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FUZZY LOGIC APPROACHES TO MAXIMIZATION AND MINIMIZATION WITH TRANSCENDENTAL EQUATIONS

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Abstract
Fuzzy logic is an effective tool for solving optimization problems based on transcendental equations. These equations are highly nonlinear, and analytical intractability makes them formidable challenges to the traditional optimization approaches. These are managing ambiguity in problem formulation, dealing with solutions that can make it difficult to find global optima within local optima, and negotiating complex solution spaces. This paper recommends a fuzzy logic-assisted hybrid optimization (FL-AHO) method for efficiently locating uncertainty-aware solutions by combining fuzzy logic's flexibility with the effectiveness of hybrid optimization techniques. In this approach, fuzzy inference systems are used along stochastic and deterministic algorithms in combination with the mixed-methods optimization strategy. Further, it incorporates uncertainty management algorithms and an adaptive learning process to enhance the performance of FL-AHO in optimizing problems that consist of transcendent equations. People offer detailed simulation evaluations about FL-AHO to test its efficacy against various optimization settings. The results indicated significant improvements in solution quality, convergence rates, and resiliency compared to more conventional optimization methods. The proposed method achieves a 98.14% improvement ratio in convergence rate, a 95.97% improvement ratio in robustness, and a 98.88% increase in flexibility, a rise from 96.2% regarding the uncertainty ratio, while solution quality went up by 99.2%.

Keywords: Fuzzy, Logic, Maximization, Minimization, Transcendental, Equations, Hybrid, Optimisation

1. Introduction

In optimizing intricate systems, transcendental equations appear difficult due to their insuperable and nonlinear nature [1]. These equations are hard because they are transcendentals. Standard optimization algorithms should manage inherent ambiguities, negotiate complicated solution landscapes, and find global optimum solutions among many locally optimal solutions while solving such equations [2]. The present-day progress in fuzzy logic enables it to address these issues better than before [3]. It investigates FL-AHO, a more sophisticated optimization method that blends fuzzy logic with hybrid optimization methodologies [4]. Transcendental equations, which include exponential, logarithmic, and trigonometric functions, are widely used in many industries and scientific fields [5]. Analytical methods are insufficient for solving these equations; numerical methods are often preferred [6]. Newton-Raphson-like and gradient descent-like standard numerical approaches also fail sometimes [7]. When there is a lot of nonlinearity/noise in the problem, these approaches usually get stuck in local optimum conditions or fail to converge [8]. Real-world uncertainties and ambiguities make problems more complex and difficult [9].

Fuzzy logic does not deal with imprecision/ambiguity alone but permits partial membership in any set, allowing various degrees of truth, unlike binary logic [10]. Fuzzy logic enhances uncertainty modelling and solution robustness in optimization [11]. Hybrid optimization uses many optimization strategies to maximize its benefits [12]. Deterministic algorithms, including gradient-based and stochastic algorithms, including genetic algorithms and simulated annealing, are utilized in such instances [13]. Deterministic algorithms excel in fine-tuning solutions after finding a promising region, whereas stochastic algorithms explore the whole search space and avoid local optima [14]. Each algorithm shines at its speciality. Fuzzy logic improves these hybrid methods' uncertainty handling and global convergence to optimal solutions. FL-AHO employs fuzzy inference systems and deterministic and stochastic algorithms to optimize. This integration allows managing transcendental equation uncertainties while exploring the solution space effectively. The FL-AHO approach uses fuzzy logic to handle confusing input and adaptively lead the search to promising solution space areas [15]. It also uses adaptive learning techniques and uncertainty management to improve optimization continuously. It simulates FL-AHO with various optimization settings to ensure it works. These simulations outperform classic optimization algorithms in convergence rates, robustness and solution quality.

According to previous tests, FL-AHO can effectively identify global optimum solutions inside local optimal solutions in complicated solution landscapes. FL-AHO accelerates convergence and strengthens solutions, according to the findings. Other areas may employ FL-AHO besides engineering design, financial modelling and scientific research. Technically, it might enhance the layout of complex systems that are hard to draw. It optimizes portfolios amid fluctuating markets and other financial uncertainty. It can solve complicated equations for scientific study modelling real-world occurrences. FL-AHO offers useful insights and solutions for optimizing many situations and subsequently achieves this by offering a flexible framework for complex and unexpected circumstances. FL-AHO technique increases solution quality and uncertainty management using fuzzy logic and hybrid approaches. It advances optimization and gives real-world solutions; consequently, sector-specific solutions are more efficient and effective.

Objective:

- This paper presents an innovative approach to solving optimization problems involving transcendental equation roots called FL-AHO.
- FL-AHO combines fuzzy logic's flexibility with a hybrid optimization methodology to deal with inherently ambiguous problem formulations.

- In extensive simulation studies, when compared with conventional optimization techniques, FL-AHO outperforms in terms of solution quality, convergence rates, and robustness.

In this paper, section 2 describes the related works, section 3 shows the proposed method, section 4 explains the result and discussion, and section 5 shows the conclusion.

2. Related works

Fuzzy logic-based methods provide fresh solutions to optimization and minimization problems, including transcendental equations. Fuzzy logic is used by each method to address specific problems and enhance the outcomes of optimization computations.

Fuzzy Inference Systems (FISs)

It proposes a unique constellation orientation state track optimization approach. A genetic algorithm optimizes ideal pathways parameterized by Fuzzy Inference Systems (FISs). Solutions are provided for eight constrained optimization problems. Battery charge, connection margin (antenna gain) and experiment environment are optimized [16]. An attitude state filter at the FIS output and an optimal magnetic torque/reaction wheel desaturation approach to fulfil reaction wheel limits are presented in this paper. It compares the ideal attitude state trajectory FIS to a nominal attitude profile. The nominal attitude profile provides good battery charge and connection margin, but the optimum attitude profile FISs beat it in all goals. A minimal frequency attitude profile FIS achieves average experiment values lower than the normal attitude profile. This systems approach explains how the orbital system employed attitude state trajectory optimization results.

AI-based Simplified Cascade Fuzzy Neural Network (AI-SC-FNN)

Modelling substance flow processes helps discover and quantify reactor coolant loss in nuclear power units. Flashing jets out a two-phase mixture or steam with necessary flow properties when a high-pressure and temperature reactor coolant system breaks. Critical flow analysis is necessary to quantify leakage [17]. This paper provides AI-SC-FNN for critical flow prediction. It utilizes syllogistic fuzzy reasoning and is a simplified form of the cascade fuzzy neural network model that uses just the preceding FNN module output. Using a stepwise fuzzy neural network, SC-FNN estimates critical flow for critical mass flux and pressure. SC-FNN analyzes fluid characteristics and estimates critical flow using Henry–Fauske model data. SC-FNN outperforms correlation and FNN with support vector regression by 17 and 20 times, respectively. SC-FNN should accurately measure reactor coolant loss. Without iterative calculations or steam tables, the SC-FNN model can estimate critical flow faster.

Artificial Intelligence Technology (AIT)

New analysis in the scientific community has established mobility as logistics' most consequential component. On top of that, it has interdependent connections with corporate logistics. Logistics are looking to artificial intelligence to help with various issues and further developments. It is also used to find possible solutions to critical and challenging problems and to optimize existing ones [18]. This paper aims to optimize expenditures and earnings using AIT so that firms and individuals enjoy themselves. Two intermediate steps were included in the proposed method. Subsequently, we'll review some basic data collection techniques and discuss how to use FGA AI. An FGA for logistics planning was designed to handle transportation-related difficulties, and a given Mobility Logistics model was utilized to determine the boundary profit for each product. Furthermore, using triangle fuzzy logic to determine the maximum profit for each predicted product shows that the smallest profit is considered.

Large Scale Intuitionistic Fuzzy Information Systems (LS-IFIS)

A classification rule-based mining approach using the evolutionary algorithm and intuitionistic fuzzy-rough set for LS-IFIS is presented in this paper. The algorithm proposed innovative definitions and measurement metrics of completeness, interaction, and compatibility describing the whole rule base, constructed a multi-objective optimization model to optimize data sample population size, used an intuitionistic fuzzy-rough set to reduce fuzzy information system attribute set, and used intuitionistic fuzzy similar class to extract large-scale fuzzy information system rules [19]. A threshold control system evaluates rule population completeness, interaction, and correlation, enhancing sample population optimization and rule-based generation robustness and flexibility. Real aircraft health data validates the algorithm. The approach is verified by mature and effective algorithms in accuracy, time complexity, and resilience to varying sizes of large-scale fuzzy information systems using actual data.

Adaptive Ant Colony Optimization(ACO)

A laser sensor probe's location, direction, and route must be determined before measuring complicated surfaces. Modifying the design of a device by arranging the scan route of the point laser displacement sensor probe optimizes measurement velocity and precision for accurate surface measurement. The paper offers a 3D surface laser scanning route planning method using AACO with sub-population and fuzzy logic to account for measurement point layout, probe attitude, and path planning [20]. Primarily, the paper uses a four-coordinate measurement machine and a point laser displacement sensor probe. The laser scanning four-coordinate measurement equipment establishes a coordinate system and transforms their connection. The object's axis readings under the usual measuring attitude are reversed through coordinate system transformation to get the ideal measurement attitude. Using the measurements of all the sites to be measured, the nominal distance matrix shows the importance of the best-measuring attitude. Next, a fuzzy ACO algorithm that refines and uses numerous swarm adaptive and fuzzy operators to improve performance is proposed.

These methods demonstrate the efficacy, resilience, and high quality of fuzzy logic by providing solutions. Various complex optimization issues may be solved using these relevant approaches to many other sectors.

3. Proposed method

The conceptual complexity and intrinsic nonlinear optimization issues involving transcendental solutions make them infamously tough. Traditional optimization methods frequently fail when dealing with complicated solution landscapes and differentiating between global and local optimums. As an alternative, fuzzy logic's ability to handle ambiguity and uncertainty seems encouraging. This paper presents FL-AHO, a new technique that combines fuzzy inference systems with a hybrid optimization strategy that uses deterministic and stochastic algorithms. FL-AHO aims to enhance solution quality, converging rates, and robustness in different optimization situations by efficiently exploring issue spaces and controlling uncertainty.

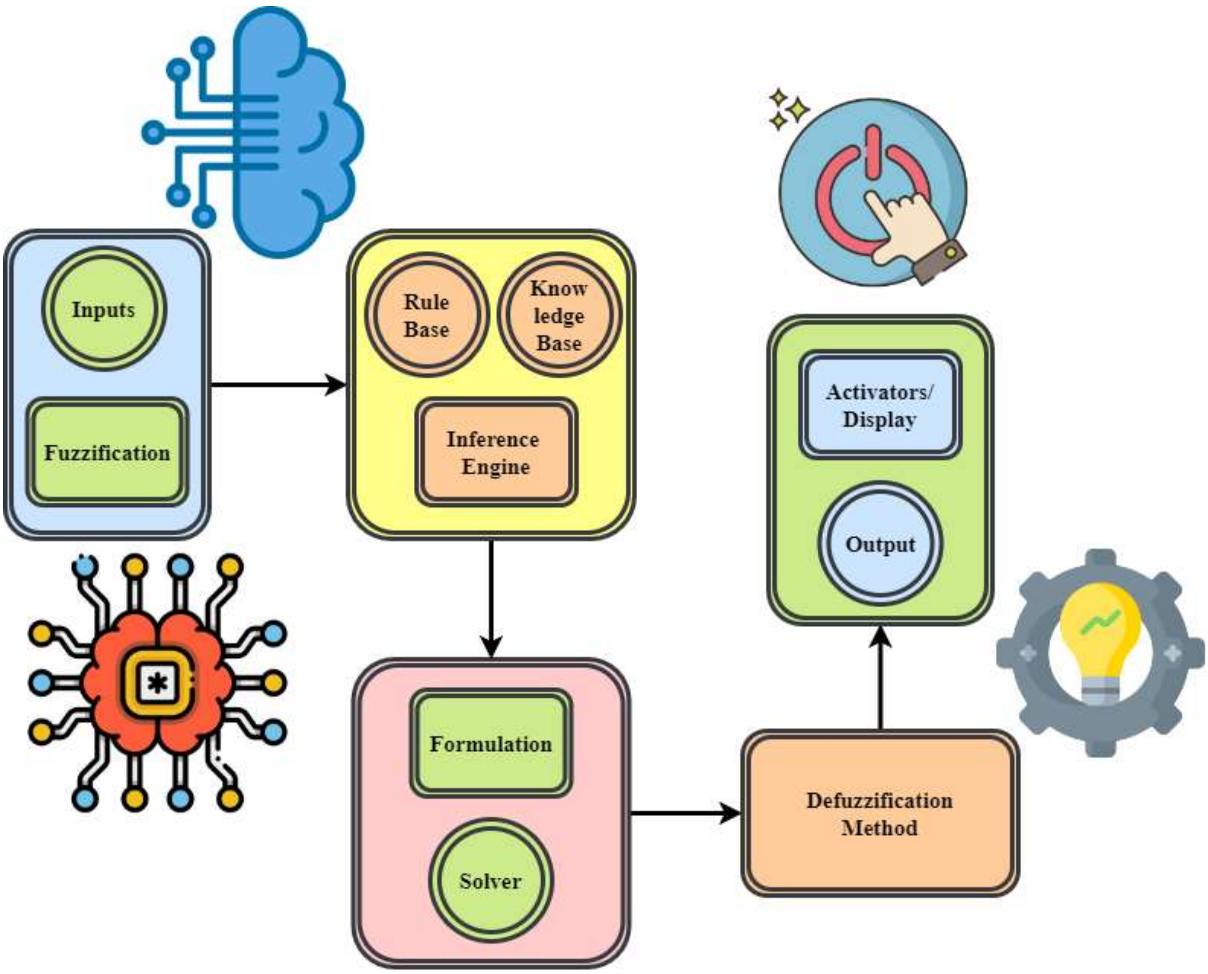

Figure 1: Fuzzy logic approaches to maximization and minimization

A complete framework for solving maximize and minimization issues using fuzzy logic, especially those containing transcendental equations, is shown in Figure 1. The procedure starts with the Intake Block, which collects Crisp Inputs, which are exact numerical values. Fuzzification converts these inputs into fuzzy sets, which are more equipped to deal with imprecision and uncertainty. The Ambiguous Reasoning System, which comprises the Knowledge Base and the Rule Base, processes the fuzzy sets afterwards. The Rule Base stores a set of fuzzy rules that describe the relationship between inputs and outputs, while the crucial knowledge and relationships of the system are contained in the Knowledge Base. The Inference Engine uses these rules and this information to infer the fuzzy output using fuzziness' resilience and ability to handle complex, nonlinear interactions. The next one is the Transcendental Equations Module, which comprises two components: Formulation and Solver. The Synthesis step uses results from the fuzzy inference to construct the transcendental equation. Complex algorithms are employed by Solver to solve these equations, taking into account their nonlinearity and the possibility of being analytically intractable. The defuzzification stage works on making it easy for people to get different results from solving higher equations that become crisp and practical usable outputs. This study can be sure these results will be valuable in real-life situations using the Defuzzification Method. Crisp Outputs presented to Actuators/Display systems through Output Blocks make decision-making and physical acts possible in this world. On this note, applied with modern optimization techniques, it would enable ease in handling maximization or minimization issues regarding such matters combined with fuzzy logic within a structured form, leading to high-quality and robust answers.

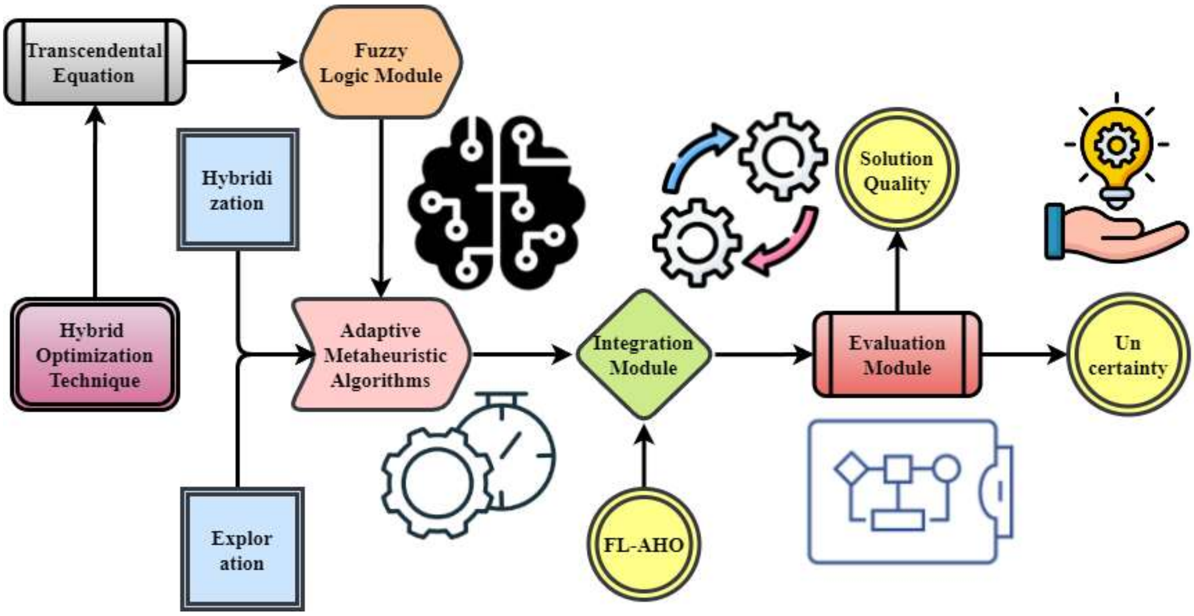

Figure 2: FL-AHO Hybrid Optimization Landscape

A better understanding of how mixed improvement landscape methodologies may be enhanced by utilizing the FL-AHO is presented in Figure 2. The first challenging task on its way is a transcendental equation, a type of equation used in many different areas of engineering and technology. These equations illustrate the complex interactions that are not linear and provide the foundation for the optimization environment. This level is further enhanced by adding fuzzier logic modules, which reflect uncertainty in optimization. This module can reliably handle scenarios that include many unknown variables whenever they occur. With the help of this Integration Module, these components are brought together to build an efficient approach known as FL-AHO.

This technique blends adaptive metaheuristic techniques with fuzzy logic concepts. By incorporating optimization into problem-solving approaches, the Output Layer becomes even more efficient at solving transcendental problems in fuzzy optimization settings. This is accomplished by including optimization in the approach. The implementation of these concepts may be found in a wide variety of packages, including engineering layout decision assistance systems, amongst others. Utilizing the Evaluate Module to do a simulated evaluation to determine robustness, recuperation cost, and convergence is used to conduct a thorough review.

A Minimization-Maximization-Based Fuzzy Linear Programming Method

Algorithm 1: Pseudocode for Solving Transcendental Equations Using Fuzzy Logic
Input: Transcendental function $f(x)$, interval $[a, b]$, max iterations max_iter, min iterations min_iter **Output:** Approximate solution $x*$ **Step 1. Initialize** population of guesses $X = \{x_1, x_2, \dots, x_n\}$ within the interval $[a, b]$ **Step 2. Define** membership functions $\mu A(x)$ and $\mu B(x)$ over the interval $[a, b]$ **Step 3. Set** iteration counter $iter = 0$ **Step 4. Repeat** until convergence or maximum iterations reached: **Step 5: Fuzzification:**   **For each** x_i in X:

Evaluate membership values $\mu A(x_i)$ and $\mu B(x_i)$

Step 6: Fuzzy Rule Application:

For each x_i in X:

If $f(x_i)$ is close to 0:

Keep x_i as a good candidate

If $f(x_i) > 0$: Adjust $x_i$to a smaller value using membership function $\mu A(x_i)$

If $f(x_i) < 0$: Adjust x_i to a larger value using membership function $\mu B(x_i)$

Step 7 Defuzzification:

For each x_i in X:

Adjust x_i based on fuzzy rules applied in step 6

Step 8: Convergence Check:

Update X with new suppositions f.

Increment iteration counter iter = $iter + 1$.

If max_iter is reached, return x_i that minimizes $|f(x_i)|$ as the approximate solution

End if

End if

End if

End for

End for

End

Algorithm 1 shows the Pseudocode for Solving Transcendental Equations Using Fuzzy Logic Validation Modules use comparative research and real-world instances, showing the approach's usefulness. As a result of its comprehensive nature, FL-AHO provides insights into various optimization issues that occur in the actual world.

$$S^{-1}(z,y) = S(y,z), \quad \propto \times \ \partial \ \ni Y \ and \ \nabla z \ni A \tag{1}$$

The symmetric relation is shown by the equation 1, $S^{-1}(z,y)$, which states that the opposite value is evaluated at $S(y,z)$. The notation $\nabla z \ni A$ means that the gradient of z is a member of the set A, and the symbol $\propto \times \ \partial \ \ni Y$ denotes a connection or operation affecting the set Y that is proportional to the partial derivative.

$$S_1\,(y,z) \ \geq \ \left\{(y,a), min_{z\ni Z} \left(max\left(\Delta_{s1}(y,z), \nabla_{S2}(z,a)\right)\right)\right\} \tag{2}$$

The expression 2 specifies a set where $S_1\,(y,z)$ is greater than or equal to a set that includes the minimum of the values obtained from the two functions, $(y,a), min_{z\ni Z}$ and $\nabla_{S2}(z,a)$. Functions or operators inside the optimization framework are denoted as Δ_{s1}, ∇_{S2}, and y,z are utilized.

$$\partial_{S1} \times s_2\,(y.a) = \bigvee_{z\ni Z}^{Q} \{\nabla_{S1}(y,z)\} \cup \nabla_{S2}(z,a) \tag{3}$$

A partial derivative is expressed in equation 3, ∂_{S1} and an operation s_2 applied to variables $y.a$ are involved. Using a logical and influenced by $\nabla_{S1}(y,z)$, the union of gradients $\nabla_{S2}(z,a)$ over $z \ni Z$ is combined.

$$\alpha_{\Delta}(z,p) = \bigvee\nolimits_{y\ni Y}^{b} \left\{\beta_{z-1}(z,y) \bigvee_{T\in W}^{K} (K+Q)\right\} \tag{4}$$

The expression $\alpha_{\Delta}(z,p)$ conveys an association calculated by the logical OR $y \ni Y$ over a set Y of functions, paired with an additional OR over a set involving a sum of constants $\beta_{z-1}(z,y)$. In this context, functions are being discussed, variables are being considered, and elements inside the sets are represented by $\bigvee_{T\in W}^{K}(K+Q)$.

$$b \geq (b \propto C) = b \cup c \geq c + (zk + jb) - \left(\sqrt{2x + yt}\right) \quad (5)$$

The variables are involved in a sequence of inequalities and relationships that are set up by the equation 5, $b \geq (b \propto C)$. In this context, decision variables are used, parameters zk and jb are mentioned, and inputs x and y are inputs that impact the optimization process. Fuzzy logic $b \cup c$ and proportionally integrate various constraints and their interdependencies in the FL-AHO technique.

$$\omega_{C\rho D}(z,a) = \beta_B(z) + \mu_D(y) + G_{L+P}, \nabla y \ni and\ z \ni Z \quad (6)$$

Equation 6 deals with the analysis of convergence rates $\omega_{C\rho D}(z,a)$ is dependent on variables z and a, and it is composed of the product of acts $\beta_B(z) + \mu_D(y) + G_{L+P}$. The equation expresses this function. Z is the domain for z, $\nabla y \ni$ is the gradient of y, is a parameter, and z are variables in this context.

$$\pi_B(w,p) = \delta_{y\ni Z}\{\alpha_{S-1}\}\beta + z_p(\gamma_{\nabla})\neg(P+Q) \quad (7)$$

The analysis of robustness $\pi_B(w,p)$ affect the terms that make up the function. Decision variables are represented by w and p, an element inside the domain is denoted by y, and parameters are denoted by P and Q. Within the framework of the FL-AHO method that has been suggested, this equation highlights how the optimization framework incorporates various components, such as logical operations, fuzzy logic α_{S-1}, and gradients ((γ_{∇})). These elements all work together to make the optimization technique more resilient.

$$\rho_{PWT}(y) = \sum_{k}^{vj} v_k + \gamma_f \times \left(x_p + \sum_{j}^{p} v_p = 1\right) \quad (8)$$

The analysis of the flexibility function ρ_{PWT} is defined by equation 8, which is dependent on the variable y. The terms involving v_k, γ_f, x_p, and v_p are defined in this equation where the suggested method is denoted with the logical fuzzy operations.

$$x = \left(\frac{1}{p}, \frac{1}{q}, \dots, \frac{1}{r}\right) = \frac{1}{m} \times \sum_{k}^{W}(w+q) + \frac{1}{p-1}(p_w) \quad (9)$$

The analysis of uncertainty is represented in equation 9 of the reciprocal values of the variables $\frac{1}{p}$, $\frac{1}{q}$, and $\frac{1}{r}$, which is a vector x that includes variables w and p_w. The symbols m for constant, W for set, and p_w for parameters are used here.

$$\forall_{Bhh}(y_w) = g\left(\propto_B (v_k), \forall_p[z_p]\right) = hj \quad (10)$$

The function $\forall_{Bhh}(y_w)$ is described by equation 10 as a function that depends on the analysis of solution quality. This function is defined as the product of functions g and $\forall_p$, which results in hj. The variables z_p and $\propto_B$ represent functions and elements inside a set, respectively, whereas v_k stands for elements within a set. Through the utilization of functions g and $\forall_p$, which most likely stands for optimization and aggregation procedures.

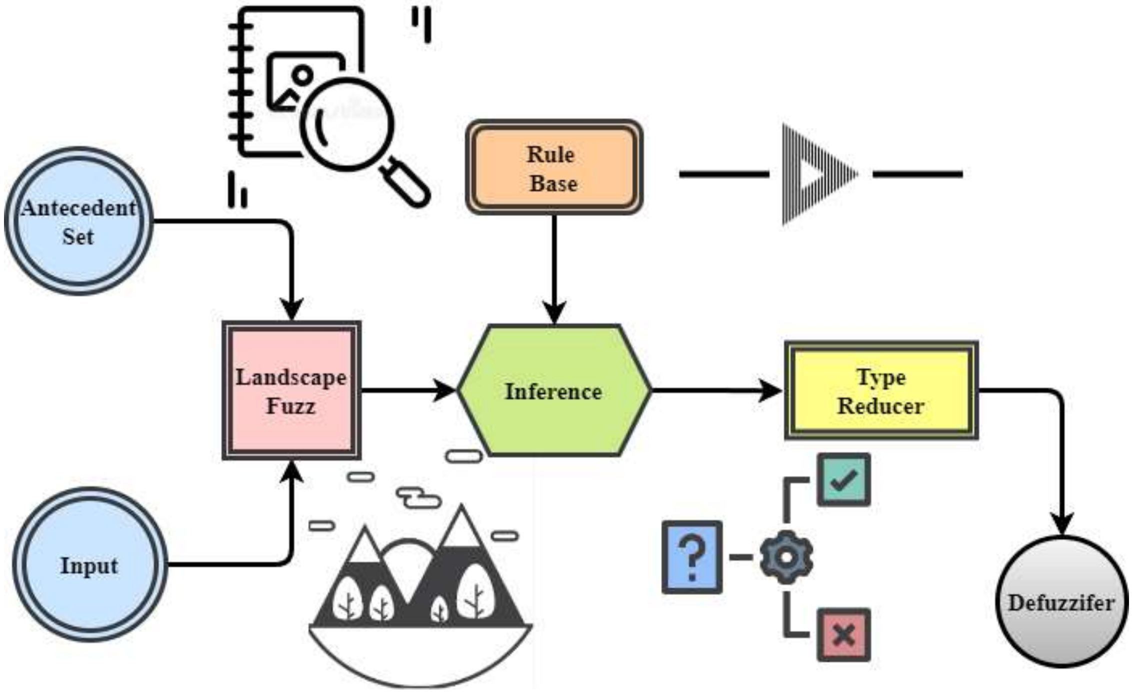

Figure 3: Illustration of the Fuzzy Adaptation of the Landscape

One method that may be utilized to address the imperfection and predictability in optimization environments is the interval method, depicted in a schematic form in Figure 3. The journey's input data begins with statistics that are either clear and quantitative, generated from measurements or discoveries. These figures serve as the beginning point. When these clean inputs are fed into the Landscapes Fuzzifier, they are transformed into fuzzy sets. These fuzzy sets are meant to replicate data's natural imperfection and instability from the actual world. The Antecedent Set comprises fuzzier logic rules, which establish the relationship between the system's behaviour and the supplied parameters.

During the Inference step, these rules are applied to the parameters that are input to determine the fuzzier result set, resulting in the answer that the system provides. As a result of the fuzzy logic rules saved within the Rule Base, the process of creating decisions is directed by these principles. All of the possible output values specified in fuzzy words are included in the fuzzy output sets. In the following step, the fuzzy source sets are transformed into a Type Reducing Set using the Type Reducer to facilitate the calculating process. With the help of the Defuzzifier, the mushy result set is transformed into useful and accurate numbers. Subsequently, the Type Reduction Set is subjected to additional treatment to obtain the comprehensive and clear output of the optimized solution. Even though it deals with imprecise data and complicated linkages, it can provide trustworthy and powerful answers.

$$r_d = \frac{1}{c_{qq}}\left(d_q - c_{r1} \times z_2 - d_{w2} \times q_3 - \cdots - d_{r,r-1} \times z_{q-1}\right) \qquad (11)$$

Equation (11) with relation to several constants and variables represented by $the\ \frac{1}{c_{qq}}$ parameters are denoted by $d_q - c_{r1} \times z_2 - d_{w2}$ and variables are denoted by z_{q-1}. This equation shows how the FL-AHO technique deals with complicated parameter-variable relationships within the framework of the approach.

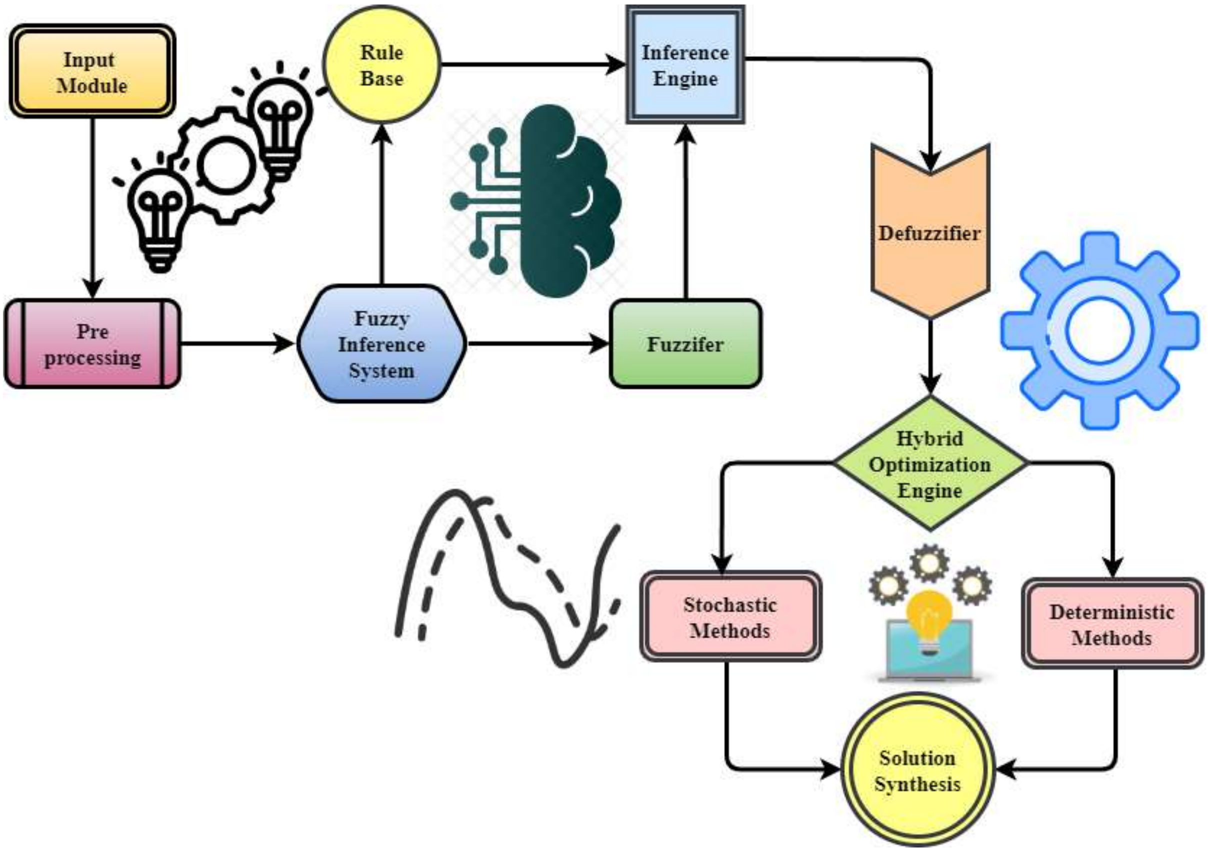

Figure 4: Flowchart Optimization of Hybrid Fuzzy Logic System

Figure 4 is the fuzzy inference system, which functions through several components and is the system's core. To begin, the Fuzzifier takes in clean data and turns it into a fuzzy set. Fuzzy outputs are generated by applying the rules stored in the Rule Base to the data in the Inference Engine. Next, the Defuzzifier handles the fuzzy outputs and converts them into crisp values. The Hybrid Optimisation Machine takes these numbers and uses a mix of Stochastic and Deterministic model methods to search for a solution efficiently. Deterministic approaches offer exact and trustworthy convergence pathways, whereas stochastic methods include uncertainty and unpredictability to sidestep local optima.

The Problem Formulation step mixes the outcomes of both methodologies to develop prospective solutions. Solution Evaluation is used to determine the quality of these solutions. A Convergence Check is a part of the process that checks if the best solution has been discovered. When convergence fails, the procedure is iterated to guarantee ongoing progress by modifying the parameters. Convergence confirms the ideal solution, and the procedure ends if yes. This adaptive and iterative method takes advantage of the best features of hybrid optimization and fuzzy logic to produce strong, high-quality solutions to complicated optimization problems.

$$zl_1 = \frac{1}{d_{11}}\left(d_1 - e_{12}t_2 - f_{13}j_3 - \cdots - k_{1p}e_r\right) \quad (12)$$

The function zl_1 using the inverse of d_{11} multiplied by the total of terms d_1, $e_{12}t_2$, $f_{13}j_3$, up to $k_{1p}e_r$ is defined by equation 12. Variables and constants that interact linearly are represented here.

$$w_{s1} - \sqrt{Z} = \frac{1}{2z_p}\left(s_p - \sqrt[2]{D}\right)^3 + \max_{0\le x\le 1} wsr^{-z^2} \quad (13)$$

Equation 13 is involved in this case; the decision variables are w_{s1} and s_p, the parameters are Z and D, and the variables inside the required ranges are z_p and x. In addition to an exponentially increasing decay term, the equation incorporates exponential and minimum functions.

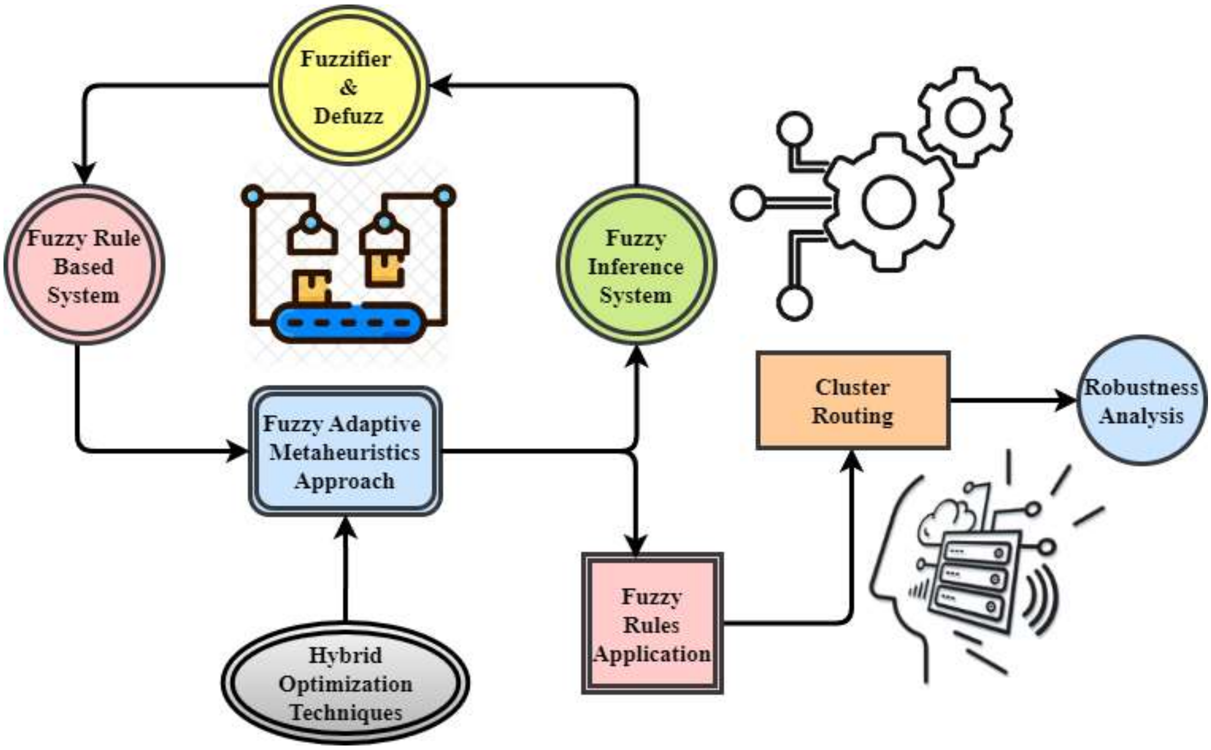

Figure 5: Fuzzy Adaptive Hierarchical Structure Optimization based on the Metaheuristic Approach

Choosing the ideal cluster head inside a cluster is accomplished by applying fuzzy hierarchical optimization, as seen in Figure 5. This is done to enhance landscape optimization. In this technique, the three most important components are the Gateway, the Fuzzy Rules for the Cluster Head Picking Process, and Optimization. During the optimization process, variables are fine-tuned to bring about the highest possible efficiency. Tools like Fuzzifier or defuzzifiers are utilized when dealing with incomprehensible or uncertain data. In other words, the Fuzzy Reactive Metaheuristic Method aims to continuously search for alternatives to increase speed when everything changes simultaneously. Fuzzy Reasoning Systems consider fuzzy policies while choosing cluster leaders and applying fuzzy logic standards. Utilization of these guidelines facilitates an improvement in selection processes. Fuzzy rules have been integrated into improving clustering head selection process accuracy, increasing panorama globally. This scheme is useful when challenging optimization problems occur within fuzzy optimization landscapes accompanied by transcendental calculations. From there, a strategy combining adaptive meta-heuristic techniques with fuzzy thinking notions of optimizing sceneries and determining cluster heads in such settings provides a real and efficient method. This happens under unforeseen and unexpected events.

$$h = k(z_a) + e' \times (m - m_2) + \left(mt + k_{3_p}\right) \times {}^1\!/_2\,(t + j) \qquad (14)$$

The combined use of terms $k(z_a) + e' \times (m - m_2)$, and a product of $\left(mt + k_{3_p}\right)$ and ${}^1\!/_2\,(t + j)$ defines h as an expression in the equation. In this instance, z_a is an inconsistent value determined in the corresponding equation.

$$t_{u+1} = z_k - \frac{1}{p} + \frac{n(r_s)}{q_t} + (n + l) \times \left(\frac{1}{j}\right) + (tz) \qquad (15)$$

The function t_{u+1} is defined by equation (15), which includes z_k, $\frac{1}{p} + \frac{n(r_s)}{q_t}$, and $n + l$. The relevant variable here is tz, whereas the other variables or parameters in the equation represent the optimization of fuzzy logic.

Algorithm 2: Fuzzy Logic System based Optimal Learning Algorithm for Transcendental Equations
Step 1: Initializing the weight vector, learning rates. Let t be iteration count, $t = 1$. Step 2: Compute the number of fuzzy rule, truth value, output, and error. Step 3: Compute the update changes of the control parameters in the premise part Let hidden node number $\mathrm{l} = 0$. For training input data $\mathrm{i} = 1, \ldots, \mathrm{N}$ Find the gradient components Step 4: Compute the gradient components Step 5: Calculate the learning rate Step 6: Implement fuzzification process Step 7: Map crisp input value to fuzzy sets based on membership functions Step 8: Implement fuzzy inference Step 9: Apply fuzzy rules to determine fuzzy step size Step 10: Implement defuzzification process Step 11: membership functions and rules (to be defined based on the problem context Update Fuzzy parameters Return End

Algorithm 2 shows the Fuzzy Logic System based Optimal Learning Algorithm for Transcendental Equations. The FL-AHO approach is an optimization algorithm that solves problems with transcendental functions. FL-AHO handles uncertainty well and negotiates a complex solution space by combining fuzzy inference systems with stochastic and deterministic algorithms. Compared to other conventional optimization techniques, simulation results show that FL-AHO significantly improves the quality of solutions, convergence rates, and robustness. The method has practical applications in engineering, finance, and science and can be used to solve intricate optimization problems.

4. Result and discussion

The FL-AHO technique presents a superior, adaptable, dependant solution for optimization issues via transcendental equations. FL-AHO can conform to different situations while managing uncertainty effectively by including fuzzy logic with deterministic and random algorithms. This unique combination makes timely convergence possible by exploring difficult solution landscapes while producing better solutions quickly. This report examines the robustness of FL-AHO and its adaptability to environmental change, how it manages uncertainty, and what it does to the quality of the problem's solutions. The focus is on how FL-AHO could potentially used in various real-world contexts to address problems posed by analytically intractable and nonlinear equations.

Dataset Description

A preference function and fuzzy logic-based resilient design optimization method are presented. This method requires expert design optimization. The company upgrade is the subject of this dataset. Optimization uses fuzzy preference functions for wing weight and drag [21]. Designers use fuzzy preference function limitations for fuel tank volume and lift coefficient. It simulates cruise velocity and altitude uncertainty. Optimization uses the non-dominated sorting genetic algorithm to find Pareto frontier solutions. Ultimate distance selects the best Pareto frontier solution. Probabilistic analysis indicates a less surprising layout.

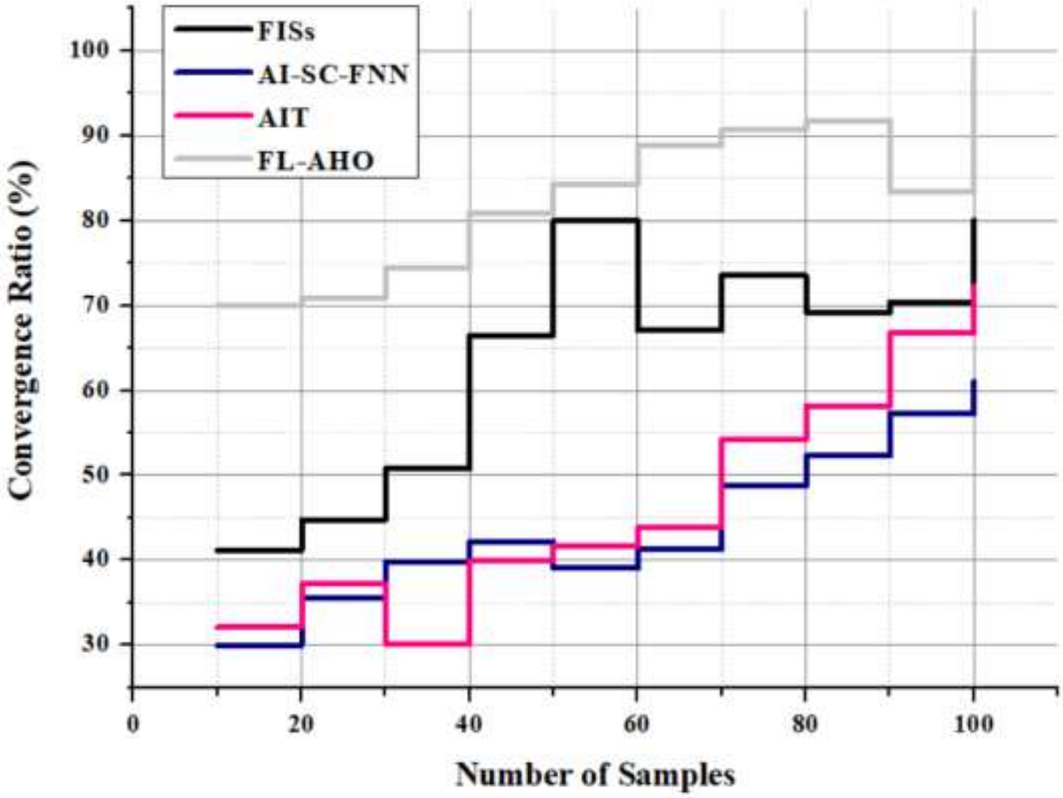

Figure 6: Analysis of convergence rates

The convergence rates of the FL-AHO method are much higher than those of existing conventional optimization methods. FL-AHO can easily navigate complex solution landscapes, reduce the probability of becoming stranded in local optima and find global optima faster. Fuzzy logic achieves this goal in conjunction with stochastic and deterministic algorithms. Figure 6 shows the simulation results, showing that FL-AHO can do the task more efficiently and with more robustness, leading to better solutions in less time. One possible explanation for the improved convergence rate is fuzzy logic's built-in adaptive learning and uncertainty management features. The analysis of convergence rates is 98.14%, which is higher than the existing methods.

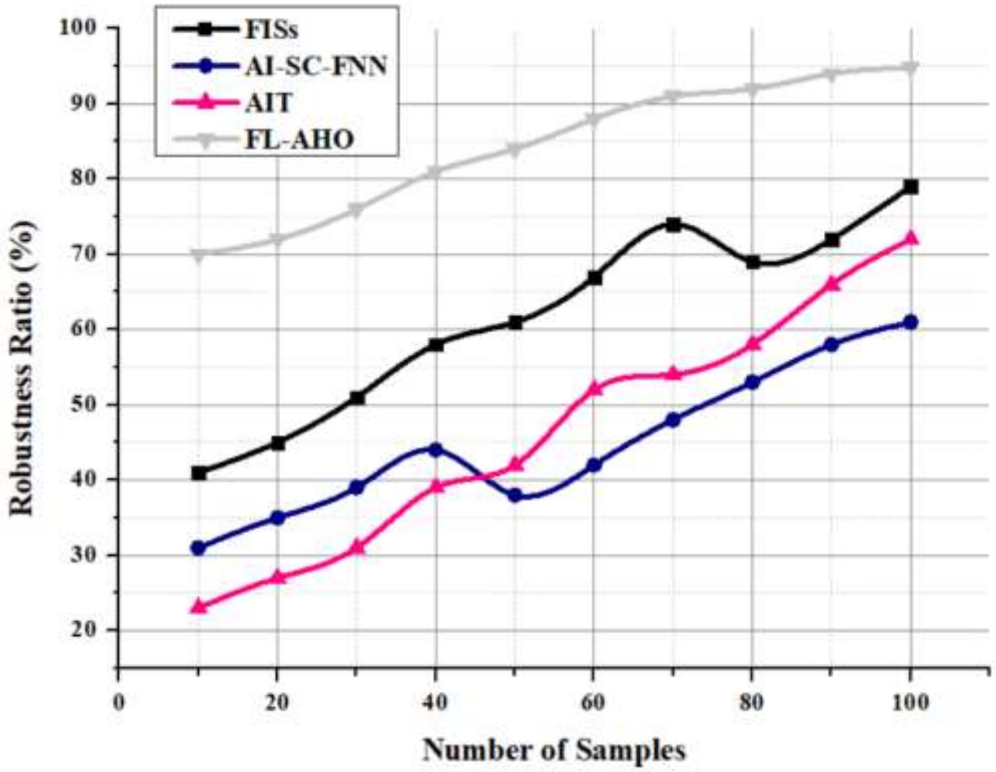

Figure 7: Analysis of robustness

The FL-AHO method's robustness is one of its main strengths, shown in Figure 7; it helps it deal with the complexity and uncertainty of transcendental equations well. Adding fuzzy logic allows FL-AHO to handle imprecise and ambiguous data and helps strengthen its resistance to changes in the scenario. Combining stochastic algorithms, which are good at exploring different solution spaces, with deterministic approaches, which can fine-tune solutions, allows FL-AHO to perform consistently across various conditions. Even in noise and nonlinearity, the hybrid approach ensures that the optimization process will remain stable and reliable. Therefore, it is quite robust in finding optimal solutions. The robustness analysis is gradually increased by 95.97% in the current method.

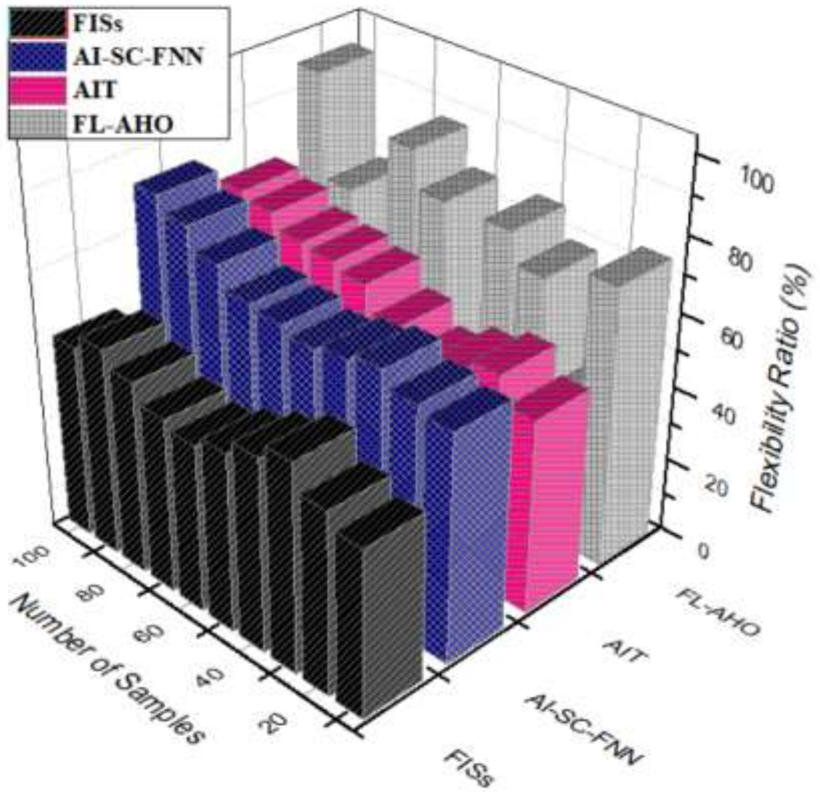

Figure 8: Analysis of flexibility

Flexibility in responding to different optimization issues and environmental factors is one of FL-AHO's many strengths, described in Figure 8. Fuzzy logic provides a versatile framework that may successfully address various uncertainties and subjective facts that might be introduced into optimization. FL-AHO's adaptability makes it a good fit, whether it's an obstacle to engineering design, financial modeling, or academic study. Furthermore, the method may switch between local exploitation and global exploration because of its hybrid structure, which uses several optimization algorithms. The dynamic flexibility of FL-AHO allows it to effectively handle a variety of optimization problems, making it a strong and adaptable tool. Compared to the existing method, the flexibility ratio is increased by 98.88% in the proposed method.

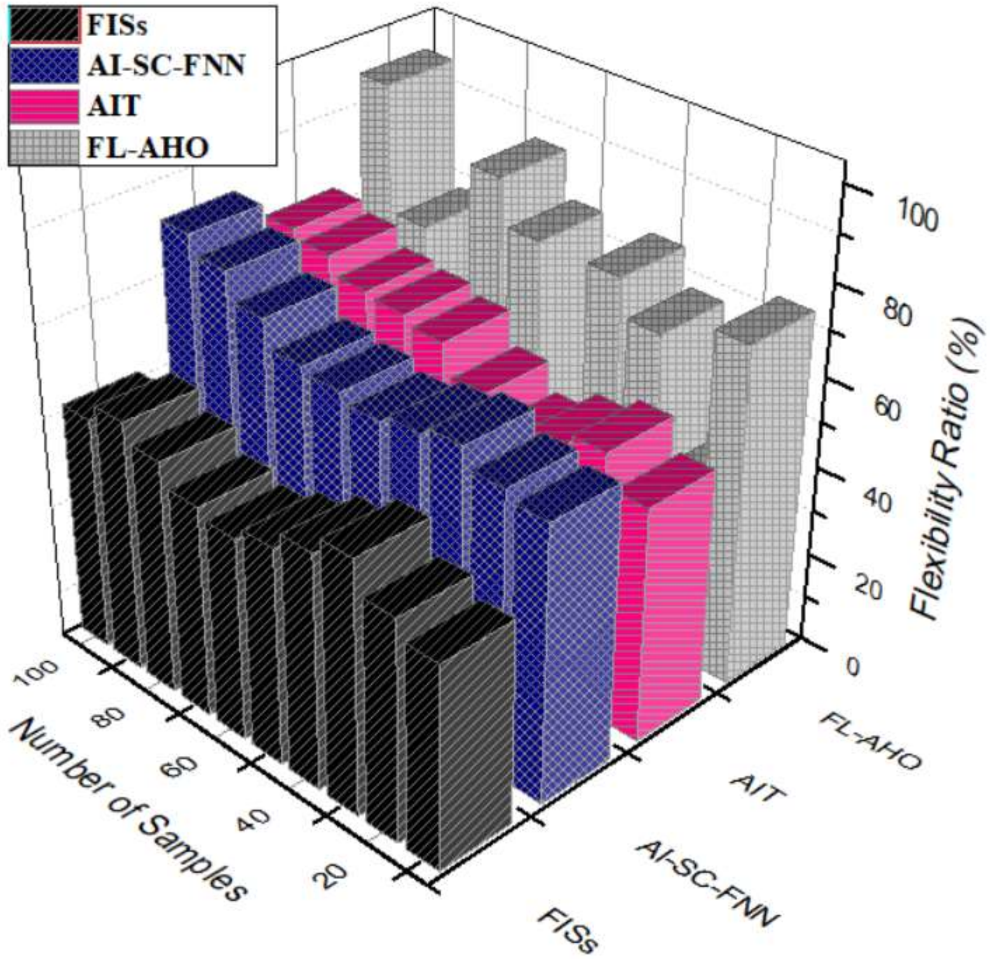

Figure 9: Analysis of uncertainty

Regarding optimizing problems involving transcendental equations, the FL-AHO method excels at managing uncertainty, as expressed in Figure 9. Using fuzzy logic's inherent capabilities to handle and understand unclear or imprecise data, FL-AHO may depict uncertainty more accurately than conventional methods. Integrating uncertainty management strategies further improves this capability by modifying the optimization process according to the degree of uncertainty. Thus, FL-AHO may maintain its performance stability regardless of how fragmentary or unclear the data utilized to solve the problem could potentially be. FL-AHO enhances the decision-making process overall while increasing the reliability of optimization outcomes. Integration and management of uncertainty are key to achieving this goal. The analysis of the uncertainty ratio is 96.2%, which is improved in the proposed method.

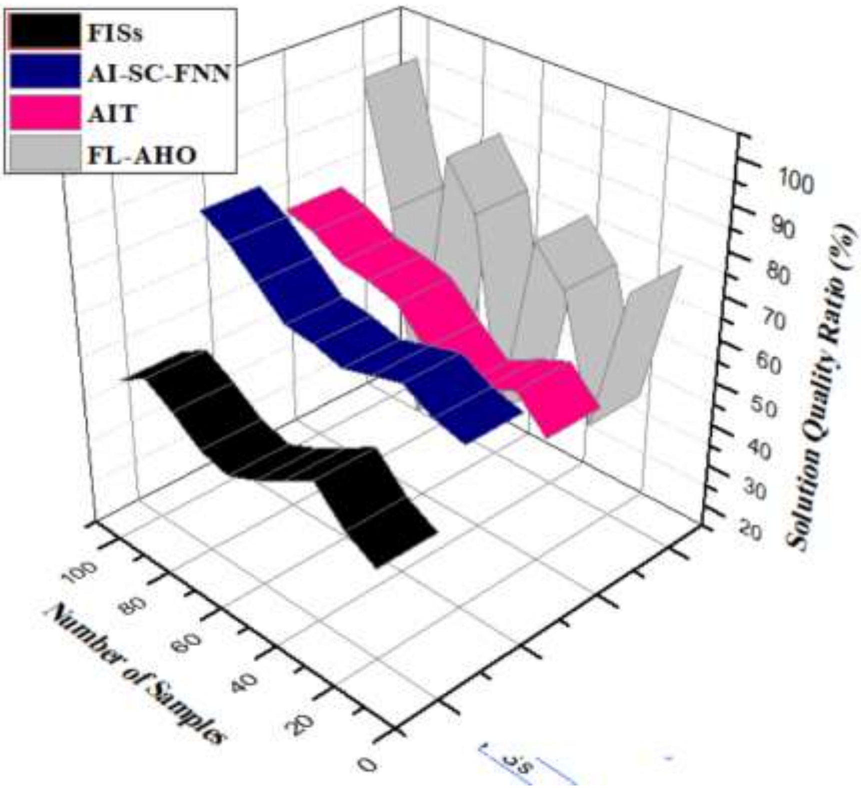

Figure 10: Analysis of solution quality

A much higher-quality solution is generated in Figure 10 when FL-AHO is used in contrast to more traditional optimization methods. FL-AHO uses fuzzy logic's properties to explore situations with complex and nonlinear solutions better. The hybrid method allows one to explore the solution space exhaustively to reduce the chances of getting bad minimal areas. For more precise results, deterministic algorithms need fine-tuning of the answers; random algorithms, on the other hand, provide a more robust search capability. Based on the results of the simulations, FL-AHO reliably generates high-quality solutions. The solutions must be optimal or nearly optimal to satisfy or exceed the performance requirements given for this attribute to be present. However, the improved performance quality has made it applicable to applications that require a high accuracy rate (99.2% increase of the proposed method).

FL-AHO technology's flexibility allows it to be easily modified for use in a wide range of diverse optimizations, whereas its ruggedness enables it to resist all kinds of predicaments. FL-AHO stands out as an effective tool that is strong enough to produce reliable results quickly but could also be trusted in consistency among modernized models with highly efficient engineers.

5. Conclusion

Implementing the transcendental equation optimization process using the FL-AHO approach has brought considerable outcomes.FL-AHO offers a robust and adaptable optimization method under its complexity and uncertainty management. It does this through hybrid strategies, a combination of fuzzy logic with stochastic and deterministic algorithms. Moreover, it can quickly and reliably provide high-quality results, another advantage. The simulation indicates that FL-AHO outperforms traditional optimization algorithms regarding solution quality, convergence speed, and managing ambiguity. This suggests that FL-AHO could be used to solve intricate optimization problems in engineering, financial modelling and science. It allows for relevant insights and effective optimization tools. In future perspectives, a lot has been done considering an analysis of the FL-AHO study from many points of view. This might include the development of real-time applications using fuzzy inference systems. The aim is to model dynamic uncertainties better when situational change occurs more frequently. To make this adaptive learning smarter and more successful, developers are considering how to introduce machine learning. An alternative approach is solving more complex real-world problems using FL-AHO, which covers multi-objective optimizations to large-scale industrial systems. Additionally, one may examine how FL-AHO performs under decentralized or distributed computing conditions scaling for big data applications. The next step will involve enhancing FL-AHO's ability to handle more complicated, diverse optimization issues.

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