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Research Article

Optimization Of Coagulation Tank Processes Through Interval Fuzzy Type 2 Logic System: A Study of Turbidity Reduction

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Abstract: This research optimizes wastewater treatment's coagulation process through a Genetic Algorithm and an Interval Type-2 Fuzzy Logic System (IT2FLS). It focuses on enhancing key parameters such as coagulant dosage, mixing speed and time, pH, and temperature. Comparison with traditional jar test results under specific conditions validates the effectiveness of these innovative approaches. Although the final turbidity was marginally higher using the Genetic Algorithm, the IT2FLS closely mirrored the trend of the jar test results, showing remarkable accuracy in predicting final turbidity. This predictive accuracy was quantified using Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error measurements. The research has significant implications for public health, safety, environmental sustainability, and economic concerns by improving wastewater treatment efficiency. It recommends further studies and validations with varied datasets for robust real-world application of the IT2FLS model. This work's novelty lies by focusing on optimization techniques for the wastewater coagulation process. Through the application of Genetic Algorithm and IT2FLS to observe key parameters, outcome and comparison with traditional methods, the study contributes to a more sustainable and efficient future in wastewater treatment.

Keywords: Wastewater; Coagulation; Fuzzy Logic; Genetic Algorithm.

1. Introduction

The problem of wastewater management has gained significant attention globally due to the increasing threats to environmental sustainability and public health. Wastewater treatment processes, including the crucial step of coagulation, serve as the primary defense against these challenges. Coagulation involves the aggregation of small particles into larger flocs, making them easier to remove from the water. The effectiveness of this process is influenced by several parameters, including the coagulant dosage, mixing speed and time, pH, and temperature. [1-6]

Optimization of these parameters has been the subject of intense research, given their direct impact on the efficiency of the coagulation process and the quality of the treated water. Traditional methods for optimizing these parameters have typically relied on empirical approaches, such as jar testing. However, these methods can be time-consuming, costly, and limited in their ability to optimize multiple parameters simultaneously [7].

To address these challenges, this study embarks on a journey of harnessing the power of advanced computational techniques, namely Genetic Algorithms and Interval Type-2 Fuzzy Logic Systems (IT2FLS). These methods, characterized by their efficiency and comprehensive approach, present a promising avenue for enhancing the coagulation process's optimization [8-10].

Genetic Algorithms (GA) are search algorithms inspired by the principles of natural selection and genetics. GA excel in navigating vast and intricate search spaces, thus rendering them apt for multi-parameter optimization problems. Additionally, their robustness against local optima positions them as a favorable tool for complex optimization tasks, such as those encountered in wastewater treatment [11 - 14].

Similarly, this research employs Interval Type-2 Fuzzy Logic Systems (IT2FLS) to simulate and model the coagulation process. Compared to traditional Type-1 fuzzy logic systems, IT2FLS demonstrate superior management of the uncertainties and imprecisions inherent in real-world systems. Their capacity to accommodate a higher degree of uncertainty renders them well-suited for modeling complex systems such as the coagulation process [15-17].

An understanding of the importance of parameters such as coagulant dosage, mixing speed, mixing time, pH, and temperature is vital to the coagulation process. Coagulant dosage directly influences pollutant removal, while the mixing speed and time govern the formation and growth of flocs. Furthermore, the pH level affects the charge of particles, and the temperature influences the rate of chemical reactions, both vital to successful coagulation.[2], [4], [18-20]

This study has four core objectives. The first involves using Genetic Algorithms to optimize critical parameters related to the coagulation process, comparing these results with conventional jar test experiments to underline computational methods' benefits. The second objective is to develop a Type-2 fuzzy logic-based model for the coagulation process that factors in parameters like coagulant dose, pH, temperature, mixing time, and mixing speed for a comprehensive representation. The third objective tests the model's robustness through a validation phase, comparing its predictions with experimental results, primarily focusing on turbidity reduction. Lastly, the fourth objective entails a thorough examination of the model's accuracy using statistical measures like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), revealing its performance and adaptability in real-world wastewater treatment scenarios.

This research hypothesizes that the Type-2 fuzzy logic-based model, given its consideration of multiple parameters, will provide a more effective optimization of the coagulation process in wastewater treatment than conventional methods. The model is anticipated to generate accurate predictions of final turbidity and demonstrate adaptability and robustness in the face of real-world complexities, potentially enhancing efficiency and reducing operational costs and time.

By utilizing Genetic Algorithm Optimization for fine-tuning key parameters and deploying a Type-2 fuzzy logic-based model for simulating the coagulation process, this study takes a significant step towards enhanced wastewater treatment processes. The successful execution and validation of this approach could contribute substantially to the realms of environmental protection and public health, while also potentially offering economic benefits through increased efficiency. The study concludes by emphasizing the need for further research and validation with more diverse datasets, solidifying the models' adaptability and robustness for real-world applications.

2. Materials and Methods

This research adopted a systematic methodology focusing on optimizing the coagulation process in wastewater treatment, specifically assessing a water sample from Teluk Mesira plant in Kelantan. Using a laboratory-simulated jar test, the study explored the turbidity reduction in the water samples to find optimal values for various parameters, including coagulant dose, pH, temperature, mixing time, and mixing speed. The optimal values obtained from the jar test were then compared with values from Genetic Algorithm Optimization. A model was developed using type-2 fuzzy logic to manage uncertainties and imprecise information, providing a more accurate optimization of the coagulation process than traditional techniques. The following sections delve into the detailed processes and procedures employed in this study.

2.1 Conventional Jar Test

2.1.1 Water Collection

The water sample is collected from Teluk Mesira water treatment plant, Kelantan, for the study. The sample's initial conditions, including its temperature, pH, and turbidity, are measured, and recorded using appropriate devices: a 2100Q Portable Turbidimeter for turbidity, a thermometer for temperature, and a pH meter for pH measurement. **Table 1** summarises the characteristics of the collected water sample.

Table 1 Characteristics of water sample collected from Teluk Mesira Water Treatment Plant.

Sample	PH	Temperature (°C)	Turbidity (NTU)
1	7.42	31.8	13

2.1.2 Coagulation Preparation

A 30% PAC solution is prepared for use as a coagulant in the jar test method. The preparation process includes the dilution of 3.3 grams of PAC powder in a 1000 mL volumetric flask [21].

2.1.3 Coagulant Dosage

The coagulant dosage levels tested range from 50 ppm to 200 ppm. A two-step mixing process is employed to simulate the coagulation process. The initial rapid mixing is conducted at 150 rpm for three minutes, followed by slow mixing at 30 rpm for 30 minutes. The flocs are then allowed to settle for 15 minutes, post which the final turbidity of the sample is measured using a turbidity meter. The specific parameters used in this experiment are summarized in **Table 2**.

Table 2 Experimental characteristics for coagulant dosage jar test experiments.

Characteristics	**Description**
Coagulant Type	Polyaluminum Chloride (PAC)
Coagulant Dosage (ppm)	50, 70, 90, 130, 150, 170, and 200 ppm
Rapid Mixing Speed	150 rpm at 3 minutes
Slow Mixing Speed	30 rpm at 30 minutes
Settling	15 minutes

2.1.4 Mixing Speed

Experiments are conducted to identify the effect of different rapid mixing speeds on the coagulation process. The coagulant dosage remains constant at 125 ppm, and the speeds tested are from 100 to 200 rpm. The experimental parameters are summarised in **Table 3**.

Table 3 Experimental characteristics for mixing speed jar test experiments.

Characteristics	Description
Coagulant Type	Polyaluminum Chloride (PAC)
Coagulant Dosage (ppm)	125
Rapid Mixing Speed	100, 130, 150, 170, 200 rpm at 3 minutes
Slow Mixing Speed	30 rpm at 30 minutes
Settling	15 minutes

2.1.5 Mixing Time

The experiment focuses on determining the effect of different rapid mixing times, ranging from 1 to 5 minutes. The experimental parameters are summarised in **Table 4**.

Table 4 Experimental characteristics for mixing time jar test experiments.

Characteristics	Description
Coagulant Type	Polyaluminum Chloride (PAC)
Coagulant Dosage (ppm)	125
Rapid Mixing Speed	150 rpm at 1, 2, 3, 4, and 5 minutes
Slow Mixing Speed	30 rpm at 30 minutes
Settling	15 minutes

2.1.6 pH Level

The experiment aims to examine the impact of varying pH levels on the coagulation process. The pH values are adjusted with Hydrochloric Acid (Hcl) and Sodium Chloride (NaOH). The trials are conducted at different pH levels, ranging from 5 to 9. The experimental parameters are summarised in **Table 5**.

Table 5 Experimental characteristics for pH jar test experiments.

Characteristics	Description
Coagulant Type	Polyaluminum Chloride (PAC)
PH Value	5, 6, 7, 8, and 9
Coagulant Dosage (ppm)	125
Rapid Mixing Speed	150 rpm at 3 minutes
Slow Mixing Speed	30 rpm at 30 minutes
Settling	15 minutes

2.1.7 Temperature

This section involves modulating the temperature of the water sample to target temperatures of 25°C to 40°C and observing the effects on the coagulation process. The experimental parameters are summarised in **Table 6**.

Table 6 Experimental characteristics for Temperature jar test experiments.

Characteristics	Description
Coagulant Type	Polyaluminum Chloride (PAC)
Temperature	25°C, 27.5°C, 30°C, 32.5°C, 35°C, 37.5°C and 40°C
Coagulant Dosage (ppm)	125
Rapid Mixing Speed	150 rpm at 3 minutes
Slow Mixing Speed	30 rpm at 30 minutes
Settling	15 minutes

2.2 Genetic Algorithm

The methodology for implementing and executing the GA in this specific optimization study comprises five key steps [11]:

1. Defining the Objective Function: The initial step involves identifying the objective function, which in this study is the ultimate turbidity. The aim is to minimize this parameter.
2. Establishing Input Variables: The lower and upper bounds for the input variables are established at [5, 25, 100, 1, 50] and [9, 40, 200, 5, 200], respectively. These define the ranges in which the GA explores for the optimal values of pH, temperature, mixing speed, mixing time, and coagulant dosage.
3. Configuring the Genetic Algorithm: This step involves setting the options for the GA, including population size and maximum generations. The population size of 200 denotes the number of potential solutions the GA sustains per generation, while the maximum number of generations, set at 500, signifies the iterations the GA will execute.
4. Execution of the Genetic Algorithm: This phase involves running the GA using the defined objective function, the number of variables (five in this case), and the predetermined input variable bounds. The GA hence navigates for the optimal values of the input variables that result in the minimum objective function.
5. Presentation of Results: Finally, the optimal input variable values and the corresponding minimum final turbidity are displayed as the outcomes of the GA optimization.

2.3 Type-2 Fuzzy Inference Modelling

The methodology of this part comprises five key components: Fuzzifier, Inference System (Rule Base), Type Reduction, and Defuzzifier. The project employs Type-1 and Interval Type-2 Fuzzy Logic Systems (T1FLS and IT2FLS), using both singleton and non-singleton fuzzifiers to map crisp inputs into fuzzy inputs.[22]

2.3.1 Fuzzifier

Fuzzification utilizes Gaussian, triangular, and trapezoidal membership functions to account for data uncertainty. In this project, a Gaussian shape is adopted to represent the inputs: mixing time, mixing speed, temperature, pH, and coagulant dosage. The Gaussian function, with its continuity and two-parameter design (mean and standard deviation), provides a comprehensive data representation, minimizing system inconsistency and facilitating uncertainty modelling.[22]

The Gaussian membership functions are defined in **Table 7**, and **Figure 1** illustrates a Type-2 Mamdani Fuzzy Logic System with these functions. The fuzzified input variables are pH, temperature, mixing speed, mixing time, and coagulant dosage, categorized into respective linguistic terms. The system models the coagulation process, where these parameters influence the sample final turbidity.[23]

Table 7 Input and Output Upper Parameters

Input	**Range**	**Classifications**	**Upper Parameters**
PH	5-9	Acid	[0.7078 5]
		Neutral	[0.7078 7]
		Alkali	[0.7078 9]
Temperature	25-40	Room Temperature	[5.308 25]
		High Temperature	[5.308 40]
Mixing Speed	100-200	Low	[17.69 100]
		Average	[17.69 150]
		High	[17.69 200]
Mixing Time	1-5	Short	[0.7078 1]
		Average	[0.7078 3]
		Long	[0.7078 5]
Coagulant Dosage	50-200	Low	[2.654 50]
		Average	[2.654 125]
		High	[2.654 200]
Output	Range	Classifications	Upper Parameters
Final Turbidity	0-8	Low	[1.416 -1.11e^{-16}]
		Average	[1.416 4]
		High	[1.416 8]

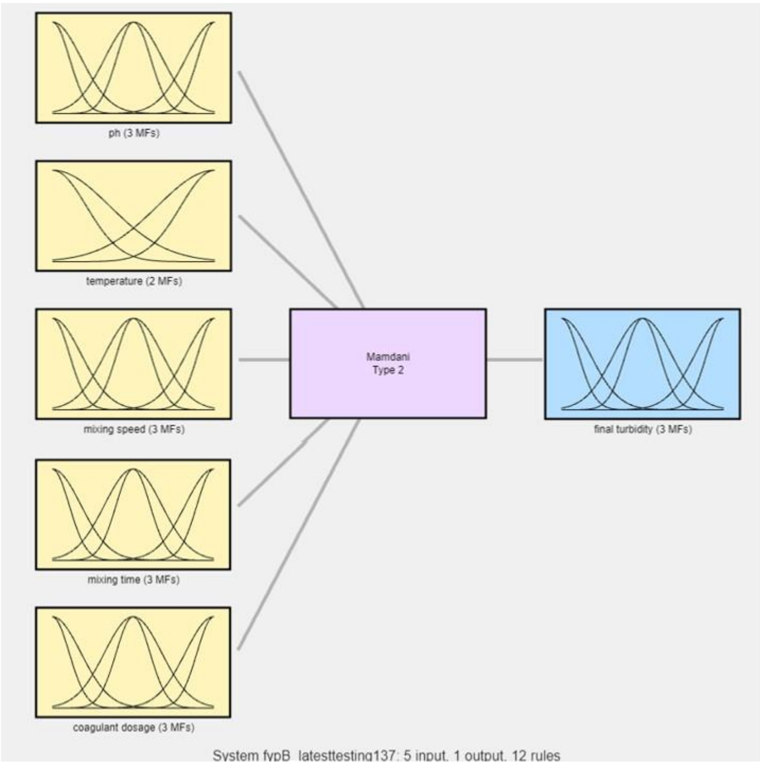

Figure 1: Interval Fuzzy Type-2 Model in Mamdani type.

2.3.2 Inference System (Rule Base)

The inference system applies a rule-base to the fuzzy input to produce a fuzzy output. Fuzzy Rule-Based Systems (FRBS) employ IF-THEN rules, where antecedents and consequents form a knowledge base (KB) and an inference engine module. The engine includes a fuzzification interface, an inference system, and a defuzzification interface.[15]

A series of rules (as detailed in the section) were formulated in alignment with Interval Type2 Fuzzy Logic Systems (IT2FLS). These rules link the inputs to the output, final turbidity, employing linguistic terms to describe system behavior naturally. The rule base and database structure provide robustness and flexibility, useful for complex real-world data scenarios.

2.3.3 Type Reduction

The type reduction phase is vital within IT2FLS, transforming the interval-valued output from the inference mechanism into a Type-1 fuzzy set. The Karnik-Mendel (KM) algorithm performs this task due to its effectiveness and computational efficiency.[8]

In the coagulation process, the KM algorithm converts the interval-valued output into a crisp value, iteratively calculating the upper and lower bounds of the output interval until convergence. The resultant crisp value represents the most probable turbidity level given the initial inputs.

2.3.4 Defuzzifier

The defuzzification process translates the fuzzy results from the inference process into a crisp output. This conversion occurs through a type reduction process, simplifying the Type-2 fuzzy set into an interval Type-1 fuzzy set. The final output value, represented as 'y', is the average of the lower limit (cL) and upper limit (cR) centroid values derived from the type reduction process. This conversion enables interpretation and decision-making in the coagulation process.[23]

2.4 Validation of Interval Type-2 Fuzzy Set Model

2.4.1 Comparing Parameter Ranges

This step involves conducting a sequence of traditional jar tests with different parameter ranges. These parameters include pH, temperature, coagulant dosage, mixing speed, and mixing time. The same range of parameters is then fed into the IT2FLS model to predict the final turbidity. The turbidity values obtained from both the jar tests and the IT2FLS model are then compared.

2.4.2 Comparing Optimal Results

The optimal values for each parameter, which resulted in the lowest final turbidity in the jar tests, are determined. These values are then input into the IT2FLS model to predict the final turbidity. The turbidity results from the optimal conditions and the IT2FLS model are compared for validation.

2.4.3 Comparing Different Water Sample Characteristics

Additional jar tests are conducted using water samples with optimal conditions but with different initial turbidity. The conditions are input into the IT2FLS model to predict the final turbidity for the second water sample. The turbidity values obtained from the jar tests with the second water sample and the IT2FLS model are then compared.

2.5 Accuracy Analysis

To evaluate the efficiency of the proposed method for modelling the coagulation process, three different metrics are used. These include Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).[24]

Mean Absolute Error (MAE): It calculates the average of the absolute differences between the predicted and actual values.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \|y_i - \hat{y}_i\|. \tag{1}$$

Mean Squared Error (MSE): Similar to MAE, but squares the differences before averaging them, emphasizing larger errors.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2. \tag{2}$$

Root Mean Squared Error (RMSE): This is the square root of MSE, giving an error rate that's more sensitive to large errors.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}. \tag{3}$$

In these formulas, yi represents the output from jar test method, yî is the actual output from the fuzzy system, and n is the total number of data samples.

3. Results and Discussion

This research developed and validated a type-2 fuzzy inference model to optimize the coagulation process in wastewater treatment, focusing on five parameters: coagulant dosage, mixing speed, mixing time, temperature, and pH. Initial results from a standard jar test on a water sample from Teluk Mesira, Kelantan, were compared to values optimized via a genetic algorithm. The robustness and adaptability of the model were assessed by comparing its turbidity predictions with experimental results, highlighting its ability to handle uncertainties and variability in real-world wastewater treatment scenarios. The research underscores the potential utility of type-2 fuzzy logic models in enhancing water treatment processes and offers insights for future improvements in coagulation process optimization.

3.1 Parameter Results

3.1.1 Coagulant Dosage Results

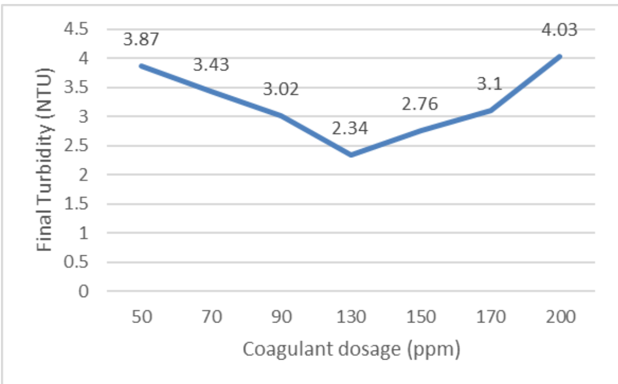

Figure 2: Effect of coagulant dosage (ppm) on final turbidity (NTU)

Analysing the effects of varying coagulant dosages on final water turbidity reveals a clear pattern based on **Figure2**. The final turbidity decreases with coagulant dosage increases from 50 ppm to 130 ppm, indicating improved water clarity (from 3.87 NTU to 2.34 NTU). The corresponding turbidity reduction percentages reflect this trend, rising from 70.23% to 82%. However, dosages exceeding 130 ppm show an inverse effect with an increase in final turbidity due to factors such as over-coagulation, over-neutralization, and exceeding solubility limits. Thus, 130 ppm emerges as the optimal dosage.

3.1.2 *Mixing Speed Results*

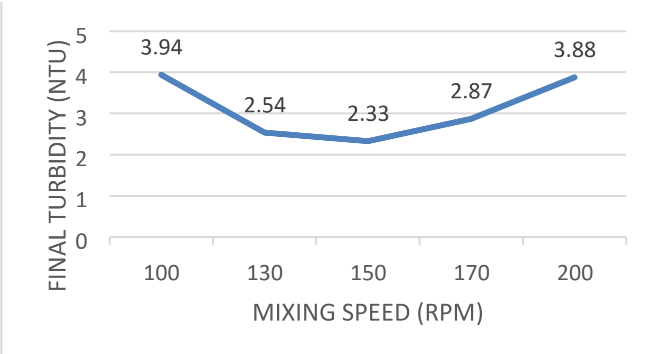

Figure 3: Effect of Mixing Speed (RPM) on final turbidity (NTU)

Based on **Figure3**, the relationship between mixing speed and final turbidity follows a similar pattern. As mixing speed increases from 100 RPM to 150 RPM, final turbidity decreases (from 3.94 NTU to 2.33 NTU) indicating enhanced particle removal. Beyond 150 RPM, turbidity rises due to over-mixing that inhibits effective particle binding. The optimal mixing speed is thus 150 RPM.

3.1.3 *Mixing Time Results*

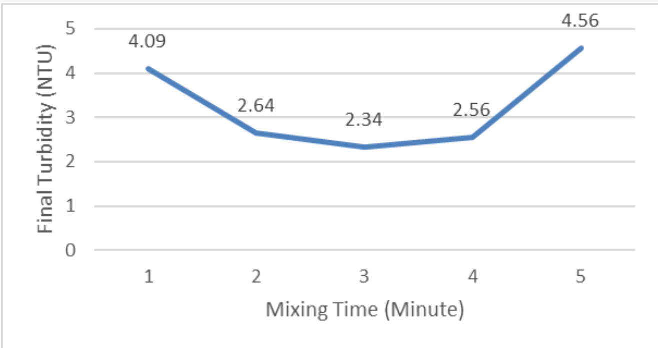

Figure 4: Effect of Mixing Time (Minutes) on final turbidity (NTU)

Based on **Figure4,** an increase in mixing time from 1 to 3 minutes sees a decline in final turbidity (from 4.09 NTU to 2.34 NTU) indicating better water clarity. Yet, an extended mixing time beyond the 3-minute mark raises turbidity due to over-mixing and subsequent floc breakage. Therefore, the optimal mixing time is 3 minutes.

3.1.4 Temperature Results

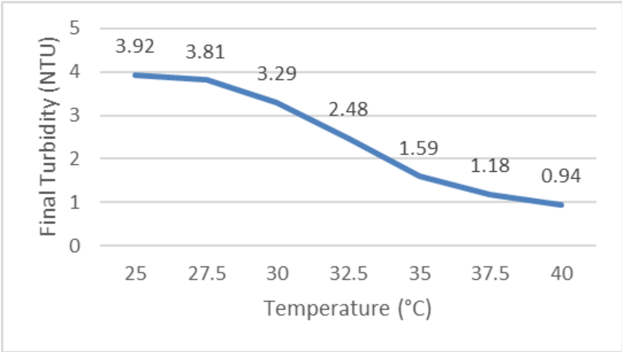

Figure 5: Effect of Temperature (°C) on final turbidity (NTU)

Based on **Figure 5**, it indicates an inverse correlation between temperature and final turbidity. As temperature rises from 25°C to 40°C, final turbidity decreases (from 3.92 NTU to 0.94 NTU) implying an enhanced coagulation process. Reasons include increased reaction rates, better coagulant performance, and heightened particle collision due to increased kinetic energy. However, excessively high temperatures may introduce other challenges.

3.1.5 pH Results

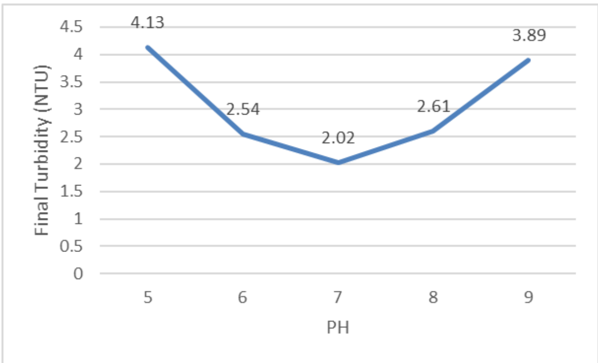

Figure6: Effect of PH on final turbidity (NTU)

Based on **Figure**6, the impact of pH on final turbidity reveals that as pH increases from 5 to 7, final turbidity decreases (from 4.13 NTU to 2.02 NTU), suggesting a more effective coagulation process. Conversely, a further increase in pH from 7 to 9 results in increased final turbidity, likely due to decreased coagulant effectiveness. The optimal pH level is thus determined to be 7.

3.2 Genetic Algorithm Optimization

The study compared the conventional Jar Test Experiment and Genetic Algorithm Optimization for optimizing the coagulation process in wastewater treatment. The comparison focused on five parameters: pH, temperature, mixing speed, mixing time, and coagulant dosage. The final turbidity was taken as the measure of success.

The findings, as summarized in **Table 8**, showed both methods yielding similar optimal values for pH (7) and coagulant dosage (125 ppm). The mixing speed suggested by Genetic Algorithm Optimization was marginally higher than that determined by the Jar Test, which was not significant enough to affect the final turbidity significantly.

However, more notable discrepancies were observed in temperature and mixing time. The Genetic Algorithm Optimization proposed a lower optimal temperature (25.0001°C vs. 40°C) and a longer mixing time (5 minutes vs. 3 minutes). These discrepancies reflected the limitations of Genetic Algorithm

Optimization, potentially stemming from its probabilistic nature, sensitivity to initial conditions, or parameter choices.

The suboptimal performance of the Genetic Algorithm Optimization was evident in the final turbidity, which was higher (1.2847 NTU vs. 0.89 NTU) than the Jar Test, suggesting less successful treatment results. This finding emphasizes the need for further improvement and fine-tuning in genetic algorithm techniques for more reliable optimization." simplify it more and with formal language.

Table 8 Comparison of Optimal Parameter Ranges: Conventional Jar Test Experiment vs. Genetic Algorithm Optimization

	PH	Temperature (°C)	Mixing Speed (RPM)	Mixing Time (Minute)	Coagulant Dosage (ppm)	Final Turbidity (NTU)
Conventional Jar Test Experiment	7	40	150	3	125	0.89
Genetic Algorithm Optimization	7	25.0001	150.0001	5	125	1.2847
Absolute Error	0	14.99	0.0001	2	0	0.3947

3.3 Type-2 Fuzzy Inference System Model

The subsequent section of the study introduces the development of a Type-2 fuzzy inference system model for the coagulation process, utilizing Gaussian membership functions. Type-2 Fuzzy Inference System Model applied, characterized by its fuzzy membership functions, which offer an additional degree of freedom to handle uncertainties, making it an ideal fit for variable processes such as water coagulation.

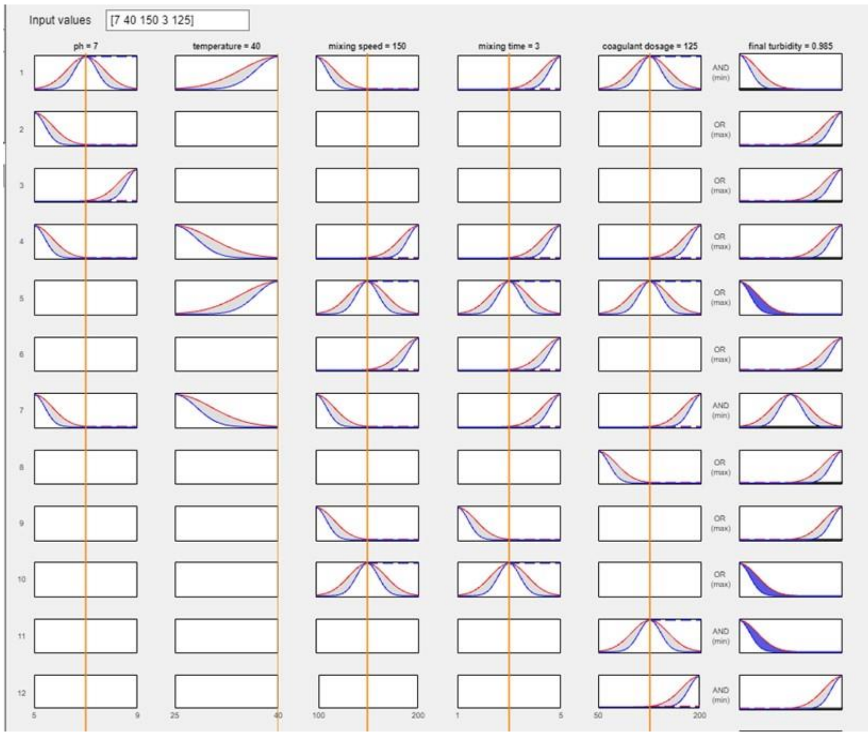

Figure 7: Coagulation process result obtained by rule inference Type-2 fuzzy inference system Model.

The Type-2 fuzzy inference system model, graphically represented in **Figure 7**, was successfully developed to simulate the coagulation process. This model, with its 12 rules, considers key parameters like coagulant dose, pH, temperature, mixing time, and mixing speed. The strength of this model lies in its ability to handle uncertainties inherent in complex processes like coagulation, accurately simulating the process and identifying optimal parameters for maximum turbidity reduction.

The model's robustness is enhanced by employing the Karnik-Mendel method for type reduction, a step known for computational efficiency and effective uncertainty handling in Type-2 fuzzy logic systems. The Karnik-Mendel method considers all possible uncertainty values, thus providing accurate and reliable results. Therefore, the creation of this Type-2 fuzzy logic-based model signifies a considerable leap in coagulation process simulation, offering a valuable tool for optimizing wastewater treatment.

3.4 Model Validation Result

Table 9 Final Turbidity: Jar Test vs. Type-2 Fuzzy Model (Coagulant Dosage)

Coagulant dosage (ppm)	Final turbidity (NTU)				
	Jar Test Experiment Result	Interval Type-2 Result	MAE	MSE	RMSE
50	3.87	4	0.192857143	0.0517	0.22737634
70	3.43	3.54			
90	3.02	2.58			
130	2.34	2.58			
150	2.76	2.58			
170	3.10	2.88			
200	4.03	4			

Table 10 Final Turbidity: Jar Test vs. Type-2 Fuzzy Model (Mixing Speed)

Mixing Speed (RPM)	Final turbidity (NTU)				
	Jar Test Experiment Result	Interval Type-2 Result	MAE	MSE	RMSE
100	3.94	4	0.152	0.03324	0.182318403
130	2.54	2.58			
150	2.33	2.58			
170	2.87	2.58			
200	3.88	4			

Table 11 Final Turbidity: Jar Test vs. Type-2 Fuzzy Model (Mixing Time)

Mixing Time (Minute)	Final turbidity (NTU)				
	Jar Test Experiment Result	Interval Type-2 Result	MAE	MSE	RMSE
1	4.09	4	0.194	0.07666	0.276875423
2	2.64	2.58			
3	2.34	2.58			
4	2.56	2.58			
5	4.56	4			

Table 12 Final Turbidity: Jar Test vs. Type-2 Fuzzy Model (Temperature)

Temperature (°C)	Final turbidity (NTU)				
	Jar Test Experiment Result	Interval Type-2 Result	MAE	MSE	RMSE
25	3.92	4	0.1	0.018257143	0.135118995
27.5	3.81	3.85			
30	3.29	3.23			
32.5	2.48	2.33			
35	1.59	1.60			
37.5	1.18	1.24			
40	0.94	1.24			

Table 13 Final Turbidity: Jar Test vs. Type-2 Fuzzy Model (PH)

PH	Final turbidity (NTU)				
	Jar Test Experiment Result	Interval Type-2 Result	MAE	MSE	RMSE
5	4.13	4	0.174	0.06902	0.262716577
6	2.54	2.58			
7	2.02	2.58			
8	2.61	2.58			
9	3.89	4			

Table 14 Final Turbidity: Optimal condition for Sample 1 and 2 comparison Jar Test vs. Type-2 Fuzzy Model

Sample	Initial Turbidity (NTU)	Coagulant dosage (ppm)	Mixing Speed (RPM)	Mixing Time (Minute)	Temperature (°C)	PH	Final Turbidity (NTU)	
							Jar Test	IT2FLS
1	13	125	150	3	40	7	0.89	0.924
2	54	125	150	3	40	7	3.18	3.74
MAE			MSE			RMSE		
0.287			0.146378			0.382593779		

The study analysed a type-2 fuzzy logic model developed to simulate the coagulation process in wastewater treatment. Optimal ranges for parameters such as pH, temperature, coagulant dosage, mixing speed, and mixing time were determined through jar tests. These optimal values were subsequently used to compare and validate the model's accuracy. It's worth noting that the model's accuracy was further challenged using a water sample from the Teluk Mesira Water Treatment Plant before the purification stage with higher initial turbidity (54 NTU) while keeping other parameters at their optimal values. The model successfully predicted the final turbidity within an acceptable range, thus showcasing its ability to adapt to varying conditions.

To assess the model's performance, error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were calculated. Based on **Table 9-14**, Although errors vary across parameters, they generally reflect fair accuracy. Coagulant dosage has an MAE, MSE, and RMSE of 0.192857143, 0.0517, and 0.22737634, respectively, while the mixing speed shows smaller errors with an MAE, MSE, and RMSE of 0.152, 0.03324, and 0.182318403, respectively. The model performs best for temperature with an MAE, MSE, and RMSE of 0.1, 0.018257143, and 0.135118995, respectively, indicating excellent predictive performance.

In conclusion, the type-2 fuzzy logic model serves as a trustworthy guide for the coagulation process and is proficient in optimizing turbidity reduction under varying conditions. Despite minor discrepancies and varied accuracy across parameters, it proves beneficial for real-world wastewater treatment scenarios. Future improvement efforts should focus on refining the model's accuracy for parameters with larger errors, utilizing advanced predictive techniques and refining experimental methods.

3.5 Model Accuracy

Table 15 Assessing the Accuracy of Final Turbidity Predictions: A Comparison between Jar Test and IT2FLS

Number of Samples	MAE	MSE	RMSE
31	0.168516129	0.054098581	0.232591016

Table 15 presents an assessment of the accuracy of final turbidity predictions provided by the Interval Type-2 Fuzzy Logic System (IT2FLS), as compared to Jar Test results. Three statistical measures - Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) - were used to evaluate the model's accuracy. With an MAE of 0.169, the results suggest that the IT2FLS predictions on average are quite close to the Jar Test outcomes. The MSE and RMSE values of 0.054 and 0.233, respectively, indicate that the IT2FLS does not often significantly deviate from Jar Test results, and the extent of typical prediction error is quite small.

The IT2FLS demonstrates considerable reliability, exhibiting high accuracy - over 70% - in predicting the final turbidity in wastewater treatment processes. The respective MAE, MSE, and RMSE values of 83.2%, 94.6%, and 76.7% for the 31 samples substantiate this conclusion. However, it is essential to consider the limitations of these measures, as they do not account for model precision and can be influenced by the small sample size or extreme values.

In summary, while the IT2FLS shows notable accuracy in predicting final turbidity, a more comprehensive evaluation would require testing with larger datasets and a wider array of accuracy metrics. Despite this, the current results suggest promising potential for practical applications of the IT2FLS in wastewater treatment.

4. Conclusion

In conclusion, the objectives of this research were successfully achieved, proving the innovative combination of Genetic Algorithm Optimization and traditional Jar Test Experiments to optimize coagulation process parameters. The findings reveal parallel optimal values for pH and coagulant dosage from both methods, affirming their collective efficacy. Additionally, the Genetic Algorithm Optimization's potential inaccuracies can be mitigated with iterative refinement, while the discrepancies observed in temperature and mixing time signal avenues for future inquiry. Similarly, the second objective, which focused on the development of a type-2 fuzzy logic-based model for simulating the coagulation process, was effectively fulfilled. The model's utility was demonstrated by its ability to manage uncertainties and complexities while identifying optimal conditions for the coagulation process parameters.

The model's validity was further underscored by its reliable alignment with jar test results, achieving the third research objective. This was confirmed despite discrepancies between the model and experimental data, attributed to the complexities and uncertainties of the coagulation process. Moreover, the robustness and accuracy of the fuzzy logic model in dealing with uncertainties and variations were confirmed through statistical measures, fulfilling the final objective. The model's strong predictive accuracy, demonstrated by low error values, asserts its value in advancing and streamlining wastewater treatment processes. Overall, the outcomes of the study signal a substantial potential for these innovative methodologies in enhancing wastewater treatment processes, with profound implications for public health and safety, economic well-being, and environmental sustainability. Therefore, this research provides a significant contribution to engineering innovation, paving the way for future work in refining the model and expanding its application.

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