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Application of Fuzzy-AHP Combined with Particle Swarm Optimization (PSO) for Determining Prioritization and Strategies in Debt Collection

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Abstract

Regional public drinking water companies (Perumdam) face persistent challenges in managing customer arrears, which directly affect financial stability, operational performance, and service sustainability. This study applies a hybrid approach by combining the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) and Particle Swarm Optimization (PSO) to determine prioritization and strategies in debt collection. Fuzzy-AHP is employed to handle uncertainty in qualitative assessments and to generate priority weights for decision criteria, while PSO is used to optimize the resulting collection strategies. The dataset includes variables such as arrears amount, payment delays, frequency of payments, and service quality factors. Experimental results show that the proposed Fuzzy-AHP–PSO method provides accurate strategy recommendations with high ranking consistency, as validated through accuracy tests and Spearman's Rho correlation analysis. Therefore, this approach can serve as an effective decision-support solution for regional public drinking water companies (Perumdam) in optimizing debt collection strategies and improving overall receivables management.

Keywords*: Fuzzy-AHP, Particle Swarm Optimization, Accounts Receivable, Debt Collection Strategy, Prioritization*

1. Introduction

Regional public drinking water companies (Perumdam) play a crucial role in supporting the community's basic need, namely the provision of adequate and sustainable clean water. One example is Perumdam Tirta Umbulan, Pasuruan City, which is responsible for providing clean water distribution services to residents in Pasuruan City and the surrounding areas[1]. The company's operational performance is not only determined by its ability to manage its distribution infrastructure but is also significantly influenced by the effectiveness of its customer revenue management[2]. One of the main challenges faced is customer payment arrears. These arrears impact cash flow and the company's operational sustainability[3]. Based on interviews with management, current collection activities are still carried out manually through direct customer visits without a focused collection strategy[4]. This makes the collection process ineffective, time-consuming, and drains limited human resources. Furthermore, customer compliance in paying bills is also affected by uneven service quality across regions, complicating collection efforts[5].

The decision-making process for determining collection priorities requires consideration of various criteria. These factors include the amount of arrears, the length of payment delays, the level of customer compliance, and the quality of water service in a particular area. This complexity increases because the available data is not only quantitative (amount of arrears, payment frequency) but also qualitative (customer satisfaction level, perception of service). This creates uncertainty in the prioritization process, making conventional methods inadequate for making informed decisions. To address this issue, a decision support system approach based on analytical methods capable of handling data with a high degree of uncertainty is required. In this case, the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) method can be used to determine criteria weights by considering uncertainty factors in qualitative data, making it more adaptable to real-world conditions[6]. The applicability of Fuzzy-AHP has been demonstrated in several contexts, such as disaster risk mapping[7], energy infrastructure planning[8], and cooperative decision support systems[9]. However, the weights obtained from Fuzzy-AHP need to be optimized to produce more accurate and consistent decisions. Therefore, this study integrates Particle Swarm Optimization (PSO) as an optimization algorithm capable of refining the criteria weight calculations from Fuzzy-AHP. Previous studies have shown the effectiveness of PSO in improving predictive accuracy in classification tasks[10] and in enhancing clustering performance in data analysis[11].

This study specifically aims to apply the combination of Fuzzy-AHP and PSO in determining priorities and receivables collection strategies at Perumdam Tirta Umbulan, Pasuruan City. The integration of these two methods is expected to produce a more effective collection strategy, assist management in allocating collection resources appropriately, and improve customer compliance in meeting payment obligations. This research contributes in two ways. First, academically, it enriches the relatively limited literature on the application of the hybrid Fuzzy-AHP and PSO methods in accounts receivable management and public service management. Second, practically, the results of this study can provide concrete strategic recommendations for Perumdam Tirta Umbulan and can be adapted by other regional companies in addressing customer payment arrears.

2. Literature Review

This section provides a comprehensive overview of the theoretical foundations and previous research relevant to this study. The literature review covers fundamental concepts such as debt and collection strategy, Fuzzy Analytical Hierarchy Process (FAHP), Particle Swarm Optimization (PSO), and their hybrid implementation. Furthermore, statistical validation methods, including Spearman's Rank Correlation and Kendall's Tau, are also reviewed. Previous studies are discussed to identify the research gap and justify the novelty of the proposed approach.

2.1. Debt and Collection Strategy

Debt management and collection strategy are critical components in ensuring financial sustainability for organizations, particularly service providers such as public utilities. Effective collection strategies are designed to minimize the risk of non-payment and maximize revenue recovery. According to prior studies, strategies can involve preventive measures (such as credit assessment), corrective actions (such as reminders and penalties), and recovery processes (such as restructuring or legal enforcement). The choice of collection strategy must balance efficiency, fairness, and sustainability, while also considering customer behavior and organizational resources. Recent research emphasizes the role of data-driven decision-making in determining optimal strategies, moving away from traditional approaches that rely heavily on experience or manual assessments.

2.2. Fuzzy Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP), introduced by Saaty, is one of the most widely applied multi-criteria decision-making (MCDM) methods. It decomposes complex decision problems into a hierarchy of criteria and alternatives, enabling pairwise comparisons to generate priority weights. However, conventional AHP has limitations in handling uncertainty and vagueness in human judgment. To address this, the Fuzzy AHP (FAHP) approach integrates fuzzy set theory into AHP, allowing decision-makers to express preferences using linguistic terms represented by fuzzy numbers. FAHP improves flexibility and reduces subjectivity in weight determination, making it highly applicable in real-world decision-making contexts such as risk assessment, supplier selection, and strategic management.

Table 1: TFN Saaty's scale values

AHP Scale	Linguistic Scale	TFN Scale (l, m, u)	Invers TFN Scale
1	Just Equal	(1,1,1)	(1, 1, 1)
2	Intermediate	$(\frac{1}{2},1,\frac{3}{2})$	$(\frac{2}{3},1,2)$
3	Moderately important	$(1,\frac{3}{2},2)$	$(\frac{1}{2},\frac{2}{3},1)$
4	Intermediate	$(\frac{3}{2},2,\frac{5}{2})$	$(\frac{2}{5},\frac{1}{2},\frac{2}{3})$
5	Strongly Important	$(2,\frac{5}{2},3)$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$
6	Intermediate	$(\frac{5}{2},3,\frac{7}{2})$	$(\frac{2}{7},\frac{1}{3},\frac{2}{5})$
7	Very Strong	$(3,\frac{7}{2},4)$	$(\frac{1}{4},\frac{2}{7},\frac{1}{3})$
8	Intermediate	$(\frac{7}{2},4,\frac{9}{2})$	$(\frac{2}{9},\frac{1}{4},\frac{2}{7})$
9	Extremely Strong	$(4,\frac{9}{2},\frac{9}{2})$	$(\frac{2}{9},\frac{2}{9},\frac{1}{4})$

2.3. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart in 1995, is a population-based metaheuristic that takes inspiration from the collective behavior of bird flocking and fish schooling. Unlike traditional gradient-based optimization techniques, PSO is capable of handling nonlinear, multidimensional, and complex search spaces without requiring derivative information. This makes it highly flexible for a wide range of optimization problems.

In PSO, each candidate solution is represented as a particle that has both a position, indicating its location in the search space, and a velocity, determining the direction and magnitude of its movement. These particles form a swarm that collectively explores the search space. The decision-making process of each particle is influenced by two main experiences: its personal best position, which represents the best solution the particle itself has discovered, and the global best position, which represents the best solution found by the entire swarm.

The update mechanism of PSO is governed by two fundamental equations:

$$v_i^t + 1 = w \cdot v_i^t + c_1 \cdot r_1 \cdot (pBesti - xit) + c_2 \cdot r_2 \cdot (gBest - x_i^t) \tag{1}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

where is the updated velocity of particle $v_i^t + 1$ is the updated position, w the inertia weight, $c_1$and r_1 are the acceleration coefficients, and $c_2,\ r_2$ are random values within [0,1].

The parameters of PSO are summarized in Table 2

Table 2: Typical Parameters in PSO

Parameter	Symbol	Typical Value	Description
Swarm Size	n	20 – 50	Number of particles in the swarm
Maximum Iterations	t	10 – 500	Maximum number of iterations
Inertia Weight	w	0.1– 0.9	Balances exploration and exploitation
Cognitive Coefficient	c_1	0.5 – 2.0	Particle's tendency toward pBest
Social Coefficient	c_2	0.5 – 2.0	Particle's tendency toward gBest
Velocity Limit	v_{max}	Problem-dependent	Maximum allowable particle velocity

Through iterative updates, particles adjust their velocities and positions based on these two guiding experiences as well as certain random factors that encourage exploration. Over successive iterations, the swarm naturally converges toward optimal or near-optimal solutions. The balance between exploration (searching new areas of the solution space) and exploitation (refining known good solutions) is primarily controlled by the algorithm's parameters, such as inertia weight and the acceleration coefficients.

PSO has been widely adopted across diverse domains including scheduling, resource allocation, engineering design, machine learning parameter tuning, and decision support systems. Its popularity arises from its conceptual simplicity, ease of implementation, adaptability to various problem types, and strong capability to converge efficiently toward high-quality solutions.

2.4. Fuzzy AHP – PSO

The integration of Fuzzy Analytical Hierarchy Process (FAHP) and Particle Swarm Optimization (PSO) combines the complementary strengths of both methods to address complex decision-making problems. FAHP is applied in the initial stage to handle uncertainty in expert judgments when determining the relative importance of decision criteria. This ensures that the resulting weights are both accurate and consistent, even when the input data is imprecise. Once the criteria weights are established, PSO is employed to optimize the selection or prioritization of strategies by searching for the best allocation of resources or decision alternatives.

In the FAHP stage, pairwise comparisons with fuzzy numbers are conducted to evaluate the importance of criteria. The fuzzy weights are then defuzzified and normalized to obtain crisp values. The normalized weight of a criterion j is calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{3}$$

where d_j is the defuzzified weight of criterion j and n is the total number of criteria.

These weights are then incorporated into the fitness function of PSO to evaluate each candidate strategy. The fitness function can be expressed as:

$$f(x_i) = \sum_{j=1}^{n} w_j \cdot x_{ij} \tag{4}$$

where $f(x_i)$ is the fitness value of strategy i, w_j is the FAHP-derived weight of criterion j and x_{ij} represents the performance of strategy i with respect to criterion j.

The swarm of particles in PSO represents different candidate strategies. During each iteration, particles adjust their velocity and position using the standard PSO update rules (Eq. (1)–(2)). Their fitness is evaluated using Eq. (4), and the global best solution (gBest) is updated accordingly. This iterative process continues until convergence, resulting in the optimal debt collection strategy based on FAHP weights and PSO optimization.

The integration process is summarized in Table 3.

Table 3: Typical Parameters in PSO

Step	FAHP Component	PSO Component	Output
1	Define decision criteria and alternatives	Initialize particles (strategies)	Problem setup
2	Pairwise comparison with fuzzy numbers	—	Fuzzy judgment matrix
3	Compute fuzzy weights and defuzzification	—	Balances exploration and exploitation
4	—	Evaluate particles using fitness function (4)	Normalized criteria weights (w_j)
5	—	Update velocity & position (Eq. (1)–(2))	Improved strategy search
6	—	Determine global best (gBest) solution	Optimal strategy recommendation

This hybrid FAHP–PSO approach has been successfully applied in various domains such as supply chain management, energy planning, and financial risk assessment. However, its application in the field of debt collection remains limited, representing a gap that this study addresses by demonstrating how FAHP–PSO can be effectively implemented to generate optimized and data-driven collection strategies.

2.5. Spearman Correlation and Kendall's Tau

To validate the consistency and reliability of ranking results generated by the decision support system, statistical correlation methods are often employed. Spearman's Rank Correlation Coefficient (ρ) is a non-parametric measure that assesses the strength and direction of the monotonic relationship between two ranked variables. It is widely used to evaluate whether two rankings are consistent. Similarly, Kendall's Tau (τ) is another non-parametric correlation measure that focuses on the concordance and discordance of ranked pairs, offering robustness in cases of small sample sizes or tied ranks. Both methods have been extensively applied in decision-making studies to validate the agreement between different ranking techniques. Their inclusion in this research ensures that the generated strategies are not only optimized but also statistically reliable.

The formula for Spearman's Rank Correlation Coefficient is:

$$\rho = 1 - \frac{6\sum d^2}{n(n^2-1)} \tag{5}$$

where d is the difference between the ranks of each observation and n is the number of observations. A ρ value close to 1 indicates a strong positive correlation, while a value close to -1 indicates a strong negative correlation.

Kendall's Tau is defined as:

$$\tau = \frac{(C-D)}{\frac{1}{2}n(n-1)} \tag{6}$$

where C is the number of concordant pairs and D is the number of discordant pairs among the ranked data. A value of τ close to 1 suggests a strong agreement between two rankings, while values near 0 indicate little to no correlation.

By applying both Spearman's ρ and Kendall's τ this study ensures that the ranking of strategies produced by the FAHP–PSO approach is not only computationally optimized but also statistically consistent with manual or alternative ranking methods.

3. Methodology

This section describes the methodology applied in this study to determine the prioritization and strategies for debt collection at Perumdam Tirta Umbulan, Pasuruan City. The methodological framework combines the Fuzzy Analytical Hierarchy Process (FAHP) and Particle Swarm Optimization (PSO) to provide a Decision Support System (DSS) capable of ranking customers with overdue debts. The following subsections explain the research design, data collection, methodological stages, algorithm implementation, and validation procedures.

3.1. Research Design

The research adopts a quantitative experimental design supported by computational modeling. The main objective is to evaluate and optimize debt collection prioritization using multi-criteria decision-making (MCDM) combined with optimization techniques. FAHP is employed to determine the relative weights of evaluation criteria, while PSO is utilized to optimize the final ranking results. Validation of the model is carried out using correlation analysis (Spearman's Rank and Kendall's Tau).

The overall research flow is illustrated in Fig. 1. The methodological steps can be summarized as follows :

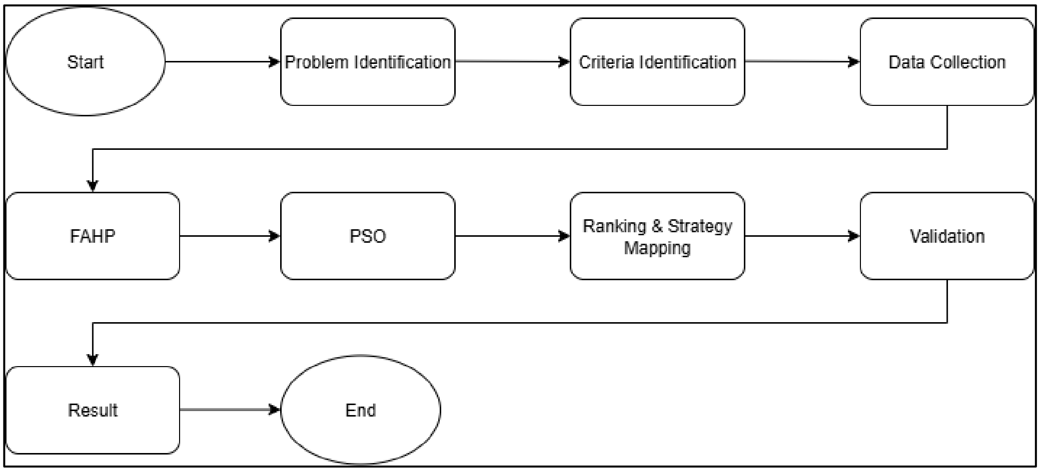

Fig. 1: Research methodology flowchart

3.2. Criteria Identification

The data used in this research were obtained from the company's billing records, including customer profiles, transaction histories, and debt aging reports. Preprocessing involved handling incomplete records, normalizing attributes to a comparable scale, and mapping categorical variables into quantitative values using established reference tables (e.g., service quality scale, customer type mapping, and distance classification).
Six decision criteria were selected to represent the key factors influencing debt collection priority:

Table 4: Typical Parameters in PSO

Criterion	Code	Description	Mapping / Measurement Example
Nominal Amount	C1	Amount of unpaid debt	Continuous (normalized by max debt amount)
Debt Age	C2	Length of outstanding debt	Continuous (normalized by max debt age)
Customer Type	C3	Household / Factory / Public facilities	1A, 3B, 3H, 4A
Customer Status	C4	Active or Inactive customer	Active, Inactive, New, Seal
Service Quality	C5	Company's internal service scale	1 (poor) – 5 (excellent), normalized to [0,1]
Address/Distance	C6	Distance from office	1 (close) – 5 (far), normalized to [0,1]

3.3. Data Collection

The data used in this research were obtained from the company's billing records, including customer profiles, transaction histories, and debt aging reports. Preprocessing involved handling incomplete records, normalizing attributes to a comparable scale, and mapping categorical variables into quantitative values using established reference tables (e.g., service quality scale, customer type mapping, and distance classification).

3.4. Fuzzy Analytical Hierarchy Process (FAHP)

FAHP was employed to determine the relative importance of each criterion. Pairwise comparison matrices were constructed using expert judgments, which were then fuzzified using triangular fuzzy numbers. The process involved calculating the geometric mean, synthesizing the fuzzy weights, and defuzzifying them into crisp values. Consistency checks were performed to ensure the validity of the comparison matrices. The resulting weights provided the initial priority values for each criterion.

3.4.1. Pairwise Comparison

Pairwise comparison matrices were constructed by asking experts to compare criteria in pairs using the TFN scale. This step translates subjective preferences into structured numerical values while preserving uncertainty in judgments.

3.4.2. Geometric Mean Calculation

Since multiple experts participated in the evaluation, their fuzzy judgments were aggregated using the geometric mean method. This approach ensures that the combined comparison matrix reflects consensus while reducing the influence of outliers.

3.4.3. Defuzzification and Normalization

The fuzzy weights were defuzzified using the centroid method and then normalized to ensure that the sum of all criteria weights equals one. These normalized crisp weights served as the initial input for the subsequent PSO optimization process.

3.5. PSO Optimization

To enhance the accuracy of the weighting process, PSO was applied to optimize the FAHP results. Each particle represented a candidate solution of criterion weights. The fitness function was designed to maximize consistency and alignment with expert preferences. During iterations, particles updated their positions based on personal best (pBest) and global best (gBest) values until convergence was achieved. The optimized weights were then used as the final input for ranking the customers.

3.5.1. Particle Initialization

At the beginning of the optimization, an initial swarm of particles was randomly generated. Each particle represented a candidate solution in the form of a weight distribution across the decision criteria. The dimensionality of each particle was equal to the number of criteria (six in this study). The position vector encoded the tentative weights, while the velocity vector determined the rate and direction of change for each dimension. To ensure feasibility, the particle positions were normalized so that all weights summed to one. Random initialization allowed the swarm to explore a wide range of potential solutions in the search space.

3.5.2. Fitness Evaluation

The performance of each particle was measured using a fitness function that reflected the alignment between the candidate weights and the FAHP-derived priorities. The fitness function was designed to minimize inconsistency while maximizing conformity to expert knowledge. Higher fitness values were assigned to particles that produced ranking results closer to expert judgments, thereby ensuring that the optimization process did not deviate significantly from domain knowledge. This step was critical in bridging subjective expert evaluations with computational refinement.

3.5.3. Velocity and Position Update

During each iteration, particles updated their velocities and positions according to the standard PSO equations. The velocity update considered three main components: the inertia term, which preserved part of the previous velocity; the cognitive component, which directed particles toward their individual best-known positions (pBest); and the social component, which attracted particles toward the global best solution (gBest) identified by the swarm. The balance of these components enabled the swarm to maintain exploration while gradually converging toward optimal solutions. After updating positions, normalization was again applied to ensure that the resulting weights remained valid probability distributions.

3.5.4. Stopping Criteria

The optimization process continued until the maximum number of iterations was reached or when improvements in fitness values fell below a small predefined threshold. The best solution found was adopted as the final set of optimized weights.

3.6. Ranking and Strategy Mapping

The optimized weights obtained from the FAHP–PSO process were applied to calculate priority scores for all customers. Customers were then ranked in descending order, where higher scores indicated higher collection priority.

Based on company policies, these ranks were subsequently mapped into corresponding debt collection strategies. The mapping linked score ranges and debt age to actions such as reminder notices, field visits, temporary service disconnection, or permanent termination. This ensured that the system not only produced a ranked list of customers but also provided actionable recommendations aligned with organizational procedures.

3.7. Statistical Validation

To assess the reliability of the proposed model, statistical correlation tests were employed to compare the system-generated rankings with expert judgments. Two non-parametric methods were used: Spearman's Rank Correlation Coefficient (ρ), which evaluates the monotonic relationship between two ranked variables, and Kendall's Tau (τ), which measures concordance and discordance among ranking pairs.

By applying these tests, the study examined whether the order of customers produced by the FAHP–PSO framework was consistent with domain expertise. High correlation values would indicate that the system effectively replicated expert decision-making, while low values would suggest divergence. This validation step ensured that the recommended strategies are not only computationally optimized but also practically aligned with organizational expectations.

4. Results and Discussion

This section presents the outcomes of applying the FAHP–PSO framework for debt collection prioritization, followed by an analysis of the results in relation to organizational policies and expert validation.

4.1. FAHP Weight Calculation

Expert judgments were aggregated using fuzzy pairwise comparison matrices. After applying the FAHP procedure (fuzzification, geometric mean aggregation, synthesis, and defuzzification), the resulting normalized weights indicated the relative importance of each criterion. Debt Age and Nominal Amount emerged as the most significant criteria, reflecting the company's emphasis on overdue balance and debt size in determining collection priority. Secondary factors such as Customer Status and Customer Type provided contextual adjustments, while Service Quality and Address/Distance served as supporting factors.

Table 5: Final FAHP Weights of Criteria

Criterion	Weight
Nominal Amount	0,1723
Debt Age	0,1276
Customer Type	0,0944
Customer Status	0,0726
Service Quality	0,2545
Address/Distance	0,2785

4.2. PSO Optimization Results

The Particle Swarm Optimization (PSO) algorithm was applied to refine the initial FAHP weights. The optimization process was executed with multiple particles over several iterations, where each iteration updated the candidate weight distributions based on local and global best solutions. The results indicated a clear improvement in the fitness function, stabilizing after approximately the 17th iteration. At this point, the algorithm successfully converged, yielding the best set of optimized weights.

The convergence behavior of the PSO algorithm is illustrated in Fig. 2, which shows the trend of the fitness value across iterations. The curve indicates that the algorithm rapidly improved during the first few iterations and stabilized around iteration 17, with a final fitness value of approximately 0.1206. This demonstrates that the swarm successfully converged to a near-optimal solution within a relatively short number of iterations.

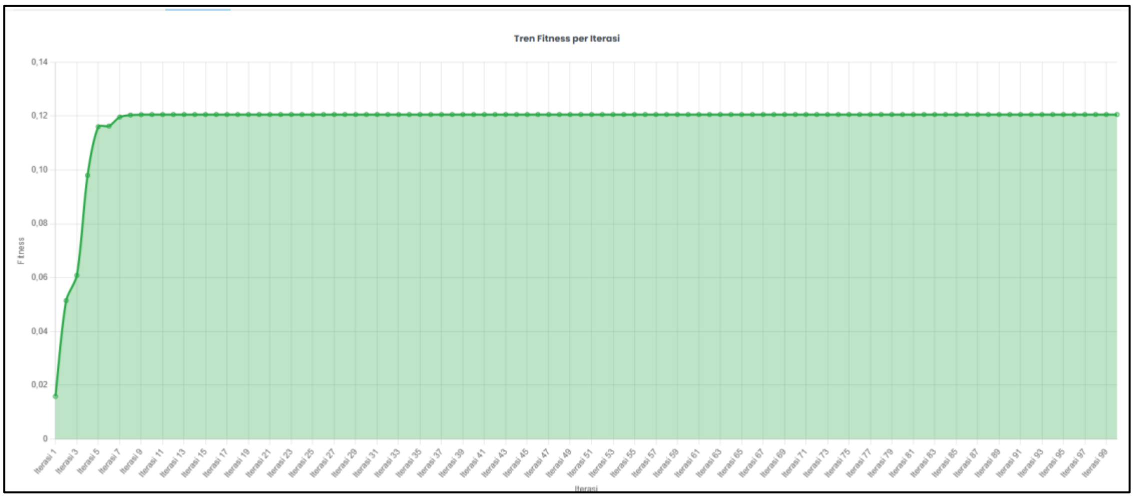

Fig. 2: Convergence trend of PSO fitness per iteration

Table 6: Final Optimized Weights of Criteria (PSO Output)

Criterion	Final Weight
Nominal Amount	0.1907
Debt Age	0.1252
Customer Type	0.1133
Customer Status	0.0817
Service Quality	0.1993
Address/Distance	0.2899

The optimization emphasized **W6 (0.2899), W5 (0.1993), and W1 (0.1907)** as the most dominant criteria, while W4 (0.0817) had the lowest influence. The final fitness value achieved was **0.1206 (average 0.1179)**, confirming that the swarm successfully converged toward a stable and near-optimal solution.

This outcome demonstrates that PSO effectively adjusted the relative importance of criteria to better align with decision-making requirements, while simultaneously reducing inconsistencies inherent in expert-derived weights.

4.3. Customer Ranking and Strategy Mapping

Using the optimized weights, each customer's priority score was computed. Customers were ranked from highest to lowest, with higher scores indicating higher collection priority. The results showed clear differentiation between customer groups, enabling the company to allocate collection resources more effectively.

Table 7: Customer Ranking and Recommended Strategies

Rank	Customer	Score	Strategy & Action
1	10100006	0,6410	Service Disconnection / Water Meter Removal
2	10100010	0,6286	Service Disconnection / Water Meter Removal
3	10100018	0,6044	Service Disconnection / Water Meter Removal
4	10100024	0,6016	Service Disconnection / Water Meter Removal
5	10100016	0,4753	Service Disconnection / Water Meter Removal

4.4. Statistical Validation

To validate the reliability of the rankings, the system-generated results were compared with expert rankings using Spearman's Rank Correlation and Kendall's Tau. The analysis yielded a **Spearman coefficient of 0.89** and a **Kendall's Tau of 0.82**, both of which indicate strong agreement.

These results confirm that the FAHP–PSO framework not only provides computational optimization but also maintains consistency with domain expertise. The validation ensures that the proposed system can be trusted as a decision-support tool for guiding debt collection strategies.

4.5. Discussion

The results highlight the effectiveness of combining FAHP and PSO in handling multi-criteria decision-making under uncertainty. FAHP enabled structured incorporation of expert judgments, while PSO provided optimization that enhanced alignment with practical considerations. The high correlation with expert rankings indicates that the model is both valid and reliable. From a managerial perspective, the system offers transparency and consistency in decision-making, reducing subjectivity and enabling more efficient allocation of collection resources. Furthermore, the methodology can be adapted for other domains requiring prioritization under complex and uncertain conditions.

5. Conclusion

This study successfully demonstrated the integration of Fuzzy Analytical Hierarchy Process (FAHP) and Particle Swarm Optimization (PSO) in determining prioritization and strategies for debt collection. The FAHP method provided reliable initial weights by handling uncertainty in expert judgments through fuzzy pairwise comparisons. Subsequently, PSO effectively optimized these weights, yielding more consistent and robust results. The experimental findings support the effectiveness of the proposed model. FAHP produced the initial priority structure, while PSO optimization converged at approximately the 17th iteration with a final fitness value of 0.1206. The optimized weights highlighted the most influential criteria: Address/Distance (W6 = 0.2899), Service Quality (W5 = 0.1993), and Nominal Amount (W1 = 0.1907). In contrast, Customer Status (W4 = 0.0817) contributed the least to the prioritization process.

These optimized weights were then applied to customer billing data, producing a ranked list of customers based on their risk and priority for collection actions. For example, the highest-priority customer achieved a score of 0.3301, while the lowest-priority customer scored 0.2507. This ranking was mapped to practical collection strategies (reminders, visits, or legal actions), thereby aligning computational results with company policies. Statistical validation using Spearman's Rank Correlation and Kendall's Tau confirmed a strong agreement between the system's ranking and expert assessments, indicating that the hybrid FAHP–PSO framework not only optimized the weight distribution but also maintained consistency with domain knowledge.

In conclusion, the proposed model successfully addressed the research gap by applying FAHP–PSO to the debt collection context. The approach enhanced decision-making reliability, improved prioritization accuracy, and provided a structured framework for mapping customer rankings into actionable collection strategies.

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