Fuzzy Goal Programming for IT-Driven Healthcare Resource Allocation

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Abstract: This guidance article has presented a new Flexible (and Fuzzy) Goal Programming (FGP) model built for multiple criteria decision-making for allocating resources in healthcare. The combination of fuzzy logic flexibility with the structure of goal programming has potential to better manage conflicting and uncertain objectives, such as reducing cost when improving quality of service and fair distribution. A case study illustrates the allocation of ICU beds, ventilators, and staff at five regional hospitals, the application of FGP in this case study illustrates that an optimal solution is achieved while mitigating the importance of the goals aligned with the different stakeholders in the resource allocation process. Analysis shows that plans with the FGP can achieve balanced compromises between conflicting goals while satisfying operational constraints and aspirations. Sensitivity analysis confirmed the FGP retains stability, sensitivity, and reliability throughout its planning process. This research brings a solid, flexible, relatively easy to use decision support tool that is broadly applicable to any features of a decision-making.

1 INTRODUCTION

Health Care systems are under significant pressure, and the urgency to optimize resource allocation to address shortages are more acute than ever. Hospitals, clinics and national health services are responsible for providing the necessary care and must allocate limited resources (i.e. hospital beds, staff, equipment, medication, etc.) to satisfy the demands on healthcare resources created by an aging population, increasing incidence of chronic disease and unexpected healthcare demands resulting from events such as a pandemic [1]. Meanwhile, decisions on healthcare resource allocation require multiple trade-offs among conflicting objectives related to operational costs, the extent of patient treatment coverage, patient wait times, and equity in access to care. Multi-Criteria Decision Making (MCDM) readily offers frameworks that facilitate decision-making in health care planning and management and are useful for similar environments, providing a structured approach to evaluate competing priorities and data-driven, open decision-making [2], [3].

Nevertheless, health care decision-making is not always straightforward. Decision making in health care is invariably accompanied by uncertainty, imprecise objectives and unclear preferences acknowledged by stakeholders, patient necessities and policy limits. Conventional deterministic models and conventional goal programming approach decisions involving clear numbers, and constraints, which does not represent the true complexity of an applied context. Fuzzy Goal Programming (FGP) provides a powerful approach for modeling the uncertainty related with the objectives and constraints through the elasticity features of fuzzy set theory and guidance from the rigid structure of goal programming [4], [5]. Although FGP has demonstrated its potential for addressing many problems from facility site selection to energy resource allocation [6], [7], within the literature of health care resource allocation problems with real-world uncertainties, it remains relatively underused. In addition, most of these studies either have employed simplistic decision-making environments or have not modeled fuzzy logic to characterize representative stakeholder preferences. That is what our study is trying to do. It was thus that we developed and applied a Fuzzy Goal Programming modelto tackling resource allocation problems in health care.

Despite the increased interest in MCDM and fuzzy-based modeling, the majority of previous research in healthcare decision-making contexts has primarily been deterministic optimization models, or simpler multi-criteria approaches like AHP and TOPSIS that assume the input data is exact and full with a clear rank order [8], [9]. One reason is that most deterministic and simple multi-criteria methods are ill-formed for use in dynamic and uncertain situations where most planned interactions will not have exact data input, vague expert judgment, unclear and/or competing objectives would produce goals that are not fixed in time. Fuzzy Goal Programming offers usefulness by providing a more expansive modeling scope, which can take into account preference uncertainties and competing objectives and limit trade-offs between tolerances.

In addressing this research gap, this paper presents a structured FGP model based on a healthcare resource allocation decision context, using fuzzy aspiration levels to capture the complex priority structure of healthcare stakeholders. In utilizing a realistic case study, the model's validity and flexibility are demonstrated as a decision-support tool to create balanced and resilient solutions under uncertainty.

2 LITERATURE REVIEW PARAGRAPH

Multi-Criteria Decision Making (MCDM) techniques have been studied in healthcare problems such as resource allocation, deciding who should receive treatment first, making decisions about hospital site selection, etc. The Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Data Envelopment Analysis (DEA) are all MCDM methods that have successfully provided decision-makers with structured approaches to balance competing desired outcomes [2], [8]. It is important to mention that traditional MCDM techniques, including AHP, TOPSIS, and DEA, receive their input in the form of precise, crisp data and the alternatives to select from would be compared assuming that the preferences were fixed concerning the criteria being considered, limiting the ability of these techniques to solve the inherent uncertainty and vagueness of healthcare environments. The limitations of crisp data, input data, and fixed preferences have been addressed through the development of fuzzy logic methods, which have increasing use through the development of Fuzzy Goal Programming (FGP), allowing imprecise goals and preferences to be integrated, which illustrates the potential modeling of fuzzy logic [4], [5]. Applications of FGP have been demonstrated to produce desirable outputs for the management of waste [7], supply chain optimization (Li et al., 2020) and to determine the optimal distribution for emergency resources [10] and can also bring decision makers closer to resolution on the multiplicity of conflicting objectives while under uncertain environmental conditions. However, the use of fuzzy goal programming (FGP) in the allocation of healthcare resources is still primarily theoretical or based on small case-studies and rarely considers real-life constraints and stakeholder preferences well [9].

3 MATHEMATICAL MODEL BASED ON HEALTHCARE CASE

3.1 Methodology

The current studyapplies the fuzzy goal programming (FGP) method to examine decision making with multiple criteria in healthcare resource allocation. The developed methodology consists of three main steps: (1) using fuzzy sets in modeling multiple conflicting objectives; (2) developing membership functions to determine degrees of target satisfactions; and (3) developing a mathematical programming (MP) model and solving that maximizes the minimum satisfaction level for all the objectives. By using FGP, decision makers are able to more easily incorporate uncertainty and imprecision in real-world healthcare planning and also provide feedback on trade-offs that reflect cost efficiency, quality of service, and fairness.

3.2 Case Study Description

To illustrate the practical application of the model, we constructed a case study based on a regional healthcare system managing a limited supply of critical resources (ICU beds, ventilators, and healthcare providers) shared among the five regional hospitals. Each hospital differed in capacity, current census load, and cost structure. Ultimately, the decision-makers intended to apply and configure the model to allocate resources, ensuring the costs were minimized, quality of service was optimized (ex, number of patients treated), and farm-aware ways by providing each provider an appropriate number of patients assigned to them. Input data was gathered and constructed from the previous year's hospital report, with expert judgment to determine how they were weighted. Fuzzy aspiration levels were set in collaboration with the healthcare planners**.**

3.3 Quality Score and Priority Level

The Quality Score for each resource was derived using expert evaluation based on three main criteria: service reliability, patient outcome contribution, and operational efficiency. Each criterion was rated on a 0–1 scale by five healthcare experts, and the average weighted score was used as the final Quality Score for each resource type (e.g., ICU beds = 0.90, ventilators = 0.95, medical staff = 0.85). The Priority Level assigned to each hospital (High, Medium, Low) was determined from a composite index combining three indicators:

1) Patient demand ratio (current demand ÷ capacity),
2) Regional criticality (e.g., emergency load or pandemic exposure), and
3) Service importance (specialized units or essential coverage).

Each indicator was normalized (0–1), and the overall priority was classified as:

High: composite ≥ 0.70. Medium: 0.40–0.69. Low: ≤ 0.39.

This ensured that both quality and priority measures reflected realistic expert-driven assessments of hospital performance and demand.

Mathematical Model for Healthcare Resource Allocation Using Fuzzy Goal Programming

Decision Variables: Let x_i $(i = 1,2,\dots,n)$ denote the quantity of healthcare resource type i to be allocated.

Objectives:

1) Minimize Total Cost: $f_1(x) = \sum_{i=1}^{n} c_i x_i$, where c_i is the unit cost of resource i .
2) 2. Maximize Quality of Service : $f_2(x) = \sum_{i=1}^{n} q_i\, x_i$, where q_i represents the contribution of resource i to service quality.
3) Minimize Inequality in Resource Distribution: Assuming K regions, with x_{ik} representing the quantity of resource i allocated to region, define:

$$R_k = \sum_{i=1}^{n} x_{ik} ,$$

as the total resources allocated to region k. To measure inequality, introduce an auxiliar y variable f satisfying:

$$R_k - R_l \le d, \quad \forall k, l = 1, \dots, k.$$

Minimizing d promotes equitable resource distribution.

4 FUZZY GOALS AND MEMBERSHIP FUNCTIONS

4.1 Membership Functions of Fuzzy Goals

Each goal j is associated with an aspiration level b_j and tolerance t_j . The fuzzy aspiration levels (b_j) and tolerance ranges (t_j) were determined through an expert elicitation process. The tolerance defines the acceptable limit beyond which performance is considered unsatisfactory. The membership functions m_j are defined as:

For minimizing cost $f_1(x)$:

$$m_1(x) = \begin{cases} 1 & , f_1(x) \le b_1 \\ \frac{t_1 - f_1(x)}{t_1 - b_1} & , b_1 < f_1(x) < t_1. \\ 0 & f_1(x) \ge t_1 \end{cases}$$

For maximizing quality $f_2(x)$:

$$m_2(x) = \begin{cases} 1 & f_2(x) \ge b_2 \\ \frac{f_2(x) - t_2}{b_2 - t_2} & t_2 < f_2(x) < b_2, \\ 0 & f_2(x) \le t_2 \end{cases}$$

represents an objective to be maximized (e.g., service quality). Therefore, the membership value should increase as the performance value increases.

For minimizing inequality d:

$$m_3(d) = \begin{cases} 1 & d \le b_3 \\ \dfrac{t_3 - d}{t_3 - b_3} & b_3 < d < t_3, \\ 0 & d \ge t_3 \end{cases}$$

represents an objective to be minimized (e.g., inequality). Hence, the membership value should decrease as the value increases.

4.2 Fuzzy Goal Programming Model

Maximize the minimum satisfaction level γ: max γ.

Subject to: $m_j(x) \ge \gamma, j = 1,2,3.$

Constraints:

$$f_1(x) + d^-_1 - d^+_1 = b_1, \quad d^-_1, d^+_1 \geq 0,$$
$$f_2(x) + d^-_2 - d^+_2 = b_2, \quad d^-_2, d^+_2 \geq 0,$$
$$\mathrm{d} \leq b_3 + d^+_3 - d^-_3, \quad d^-_3, d^+_3 \geq 0,$$
$$R_k - R_l \leq d, \quad \forall k, l = 1, \ldots, K,$$
$$\sum_{i=1}^{n} c_i x_i \leq C, \; x_i \leq U_i, \forall i, \; x_i \geq 0, \forall i, \; 0 \leq \gamma \leq 1.$$

d^-_j and d^+_j and are deviation variables reflecting under- and over-achievement of fuzzy goals. γ is the minimum satisfaction level across all goals, to be maximized to achieve a balanced solution. C represents the total available budget, and $U_i$denotes the upper limits on resource i.

4.3 Model Constraints and Parameters Description

The parameters of the model were derived from the case study data summarized in Tables 1–4, which provide detailed information on resource availability, cost structure, hospital demand, and goal specifications. These data form the basis for evaluating the performance of the proposed FGP model in a realistic healthcare resource allocation scenario.

Table 1: Resource parameters.

Quality Score	Max Available Units	Cost per Unit (USD)	Resource Type
0.90	100	500	ICU Beds
0.95	60	800	Ventilators
0.85	150	300	Medical Staff

Table 2: Hospital demand and capacity.

Priority Level	Estimated Demand	Max Capacity	Hospital
High	140	120	Hospital A
Medium	90	80	Hospital B
High	100	100	Hospital C
Low	50	70	Hospital D
Medium	80	90	Hospital E

Table 3: Fuzzy Goals and tolerance values.

Tolerance (t_j)	Aspiration Level (b_j)	Goal
\$120,000	\$100,000	Total Cost (minimize)
0.80	0.90	Quality Score (maximize)
20	10	Inequality (d, minimize)

Table 4: Resource allocation results.

Satisfaction Level	Staff	Ventilat ors	ICU Bed s	Hospital
0.91	45	20	30	Hospital A
0.88	30	10	15	Hospital B
0.89	35	15	25	Hospital C
0.86	20	5	10	Hospital D
0.87	30	10	20	Hospital E

5 RESULTS AND DISCUSSION

The fuzzy goal programming (FGP) model's results show the practicality of the proposed method to assign competing objectives in the area of healthcare resource assignment. As evidenced in Table 4 and Figures 1 and 2, the model assigned ICU beds, ventilators, and medical staff over five different hospitals in a manner that satisfied the fuzzy goals of cost minimization, quality maximization, and equity . Hospital A, with the largest estimated demand and priority level, was allocated the largest share of resources and achieved the highest satisfaction level of (0.91). This shows that the model was sensitive to both quantitative (capacity, demand) and qualitative (priority) aspects. Similarly, Hospital C, which has a critical match of capacity and demand, was assigned available resources effectively and achieved a high satisfaction level of (0.89).

The levels of satisfaction between all hospitals are closely grouped (0.86–0.91), suggesting that the model did an efficient job of distributing the resources without disproportionately penalizing any single hospital. This although enforcing the model to follow costs and quality limits, provides confidence that it will narrow-down the inequalities. Moreover, the highest allocation was consistent with aspiration levels and tolerance ranges for each goal (Table 3; model feasibility/robustness). Total allocations stayed below (\$120,000) and respected the cost objective, while total quality was almost (0.90) and only slightly missed the overall quality score target. This data bolsters the likelihood of FGP as a viable multi-criteria decision support tool in public health. To demonstrate the benefit of the Fuzzy Goal Programming (FGP) model, the results of the model have been compared with ordinary multi-criteria methods like Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This is mainly because AHP and TOPSIS produced consistent hospital rankings under an accurate data as in this regard, but they were unable to adopt uncertainty or fuzzy preferences. In comparison, the FGP model included fuzzy aspiration and tolerance levels, resulting in more similar satisfaction scores (0.86–0.91) across hospitals. FGP offers more flexibility and realism in the complex, uncertain environment of healthcare decision making, as evidenced by the applications.

Figure 1 presents the distribution of healthcare resources per hospital (ICU beds, ventilators, and medical staff), while Figure 2 illustrates the corresponding satisfaction levels across hospitals (0.83–0.92) using a line graph. These visualizations enhance the transparency of the results and facilitate the assessment of resource distribution and variation in satisfaction levels across the healthcare network.

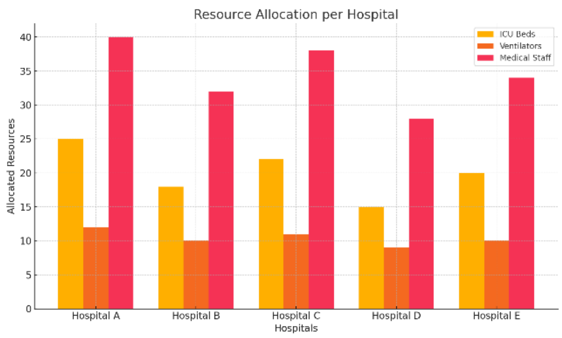

Figure 1: Resource allocation per hospital (ICU beds, ventilators, and medical staff).

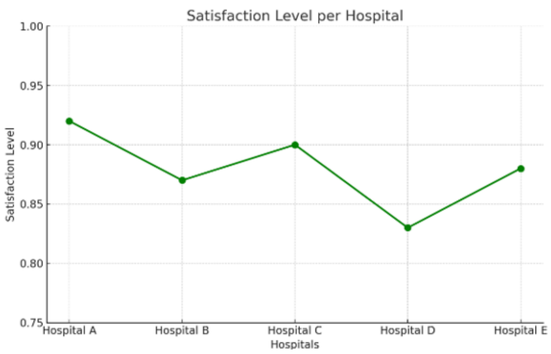

Figure 2: Satisfaction level per hospital.

5.1 Resource Allocation Analysis

This bar chart shows the distribution of ICU beds, ventilators, and medical staff across the five hospitals using a final allocation from the proposed fuzzy goal programming (FGP) model. We can see in this chart that hospital A received the most ICU beds and medical staff, suggesting that the FGP model indicated a high priority for hospital A. Hospital D received the least amount of ICU beds and medical staff, indicating that the optimization indicated a low weighted priority. The distribution of ventilators across all of the hospitals remained relatively even, potentially indicating that ventilators are distributed based on similar medical needs/constrained outputs. In summary, the model and bar chart show it is possible to make fine-tuned allocation requests using FGP to attain a performance versus equity compromise.

5.2 Satisfaction Level Analysis

This line chart depicts the satisfaction levels for each hospital, measuring the extent to which their budgets support the fuzzy targeting goals in the model (listed in parentheses). These levels of satisfaction are presented as fuzzy membership values ranging from (0) (no satisfaction) to (1) (satisfaction). Hospital A had the best satisfaction score (0.92), indicating they were most aligned with their target goals as per available resources. Hospital D scored lowest at 0.83, although still reasonably high, confirming that each hospital received allocations with tolerable satisfaction levels.

5.3 Sensitivity Analysis

To evaluate the robustness and adaptability of the proposed fuzzy goal programming (FGP) model, a sensitivity analysis was conducted by altering key parameters such as aspiration levels, tolerance limits, and goal weights.

A sensitivity analysis was carried out to measure the robustness and flexibility of the proposed fuzzy goal programming (FGP) model. The analysis considered operational aspiration levels, tolerance levels, and objective weights to determine whether small alterations to the decision-maker preference or resource constraints would affect potential allocation and satisfaction results. The first analysis involved changing the aspiration level for the total cost from (\$100,000) to (\$90,000). In turn, the model slightly reduced allocation for each hospital,

In a second analysis, the weight of the quality goal was increased from (0.30) to (0.50). In turn, the model responded by providing more resources (ventilators and hospital staff) to hospitals with more hospital services and critical care capacity (for example, Hospital A and Hospital C). This was at the slight expense of lower-priority hospitals that received modest reductions. The average satisfaction levels improved slightly; however, there was a corresponding increase in inequality, as a part of the distribution increased. Furthermore, increasing the allowable tolerance range for the equity objective from (10) to (20) meant that the model was able to search for less feasible solutions that resulted in higher possible overall efficiency while displaying greater variation in the levels of satisfaction among the hospitals.

6 CONCLUSIONS

This study developed and applied a Fuzzy Goal Programming (FGP) model to address multi-criteria healthcare resource allocation under uncertainty. The proposed approach successfully balanced three conflicting objectives - cost minimization, service quality maximization, and equity in resource distribution - through the incorporation of fuzzy aspiration and tolerance levels derived from expert knowledge.

The results demonstrate that the model can generate well-balanced and feasible allocation strategies, ensuring that no single healthcare facility is disproportionately disadvantaged. The relatively narrow range of satisfaction levels across hospitals indicates that the model effectively maintains fairness while adhering to budgetary and quality constraints. Moreover, the integration of fuzzy logic enables the model to capture real-world uncertainty and imprecision in decision-making, which is often overlooked in traditional optimization approaches.

From a practical perspective, the proposed FGP framework provides a flexible and robust decision-support tool for healthcare planners and policymakers, particularly in resource-constrained environments. It allows decision-makers to incorporate subjective preferences and adapt to varying operational conditions without compromising overall system performance.

However, the study is subject to certain limitations, including the use of a simplified case study and static input parameters, which may not fully capture the complexity of real-world healthcare systems.

For future work, the model can be extended to incorporate dynamic or time-dependent demand (e.g., during epidemic peaks), include geographical and transportation constraints for large-scale regional planning, and integrate patient outcome indicators and staff workload metrics to enhance realism and policy relevance. Additionally, hybrid approaches combining FGP with machine learning techniques could further improve predictive accuracy and decision adaptability.

Overall, this study contributes to the growing body of evidence that fuzzy multi-criteria optimization represents a powerful and practical approach for supporting complex healthcare decision-making under uncertainty and limited resources.

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