Multiobjective Assignment of Citizens to INE Service Modules Using NSGA-II: An Efficient Optimization Approach

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Abstract. Efficient allocation of citizens to service modules is crucial for the National Electoral Institute (INE) of Mexico, particularly for those applying for their voter identification card for the first time. This study focuses on a multi-objective optimization approach, using the Second Generation Non-Dominated Genetic Algorithm (NSGA-II), to assign citizens from 16 municipalities in the Toluca Valley to 10 INE service modules. The involved municipalities include Almoloya de Juárez, Calimaya, Chapultepec, Lerma, Metepec, among others, and the service modules are distributed in locations such as Almoloya de Juárez, Metepec, Lerma, and more. Two objective functions are utilized: (1) Maximizing facility coverage, ensuring that the largest number of citizens is assigned to a module, subject to the capacity constraints of each module, and (2) Minimizing transportation costs by reducing the total distance citizens need to travel to reach the modules. The NSGA-II algorithm is compared to alternative optimization methods, and fuzzy logic is employed to evaluate the quality of the generated solutions. The results demonstrate that the NSGA-II-based approach outperforms alternative methods in both efficiency and solution quality, and its impact on INE practice is discussed.

Keywords: Allocation problem · Urban planning · NSGA-II

1 Introduction

Strategic decision making on resource management requires optimal solutions, due to their implementation affects the future state of various scenarios. An example is the budget decisions making and the public demand that the government implements each year, since these decisions could have a long-term impact on the quality of citizens life [8].

Therefore, it is necessary to have quality information, from reliable sources, whether they are public or private institutions that use methodologies according to current needs, since this contributes to the generation of studies for the benefit of social development. An example is the National Electoral Institute (INE),

E. Mezura-Montes et al. (Eds.): MCPR 2024, LNCS 14755, pp. 73–83, 2024.
https://doi.org/10.1007/978-3-031-62836-8_8

which is an autonomous body in Mexico and it is in charge of regulating electoral processes, citizen participation and establishing the guidelines that citizens must respect.

Such information highlights the importance of social dynamics that exist in the current environment, which demands the implementation of methods for geographical analysis, whose objective is to optimize the planning of services [1].

One of the most relevant issues for decision-makers, both in the governmental and private sectors, is the efficient allocation of clients and services. This issue becomes particularly important in contexts such as the National Electoral Institute (INE), where the proper allocation of resources and service management directly impacts citizen participation and democratic exercise [7].

In this regard, the present research focuses on addressing the specific challenge of allocating citizens from the Toluca Valley, aged between 17 and 18 years old (Table 1 shows the population of 17 and 18-year-olds per municipality in the Valley of Toluca), who are applying for their voter identification card for the first time at the INE modules closest to their homes. This population represents a significant portion of the electoral base, and their adequate access to INE services is essential to ensure the representativeness and legitimacy of electoral processes.

Table 1. Inhabitants from the valley of Toluca between 17 and 18 years old

INEGI ID	Municipality	Inhabitants
005	Almoloya de Juárez	6,748
018	Calimaya	2,645
027	Chapultepec	498
051	Lerma	6,521
054	Metepec	8,248
055	Mexicaltzingo	543
062	Ocoyoacac	2,752
067	Otzolotepec	3,684
072	Rayón	625
073	San Antonio la Isla	1,285
076	San Mateo Atenco	3,803
087	Temoaya	4,269
090	Tenango del valle	3,444
106	Toluca	32,815
115	Xonacatlán	2,122
118	Zinacantepec	8,105
	Total	**88,107**

The implementation of a resource optimization model in this context not only aims to improve the operational efficiency of the INE but also has a direct impact on the quality of life of citizens. By ensuring proper allocation of available resources, waiting times are reduced, transportation costs are minimized, and the exercise of the right to vote for this specific population is facilitated.

1.1 Solution Proposal

To ensure effective client-to-service assignments, a model based on NSGA-II (Non-dominated Sorting Genetic Algorithm II) coupled with fuzzy logic will be implemented. This fusion enables multi-objective optimization, simultaneously considering criteria like maximizing service coverage, minimizing citizen travel costs, and ensuring equitable resource distribution.

NSGA-II is renowned for its efficiency in identifying optimal solutions across multiple objectives. By leveraging this approach, diverse resource allocation configurations can be explored, striking an optimal balance between criteria.

Additionally, integrating fuzzy logic enhances adaptability and robustness. It allows handling inherent uncertainties, ensuring a context-sensitive assignment process that dynamically adjusts to changing conditions.

1.2 Related Work

In this section, we will explore previous research that addresses the use of NSGA-II for service allocation. These studies demonstrate the effectiveness and advantages of using NSGA-II in similar allocation problems, highlighting its ability to obtain Pareto-optimal solutions.

The research by [3] presents NSGA-II as a fast and elitist multi-objective genetic algorithm. The study demonstrates the effectiveness of NSGA-II in solving assignment problems by providing non-dominated solutions on the Pareto front and maintaining effective diversity among them.

Similarly, [2] propose a multi-objective evolutionary algorithm based on NSGA-II for dynamic service composition. The algorithm aims to optimize multiple objectives such as cost, reliability, and latency to adapt to real-time changes and enhance the quality of service composition.

In another study, [10] propose a hybrid approach that combines NSGA-II with the search algorithm to solve the service allocation problem in cloud computing environments. The results demonstrate that the combination of these two algorithms improves the quality of solutions in terms of efficiency and user satisfaction.

In additional research conducted by [9], a multi-objective genetic algorithm based on NSGA-II is proposed to address the dynamic task allocation problem in service-oriented manufacturing systems. The results show that the proposed algorithm can find efficient solutions that balance performance and cost objectives in real-time.

These studies consistently demonstrate that NSGA-II is an efficient and effective tool for service allocation in various domains. Its ability to generate Pareto-optimal solutions and maintain diversity among solutions makes it a promising approach for addressing multi-objective assignment problems.

2 Methodology

In this section, the methodology used to design and evaluate a multi-objective assignment model based on NSGA-II is presented, with the aim of managing decision-making in the allocation of public services.

2.1 Methodological Framework

Efficient allocation of public services is crucial to improve the quality of life for the population and ensure equitable distribution of resources. In this section, a detailed guide consisting of 6 stages is provided (see Fig. 1): 1. Problem Analysis, 2. Selection of Involved Variables, 3. Possible Solution Selection for the Assignment Problem, 4. Creation of a Set of Potential Solutions, 5. Selection of the Best Solution, and 6. Final Results.

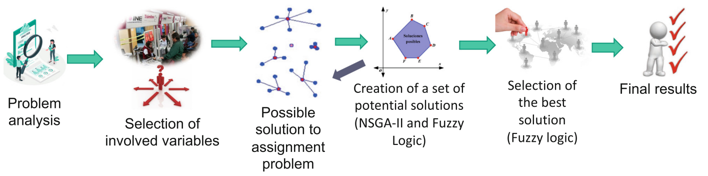

Fig. 1. Stages of the proposed methodology.

Problem Analysis. In the problem analysis stage, a comprehensive study is conducted to define the objectives, constraints, and requirements associated with decision-making in public service allocation. This involves examining the socioeconomic, geographic, and demographic context. The goal is to identify user needs, as well as challenges in service provision. Factors like population density, demand distribution, socioeconomic characteristics, and budget constraints are considered. Additionally, objectives for public service allocation are analyzed.

Selection of Involved Variables. In the variable selection stage, a detailed process identifies and selects the most relevant variables for the multi-objective optimization model in public service allocation. This steps ensures the model covers all critical aspects and considerations.

1. Accessibility and Connectivity
2. Expected Demand
3. Objectives and Constraints

Possible Solution Selection for the Assignment Problem. During the solution selection stage, a detailed analysis aims to optimize public service allocation, maximizing efficiency and effectiveness. Various techniques are used for this purpose:

1. Assignment Models
2. Workload Balancing
3. Spatial Considerations

Creation of a Set of Potential Solutions. In creating a set of potential solutions, a detailed process is undertaken to generate diverse alternatives for addressing the multi-objective optimization problem in public service allocation. This involves specific steps, such as:

1. Definition of Variables
2. Generation of Initial Solutions
3. Evaluation of Generated Solutions
4. Diversification of Solutions

Selection of the Best Solution. During solution selection, a thorough analysis is conducted to identify the optimal solution from various options. This involves evaluating and comparing potential solutions using different techniques [6].

1. Definition of Evaluation Criteria
2. Sensitivity Analysis
3. Comparison and Selection
4. Feedback from Experts and Stakeholders

Final Results. In the final results stage, the obtained results from the selection of the best solution in the multi-objective optimization process for public service allocation are presented and analyzed. This stage involves a thorough evaluation of the results and effective communication of the findings to stakeholders and decision-makers [4,5].

3 Experimentation

In this section, we present the results of applying the multi-objective assignment approach to INE service modules using NSGA-II. We outline the simulation scenarios, parameters used, and analyze the results. Additionally, we compare the application of genetic algorithms, local search, and tabu search, with comparative tables for each aspect evaluated. Furthermore, a table is included to show solution classification using fuzzy logic.

- Simulation scenarios: Three simulation scenarios were generated with the aim of covering different representative situations of the INE service module assignment problem. Each scenario was designed considering a specific distribution of the population of citizens among the municipalities of the Valle de Toluca and the capacities of the INE service modules.
  1. Equal distribution of population: In this scenario, an equal distribution of the population of citizens among the municipalities of the Valle de Toluca is assumed. This implies that the number of citizens in each municipality is approximately the same. Additionally, the capacities of the INE service modules are distributed proportionally to cover this equal distribution of the population.
  2. Unbalanced population distribution: In this scenario, an unbalanced distribution of the population of citizens among the municipalities of the Toluca Valley is considered. Some municipalities have a higher concentration of citizens in the age range of 17 to 18 years, while others have fewer citizens in this age range. The capacities of the INE service modules are adjusted to reflect this unbalanced population distribution.
  3. Scenario 3: Heterogeneous distribution of module capacities: In this scenario, a heterogeneous distribution of the capacities of the INE service modules is considered. Some modules have a higher capacity than others, reflecting situations where certain areas have a greater demand for attention than others. The distribution of the population of citizens among the municipalities remains equitable.
- Simulation parameters:
  1. Population Size: A population size of 100 individuals was configured for each simulation scenario.
  2. Crossover Rate: An 80% crossover rate was used to encourage exploration of the solution space.
  3. Mutation Rate: A mutation rate of 5% was established to maintain genetic diversity in the population.

The capacity of the service modules of the INE (within a 9-day period) is a crucial aspect to consider in the process of assigning citizens. The following table provides details on the capacity of each service module in the Valle de Toluca:

Table 2 displays the names of the service modules and their respective capacity in terms of the number of citizens that can be attended simultaneously at each module.

3.1 Model Formulation

This section presents in detail the variables, parameters, and constraints used to model the multi-objective assignment problem of citizens to INE service modules using NSGA-II. The following variables are introduced:

- n: Total number of clients (population of citizens between 17 and 18 years old).

Table 2. Attention capacity for each municipal module in a period of nine days

INEGI ID	Module	Working hours	Service desks	Attendees
005	Almoloya de Juárez	8:00–15:00	Basic +1 Basic +1	4,536
051	Lerma	8:00–20:00	Basic +2 Basic +2	10,692
054	Metepec	8:00–15:00	Basic +3 Basic +3	9,072
076	San Mateo Atenco	8:00–15:00	Basic +2 Basic +1	6,804
087	Temoaya	8:00–20:00	Basic +2	5,346
090	Tenango del valle	8:00–15:00	Basic +2	3,402
106	Toluca 1	8:00–20:00	Basic +7 Basic +7	28,512
106	Toluca 2	8:00–15:00	Basic +7 Basic +7	18,144
115	Xonacatlán	8:00–20:00	Basic +1	3,564
118	Zinacantepec	8:00–20:00	Basic +3	7,128

- m: Total number of facilities (INE service modules).
- d_{ij}: Distance between client i and facility j.
- α: Coefficient representing the transportation cost per unit distance.
- X_{ij}: Binary variable indicating if the demand of client i is assigned to facility j. Takes the value 1 if the assignment is made and 0 otherwise.

Minimizing Transportation Cost from Clients to Facilities. The Eq. 1 aims to minimize the total transportation cost from the clients (citizens) to the facilities (service modules). The transportation cost is calculated as the sum of the distance d_{ij} between each client i and the facility j, multiplied by a binary variable αX_{ij} that indicates whether client i is assigned to facility j.

$$Min\ f_1 = \sum_{i}^{n} \sum_{j}^{m} d_{ij} \alpha X_{ij} \tag{1}$$

$$X_{ij} = \begin{cases} 1\ Customer\ demand\ (i)\ is\ assigned\ to\ facility\ (j) \\ 0 \qquad\qquad\qquad\qquad Another\ case \end{cases} \tag{2}$$

Maximize Facility Coverage, Subject to Capacity Constraints. The Eq. 3 aims to maximize the coverage of facilities, that is, to ensure that the largest possible number of clients is assigned to a facility. This is achieved by multiplying a binary variable D_{mij} that indicates whether the distance d_{ij} between client

i and facility j is less than or equal to a predefined maximum distance d_{mij}, where $d_{mij} = 6$ km. Additionally, another binary variable Y_{ij} is used to indicate whether the capacity of facility j (c_{ij}) is greater than or equal to the demand r_{ij} of the clients assigned to it.

$$Max\ f_2 = \sum_{i}^{n} \sum_{j}^{m} r_{ij} D_{mij} Y_{ij} \tag{3}$$

$$D_{mij} = \begin{cases} 1 & Si\ d_{ij} \le d_{mij} \\ 0 & Another\ case \end{cases} \tag{4}$$

$$Y_{ij} = \begin{cases} 1 & Si\ c_{ij} \ge r_{ij} \\ 0 & Another\ case \end{cases} \tag{5}$$

4 Results Analysis

In this section, the results of the citizen assignment to the INE service modules are examined, and the benefits and limitations of each approach are analyzed.

1. Facilities Coverage: The number of citizens assigned to each service module was evaluated, considering the capacity constraints of each module. The results revealed a balanced and efficient allocation of citizens to the available modules.
2. Travel cost: The total distance traveled by citizens to reach the assigned modules was calculated. The results demonstrated a significant reduction in travel cost compared to non-optimized assignments.
3. Efficiency of the assignment: The overall quality of the obtained solutions was analyzed in terms of the satisfaction of the stated objectives. The results showed that the multi-objective assignment approach using NSGA-II generated optimal and high-quality solutions.
4. A comparison was conducted between the results obtained using the NSGA-II approach and those generated by traditional genetic algorithms, local search, and tabu search.
5. Measurements were conducted for each evaluated aspect, including facility coverage (see Table 3), transportation cost (see Table 4), assignment efficiency (see Table 5), and execution time (see Table 6).
6. Comparative tables will be presented to summarize and visualize the differences and advantages of NSGA-II in relation to the other evaluated algorithms.

The Table 3 shows that in scenarios 2 and 3, it can be observed that NSGA-II achieved a coverage of 98% and 97% respectively, while the genetic algorithms, local search, and tabu search algorithms obtained coverages lower or equal to 90%. This demonstrates that NSGA-II is the algorithm that achieves a more efficient and balanced assignment of citizens to service modules. In scenario 2, it is also observed that NSGA-II outperforms the other algorithms in terms of facility coverage. The coverage percentages for NSGA-II are 98% and 97% respectively, while the genetic algorithms, local search, and tabu search algorithms have lower coverages in both scenarios. The same case occurs in scenario 3.

Table 3. Comparison of facility coverage

Algorithm	Scenario 1	Scenario 2	Scenario 3
NSGA-II	100%	98%	97%
Genetic algorithms	100%	90%	85%
Local Search	100%	82%	78%
Tabu Search	100%	81%	76%

The Table 4 presents the comparison of travel cost. In scenario 2 and 3, NSGA-II achieved a travel cost of 5,108 m, while the genetic algorithms, local search, and tabu search algorithms had costs of 5,089 m, 5,091 m, and 5,089 m, respectively. Despite NSGA-II having slightly longer distances, it achieves greater coverage, making the solution more efficient. This same situation occurs in scenario 3.

Table 4. Comparison of transportation cost (in meters)

Algorithm	Scenario 1	Scenario 2	Scenario 3
NSGA-II	4,960.5 m	5,108 m	5,356 m
Genetic algorithms	4,965.5 m	5,089 m	5,223 m
Local Search	4,965.5 m	5,091 m	5,133 m
Tabu Search	4,965.5 m	5,089 m	5,433 m

The Table 5 presents the classification of solutions generated by NSGA-II in each simulated scenario using fuzzy logic. Quality categories such as "Optimal", "Good", "Acceptable", and "Non-optimal" were established and assigned to each solution based on the obtained results. In all scenarios, NSGA-II obtains an "Optimal" ranking in assignment efficiency. This indicates that the solutions generated by NSGA-II excel in meeting the assignment objectives, outperforming the other algorithms that receive "Good" or "Acceptable" rankings.

Table 5. Efficiency comparison of the assignment

Algorithm	Scenario 1	Scenario 2	Scenario 3
NSGA-II	Optimal	Optimal	Good
Genetic algorithms	Good	Good	Acceptable
Local Search	Acceptable	Acceptable	Acceptable
Tabu Search	Acceptable	Acceptable	Acceptable

Table 6 compares the execution times required by each algorithm (programmed in Python 3.2) to complete the assignment of citizens to the service modules in each of the simulated scenarios, using a computer with Windows 10 operating system, 6 GB of RAM, and 500 GB of SSD, Intel Core i7 10th gen. The execution time is measured in seconds and is an important metric for evaluating the efficiency and speed of the algorithms in solving the assignment problem.

Table 6. Runtime Comparison

Algorithm	Scenario 1	Scenario 2	Scenario 3
NSGA-II	210 s	235 s	256 s
Genetic algorithms	270 s	293 s	310 s
Local Search	138 s	150 s	178 s
Tabu Search	160 s	172 s	195 s

5 Conclusions and Future Work

The proposal of assigning the municipal population to the INE modules using the multi-objective optimization approach based on NSGA-II has proven to be an effective solution for the citizen assignment problem. Although this study focused on the population of the Toluca Valley, this methodology can be replicated in other areas of the country, as long as information on the capacity of each module and the population size is available.

In summary, this study presents a robust and efficient methodology that can be highly useful for the INE and other organizations facing similar assignment problems. It establishes a precedent for integrating multi-objective optimization and fuzzy logic in solving complex assignment problems. The NSGA-II based approach, evaluated using fuzzy logic, has demonstrated superior results compared to alternative methods such as traditional genetic algorithms, local search, ant colony optimization, and tabu search.

In conclusion, the presented methodology has a significant impact on the INE's practice by enabling a more efficient and effective assignment of citizens to the service modules. Furthermore, areas for future research are suggested, including the development of adaptive heuristics, the incorporation of additional decision criteria, and the application of the assignment approach in different geographical contexts. Additionally, exploring the integration of artificial intelligence and machine learning techniques to further improve assignment outcomes is recommended.

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