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Forecasting the Environmental Situation at Mining Company Treatment Facilities Based on Fuzzy Logic

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Abstract: This study analyzes wastewater treatment processes at a mining company in the Almaty region, Kazakhstan. Four treatment schemes were developed and assessed, with a focus on optimizing efficiency. The discharged water quality from different technological lines was evaluated using integral functions for a quantitative comparison of each scheme's performance. Additionally, an expert system was developed to validate the results and support future research in wastewater treatment.

Index Terms: Fuzzy Logic, Wastewater Treatment Plants, Databases, Intelligent Analysis Methods.

1. Introduction

The mining industry is one of the key contributors to environmental pollution due to the complex and hazardous composition of wastewater. Efficient wastewater treatment is crucial for minimizing environmental damage and ensuring sustainable operations. This research addresses the critical need for advanced treatment solutions by introducing a fuzzy logic-based system tailored specifically for mining wastewater treatment facilities.

The application of fuzzy logic in wastewater treatment has gained significant attention due to its ability to handle uncertainties and complex, non-linear systems. Saravana Kumar and Latha [1] proposed a supervisory fuzzy logic control scheme for improving the effluent quality of wastewater treatment plants. Their study demonstrated that fuzzy logic controllers (FLC) can significantly enhance the efficiency of ammonia and nitrogen control in treatment plants by adjusting aeration and other critical parameters, which directly impacts the environmental safety of effluent discharge.

Fatma Erdem [2] applied fuzzy logic for risk assessment in wastewater treatment at the Ankara OIZ plant, revealing that traditional methods often fail to manage the complexity and variability of such systems. Fuzzy logic, on the other hand, provided a more nuanced approach to quantifying risks, particularly in operational settings prone to high levels of uncertainty.

The internal recirculation flow rate plays a critical role in the performance of biological wastewater treatment processes, particularly in controlling nitrogen and ammonia levels. Sant ń et al. [3] proposed a novel fuzzy logic-based control strategy to manipulate the internal recirculation flow rate in wastewater treatment plants. By adjusting this flow rate, their fuzzy controller reduced violations of nitrogen and ammonia concentration limits and lowered operational costs associated with pumping energy. This fuzzy-based approach demonstrated improvements of up to 57.94% in reducing nitrogen limit violations and a reduction of up to 79.69% in ammonia limit violations. This control strategy offers a compelling solution for managing the complex interactions within biological treatment processes, where conventional control methods may struggle to maintain balance across fluctuating operational parameters.

The evaluation of wastewater treatment quality [4, 5, 6, 7, 8] is a complex task that necessitates the application of integral indicators for effective resolution [9, 10, 11, 12, 13]. A prevalent approach in this assessment utilizes a Generalized Desirability Function (GDF), serving as a comprehensive metric for wastewater (WW) quality evaluation. This function is intricately linked to Partial Desirability Functions (PDFs), which assess the quality of a water body based on distinct, individual indicators [14, 15].

$$D = \sqrt[k]{\left(d_1^{a_1,b_1} \cdot d_2^{a_2,b_2} \cdot \ldots \cdot d_n^{a_n,b_n}\right)}, \tag{1}$$

where n number of indicators; d_i a partial function of desirability; a_i coefficient taking into account the hazard class of the i-th pollutant; b_i coefficient that takes into account the excess of the average measured value of the indicator concentration over the standard. The flexibility of the desirability function allows for various interpretations, leading to potential inconsistencies in outcomes, especially when a rigid model of pollution accounting is applied. However, with the progression of intelligent analytical methods, the range of potential solutions for such issues has broadened. Presently, systems based on fuzzy logic for both assessment and management are being effectively utilized and continuously improved. This progress in methodology underpins their application in the research at hand.

Fuzzy logic was chosen for this system due to its ability to effectively handle uncertainties and complex nonlinear processes in wastewater treatment systems. The Sugeno model was used for accurate predictions and system adaptation, while the Mamdani model was employed for more intuitive management of treatment processes.

2. Equipment and Methods

The assessment of wastewater quality involved a comprehensive approach. It incorporated statistical research methods using the STATISTICA applied data analysis software, which provided robust analytical capabilities. Additionally, standard techniques based on the construction of desirability functions were employed, offering a systematic way to evaluate various water quality parameters. To complement these methods, intelligent analysis techniques, particularly those based on fuzzy logic, were implemented within the Matlab environment. This combination of tools and approaches ensured a comprehensive and nuanced analysis of wastewater quality.

The developed expert system uses a database that includes key water quality parameters such as suspended solids, COD, BOD, and nitrates. For each parameter, membership functions were defined. For instance, for suspended solids, triangular membership functions were used with ranges for low, medium, and high levels.

To assess the significance of differences between the parameters for the two protocols (PR1 and PR2), statistical significance tests were employed. Methods such as ANOVA and t-tests for independent samples were employed to test hypotheses regarding significant differences in pollutant concentrations. Statistical significance was determined at a p-value threshold of < 0.05. Correlation analyses were also conducted to evaluate relationships between the parameters and their impact on overall wastewater quality. The reliability of the data was assessed using the coefficient of determination (R^2), which allowed for evaluating the accuracy of the prediction models.

Possible sources of error include inaccuracies in measuring pollutant concentrations due to environmental condition fluctuations and the limitations of the equipment used. Additionally, fuzzy logic-based models may be sensitive to variations in input data, which could affect the accuracy of predictions. To minimize errors, reliable calibration methods were used for the equipment, and correlation analysis was performed to evaluate the relationships between parameters

The developed fuzzy logic system offers a flexible and adaptive solution that can be applied to wastewater treatment in other mining facilities. This system dynamically adjusts to varying pollutant concentrations, ensuring optimal treatment performance and regulatory compliance. By integrating advanced analytical methods, this study contributes to the development of more efficient wastewater management practices across the mining industry

3. Analysis of TF Performance Quality Using Standard Methods

Unlike standard methods, which provide static analysis, fuzzy logic allows for dynamic adjustments of operational parameters based on pollutant concentrations. This enables more accurate management of treatment processes, especially when interacting parameters like nitrogen and ammonia are considered.

For each parameter in Tables 1-7, a significance analysis was conducted to assess differences between protocols PR1 and PR2. A t-test for independent samples with a significance level of $p < 0.05$ was applied. Confidence intervals for the mean were used to enhance the reliability of the results and determine the ranges of possible parameter variations.

In the initial phase of the research, the Generalized Desirability Function (GDF) algorithm was employed. This method involved calculating both the partial and overall desirability functions. To facilitate this calculation, Table 1 was constructed.

This table provides the average values and Maximum Desirable Concentrations (MDC) for various pollutants measured under two protocols (PR1 and PR2). The pollutants include suspended solids, COD, BOD, ammonium ions, nitrates, nitrites, and heavy metals like iron and copper.

Both protocols show relatively high values for suspended solids and COD compared to their MDCs. This indicates that, even after treatment, these pollutants remain at significant levels, potentially signaling inefficiencies in the removal of solids and organic matter in the treatment process.

The values for ammonium ions and nitrates are within acceptable limits under both protocols, suggesting that the nitrification process is functioning well.

Utilizing the data from Table 1, the research proceeded to calculate the Partial Desirability Functions (PDFs). This calculation incorporated the hazard classifications of various pollutants, ensuring a comprehensive analysis of the environmental impact. Subsequently, Overall Desirability Functions (ODFs) were derived for both protocols 1 and 2. These ODFs provided a holistic view of the effectiveness of each treatment protocol. For detailed insights and numerical values, refer to Table 2 and Table 3, where these calculations and their results are systematically presented.

These tables calculate the Partial Desirability Functions (PDF) and the Overall Desirability Function (ODF) for the treatment facility under both protocols, using the values from Table 1.

Table 1. Summary Table of TF (Control Scheme) Indicator Values.

	PR1		**PR2**	
name	**avg.**	**MDC**	**avg.**	**MDC**
suspended solids	9.95	13.95	12.62	13.95
COD	10.81	30	9.82	30
BOD	7.232	2.1	6.552	2.1
Ammonium ion	0.203	0.5	0.213	0.5
Nitrates	2.988	40	2.458	40
Nitrites	0.023	0.08	0.021	0.08
Chlorides	965.3	300	963	300
Petroleum products	0.067	0.05	0.081	0.05
Fluorides	3.93	0.75	3.919	0.75
Iron	0.363	0.1	0.286	0.1
Manganese	0.03	0.01	0.03	0.01
Nickel	0.004	0.01	0.003	0.01
Copper	0.053	0.001	0.015	0.001
Zinc	0.015	0.01	0.013	0.01
Lead	0.005	0.006	0.005	0.006

Both protocols exhibit low PDF values for BOD and fluoride, which means that the treatment plant is not efficiently reducing these pollutants. The BOD indicator shows significant room for improvement in meeting optimal standards for biological oxygen demand.

Chlorides and petroleum products show varying results between PR1 and PR2. PR1 shows a higher reduction in petroleum products, while PR2 is slightly more efficient in removing chlorides. These differences point to the need for optimizing the treatment sequence to enhance specific pollutant removal.

Table 2. Calculation Data for PDFs and ODF for TF Protocol 1 (Control Scheme).

PR1					
name	**Class**	**avg.**	**MDC**	**PDF**	**ODF**
1	**2**	**3**	**4**	**5**	**6**
suspended solids	4	9.95	13.95	1	
COD		10.81	30	1	
BOD		7.232	2.1	0.116454497	
Ammonium ion	4	0.203	0.5	1	
1	**2**	**3**	**4**	**5**	**6**
Nitrates	4	2.988	40	1	
Nitrites	4	0.023	0.08	1	
Chlorides	4	965.3	300	0.633385021	
Petroleum products	3	0.067	0.05	0.981314073	0.094264
Fluorides	4	3.93	0.75	0.174675258	
Iron	4	0.363	0.1	0.545219957	
Manganese	4	0.03	0.01	0.676818535	
Nickel	3	0.004	0.01	1	
Copper	3	0.053	0.001	1.30659E-25	
Zinc	3	0.015	0.01	0.964840151	
Lead	2	0.005	0.006	1	

Table 3. Calculation Data for PDFs and ODF for TF Protocol 2 (Control Scheme).

PR2					
name	**Class**	**avg.**	**MDC**	**PDF**	**ODF**
suspended solids	4	12.62	13.95	1	
COD		9.82	30	1	
BOD		6.552	2.1	0.184055696	
Ammonium ion	4	0.213	0.5	1	
Nitrates	4	2.458	40	1	
Nitrites	4	0.021	0.08	1	
Chlorides	4	963	300	0.635074942	
Petroleum products	3	0.081	0.05	0.941253924	0.330609
Fluorides	4	3.919	0.75	0.176328781	
Iron	4	0.286	0.1	0.712153673	
Manganese	4	0.03	0.01	0.68329565	
Nickel	3	0.003	0.01	1	
Copper	3	0.015	0.001	3.28671E-05	
Zinc	3	0.013	0.01	0.984759861	
Lead	2	0.005	0.006	1	

In assessing the efficiency of treatment protocols PR1 and PR2, the research utilized the Overall Desirability Function (ODF) previously calculated for the incoming water, which had a value of 0.38. A detailed analysis of the data presented in Tables 2 and 3 highlighted a significant decline in the quality of wastewater after undergoing PR1 treatment, with the ODF dropping from 0.38 at the facility's inlet to 0.09 at the outlet. Similarly, PR2 also exhibited a reduction in water quality, with the ODF decreasing from 0.38 to 0.33.

An important observation from this analysis was the notably small Partial Desirability Function (PDF) value for the 'copper' parameter, which negatively influenced the overall ODF. Due to this, and the need for further investigation into the 'copper' parameter, it was temporarily excluded from the ODF calculations. Consequently, revised ODF values were computed and are documented in Tables 4 and 5 for reference.

In these tables, the copper parameter is excluded due to its disproportionate influence on the overall desirability function. This adjustment leads to a recalculated ODF, which provides a more accurate reflection of treatment performance without the skew caused by the copper parameter.

The exclusion of copper leads to higher ODF values, particularly for PR2, indicating better overall performance when copper's influence is minimized. This suggests that the disproportionate weight of certain heavy metals can obscure the broader effectiveness of the treatment facility.

By excluding copper, both PR1 and PR2 protocols exhibit improved performance metrics, though PR2 still maintains a slight edge in overall pollutant removal efficiency.

Table 4. Calculation Data for PDFs and ODF for TF PR1 (Control Scheme) withouttaking into account the influence of the 'copper' parameter values.

PR1					
name	**Class**	**avg.**	**MDC**	**PDF**	**ODF**
1	**2**	**3**	**4**	**5**	**6**
suspended solids	4	9.95	13.95	1	
COD		10.81	30	1	
BOD		7.232	2.1	0.116454497	
Ammonium ion	4	0.203	0.5	1	
Nitrates	4	2.988	40	1	
Nitrites	4	0.023	0.08	1	
Chlorides	4	965.3	300	0.633385021	
1	**2**	**3**	**4**	**5**	**6**
Petroleum products	3	0.067	0.05	0.981314073	0.545677
Fluorides	4	3.93	0.75	0.174675258	
Iron	4	0.363	0.1	0.545219957	
Manganese	4	0.03	0.01	0.676818535	
Nickel	3	0.004	0.01	1	
Copper	3	0.053	0.001	1	
Zinc	3	0.015	0.01	0.964840151	
Lead	2	0.005	0.006	1	

Table 5. Calculation Data for PDFs and ODF for TF PR2 (Control Scheme) without taking into account the influence of the 'copper' parameter values.

PR2					
name	**Class**	**avg.**	**MDC**	**PDF**	**ODF**
suspended solids	4	12.62	13.95	1	
COD		9.82	30	1	
BOD		6.552	2.1	0.184055696	
Ammonium ion	4	0.213	0.5	1	
Nitrates	4	2.458	40	1	
Nitrites	4	0.021	0.08	1	
Chlorides	4	963	300	0.635074942	
Petroleum products	3	0.081	0.05	0.941253924	0.57394
Fluorides	4	3.919	0.75	0.176328781	
Iron	4	0.286	0.1	0.712153673	
Manganese	4	0.03	0.01	0.68329565	
Nickel	3	0.003	0.01	1	
Copper	3	0.015	0.001	1	
Zinc	3	0.013	0.01	0.984759861	
Lead	2	0.005	0.006	1	

The analysis of the obtained results led to several noteworthy conclusions.

The overall desirability functions (ODFs) for protocols PR1 and PR2, valued at 0.551 and 0.554 respectively, demonstrate a significant removal of pollutants from the stream when compared to the inlet flow's ODF of 0.44.

Despite the small size of the experimental dataset, which introduces some calculation errors, the efficiency of both PR1 and PR2's operation is found to be similar.

The lowest PDF values for PR1 and PR2 are associated with BOD and fluoride indicators. Notably, the BOD5 indicator's PDF increases significantly (over 3 times for PR1 and over 5 times for PR2), indicating an improvement that meets regulatory requirements, yet falls short of optimal sanitary standards. Conversely, the negligible change in the Maximum Desirable Concentration (MDC) value for fluoride implies minimal impact by the treatment facilities on this pollutant.

According to the Harrington desirability function, the water quality post-treatment is classified as 'satisfactory'. This categorization places it at the higher end of the satisfactory range, closely approaching the 'good' category.

For a more detailed understanding of the purification process analyzed, readers are directed to the conclusions at the article's end. However, it is pertinent to note that these conclusions might possess lower reliability due to the study's limitations.

Parallel research was conducted to assess the operational quality of different treatment protocols, extending the scope of analysis to encompass a broader range of treatment options.

Measurement errors can influence the values of Partial and Overall Desirability Functions (PDF and ODF), potentially leading to variations in the interpretation of treatment facility performance. These variations may affect recommendations for optimizing the treatment sequence. In this study, confidence intervals were used to reduce the impact of random errors.

4. Quality Analysis of the Treatment Facility's Operation Using Fuzzy Logic Methods

The developed system utilized IF-THEN inference rules to manage the treatment processes. For example, if the ammonia concentration is higher than the allowable limit and nitrate concentration is within normal ranges, the system reduces aeration intensity. The Mamdani model was used to analyze interactions between pollutants, while the Sugeno model provided more precise control of the system

In the second phase of the research, we developed an expert system based on fuzzy logic. This system was designed to validate key findings from the initial phase and to provide actionable recommendations for enhancing wastewater characteristics.

The system's architecture involved the integration of a collaboratively developed database. This database comprised fuzzy inference rules, complete with weight coefficients and membership functions for all the input parameters. The development process engaged wastewater treatment specialists, ensuring a robust and practical approach.

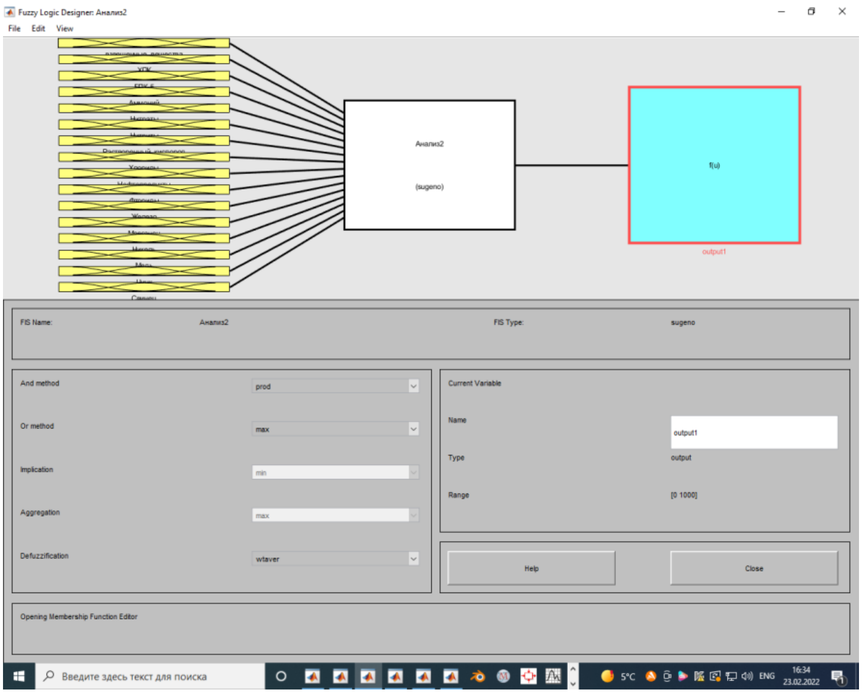

Fig. 1. Expert System built using the Sugeno algorithm.

The resultant expert system, illustrated in Figure 1, demonstrated its effectiveness in the testing phase. It showed adaptability as changes in the input values of each parameter led to corresponding variations in the output function value, as exemplified in Figure 2.

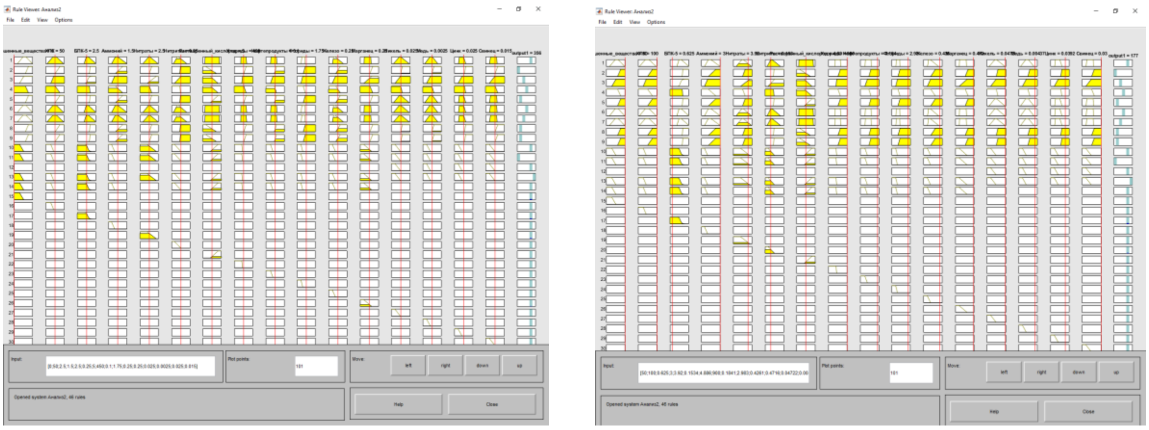

Fig. 2. Results of preliminary testing of the functionality of the expert system with the Sugeno algorithm when changing input values.

5. Analysis of the Performance of Technological Lines Using the Constructed System

In the final stage of our research, we conducted a comprehensive evaluation of the effectiveness of individual sections across all technological lines of the treatment facility. This assessment involved a comparative analysis of the results obtained from both Sugeno and Mamdani models against those derived from the Overall Desirability Function (ODF) method.

The comparative analysis revealed that both the Sugeno and Mamdani models displayed satisfactory performance, aligning closely with the initial assessment results. However, notable differences in the performance evaluations of the treatment facility underscored the significance of our developed comprehensive approach. This approach enhances the robustness of the analysis, wherein the outcomes of one model serve as a benchmark for another. Furthermore, it includes a verification process using additional analytical methods.

For streamlined analysis and reference, we have consolidated the performance evaluation results of the treatment facility using the Mamdani and Sugeno models into unified tables. These consolidated findings are summarized in Tables 6 and 7.

These tables compare the performance of the treatment facility using fuzzy logic models (Mamdani and Sugeno) with generalized desirability functions. The data offer insights into how each model interprets the effectiveness of pollutant removal across various parameters like COD, BOD, nitrates, and heavy metals.

The Mamdani and Sugeno models provide consistent results for critical pollutants such as suspended solids, COD, and BOD. Both models show that the treatment plant effectively reduces these pollutants, although there remains room for improvement in the reduction of BOD.

Both models indicate strong performance in removing ammonium ions and nitrates, confirming the facility's efficient biological treatment processes for nitrogen.

The Sugeno model generally shows slightly higher performance values for petroleum products and heavy metals, suggesting that it may offer a more optimistic assessment of treatment efficacy compared to the Mamdani model. This discrepancy could guide further optimization of the fuzzy logic system to harmonize predictions.

Table 6. Assessments of the treatment facility’s performance 1st protocol based on the application of generalized desirability functions and fuzzy logic inference methods (Mamdani and Sugeno).

		average values			by ODF*1000	
name	**Class**	**MDC**	**Nutrition**	**Scheme1**	**Nutrition**	**Scheme1**
suspended solids	4	13.95	15	9.05		
COD		30	13.22	12.55	437	524
BOD		2.1	8.852	8.398		
Ammonium ion	4	0.5	0.498	0.204	by the Mandani scheme	
Nitrates	4	40	1.922	0.671		
Nitrites	4	0.08	0.28	0.019	411	486
Chlorides	4	300	948	982.9		
Petroleum products	3	0.05	0.08	0.069		

Fluorides	4	0.75	3.964	3.811	by the Sugeno scheme	
Iron	4	0.1	1.008	0.307		
Manganese	4	0.01	0.044	0.029	385	463
Nickel	3	0.01	0.005	0.008		
Copper	3	0.001	0.001	0.027		
Zinc	3	0.01	0.029	0.024		
Lead	2	0.006	0.014	0.0051		

Table 7. Assessments of the treatment facility's performance 2st protocol based on the application of generalized desirability functions and fuzzy logic inference methods (Mamdani and Sugeno).

		average values			by ODF*1000	
name	**Class**	**MDC**	**Nutrition**	**Scheme1**	**Nutrition**	**Scheme1**
suspended solids	4	13.95	15	11.63		
COD		30	13.22	8.58	437	598
BOD		2.1	8.852	5.755		
Ammonium ion	4	0.5	0.498	0.197	by the Mandani scheme	
Nitrates	4	40	1.922	0.879		
Nitrites	4	0.08	0.28	0.022	411	497
Chlorides	4	300	948	997		
Petroleum products	3	0.05	0.08	0.073		
Fluorides	4	0.75	3.964	3.761	by the Sugeno scheme	
Iron	4	0.1	1.008	0.283		
Manganese	4	0.01	0.044	0.03	385	474
Nickel	3	0.01	0.005	0.009		
Copper	3	0.001	0.001	0.01		
Zinc	3	0.01	0.029	0.014		
Lead	2	0.006	0.014	0.005		

The Sugeno model showed higher values for some parameters, such as petroleum products, due to its ability to better handle linear dependencies. In contrast, the Mamdani model provided more accurate results when analyzing complex nonlinear interactions between parameters, making it particularly useful for assessing heavy metal pollution.

The application of fuzzy logic in optimizing the treatment process has led to significant reductions in critical pollutants, including ammonia and heavy metals, ensuring compliance with stringent environmental regulations. This result highlights the system's potential to improve the environmental performance of mining operations while reducing operational costs and energy consumption

6. Conclusion

This study demonstrates the successful application of fuzzy logic for optimizing the performance of wastewater treatment facilities at a mining company. The developed fuzzy expert system effectively handled the uncertainties inherent in the treatment process, significantly improving the removal of key pollutants such as suspended solids, COD, and nitrogen compounds. By employing both Sugeno and Mamdani models, the system provided robust predictions and operational adjustments that enhanced the overall efficiency of the treatment process.

The results of the statistical analysis confirmed the significance of differences between protocols PR1 and PR2, demonstrating the effectiveness of the proposed model. Confidence intervals and the analysis of statistical significance confirmed the high reliability of the predicted data, making the proposed methods recommended for further use in wastewater treatment management.

Despite the measures taken to minimize errors, such as the use of confidence intervals and multiple tests, the presence of random errors is unavoidable. These errors may impact the accuracy of predictions and the interpretation of results. To further improve the reliability of conclusions, it is recommended to implement additional data quality control methods and enhance the equipment calibration process.

The integration of fuzzy logic into wastewater treatment has shown clear advantages over traditional control methods, particularly in handling the complexity of pollutant interactions and ensuring compliance with environmental standards.

The system's ability to dynamically adjust operational parameters in real time based on input data from various pollutant indicators resulted in reduced violations of permissible limits for nitrogen and ammonia, as well as improved operational cost-efficiency.

The fuzzy logic system can be applied not only to the current facility but also to other wastewater treatment plants facing similar challenges in pollutant variability and regulatory compliance.

By reducing energy consumption and optimizing pollutant removal processes, the system offers a cost-effective and environmentally friendly solution for industries with complex wastewater compositions, such as mining, chemical, and manufacturing sectors.

Future studies should explore the integration of additional pollutant indicators, such as heavy metals and emerging contaminants, to further enhance the system’s predictive capabilities.

Expanding the use of machine learning algorithms alongside fuzzy logic could lead to even more precise control and optimization of treatment processes.

Real-time monitoring systems combined with the fuzzy logic framework could provide continuous feedback and automation, further improving the responsiveness and efficiency of the treatment plant.

This study marks a significant advancement in wastewater treatment technology for the mining industry by introducing an intelligent system based on fuzzy logic. The developed system not only ensures compliance with environmental standards but also optimizes operational efficiency. Future applications of this technology could extend to other industrial sectors facing similar wastewater challenges, contributing to a more sustainable and environmentally friendly industry.

In summary, this research lays a strong foundation for the application of intelligent systems in wastewater treatment, highlighting the potential of fuzzy logic in environmental management. With further development and refinement, this approach could become a standard for managing complex treatment facilities, contributing to both economic efficiency and environmental sustainability.

References

[1] S. Saravana Kumar and K. Latha. A supervisory fuzzy logic control scheme to improve effluent quality of a wastewater treatment plant. Water Science & Technology. Vol 84 No 10-11, 3415.

[2] Fatma Erdem. Risk assessment with the fuzzy logic method for Ankara OIZ environmental waste water treatment plant. Turkish Journal of Engineering – 2022; 6(4); 268-275.

[3] I. Santín, R. Vilanova, C. Pedret and M. Barbu. New approach for regulation of the internal recirculation flow rate by fuzzy logic in biological wastewater treatments. ISA Transactions 120 (2022) 167–189.

[4] L. Zhou, L. Sun, D. and J. Xu, Zoning assessment of water environmental suppoting capacity for socioeconomic development in the Huaihe River Basin.China. J. Geogr. Sci. 25 (2015), 1199–1217.

[5] K. Väänänen, M. T. Leppänen, X. Chen and J. Akkanen, Metal bioavailability in ecological risk assessment of freshwater ecosystems: From science to environmental management. Ecotoxicology and Environmental Safety 147 (2018), 430–446.

[6] N. Khatri and S. Tyagi, Influences of natural and anthropogenic factors on surface and groundwater quality in rural and urban areas. Frontiers in Life Science 8:1 (2005), 23–39.

[7] W. Hou, S. Sun, M.n Wang, X. Li, N. Zhang, X. Xin, L. Sun, W. Li and R. Jia, Assessing water quality of five typical reservoirs in lower reaches of Yellow River. China: Using a water quality index method, Ecological Indicators 61 (2016), 309–316.

[8] K. Brindha and R. Kavitha, Hydrochemical assessment of surface water and groundwater quality along Uyyakondan channel, south India. Environ Earth Sci 73 (2015), 5383–5393.

[9] S. L. Prabu, T.N.K. Suriyaprakash and J. A. Kumar. Wastewater Treatment Technologies: A Review. Pharma Times 43 (2011).

[10] D. T. Muhamedieva and N. A. Niyozmatova, Assessment of the ecological state of a water body for biodiversity monitoring according to biological and hydrochemical indicators. VI International Conference on Actual Problems of the Energy Complex and Environmental Protection (APEC-VI-2023) 411 (2023).

[11] Wodecka, B.; Drewnowski, J.; Białek, A.; Łazuka, E.; Szulżyk-Cieplak, J. Prediction of Wastewater Quality at a Wastewater Treatment Plant Inlet Using a System Based on Machine Learning Methods. Processes 2022, 10, 85.

[12] Jones, E.R., Bierkens, M.F.P., Wanders, N. et al. Current wastewater treatment targets are insufficient to protect surface water quality. Commun Earth Environ 3, 221 (2022).

[13] Mukhtar Nuhu Yahya, Hüseyin Gökçekuş, Dilber Uzun Ozsahin, Berna Uzun. Evaluation of wastewater treatment technologies using TOPSIS. Desalination and Water Treatment. Volume 177, February 2020, Pages 416-422

[14] D. B. Gelashvili, T. D. Zinchenko, L. A. Vykhristyuk and A. A. Karandashova, Integral assessment of the ecological state of water bodies based on hydrochemical and hydrobiological indicators. Izv. Samar. Scientific Center RAS. 2 (2002) 270–276 [in Russian].

[15] D. B. Gelashvili, A. V. Lisovenko, N. I. Zaznobina and A. A. Korolev, It is advisable to note the use of a generalized function on objects of different scales: city, region. Problems of the region. Ecology. 2 (2009), 83–87 [in Russian]

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