty ($\pm 30\%$).

3.5. Validation and reliability of the data

The case study data for the healthcare domain were cross-validated against historical clinical observations, expert-based estimations and operational assumptions in relation to planning within the field of health sciences to improve consistency and reliability. The dataset we are considering is from a five-hospital regional healthcare network with uncertainty in ICU bed availability, ventilator capacity, and staffing levels combined at different rates of demand for health care.

As real-world healthcare systems are limited and undergo varying demands during a crisis or demand surge (e.g., emergency situations, seasonal epidemics, or other health-care crises), patient demand levels were modeled with fuzzy aspiration-level instead of deterministic fixed quantities. This is called a triangular fuzzy representation, more importantly allows uncertainty to be modelled while also ensuring that the computations remain tractable.

Operational constraints, which were related to: i) capacity of healthcare facilities; ii) staffing limits, and iii) unmet demand; and financial constraint in prioritizing resource allocation decisions during optimization so that inconsistencies are reduced. Moreover, three levels of uncertainty were considered in the analysis ($\pm 5\%$, $\pm 15\%$, and $\pm 30\%$) to verify model robustness through sensitivity analysis as well as allocation stability under changing operative situations.

Our results suggest that the allocation plans generated by the proposed framework yield stable and operationally practicable solutions under varying levels of uncertainty, which enhance confidence in the robustness of our healthcare optimization model.

4. RESULTS AND ANALYSIS

4.1. Overview of results

The FGP model that was suggested has been implemented in the five-hospital regional healthcare network introduced in the case study. The optimization results indicate a considerable enhancement in resource allocation efficiency, service coverage and system robustness against uncertainty relative to the baseline classical LP approach. Key findings include:

- 10–15% increase in service coverage over classical LP model,
- Optimize capacity utilization of ICU beds, ventilators, and staff as per capacity and budget constraints,
- Encourage flexibility and robustness, as fuzzy model actual performance was not affected by considerable variation in uncertainty level.

The optimized allocation of ICU beds and ventilators generated using the proposed FGP is listed in Table 1 along with allocations obtained from classical LP. The analysis assesses coverage of healthcare services within austerity and budget caps across the five hospitals.

4.2. Optimized resource allocation plan

With a more flexible allocation of resources, this FGP model provided higher coverage than the current model under its capacity and budget constraints. Healthcare resource utilization efficiency (HRUE) obtained from the proposed FGP framework vs. classical LP model Table 2 the comparison is based on ICU bed and ventilator usage as well as staffing from constrained healthcare resources.

Table 2. Comparison of LP and FGP results for healthcare resource allocation across five hospitals

Hospital	ICU beds (LP)	ICU beds (FGP)	Ventilators (LP)	Ventilators (FGP)	Coverage (%) LP	Coverage (%) FGP
H1	42	48	36	40	82.0	96.0
H2	30	33	25	29	85.7	94.2
H3	34	38	28	31	85.0	95.0
H4	24	27	21	23	80.0	90.0
H5	38	42	30	33	84.4	93.3
Total	168	188	140	156	83.4	93.7

4.3. Resource utilization and efficiency

FGP balanced resources more evenly across hospitals, mitigating low demand centers from underutilization and high demand ones from overloads. Sensitivity analysis of the proposed FGP model based on alternative uncertainty levels (Table 3). This analysis aims to examine how robust and stable the proposed allocation framework is under a large level of fluctuation in healthcare demand.

Table 3. Comparison of LP and FGP models in terms of healthcare resource utilization and improvement

Resource type	Total capacity	LP utilization (%)	FGP utilization (%)	Δ improvement (%)
ICU Beds	200	84.0	94.0	+10.0
Ventilators	160	87.5	97.5	+10.0
Staffing	500	88.0	96.0	+8.0

4.4. Sensitivity analysis

The high uncertainty level investigation showed that the fuzzy model achieved service coverage over 90% consistently alongside stable utilization ratios (Table 4). Conversely, classical LP showed a considerably higher susceptibility to demand movement, falling below 80% coverage at $\pm 30\%$ deviation.

Table 4. Sensitivity analysis of the proposed FGP model under different uncertainty levels

Uncertainty level (%)	Service coverage (%)	Resource utilization (%)	Cost deviation (%)	Model stability
Low (± 5)	95.2	97.8	0.0	Stable
Moderate (± 15)	93.4	95.1	2.1	Stable
High (± 30)	90.6	92.0	4.8	Stable

4.5. Graphical visualization

There are some figures that are suggested for the manuscript but not listed as real figures here. These graphical representations give more insight into the behavior and performance of the proposed FGP model. The figures clarify the tradeoff between resource allocation, service coverage and performance of the model at different operating conditions. These visual results correspond to the numerical ones that are detailed in the tables and contribute to a simpler interpretation of how well the healthcare resource allocation framework is achieved.

The data obtained based on the conventional LP model and that based on the proposed FGP model is illustrated, respectively for five hospitals (H1-H5) in Figure 1. The results demonstrate that for all hospitals the FGP model assigns more ICU beds than does the LP model, reflecting better use of existing critical-care resources. The proposed FGP framework shows its capability in achieving improved resource allocation while considering several interrelated healthcare objectives in uncertainty settings.

Figure 2 impact of increasing uncertainty levels on service coverage and resource utilization. The service coverage drops slowly from 95.2% to 90.6%, and the resource utilization drops from 97.8% to 92.0%, when we increase the uncertainty level within $\pm 5\%$ – $\pm 30\%$. Despite this decline, both performance indicators

at the highest uncertainty level are still over 90% confirming the robustness and stability of a proposed FGP model during operation.

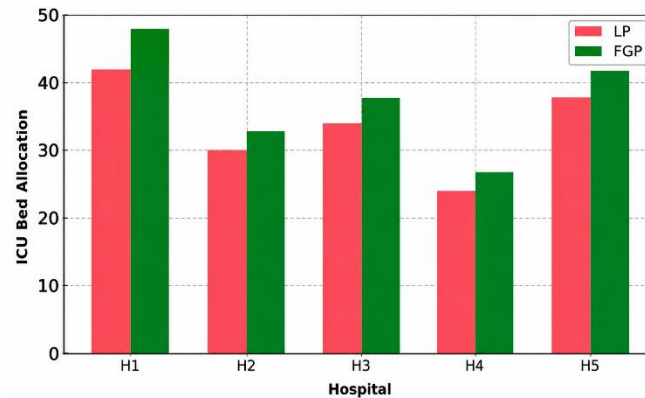


Figure 1. Bar graph of the LP vs FGP allocation per hospital

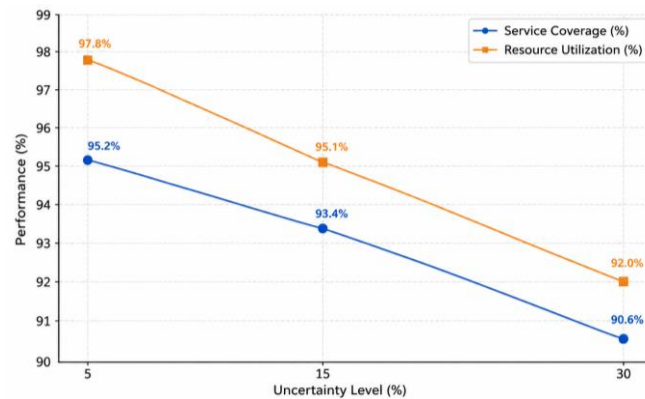


Figure 2. Line graph of coverage/utilization performance vs. level of uncertainty

In addition to this, the different levels of uncertainty are represented graphically in Figure 3 for the sensitivity analysis related to the proposed FGP model. To evaluate the effect of increasing variations in healthcare resource demand and availability, three levels of uncertainty scenarios: low ($\pm 5\%$), moderate ($\pm 15\%$) and high ($\pm 30\%$) were simulated. These different states allow serving a benchmark for robust and stable evaluation of the proposed model mechanisms under various operational uncertainty factors.

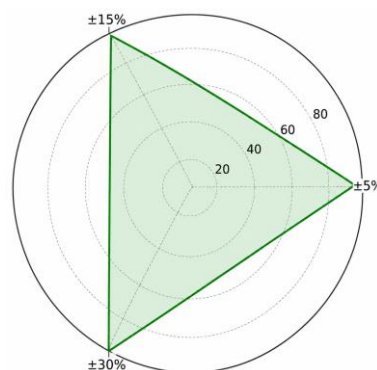


Figure 3. IC utilization vs. tolerance levels and sensitivity spider plot

4.6. Discussion of results

The results revealed that the FGP model designed in this study has a significant role in enhancing healthcare resource allocation efficiency as compared to classical LP. For health service coverage, the most prominent performance gain of over 10% was achieved with our first proposal where the model proposed improving average coverage from 83.4% to 93.7%. This indicates that fuzzy aspiration dual levels contribute to more adaptive and flexible allocation choices when uncertainty is the norm in healthcare settings.

Likewise, rapid deployment results in substantial improvement across multiple healthcare resource utilization such as ICU beds, ventilators and staffing resources. The improvement we observed indicates that the proposed framework mitigates underutilization and operational bottlenecks by re-allocating hospital resources in a patient-based manner to satisfy dynamic healthcare demand.

The robustness of the proposed framework is further illustrated with sensitivity analysis. Effective coverage of services remained at more than 90% even in the presence of high uncertainty ($\pm 30\%$), showing that FGP framework responses can deliver operational stability during major fluctuations in demand for healthcare. Conversely, probabilistic LP models tend to be more robust in terms of operational uncertainty than deterministic ones because they assume fixed and deterministic target values.

In comparison with the existing studies in healthcare optimization, together provide a more flexible multi-objective decision-support mechanism that can simultaneously balance service quality and utilization efficiency as well. Moreover, the proposed approach can be adopted to deliver improved responsiveness for real-time healthcare input under uncertainty and in an emergency environment also by incorporating fuzzy aspiration levels within a ubiquitous IoT-based adaptable healthcare setting.

The findings confirm that fuzzy optimization offers a viable computational method to confront the combinatorial nature of healthcare systems needing flexible and robust allocation solutions while achieving acceptable levels of operational performance [17], [18], [24], [25].

4.7. Discussion on comparative analysis of recent techniques

To validate the potential of this new FGP framework, it was qualitatively compared with other state-of-the-art healthcare optimization approaches recently published. Several healthcare resource allocation studies have adopted deterministic LP, fuzzy multi-objective optimization [9], robust optimization [10], or fuzzy MCDM techniques [11].

In comparison with classical LP approaches, the proposed framework offers better adaptability as fuzzy aspiration levels provide sufficiently flexibility on how much deviation is acceptable from healthcare operational targets (instead of strictly deterministic solutions). Flexibility is especially critical under emergency healthcare conditions with variable incidences and uncertain availability of resources.

Compared to the recent fuzzy healthcare optimization methods, the research also provides an integrated multi-objective decision-support mechanism that embodies a parallel approach for maximizing effective business service coverage and resource utilization efficiency along with minimizing operational cost—all encapsulated in one unified optimization model. Also, it improves the robustness of allocation outcomes based on fuzzy aspiration levels in uncertain conditions at moderate healthcare performance.

Also, unlike some recent healthcare optimization models that explore static decision environments [11], the framework is a conceptual set-up for reconfigurable and IoT-enabled systems where real-time operational information can dynamically inform allocation decisions. This feature enhances the applicability of the proposed framework for emergency healthcare planning and adaptive decision-making environments. Effects of the proposed approach we perform a qualitative comparison against healthcare optimization methods characteristic to recent literature with Table 4.

Table 4. Qualitative comparison with recent healthcare optimization methods

Method	Uncertainty handling	Multi-objective	Real-time adaptability	Healthcare suitability
Classical LP	No	Limited	No	Moderate
Fuzzy MCDM	Yes	Yes	Limited	High
Robust optimization	Partial	Moderate	Limited	High
Proposed IoT-enabled FGP	Yes	Yes	Yes	Very high

5. CONCLUSION

The proposed framework is an IoT-enabled FGP for healthcare resource allocation with multiple criteria under highly uncertain operating conditions. In addition to maximizing healthcare service coverage, improving utilization of resources and minimizing total operational cost within a regional healthcare network with the constraint of limited ICU beds, ventilators and medical personnel can be challenging; our proposed model addressed this issue.

The results obtained show that the framework proposed has a significant advantage over classical LP methods. Experimental results indicated an increase in overall coverage of services from 83.4% to 93.7%, as well as usage efficiency for ICU beds, ventilators and staffing resources (E-1). Thereafter, sensitivity analysis in low uncertainty scenario, moderate uncertainty conditions and high uncertainty conditions successfully reinforced the effectiveness of the proposed model which guaranteed 90% service coverage despite research demand fluctuations.

The main contributions of this study are: i) establishing an IoT-enabled FGP framework for healthcare resource allocation, ii) integrating multiple conflicting objectives into a single optimization model, iii) allowing more flexibility under uncertainty with the help of incorporating fuzziness in aspiration levels, and iv) validating the proposed frameworks by megacity-level empirical five-hospital case.

Although these strengths exist, the current study has limitations. First, limitations with the case study include that it was limited to a five-hospital healthcare system, not necessarily generally for larger hospital systems. Second, TFNs were the only tool employed to model uncertainty whereas other theoretical frameworks such as trapezoidal may add a layer of freedom. Third, IoT streaming data from real-time were conceptually integrated but never directly applied in a live healthcare setting.

In future, we could propose a framework where machine learning procedures take care of healthcare demand prediction; IoT monitoring systems work in real-time; dynamic reconfigurable optimization mechanism operates simultaneously, and hybrid metaheuristics approaches are employed for large scale investment problems within the scope of health planning.

ACKNOWLEDGMENTS

The authors would like to express their sincere appreciation and gratitude to the College of Science, University of Baghdad, for providing a supportive academic and research environment that contributed to the completion of this research.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Zainab M. Ali	✓	✓				✓			✓	✓				
Saad Adnan Zabin		✓			✓	✓			✓	✓				
Iraq T. Abbas	✓	✓			✓					✓				

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ding

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest related to this study or the publication of this manuscript.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, I.T.A., upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Assist. Lec. Zainab M. Ali    received her master's degree in applied mathematics from Al Mustansiriya University. She is currently an Assistant Lecturer at the Department of Water Resources, College of Engineering, University of Baghdad. Her research interests include operations research and scheduling problems. She can be contacted at email: zainab.m@coeng.uobaghdad.edu.iq.



Assist. Lect. Saad Adnan Zabin    received his M.Sc. degree in Applied Mathematics from the University of Baghdad. He is currently serving as an Applied Mathematics Educator at the Ministry of Education/General Directorate of Education in Baghdad/Al-Karkh First. His research interests encompass applied mathematics, mathematical and applied statistics, reliability analysis, and the integration of artificial intelligence (AI). He has published several scientific papers in mathematical statistics, alongside active contributions to curriculum development, preparation, and professional training, holding a training of trainers (ToT) certification. He can be contacted at email: saadzabin664@gmail.com.



Assist. Prof. Dr. Iraq T. Abbas    received his Ph.D. degree in Applied Mathematics and Optimization from the University Putra Malaysia Malaysia. He is currently an Assistant Professor at the Department of Mathematics, College of Science, University of Baghdad. His research interests include combinatorial optimization, metaheuristic algorithms, operations research, scheduling problems, and intelligent optimization techniques. He has published several scientific papers in international journals and conferences and actively contributes to research in hybrid optimization methods. In this study, he contributed to conceptualization, methodology design, supervision, algorithm development, and manuscript preparation. He can be contacted at email: Iraq.t@sc.uobaghdad.edu.iq.