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New Technique for Solving P-Median Problems based on Fuzzy System and Genetic Algorithm

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Abstract

Position analysis issues such as the placement of public service facilities, power stations, telecommunication network switches, and similar infrastructure constitute a broad and extensively studied domain within operations research. Due to their significant impact on resource utilization and operational efficiency, these problems are highly valued by managers across various service industries. Among the most prominent problems in this field is the P-Median Problem (PMP), for which numerous deterministic and heuristic solution methods have been developed. This research introduces a hybrid fuzzy approach to address the PMP. A bi-objective optimization model is formulated, with the first objective focusing on the minimization of total transportation cost and the second on maximizing the coverage of demand points by the facilities. The proposed algorithm is validated using benchmark problems available in the existing literature.

Keywords: P-median problems, Bi-objective function, Genetic algorithm, Sexual selection, Fuzzy system.

1 | Introduction

The P-Median Problem (PMP) is a fundamental issue in facility location planning, aiming to optimize the placement of a fixed number of facilities to minimize the total service cost or distance to demand points [1]. Traditional exact methods often struggle with computational complexity when dealing with large-scale or real-world problems, prompting widespread interest in heuristic and meta-heuristic solutions. Early research primarily focused on classical optimization techniques, yet the inherent uncertainties and vagueness associated with real-world data require more flexible and robust approaches.

Fuzzy logic has gained prominence as a powerful tool for modeling uncertainty and imprecision in location allocation problems. Notably, Eslami and Mirbaha [2] introduced a fuzzy system combined with Genetic

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Algorithms (GAs) for a multi-objective location problem, demonstrating enhanced capability in handling ambiguous information, such as congestion and service quality. Similarly, Syzonov et al. [3] explored fuzzy GAs, offering new perspectives on their effectiveness for complex optimization challenges. These advances highlight the potential of integrating fuzzy systems with evolutionary algorithms to improve solution robustness and adaptability in uncertain environments.

Parallel to fuzzy approaches, bio-inspired meta-heuristics such as GAs and Particle Swarm Optimization (PSO) have shown substantial success in solving location problems [4–6]. For instance, Taghikhani et al. [7] developed a hybrid PSO algorithm modified for the inverse PMP in fuzzy-random settings, emphasizing the importance of hybridization techniques for enhancing convergence and solution quality. Other studies, such as Subburaj et al. [8], proposed adaptive memetic algorithms incorporating population diversity control to address multi-objective and complex location problems, illustrating the continuous evolution of meta-heuristics in this domain.

The integration of fuzzy systems with GAs represents a promising frontier for addressing the complexities inherent in PMPs, especially under uncertainty and vagueness. By leveraging fuzzy logic's capability to model imprecision and GAs' robustness as search heuristics, innovative solution techniques can be developed for real-world applications that demand flexibility, efficiency, and accuracy. Recent advancements, including fuzzy GAs and hybrid meta-heuristics, demonstrate the efficacy of these combined approaches in producing high-quality solutions for various location problems, including healthcare, transportation, and logistics [9].

Building upon this foundation, the present study proposes a novel technique that combines fuzzy systems with GAs explicitly tailored for the PMP. This hybrid approach aims to capitalize on the strengths of both methodologies-fuzzy logic's capacity for uncertainty modeling and GAs' evolutionary search capabilities to enhance solution quality, convergence speed, and resilience against data vagueness. Such a method is expected to outperform existing algorithms, particularly in complex or uncertain environments, thus contributing significantly to the body of knowledge in location allocation optimization.

The proposed framework also addresses some limitations observed in previous works, such as premature convergence and local optima entrapment in GAs, by incorporating fuzzy logic to guide search processes more intelligently. Furthermore, by utilizing adaptive mechanisms inspired by biological evolution, the method ensures dynamic adjustment to varying problem conditions, enhancing its applicability across diverse real-world scenarios. This aligns with ongoing research trends emphasizing hybrid and intelligent algorithms for facility location problems, especially given their immediate relevance to urban planning, supply chain management, and service delivery systems.

The development of a new technique for solving PMPs based on a fuzzy system and genetic algorithm is both timely and necessary. It synthesizes recent research insights-ranging from the application of fuzzy logic in location problems to the hybridization of meta-heuristics and the adaptive features of memetic algorithms [2], [7], [8]. This integrated approach aims to improve solution effectiveness in uncertain environments, advancing theoretical understanding and practical implementation of facility location optimization. Such innovations are crucial for addressing the increasingly complex spatial and operational challenges faced by modern public, private, and healthcare systems.

Suppose a set F ($|F| = N$) of possible facilities, p is the number of facilities that are considered for the UPMFLP, and let U be a set of users that these facilities must serve. The cost of serving user u with facility f is given by the distance $d(u, f)$ between them. If $S_i \subseteq N$ such that $|S_i| = P$ $(i = 1, .. C(N, P))$, then there are $C(N, P)$ordered pair $((\mathrm{Cost}(S_i), \mathrm{Cover}(S_i))$. The UPMFLP consists of determining a set $S_i \subseteq F$ of facilities ($|S_i| = P$) so as to minimize the total $\mathrm{Cost}(S_i)$ and maximize $\mathrm{Cover}(S_i)$.

$$\mathrm{Cost}(S_i) = \sum_{u \in U} \min d_{f \in S_i}(u, f). \quad (1)$$

$$\mathrm{Cover}(S_i) = \text{ number of demand points which are serviced by facilities in.} \quad (2)$$

To solve the UPMFLP, different types of GAs have been used before. In contrast to Herrera and Lozano [10], who considered almost all chromosomes in each generation and found a probability crossover for the next generation, we will consider a unique probability for each parent. GA and the fuzzy system will be utilized such that the fuzzy system will be used to control the two parameters of the GA, i.e., the selection of chromosomes and crossover probability.

2|Literature Review

The study of facility location problems has stood at the core of operations research and decision sciences for decades, owing to their critical importance in various logistics, service provision, and infrastructure design contexts. Among these, the PMP has received particular scholarly attention due to its practical relevance and computational complexity.

The fundamental objective of the PMP is to identify the optimal placement of p facilities among potential sites to minimize the total transportation or service cost to demand points, a formulation that inherently blends combinatorial optimization with spatial analysis. This classical problem has inspired a prolific body of scholarship, leading to diverse solution methodologies, from exact algorithms to heuristic and metaheuristic techniques aiming to balance computational efficiency with solution quality.

Early significant contributions by Alp et al. [11] developed an efficient genetic algorithm tailored explicitly for the PMP, pioneering the application of evolutionary computation to this class of problems. Their work demonstrated that GAs could be adapted effectively to combinatorial location tasks, achieving high-quality solutions within reasonable computational times. This foundational research set the stage for subsequent investigations expanding on metaheuristic frameworks, with Chaudhry et al. [12] extending GAs' applicability to broader classes of facility location problems, emphasizing the flexibility of genetic operators and their capacity to model complex constraints.

Subsequently, Bozkayaet al. [13] revisited the genetic algorithm approach, enhancing algorithmic efficiency and robustness for larger instances of the PMP, thus reinforcing the GA's viability as a primary solution technique. Their work underscored the significance of initialization strategies, crossover, mutation operators, and selection mechanisms in shaping the algorithm's performance, aligning with the broader exploration of genetic operator efficacy documented by Erdoğmuset al. [14].

In parallel, soft computing methodologies, particularly hybrid algorithms combining fuzzy logic with metaheuristics, gained prominence. Cadenas et al. [15], [16] pioneered such efforts by proposing hybrid algorithms and heuristics that integrated fuzzy logic principles into PMP frameworks. Their models, incorporating fuzzy data and uncertainty, reflect an evolving realization that real-world facility location issues seldom adhere to precise data assumptions. Their subsequent work demonstrated that hybrid fuzzy algorithms could yield solutions that better capture the ambiguity inherent to practical decision-making environments.

The application of fuzzy theory extends further into the probabilistic and fuzzy environments, with Yazdi and Abbasi [17] modeling fuzzy probability-based PMPs and Taghi-Nezhad [18] establishing fuzzy vertex optimality theorems, both attempting to formalize and solve the problem under uncertainty. These studies integrate soft computing techniques, such as fuzzy logic, with traditional optimization to produce solutions adaptable to uncertain or incomplete data, thus broadening the classical deterministic models popularized by prior research.

Metaheuristic algorithms, beyond GAs, have also been intensely explored. Basti and Sevkli [19] employed Artificial Bee Colony (ABC) algorithms to efficiently solve the PMP, illustrating the potential of swarm intelligence techniques. Similarly, Lin and Guan [5] introduced hybrid binary PSO strategies tailored for the obnoxious PMP, an extension incorporating adverse factors highlighting the ongoing diversification of solution approaches to encompass more complex variants.

The importance of hybrid algorithms combining multiple metaheuristics and exact methods has become increasingly apparent. Taghikhani et al. [7] proposed a hybrid modified PSO algorithm for solving inverse

PMPs in fuzzy random environments, demonstrating the maturity of hybrid approaches to handle inverse modeling and uncertainty simultaneously. Correspondingly, other works, such as Ekin [20], utilize integer programming frameworks integrated with GAs to improve scalability and precision in solving large-scale instances

A recurring theme across these studies is the emphasis on heuristic hybridization and adaptive strategies. Cadenas et al. [16] explored soft computing heuristics, while Syzonov et al. [3] contributed a comprehensive review of Fuzzy Genetic Algorithms (FGA), emphasizing their robust performance in multi-objective and uncertain environments. These efforts are complemented by research focusing on multi-objective formulations, as seen in the works by Shafiei et al. [21], employing hybrid GAs for multi-criteria facility locations in emerging network contexts such as 5G and IoT infrastructure.

The evolution of algorithms for the PMP also encompasses techniques adapted for large-scale and distributed settings. Gwalani et al. [22] proposed a distributed expectation-maximization algorithm capable of tackling vast datasets, addressing the computational challenges faced when scaling traditional algorithms to real-world, big-data environments. Such developments are crucial, given the increasing complexity of facility location problems in the era of big data, big networks, and distributed decision-making. These models align with the reality that facility location decisions often operate under conflicting objectives, incomplete data, and dynamic environments.

Furthermore, recent scholarship emphasizes the importance of assessing the efficacy of various metaheuristic operators in different contexts, with studies like Erdoğmus et al. [14] providing comparative analyses of genetic crossover operators with implications for algorithm selection and tuning. Such comparative analyses are essential for understanding the relative strengths and weaknesses of different heuristic strategies, especially as the field moves toward more sophisticated algorithms that combine multiple techniques, such as memetic algorithms, GAs, PSO, and hybrid metaheuristics. Concurrently, there is increasing awareness of the importance of robustness and adaptability in these algorithms.

Subburaj et al. [8] reviewed meta-heuristic methods with a focus on their robustness and proposed fuzzy-system-based self-adaptive memetic algorithms incorporating population diversity control to efficiently address multi-objective problems in complex environments, including health and communication networks.

The relationship between exact and approximate methods continues to be a pertinent area of investigation. While precise models like those discussed by Ekin [20] provide benchmark solutions and theoretical insights, their computational intensity limits application to smaller instances. Consequently, hybrid, metaheuristic, and approximation algorithms have gained prominence for their practicality in solving large, complex instances, especially when combined with concepts like decomposition or distributed algorithms [18], [22–24].

Finally, the trajectory of the literature indicates an increasing integration of soft computing paradigms, fuzzy logic, neural networks, and evolutionary algorithms with the overarching goal of enhancing solution quality, handling uncertainty, and increasing computational scalability. Studies such as Taghikhani et al. [7], Syzonov et al. [3], and Subburaj et al. [8] exemplify this trend, deploying hybrid algorithms that leverage the strengths of different soft computing and metaheuristic approaches, often within multi-objective and uncertain environments.

3 | Fuzzy Genetic Algorithm

GA is a search optimization technique that mimics some of the processes of natural selection and evolution. There are four stages in utilizing the GA: Encoding, selection, recombination, and mutation. The one-to-one association between a chromosome and the corresponding solution is determined by proper encoding. In GA, there is a function that evaluates the quality of a chromosome. For each problem to be solved, one has to supply a fitness function, and certainly, its choice is critical to the good performance of the GA. Given a chromosome, the fitness function must return a response that represents the chromosome's utility.

In optimization, when a GA fails to find the global optimum, the problem is often credited to premature convergence, which means that the sampling process converges on a local optimum rather than the global optimum. This problem happens when the diversity of the population is low. In a GA, crossover and mutation are used to promote genetic diversity.

In this study, a hybrid of genetic algorithm and fuzzy system is considered for solving UPMLP. In this FGA, a sexual selection scheme is proposed, and a novel technique based on the fuzzy system for controlling the probability of crossover is introduced. The fuzzy system used in this study is based on the linguistic fuzzy rules. For the recombination of two chromosomes, the male and female are selected randomly. The fuzzy system considers membership functions of inputs, output, and fuzzy rules, and consequently, a suitable probability for the recombination of these chromosomes is calculated. The general framework of FGA is shown as follows:

Algorithm 1. FGA.

```
begin
Initialise population (Randomly generated),
Fitness evaluation,
Population is divided into two categories: Male and female,
Selection
Male and female are selected randomly,
Crossover
The probability of crossover is calculated by a fuzzy system,
2-point_crossover,
 Mutation,
Fitness evaluation,
Elitism,
until the end condition is satisfied,
return the fittest solution found,
End.
```

3.1|Encoding

Suppose that in one UPMFLP, the N facilities are indexed to numbers 1, 2… and N. A simple encoding is used where the genes of chromosomes correspond to the indices of the selected facilities. For example, the uncapacitated 6-median facility location problem (2, 5, 6, 23, 19, 7) is a chromosome where demand points 2,5,6,23,19 and 7 are selected as facility locations. Note each gene in each chromosome appears at most one time.

3.2|Fitness Function

The fitness function must be able to reflect the objective and direct the search toward an optimal solution. The fitness of a chromosome is the same as the objective function value of the solution it corresponds to, and it can be calculated using the problem data. In this research, the fitness function is a bi-objective function of UPMFLP. For each chromosome, the fitness function is calculated as an ordered pair (Cost, cover) as defined in Section 1.

3.3 | Selection

For each chromosome, a sexual characteristic is considered. The population is divided into two categories, male and female so that the male and female can be selected in an alternate way. In each generation, the layout of the selection of males and females is different. It means that if in the generation number t chromosome c_i is a male, but in the next generation c_i is a female chromosome. During sexual selection, the male chromosome and female chromosome are selected randomly.

3.4 | Crossover

3.4.1 | Method of crossover

In a typical GA, two chromosomes are selected for crossover, and their genes are merged in an approved way to produce two offspring. In this study, we considered two-point crossovers, but the layout of genes is different in each generation. Crossover occurs as follows:

If the number of generations is even:

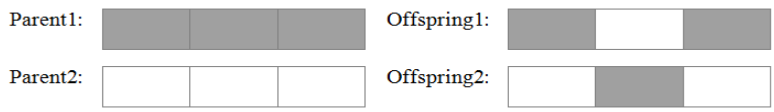

Fig. 1. Two-point crossover with dynamic gene layout for each generation.

If the number of generations is odd:

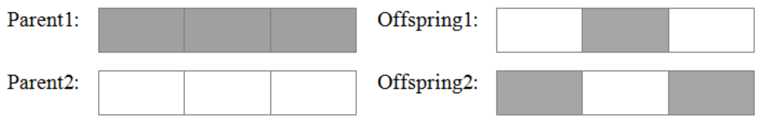

Fig. 2. Crossover method for odd generations in GA.

If the two parents are the same as each other, one of the parents is kept unchanged for the next generation, and the other parent is deleted. These techniques guarantee that there will be no duplicate facility indexes in any of the two offspring created by crossover.

3.4.2 | Probability of crossover

The fitness values of chromosomes are considered for controlling probability in each generation. Since fitness value is calculated based on two objective functions, two membership functions corresponding to objective functions are defined: The membership function for minimum summation and the membership function for maximum covering.

Membership function for minimum summation

Postulate F_D is desirable summation, and δ is the difference between maximum summation and minimum summation. Three level summations are considered: low summation (F_L), medium summation (F_M) and high summation (F_H). The corresponding triangular membership function is shown in *Fig. 1*.

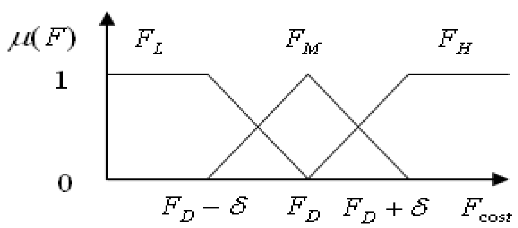

Fig. 3. Membership function for minimum summation distances.

Membership function for maximum covering

This computation is performed in every generation for all chromosomes. The corresponding triangular membership function is shown in *Fig. 2*.

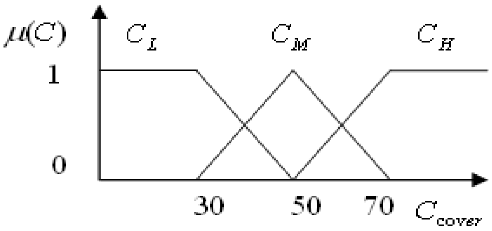

Fig. 4. Membership function for maximum covering.

Membership function for probability crossover

Corresponding inputs in the system for the probability of crossover are considered for three levels: Low, medium, and high. The corresponding triangular membership function is shown in *Fig. 3*.

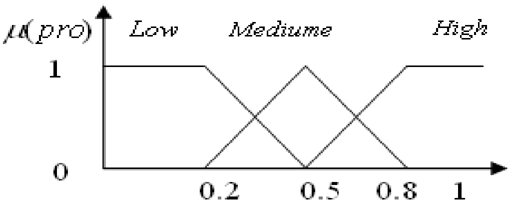

Fig. 5. Membership function for probability of crossover.

3.4.3 | Fuzzification

The system consists of four fuzzy inputs, namely summation distance and covering for male and female chromosomes, and one fuzzy output, namely probability of crossover, as illustrated in *Fig. 4*.

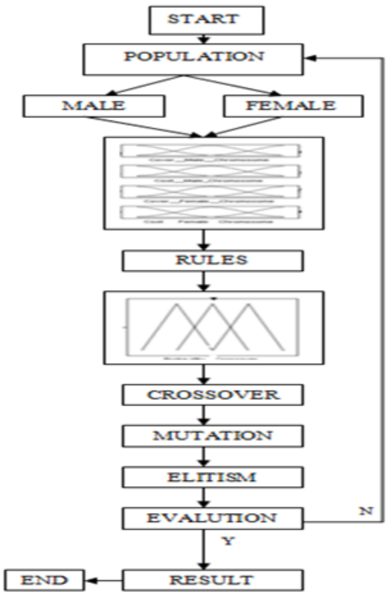

Fig. 6. Order of performances in the new genetic algorithm.

Fuzzy rule base

A fuzzy rule base is a set of "if-then" rules used in fuzzy logic systems to encode expert knowledge or decision criteria. It forms the core of a fuzzy inference system and allows the system to interpret uncertain, imprecise, or qualitative information. On the other hand, fuzzy rules explain the relative between the inputs and outputs. A sample fuzzy rule base: Fuzzy logic control governing the probability control is given in *Table 1*.

Table 1. Fuzzy rule base for the control of probability crossover.

Rule	S_{Male}	C_{Male}	S_{Fmale}	C_{Fmale}	$\mathbf{Prob.\,Crossover}$
1	F_L	C_L	F_L	C_L	High
2	F_L	C_L	F_M	C_M	High
3	F_L	C_L	F_H	C_H	Medium
4	F_M	C_M	F_M	C_M	Medium
5	F_M	C_M	F_H	C_H	Low
6	F_H	C_H	F_H	C_H	Low

3.4.4 | Defuzzification

As is shown in *Fig. 4*, there are four inputs that are considered for making linguistic rules and membership functions [25]. The inputs are combined logically using the AND operator to produce output response values for all expected inputs, which means that the rule strengths are obtained by computing the minimum of the membership functions of antecedents.

The center of gravity method is applied to defuzzify the output. The fuzzy output of the system is the 'fuzzy OR' of all the fuzzy outputs of the rules with non-zero rule strengths.

3.5 | Mutation

The mutation operator is essential in a genetic algorithm. Although crossover supplies much of the processing power, sometimes a particular demand point (Facility) from the set of demand points (Facilities) may not appear or be eliminated very soon. Then, the mutation is used in GA for the improvement of these problems. Mutation is performed in two steps:

I. Each chromosome is assigned a random natural number k, $k \in [1, L]$, where L is the length of the chromosomes.

II. The k^{th} gene is replaced by another randomly generated gene (A facility index), subject to the constraint that the new facility index is not there in the current genotype of the chromosome.

3.6 | Elitism

In each generation, a bound for error and a bound for cover are considered, and a percentage of the best chromosomes that are inbound condition is selected for the next generation.

3.7 | Stopping Condition

In this study, the stopping condition for the fuzzy genetic algorithm is the maximum number of generations.

4 | Computational Results

The algorithm was tested on 40 test problems from the ORLIB library [25]. The problem sizes range from 100 to 900, and p =5 to 200. The number of generation 1000 and the number of initial populations 100 are considered. These problems are reported:

The average of minimize total: $\mathrm{Cost}\ (S_i)$

The average error: Error is the difference between the desirable solution and the best result.

The average of minimize total: $\mathrm{Cover}(S_i)$

The average number of generations: N

4.1 | Experiment 1

The simple genetic algorithm was tested. The probability of crossover is 0.50, and the probability of mutation is considered, where L is the length of chromosomes. The experiment was tested on 40 UPMFLP test problems from the OR Library [25]. In this method for elitism, errors belong to [-2, 2] and cover at least 85%. The results of the test problems are listed in *Table 2*.

4.2 | Experiment 2

The fuzzy genetic algorithm was tested in two traditions. The number of generation 1000 and the number of initial populations 100 are considered, and 40 UPMFLP are considered [25]. The probability of crossover is different, and the probability of mutation is considered to be, where L is the length of chromosomes.

I. The fitness values are calculated as an ordered pair (Cost, cover) on UPMFLP for the whole number of generations. The results of the test problems are listed in *Table 3*.

II. In this method, the number of generations is different. We calculated the first result such that errors belong to the interval [-3,3] and covers are more than 70%. The results of the test problems are listed in *Table 4*.

5 | Conclusion

In this study, a bi-objective function is introduced for UPMFLP, and fuzzy tools have been presented for controlling the probability of crossover. Looking over the results in *Tables 2*, *3,* and *4*, we can safely conclude that the FGA is a very robust GA since it can take the best results for summation distance such that the covering of facilities is high too. This FGA is convenient because it adapts the probability of crossover to the setting that returns the best results. This technique supplies reasonable levels of diversity to be administered using the FGA. Therefore, we may conclude that this bi-objective function and control probability of crossover by fuzzy tools is a suitable way to improve the results of GAs on UPMFLP.

Table 2. Simple genetic algorithm for UPMLP.

Test	N	P	Min. Cost	Error	Cover	Time (s)	Nu. Generation
1	100	5	5819.33	0.99	86.00	1.33	978.96
2	100	10	4093.00	0.00	73.01	2.58	753.71
3	100	10	4251.00	-0.98	63.00	4.83	960.53
4	100	20	3038.00	-3.99	57.00	8.05	322.00
5	100	33	1400.00	-44.9	99.98	21.88	500.00
6	200	5	7824.57	-0.53	97.00	3.75	251.24
7	200	10	5630.05	0.95	91.95	8.71	759.95
8	200	20	4445.00	-0.01	91.53	22.61	526.55
9	200	40	2734.44	-0.47	90.01	80.04	630.38
10	200	67	1255.00	0.00	91.25	299.13	632.75
11	300	5	7696.48	-0.44	96.25	8.13	653.83
12	300	10	6634.99	-0.99	96.00	16.15	742.45
13	300	30	4346.01	0.99	93.40	73.91	556.67
14	300	60	2967.57	0.43	94.46	352.26	673.28
15	300	100	11728.34	0.66	86.14	893.94	725.23
16	400	5	8161.99	0.02	96.07	14.45	611.71
17	400	10	6999.02	-0.18	96.58	27.53	659.84
18	400	40	4808.67	0.33	95.45	199.69	560.50
19	400	80	2844.31	0.69	95.88	1067.28	663.706
20	400	133	1788.89	0.11	96.69	4354.09	554.98
21	500	5	9141.00	-1.50	97.00	25.10	262.00
22	500	10	8577.58	0.42	97.11	2500.08	563.70
23	500	50	4619.58	-0.57	96.81	485.08	518.63
24	500	100	2960.72	0.28	96.52	2500.07	563.70
25	500	167	1827.81	1.20	96.56	6023.41	892.23
26	600	5	9916.67	0.25	98.33	43.51	677.00
27	600	10	8307.50	-0.33	97.00	62.789	590.00
28	600	60	4497.05	0.95	97.08	914.25	653.17

Table 2. Continued.

Test	N	P	Min. Cost	Error	Cover	Time (s)	Nu. Generation
29	600	120	3031.74	1.67	96.24	3561.27	743.25
30	600	200	1987.43	2.35	96.42	15023.41	856.39
31	700	5	10085.20	0.77	99.00	71.48	665.69
32	700	10	9297.00	-0.01	97.01	109.99	705.41
33	700	70	4699.87	0.12	98.01	1591.03	687.52
34	700	140	3011.41	2.11	93.21	5983.21	518.49`
35	800	5	10403.00	-2.99	98.00	115.85	723.50
36	800	10	9932.04	1.95	98.01	212.34	760.01
37	800	80	5057.10	-0.10	98.78	2699.16	558.11
38	900	5	11059.20	0.761	98.21	167.51	920.70
39	900	10	9423.99	-0.97	98.99	306.75	613.905
40	900	90	5124.42	2.01	96.02	3445.91	782.93

Table 4. The first result of FGA based on (Cost, cover) function such that.

Test	N	P	Min. Cost	Error	Cover	Time(s)	Nu. Generation
1	100	5	5819	-1.00	84	0.36	329
2	100	10	4093	-1.00	80	1.68	605
3	100	10	4250	-1.00	80	1.02	201
4	100	20	3034	-2.00	79	1.05	253
5	100	33	1356	-1.00	100	0.05	2
6	200	5	7824	0.00	96	0.135	28
7	200	10	5631	0.00	93	6.36	876
8	200	20	4445	0.00	91	14.37	976
9	200	40	2734	0.00	94	15.62	292
10	200	67	1255	0.00	96	92.02	521
11	300	5	7696	0.00	97	1.47	177
12	300	10	6634	0.00	95	3.81	243
13	300	30	4347	0.00	95	35.50	606
14	300	60	2968	0.00	97	159.03	706
15	300	100	1729	0.00	96	246.60	300
16	400	5	8162	0.00	97	7.43	501
17	400	10	6999	0.00	99	16.35	548
18	400	40	4809	0.00	98	77.52	485
19	400	80	2845	0.00	98	92.98	138
20	400	133	1789	0.00	94	472.87	186
21	500	5	9137	1.00	97	2.37	94
22	500	10	8578	0.00	97	31.26	748
23	500	50	4619	0.00	99	42.26	129
24	500	100	2961	0.00	96	178.60	118
25	500	167	1828	0.00	98	2480.06	385
26	600	5	9917	0.00	98	33.76	989
27	600	10	8307	0.00	97	31.20	494
28	600	60	4498	0.00	94	13.48	17
29	600	120	3033	0.00	94	281.07	88
30	600	200	1990	-1.0	94	2697.71	205
31	700	5	10086	0.00	94	0.87	2
32	700	10	9297	0.00	97	30.72	292
33	700	70	4700	0.00	98	87.53	68
34	700	140	3013	0.00	98	17.85	2
35	800	5	10400	0.00	98	1.04	2
36	800	10	9934	0.00	98	4.07	2
37	800	80	5057	0.00	98	4.62	2
38	900	5	11060	0.00	100	0.18	2
39	900	10	9423	0.00	100	0.20	2
40	900	90	5128	0.00	99	6.37	2

Conflict of Interest

The authors declare no conflict of interest regarding the publication of this paper.

Data Availability

The dataset used in this study is publicly available in the Scikit-learn library (Breast Cancer Wisconsin dataset). No additional data were generated or analyzed in this research.

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