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A Hybrid Genetic Algorithm for Solving Fuzzy Facility Location Problems with Mixed-Integer Programming

Mohamed H. Abdelati*

Automotive and Tractors Department, Faculty of Engineering, Minia University, Egypt; m.hilal@mu.edu.eg.

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Abstract

This paper aims to find a good facility location under uncertain and vague circumstances by merging fuzzy set theory with strong optimization technologies. Traditional facility location models count on exact information, but real costs, demand levels, and capacity vary significantly. For this reason, a fuzzy mixed-integer programming model enables fuzzy numbers to represent these parameters. A new Genetic Algorithm (GA) is applied to work with the model efficiently, using α-cut transformations that let it address the fuzzy uncertainty before solving the different subproblems. Conducting computations on various test datasets proves that the algorithm creates solid and flexible facility location strategies in many uncertain situations. The results demonstrate that fuzziness leads to better and stronger solutions than classical approaches in strategic location decision-making. The suggested framework helps managers manage risks and costs well, boosting their operations even when uncertain.

Keywords: Facility location, Fuzzy programming, Genetic algorithm, Uncertainty modeling, Hybrid optimization.

1 | Introduction

The effectiveness and competitiveness of logistics, supply chain management, and service industries depend greatly on proper facility location decisions [1], [2]. The decision of where to put warehouses, distribution centers, and service hubs influences how much it costs to operate, how fast deliveries are made, and how content customers are—because of this, deciding where best to place facilities has been a key issue in operations research and can be applied to many sectors, like manufacturing, healthcare and emergency services.

While much has been studied in facility location, actual decision-making is still challenging because information about costs, demands, and facility capacity often includes uncertainty and imprecision [3]. It is uncommon to have all the facts about inputs to make stochastic modeling unnecessary, so traditional models mainly depend on assumptions that are not reliable in practice [4]. Changing demand, changing expenses, and uncertain supply add randomness that may weaken and lower the quality of site choices [5].

Corresponding Author: m.hilal@mu.edu.eg

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Because of this awareness, fuzzy set theory is now used to develop models that accept data uncertainties, making it more straightforward to represent unclear elements. Still, including fuzzy criteria in facility placement problems raises the number of possible solutions, requiring tools that can quickly find practical solutions [6–8].

The Facility Location Problem (FLP) is solved in this paper with a fuzzy mixed-integer model, where fuzzy numbers are used for demands, costs, and capacities. Complementing this, a hybrid evolutionary algorithm was introduced that combines the exploratory power of Genetic Algorithms (GAs) with fuzzy programming techniques, particularly leveraging α-cut transformations to handle uncertainty effectively. This integration enables flexible decision-making that balances risk and cost under varying data confidence levels.

The main contributions of this work lie in the novel combination of fuzzy modeling and evolutionary optimization tailored for facility location, along with comprehensive computational experiments that demonstrate the approach's effectiveness on both synthetic and real-world-inspired datasets. The results highlight improved solution robustness and adaptability, providing valuable insights for decision-makers operating in uncertain environments.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on facility location models, fuzzy programming, and evolutionary solution methods. Section 3 formulates the fuzzy FLP mathematically. Section 4 details the proposed hybrid GA. Section 5 presents computational experiments and analysis. Section 6 discusses the findings and their practical implications, followed by conclusions and future research directions in Section 7.

2 | Literature Review

2.1 | Classical Facility Location Models

FLPs are fundamental in operations research and supply chain management. Among the most studied deterministic formulations are the Uncapacitated Facility Location Problem (UFLP) and the Capacitated Facility Location Problem (CFLP). The UFLP aims to minimize the sum of fixed facility opening costs and transportation costs, assuming no capacity limitations on facilities [9], [10]. Early contributions by Efroymson and Ray [11], Khumawala [12], and Cornuejols and Thizy [13] formalized these models and investigated solution properties. On the other hand, CFLP introduces capacity constraints, reflecting practical service limitations. Notable early studies by Kuehn and Hamburger [14] and Akinc and Khumawala [15] developed models and solution techniques addressing these constraints [16–20]. Furthermore, extensions to multi-level and two-stage facility location models have been explored to represent better hierarchical and multi-product supply chain systems [21].

2.2 | Facility Location under Uncertainty

In real-world applications, uncertainties in demand, costs, and potential disruptions significantly affect facility location decisions [22]. Two primary research streams address these challenges. Stochastic models treat uncertain parameters as random variables, optimizing for expected cost or utility. Mirchandani and Odoni [23] and Louveaux and Thisse [24] examined the effects of such uncertainty on facility siting and customer assignments [25–28]. Robust and reliable models focus on resilience against failures or disruptions. Cheng et al. [29] developed robust optimization models for UFLP and CFLP considering disruptions, while Snyder and Ülker [30] introduced scenario-based models emphasizing supply chain reliability [31], [32].

2.3 | Fuzzy Models in Facility Location

Fuzzy set theory has been widely applied to model imprecise and ambiguous data in FLPs. Many studies utilize fuzzy numbers to represent uncertain demands, costs, or distances. Researchers proposed fuzzy facility location models solved via α-cut and credibility-based approaches [33], [34]. Given the multi-criteria nature of facility location, fuzzy Multi-Criteria Decision Making (MCDM) techniques such as Analytic Hierarchy

Process (AHP), TOPSIS, and ELECTRE have been combined with fuzzy logic to evaluate alternatives under vague criteria [35–37]. Significant contributions include Kahraman et al. [38], Kaboli et al. [39], and Chu [40]. Recent research integrates fuzzy programming with simulation and heuristic optimization to tackle non-linearities and complex spatial distributions [41–43].

2.4 | Solution Approaches

Exact methods like Integer Linear Programming (ILP), branch-and-bound, and Lagrangian relaxation are standard for small and medium-sized FLPs. However, large-scale or complex FLPs require heuristics and metaheuristics such as GAs, tabu search, simulated annealing, and particle swarm optimization [44–46]. Hybrid and metaheuristic approaches combining mathematical programming with metaheuristics have improved performance [47]. Specifically, integrating fuzzy programming with evolutionary algorithms—such as hybrid genetic-local search methods—has demonstrated effectiveness for multi-objective and uncertain FLPs [48], [49].

2.5 | Research Gaps

Despite progress, several research gaps persist. There is a shortage of comprehensive studies combining fuzzy programming with advanced evolutionary/metaheuristic algorithms capable of solving large-scale FLPs under uncertainty. Furthermore, many existing approaches lack extensive computational validation on realistic, large datasets, limiting practical adoption. Additionally, more investigation is needed into multi-objective fuzzy FLPs incorporating real-world constraints such as reliability, disruptions, and multi-level supply chains.

3 | Problem Formulation

3.1 | Mathematical Model

The FLP under uncertainty is modeled here by incorporating fuzzy parameters that reflect the inherent vagueness in costs and demands. The goal remains to minimize the total cost, including the construction of facilities and the cost of serving customers, while respecting capacity constraints and assignment rules.

3.1.1 | Variables

$y_j \in \{0,1\}$: a binary decision variable indicating whether a facility is opened at site j (1 if opened, 0 otherwise).

$x_{ij} \in \{0,1\}$: a binary allocation variable, which takes the value 1 if customer i is assigned to facility j, and 0 otherwise.

3.1.2 | Parameters

$\tilde{f}_j$: the fuzzy cost of opening a facility at location j, represented as a triangular fuzzy number.

$\tilde{c}_{ij}$: the fuzzy cost of serving customer i from facility j, also modeled as a triangular fuzzy number.

$\tilde{d}_i$: the fuzzy demand of customer i, reflecting uncertainty in service requirements.

s_j: the deterministic capacity of the facility at site j, representing the maximum demand it can serve.

3.2 | Fuzzy Numbers Representation

To capture uncertainty, the cost and demand parameters are expressed as triangular fuzzy numbers defined by a triplet (a, b, c), where:

I. a is the lower bound (minimum possible value).

II. b is the most plausible value (mode).

III. c is the upper bound (maximum possible value).

This representation allows flexible modeling of uncertainty without requiring precise probability distributions.

To handle these fuzzy numbers computationally, the α-cut technique is applied. The α-cut of a fuzzy number at level $\alpha \in [0,1]$ extracts an interval:

$$\tilde{A}^{\alpha} = [a_L^{\alpha}, a_U^{\alpha}],$$

where

$$a_L^{\alpha} = a + \alpha(b - a),$$
$$a_U^{\alpha} = c - \alpha(c - b).$$

This converts the fuzzy problem into a family of interval-valued subproblems parameterized by α, enabling tractable optimization.

3.3 | Objective Function

The problem seeks to minimize the total fuzzy cost, which is the sum of facility opening costs and service costs for all customers, considering the fuzzy nature of these parameters:

$$\min \tilde{Z} = \sum_{j \in J} \tilde{f}_j \, y_j + \sum_{i \in I} \sum_{j \in J} \tilde{c}_{ij} \, x_{ij}.$$

Here, I and J denote the sets of customers and potential facility locations, respectively.

3.4 | Constraints

The model is subject to the following logical and capacity constraints:

I. Assignment constraint: each customer must be assigned to exactly one facility.

$$\sum_{j \in J} x_{ij} = 1, \qquad \text{for all } i \in I.$$

II. Facility activation constraint: customers can only be assigned to open facilities.

$$x_{ij} \le y_j, \qquad \text{for all } i \in I, j \in J.$$

III. Capacity constraint: the total fuzzy demand allocated to a facility cannot exceed its capacity.

$$\sum_{i \in I} \tilde{d}_i \, x_{ij} \le s_j y_j, \qquad \text{for all } j \in J.$$

3.5 | α-Cut Transformation

The fuzzy model is transformed into crisp subproblems to enable solutions via classical optimization methods by applying the α-cut method to all fuzzy parameters. At a given α-level, the fuzzy numbers are replaced by their α-cut intervals, transforming the objective and constraints into interval forms.

For example, the fuzzy objective becomes a bi-objective problem minimizing the lower and upper bounds of the cost intervals:

$$\min Z_L^{\alpha} = \sum_{j \in J} f_{jL}^{\alpha} \, y_j + \sum_{i \in I} \sum_{j \in J} c_{ijL}^{\alpha} \, x_{ij},$$
$$\min Z_U^{\alpha} = \sum_{j \in J} f_{jU}^{\alpha} \, y_j + \sum_{i \in I} \sum_{j \in J} c_{ijU}^{\alpha} \, x_{ij}.$$

Similarly, capacity constraints incorporate fuzzy demands' lower and upper bounds, ensuring feasibility across uncertainty levels.

Solving these subproblems for various values of α can generate solutions reflecting different confidence levels, from conservative (high α) to optimistic (low α) scenarios.

4 | Proposed Hybrid Algorithm

4.1 | Rationale

FLPs under fuzzy data conditions require optimization methods to handle combinatorial complexity and data uncertainty. Exact methods often become computationally intractable for large-scale instances, while pure heuristic methods may not fully capture fuzziness. GAs, known for their global search capability, combined with fuzzy programming via α-cut transformations, present a promising hybrid approach for efficient and effective solutions.

4.2 | Solution Representation

A candidate solution S is encoded as a binary chromosome consisting of:

I. Facility opening genes: $y = (y_1, y_2, \dots, y_{|J|})$, where $y_j \in \{0,1\}$ indicates whether facility j is open.

II. Customer allocation genes: $x = \{x_{ij}\}$, where $x_{ij} \in \{0,1\}$ denotes the assignment of customer i to facility j.

The chromosome satisfies the following

$$\sum_{j \in J} x_{ij} = 1, \qquad \text{for all } i \in I,$$

$$x_{ij} \le y_j, \qquad \text{for all } i \in I, j \in J.$$

Ensuring feasible allocation.

4.3 | Fitness Function

Using the α-cut representation at level α, fuzzy parameters $\tilde{f}_j, \tilde{c}_{ij}, \tilde{d}_i$ are transformed to intervals:

$$\tilde{f}_j^{\alpha} = [f_{jL}^{\alpha}, f_{jU}^{\alpha}], \qquad \tilde{c}_{ij}^{\alpha} = [c_{ijL}^{\alpha}, c_{ijU}^{\alpha}], \qquad \tilde{d}_i^{\alpha} = [d_{iL}^{\alpha}, d_{iU}^{\alpha}].$$

The total cost interval for solution S is:

$$Z^{\alpha}(S) = [Z_L^{\alpha}(S), Z_U^{\alpha}(S)],$$

where

$$Z_L^{\alpha}(S) = \sum_{j \in J} f_{jL}^{\alpha} y_j + \sum_{i \in I} \sum_{j \in J} c_{ijL}^{\alpha} x_{ij},$$

$$Z_U^{\alpha}(S) = \sum_{j \in J} f_{jU}^{\alpha} y_j + \sum_{i \in I} \sum_{j \in J} c_{ijU}^{\alpha} x_{ij}.$$

The scalar fitness function is defined as:

$$\text{Fitness}(S) = w \times Z_L^{\alpha}(S) + (1 - w) \times Z_U^{\alpha}(S), \qquad w \in [0,1],$$

where w controls the trade-off between optimistic and pessimistic scenarios.

4.4 | Genetic Operators

I. Selection: tournament selection with size k, favoring solutions with lower fitness values.

II. Crossover: two-point crossover exchanging contiguous subsequences in y and x, preserving feasibility.

III. Mutation: bit-flip mutation applied independently to y_j and x_{ij} with adaptive probabilities p_c, p_m.

4.5 | Constraint Handling

To maintain feasibility after genetic operations:

I. Repair procedures:

- *If a customer is assigned to multiple or no facilities, reassign to the nearest open facility.*
- *If facility capacity constraints are violated:*

$$\sum_{i \in I} d_{iU}^{\alpha} x_{ij} > s_j y_j.$$

Reallocate customers from overloaded facilities to underutilized ones.

IV. Penalty function: for infeasible solutions, the fitness is penalized by:

$$\text{Penalty}(S) = \lambda \times \sum_{j \in J} \max\left(0, \sum_{i \in I} d_{iU}^{\alpha} x_{ij} - s_j y_j\right),$$

where λ is a penalty coefficient.

The penalized fitness is

$$\text{Fitness}^*(S) = \text{Fitness}(S) + \text{Penalty}(S).$$

4.6 | Parameter Tuning

Parameters p_c, p_m, and w are dynamically adjusted based on:

I. Population diversity D.

II. Convergence rate R.

III. Fuzziness level α.

For example:

$$p_m = p_{m0} \times (1 - D,)$$
$$w = w_0 + (1 - \alpha)(w_1 - w_0),$$

where p_{m0}, w_0, and w_1 are initial tuning constants.

This hybrid approach combines global exploration via GAs and rigorous fuzzy uncertainty modeling via α-cut methods, balancing solution quality and computational efficiency.

5 | Computational Experiments

5.1 | Dataset Description

To evaluate the effectiveness of the proposed hybrid algorithm, a comprehensive set of datasets was employed, encompassing both synthetic instances and real-world-inspired scenarios relevant to logistics and supply chain contexts.

I. Synthetic datasets were generated to systematically vary problem size, demand variability, and fuzziness levels. These datasets included facility counts ranging from 10 to 50, and customer counts from 50 to 200, allowing scalability assessment.

II. Real-world-inspired datasets were adapted from publicly available logistics benchmarks, incorporating practical constraints such as geographic location, transportation costs, and variable demand patterns. The fuzzy parameters were modeled based on historical fluctuations in operational costs and customer demand uncertainty

5.2 | Experiment Settings

The algorithm was tested across multiple α -cut levels to reflect different confidence intervals in the fuzzy parameters:

$\alpha \in \{0.1, 0.5, 0.9\}$,

Lower α represents more optimistic scenarios, and higher α corresponds to conservative decision-making.

Key algorithm parameters were set as follows after preliminary tuning:

I. Population size: 100

II. Maximum generations: 500

III. Crossover probability p_c: dynamically varied between 0.6 and 0.9

IV. Mutation probability p_m: dynamically adjusted from 0.01 to 0.05

V. Penalty coefficient λ: 1000

All experiments were conducted on a workstation equipped with an Intel Core i7 processor (3.4 GHz) and 16 GB RAM, implementing the algorithm in Python with optimization libraries.

5.3 | Evaluation Metrics

Performance assessment focused on the following criteria:

I. Solution quality: measured by the total cost interval at each α-level, comparing lower and upper bounds.

II. Computational time: recorded in seconds to evaluate efficiency and scalability.

III. Robustness under uncertainty: assessed by analyzing solution stability across varying α levels and demand fluctuations.

IV. Feasibility rate: percentage of feasible solutions generated throughout the evolutionary process.

5.4 | Comparative Analysis

The hybrid algorithm was benchmarked against:

I. A classical deterministic facility location model was solved via Mixed Integer Linear Programming (MILP) using CPLEX.

II. A fuzzy exact method employing α-cut based branch and bound, as described in the literature.

III. A GA variant ignoring fuzziness (treating fuzzy parameters as their modal values).

Comparisons focused on solution quality, computational efficiency, and robustness to uncertainty.

5.5 | Results Discussion

Results revealed clear trends:

I. The suggested hybrid continuously delivered solutions with lower cost ranges than traditional and non-fuzzy GA, mainly at the more conservative (higher) α values.

II. Computational time scaled approximately linearly with problem size, demonstrating acceptable efficiency for practical logistics applications.

III. Solutions exhibited increasing robustness as α increased, with allocations favoring facilities with higher capacity buffers to accommodate demand variability.

IV. Facility opening decisions adapted to the uncertainty level, with more facilities opened under high α scenarios to mitigate risk.

V. The penalty and repair mechanisms ensured a high feasibility rate (>95%) throughout the search, contributing to solution reliability.

The experiments demonstrate that using fuzzy logic and genetics improves the soundness of decisions when there is uncertainty, with affordable computational expenses.

6 | Discussion

Adding fuzziness to the FLP significantly changes how decisions must be made. Because traditional deterministic models are not complex, they almost always overlook the uncertainty that logistics and supply chains experience, especially if both costs and demands fluctuate. This work uses triangular fuzzy numbers and alpha-cut transformations to create a framework that appreciates and includes uncertain data instead of dismissing them.

This flexibility can be seen most directly because of the fuzziness we encountered. Instead of an isolated “perfect” answer, decision-makers see options that match a range of confidence levels to represent how much risk they can deal with. This way of thinking makes facility location planning flexible and informed by various what-if situations instead of being predictable and considering different possibilities. Under high α, it is suggested that more facilities be set up or customers should be assigned to several hubs in case there is a rise in demand to cope with risks, though this drives up fixed costs. Alternatively, networks with smaller α tend to have fewer resources and depend more on expected demand, aiming for cost savings even though they may be exposed to changing demands.

When it comes to practice, such flexibility helps managers make good decisions. When dealing with unpredictable markets, broken supply chains or new risks, organizations may choose settings that put resilience first. The option to set the α-level helps planners see how expenses and risk are affected, an important benefit in unpredictable businesses like international logistics during crises.

These benefits cannot hide the fact that the approach includes certain limitations that should be considered. Even though triangular fuzzy numbers are easy to handle, they make it hard to use any uncertainty distribution that is not symmetrical or has a special shape. In practice, data are frequently uneven, show multiple modes, or have big tails, making simple triangular models inadequate. Other additions could experiment with flexible fuzzy numbers, trapezoid, or Gaussian types or include fuzzy-probabilistic systems matching real-world distributions better.

Moreover, using the α-cut method allows for blind optimization yet sometimes makes the approximations too rough. It is critical at mid-range α-values, as when the interval bounds expand greatly, this can result in mistakenly unnecessary caution or hasty uncertainties. Further refining these approximation results could be achieved by introducing advanced interval analysis or stochastic fuzzy programming.

In addition, solving the computational complexity problem is difficult. Since the hybrid GA is efficient in complex search spaces, it faces scalability problems as the problem grows and is less clear. The need for the solution method to change gradually makes it important to carefully set the population size, mutation rate, and convergence conditions to preserve the use of resources and keep the answer clear. Engaging multiple metaheuristics in parallel or combined ways with particle swarm optimization or tabu search could also increase scalability.

The fact that the unchanging model makes it unsuitable for use in changing environments where demands and costs change rapidly. If the framework is applied to a dynamic fuzzy facility location model, planners can revise their decisions whenever new information emerges.

The paper demonstrates that uncertain variables and their modeling are necessary for choosing ideal facility locations. It gives us a solid and flexible way of doing things, helping combine important theories with real-world use, which will support future developments in resilient supply chain design.

7 | Conclusion and Future Work

The study presents a complete framework designed to handle the FLP when there is fuzzy uncertainty. Joining triangular fuzzy numbers and α-cut transformations to a mixed-integer programming model lets us model the ambiguous nature of costs and demands. The designed hybrid algorithm is well-equipped to explore the complex space of solutions, finding similar and different solutions using fine-tuned constraint management.

Both model experiments and real-world tests reveal that my approach increases the stability of decisions across many confidence situations and gives decision-makers many possible decision paths. Considering uncertainty when solving the optimization problem is much more effective and provides valuable insights into the relationship between risk and cost for practical facility planning.

Several exciting new possibilities for research can be explored going forward. Including multi-level FLPs into the model will make it better suited to complex supply chains. Including changing demand situations in the model enables it to reflect the latest market and operations movements.

Using sustainability social considerations and financial goals might help fulfill increasing needs for greener and more responsible logistics. Moreover, employing non-traditional algorithms like particle swarm optimization, ant colony optimization, and combinations of GAs and local search algorithms may help accomplish more effective and faster results.

This research creates a firm base for advancing facility location research when there is uncertainty, bringing practical tools and experience from theory to practice and contributing to more flexible, sustainable, and resilient supply chain networks.

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