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Recycling Waste for Wastewater Treatment and Evaluation Using Artificial Intelligence for Irrigation Purposes

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Abstract
Water resources are facing increasing pressures due to population and industrial expansion and climate change, calling for the development of innovative solutions for wastewater treatment and reuse. This study aims to prepare alum (aluminum sulfate) from industrial waste (aluminum waste and spent battery fluid) and evaluate its efficiency in removing pollutants from industrial wastewater, particularly turbidity and oily substances, and the potential for reusing the treated water for irrigation of non-food plants. Fifty water samples were collected from the Kawashi Industrial Area in northern Iraq, and multiple chemical analyses were conducted to assess water quality according to irrigation standards. The results showed that the prepared alum was highly effective in removing turbidity, with a removal rate of 98.97%, and oily substances, with a removal rate of 98.97% at an optimum pH (pH = 8.5) and a dosage of 200 mg/L. An adaptive neuro-fuzzy inference (ANFIS) model was also applied to evaluate the suitability of the treated water for irrigation purposes, based on indicators such as SAR, KR, and PI. The model results showed that the water ranged from good to excellent for irrigating non-food plants. The study suggests the potential for developing a sustainable environmental model that combines waste recycling, water treatment, and the use of artificial intelligence in assessment, supporting the circular economy and enhancing water and agricultural security in emerging industrial regions.
Keywords: *Recycling, AI, Alum, Irrigation, wastewater*

INTRODUCTION

Water resources are currently facing increasing pressure due to accelerating population growth, urban and industrial expansion, and climate change. These pressures have exacerbated water scarcity and quality deterioration in many regions of the world, particularly in developing and semi-arid countries. Since water represents one of the most important elements of environmental, food, and health security, effective management of this resource has become a necessity in sustainable development plans. Water plays a fundamental role in supporting all forms of life, as it is involved in the vital processes of plants, animals, and humans, and forms the basis for numerous activities, including agriculture, industry, energy generation, and domestic uses. Therefore, finding innovative ways to conserve and reuse water is a scientific and societal priority in the modern era[1-3].In this context, wastewater treatment has become one of the main pillars of water resource management, not only to reduce aquatic pollution but also to provide new opportunities for reusing this water in various fields. However, conventional treatment techniques may face challenges related to cost, efficiency, and environmental impact, calling for the search for alternative solutions that are highly effective and environmentally and economically sustainable[4-6]. One promising solution that has recently emerged is the use of industrial waste to prepare water treatment materials, such as alum (aluminum sulfate), which is one of the most widely used materials as a coagulant in the processes of removing turbidity, petroleum products, and impurities from water. Alum can be prepared in innovative ways using aluminum residues (from factories) with spent car battery fluid as a source of acid (sulfuric acid), providing an economical and sustainable alternative to conventional methods. This method contributes to converting hazardous waste into useful resources, supports the principles of the circular economy, and addresses environmental issues from an integrated perspective[7-9].The efficiency of this treatment requires careful assessment to ensure the safety of the produced water and its suitability for various uses. This is where artificial intelligence (AI) comes in as a modern tool that enhances assessment and prediction capabilities. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the most prominent hybrid models in this field, combining the capabilities of artificial neural networks and fuzzy logic, allowing for efficient analysis of complex environmental data[10, 11]. ANFIS is used to evaluate treated water properties such as pH, electrical conductivity, and irrigation parameters, to predict water quality for irrigation, and compare it to approved environmental standards. This system provides an effective tool to support decision-making in treated water management and helps reduce the need for costly and time-consuming laboratory experiments[12, 13].This work proposes the use of reclaimed water for irrigating non-food plants (because reclaimed water contains low concentrations of petroleum substances). These plants are not directly consumed by humans and are therefore safer when used with non-conventional water. Among these plants, Linum usitatissimum[14] and Cannabis sativa stand out as promising options due to their economic value and multiple industrial applications. Flax is used in the production of fibers, textiles, and industrial oils, while industrial hemp is an important source of high-quality fibers used in the manufacture of paper, textiles, and bio-building materials. These two plants also exhibit a high ability to grow in diverse environmental conditions and a relative tolerance to pollutants, making them suitable for irrigation programs using reclaimed water while preserving the environment and soil[15-17].By combining wastewater treatment with innovative waste-recycling technologies, water quality assessment using artificial intelligence tools, and directing agricultural use toward non-food crops, the potential for an integrated water resource management model that promotes environmental and economic sustainability and meets societal aspirations for a more water-secure and healthy future emerges[18, 19].

MATERIALS AND METHODS

I. Method of study

The Kwashe area is located within the administrative boundaries of Sumail District in Duhok Governorate, Kurdistan Region of Iraq. It represents one of the most important emerging industrial areas in northern Iraq, along with several residential villages. Kwashe is located midway between the cities of Duhok and Zakho, providing it with a strategic location for developing industrial and service activities. It is also connected to a vital road network, enhancing its economic position in the region. In recent years, the area has witnessed a significant expansion in industrial activity, with the establishment of a number of factories and plants, including small oil refineries, cement factories, aluminum plants, and factories for the plastics and dyes industries. Kwashe is currently the first integrated industrial zone in Duhok Governorate, playing a key role in creating job opportunities and promoting local economic development[20].Despite the economic gains, the Kwashe area faces serious environmental challenges resulting from the uncontrolled growth of industries, particularly the lack of effective systems for treating industrial and sanitary wastewater. Figure (1) shows a map of the Kwashe area, which extends to the Mosul Dam Lake. Table (1) shows the coordinates of the sample collection sites along with their elevation above sea level[21].

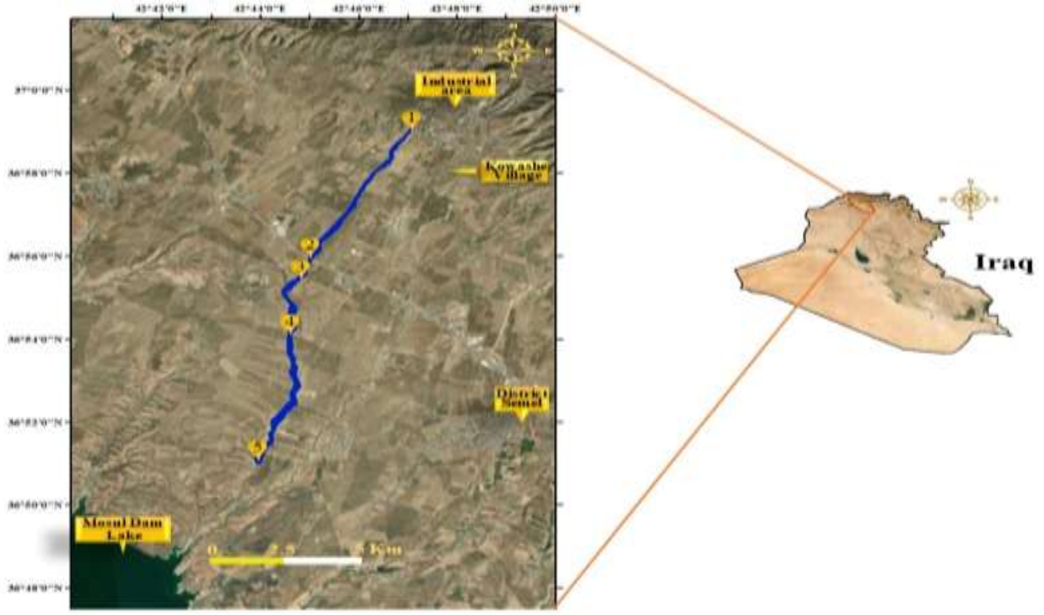

Fig. 1. Map showing the Kwashe area

Table 1: Coordinates and altitude of the studied sites

Site	E	N	Altitude (m)
1	42.78507	36.98445	651
2	42.75046	36.93297	496
3	42.74748	36.92506	481
4	42.74348	36.90257	447
5	42.73282	36.85186	378

II. Data Collection

The research methodology was based on the analysis of water quality data collected from five different sites within the study area, during the period from September 2024 to February 2025. A total of 50 samples were collected, with ten replicates for each site, to ensure the accuracy and reliability of the results. Samples were collected using clean, sterile plastic containers and transported directly to the laboratories of the College of Science at the University of Zakho, where chemical analyses were conducted within 24 hours of collection to minimize the influence of environmental factors and ensure the preservation of the water's chemical properties. The analyses were conducted according to standard procedures, including measuring electrical conductivity using a portable device and analyzing cations (calcium and magnesium) using volumetric titration methods. Sodium and potassium concentrations were determined using a flame photometer. For anions, chloride and bicarbonate concentrations were estimated using volumetric titration, while sulfate concentrations were measured using a turbidimetric method. The petroleum materials were measured using a TD-500 oil in water Analyzer[22].The chemical measurements of cations and anions obtained from each well were used to calculate several water suitability indicators for irrigation purposes. These indicators included: permeability index, potential salinity index (PS), sodium adsorption ratio, magnesium ratio (MAR), Kelley's ratio (KR), sodium percentage (Na%), and residual sodium carbonate (RSC) in meq/l[23].These parameters were calculated using standard equations, as shown in the following equations:

$$\mathrm{PI} = [\mathrm{Na} + (\sqrt{\mathrm{HCO_3}})/\mathrm{Ca} + \mathrm{Mg} + \mathrm{Na}] \times 100$$
$$\mathrm{PS} = \mathrm{Cl} + 1/2\,\mathrm{SO_4}$$
$$\mathrm{SAR} = \mathrm{Na}/\sqrt{\mathrm{Ca} + \mathrm{Mg}/2}$$
$$\mathrm{MAR} = [\mathrm{Mg}/\mathrm{Ca} + \mathrm{Mg}] \times 100$$
$$\mathrm{KR} = \mathrm{Na}/\mathrm{Ca} + \mathrm{Mg}$$
$$\mathrm{Na\%} = [\mathrm{Na}/\mathrm{Na} + \mathrm{K} + \mathrm{Ca} + \mathrm{Mg}] \times 100$$
$$\mathrm{RSC} = (\mathrm{CO_3} + \mathrm{HCO_3}) - (\mathrm{Ca} + \mathrm{Mg})$$

III. Preparing Aluminum Alum from Industrial Waste

In this study, aluminum alum (Alum) was used as a coagulant to treat contaminated wastewater. It was prepared economically based on recycling aluminum waste. Solid aluminum waste resulting from mechanical processing in factories was used in this method, as it is an inexpensive and widely available resource.Ten grams of aluminum waste (fragments or small pieces, as shown in picture (1)) were taken and placed in a 250 ml conical flask. 100 ml of 6 mol/L sodium hydroxide (NaOH) solution was then added to the flask. The mixture was left for a sufficient time until the aluminum was completely dissolved, resulting in a chemical reaction that produced a solution containing aluminum ions.After ensuring that the aluminum was completely dissolved, sulfuric acid (H_2SO_4), obtained from used car batteries, was added to the resulting solution as a secondary source. The reaction between the aluminum solution and sulfuric acid resulted in the formation of aluminum sulfate, the primary component of alum. The solution was left at room temperature for 24 hours to allow crystals to form, with the alum crystals settling at the bottom of the container, as shown in picture (2).This method for preparing alum is based on the principles of analytical and environmental chemistry and provides a practical solution for reducing economic costs and utilizing industrial waste, in line with circular economy trends and sustainable development standards[24].

Pic. 1. Aluminum factory waste in the study area

Pic. 2. Laboratory-prepared alum

IV. Preparing an alum solution

Weigh 5 grams of alum and dissolve it in 500 ml of distilled water to obtain a solution containing 10 mg/L of alum per ml.

V. Jar Test

The jar test is used to determine the effectiveness of coagulation and flocculation processes in water treatment. This test helps determine the optimal dosage of coagulants such as alum, as well as the optimal pH and mixing speeds for optimal turbidity and suspended solids removal efficiency.A half-liter of the water sample to be treated is taken into a one-liter beaker. A fixed amount of alum is added, varying the pH value (5, 5.5, 6, 6.5, 7, 7.5, 8, 8.5, 9, 9.5, 10, 10.5, 11, 11.5, 12, and 12.5). To determine the optimal value, the pH is controlled by raising or lowering it using 0.2 N NaOH and 0.025 N HCl solutions, adding a few drops to the sample. Different doses (10–100 mg/L) of alum are then taken at the optimum pH. Each beaker is placed on a magnetic stirrer at a fixed speed and time, after which the solutions are left to stand for two hours to settle the suspended matter. 200 ml of the solution is withdrawn, and the turbidity (NTU - Nephelometric Turbidity Units) is measured for all samples before and after treatment, as well as the amount of petroleum materials measured using a device TD 500D Oil in Water Analyzer[8, 25].

VI. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS (Adaptive Neural Fuzzy Inference System) is a multi-layer feed-forward network model proposed in 2012 that aims to combine the advantages of both artificial neural networks and fuzzy logic systems. This system is characterized by its superior ability to represent nonlinear relationships, making it more efficient than traditional linear models, especially in analyzing nonlinear time series. ANFIS relies on neural network learning algorithms combined with fuzzy inference mechanisms to map the input space to the output space flexibly and accurately. In this study, the ANFIS architecture is based on the first-order Takagi–Sugino–Kang (TSK) model, which relies on fuzzy if-then rules, as follows[12].)

Rule 1 : if x is A_1 and y is B_1 then $f_1=a_1x+b_1y+c_1$ ......(1)
Rule 2 : if x is A_2 and y is B_2 then $f_2=a_2x+b_2y+c_2$ ......(2)
A_1, A_2, B_1, and B_2 represent the membership functions associated with the model inputs x and y, and are used to determine the degree to which each input belongs to a particular fuzzy set. The parameters a_i, b_i, and c_i represent the coefficients of the linear regression function in the first-order fuzzy model, which are estimated using the least squares estimation (LSE) method. Figure 2 illustrates how the fuzzy inference system works, where membership functions are combined with a neural network's learning strategy to derive outputs based on the input values x[26].

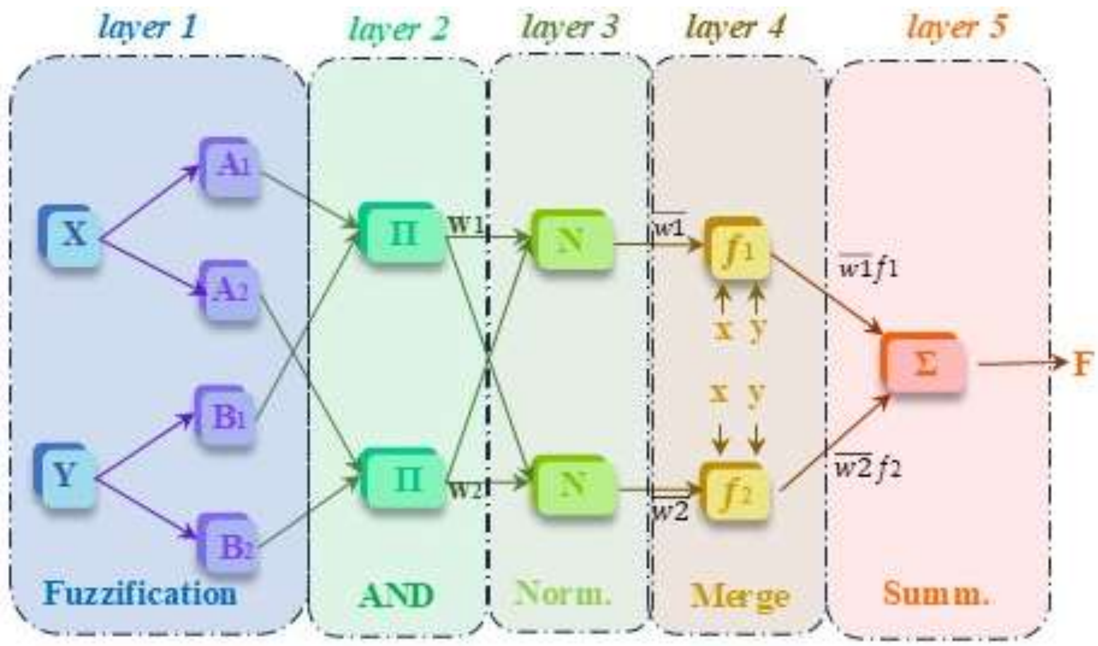

Fig. 2. Design of ANFIS architecture using Sugeno first-order fuzzy model based an inference system with two inputs and two fuzzy (If–Then) rules.

The ANFIS system consists of five layers, each performing a specific function, and all nodes within each layer perform a similar type of operation. Let's assume that the membership functions of the two fuzzy sets A_i and B_i are denoted by μ_{Ai} and μ_{Bi}
, respectively. Both d_i and σ_i are essential parameters of the membership functions and are optimized using the gradient descent algorithm. The output of node ith in layer j is denoted by the symbol O_i^j, and the function implemented by each layer is defined below:

Layer 1: In this layer, each node calculates the value of the membership function associated with each input, using a fuzzification process. For example, the output of a node can be represented as follows:

$O_i^1 = \mu_{Ai} = \exp\left(\frac{-(x-d_i)^2}{\sigma_i^2}\right)$.......(3)

Layer 2: Each node in this layer calculates the firing strength of the rule by multiplying the signals it receives, i.e., it performs a logical coupling process between the membership functions of the inputs. The output of each node is calculated as follows:

$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y)$........(4)

Layer 3: In this layer, each node normalizes the firing strength of the rules by dividing the weight of each input signal by the sum of the weights of all signals. The output of the node is calculated as follows:

$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{4} w_i}$.........(5)

For Layer 4: Each node in this layer calculates a weighted output by combining the normalized firing strength with the linear regression function associated with the corresponding rule. The output of each node is expressed by the following equation:

$O_i^4 = \overline{w}_i z_i = \overline{w}_i(a_i x + b_i y + c_i$ ....(6)

For Layer 5: In this layer, a single node collects all the weighted outputs from Layer 4 to calculate the final output of the system. The output of this layer is expressed as[13]:

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$$O_i^5 = \sum_{i=1}^{4} \bar{w}_i y_i = \frac{\sum_{i=1}^{4} w_i y_i}{\sum_{i=1}^{4} w_i} \quad \text{................(7)}$$

RESULTS AND DISCUSSION

I. Preparing the Alum

The XRD pattern (Figure 3) shows sharp, high-intensity peaks at specific angles, reflecting a regular atomic arrangement within the material. This regular distribution of peaks is conclusive evidence of the material's crystallinity and the presence of a single dominant crystalline phase. The peaks are consistent with those of aluminum sulfate. The absence of random or broad peaks also indicates high purity and a low incidence of structural defects. The XRD results thus confirm that the material possesses a clear and coherent crystal structure[27, 28].

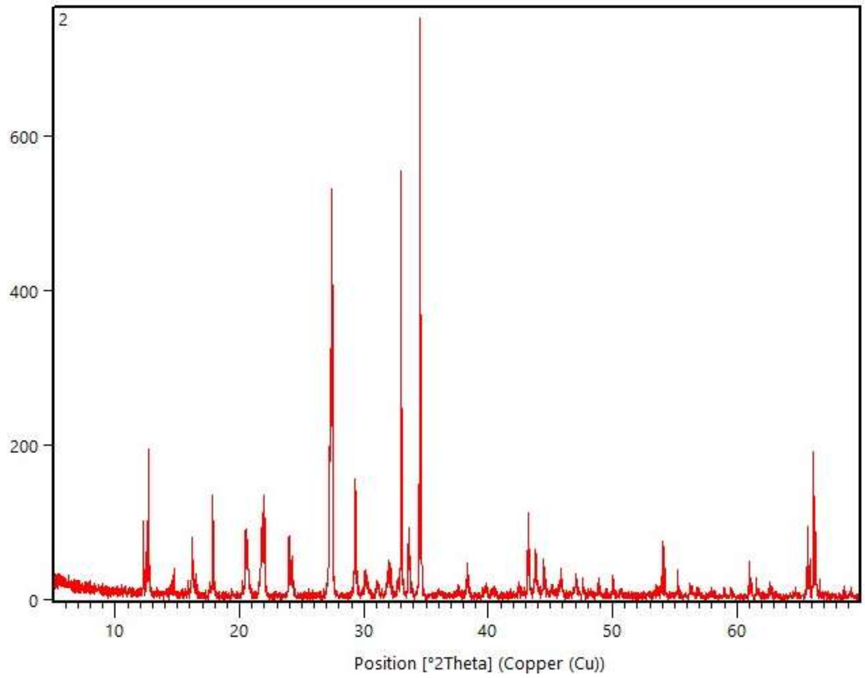

Fig. 3. XRD of the laboratory-prepared alum

II. Wastewater Treatment

The treatment used alum prepared from waste as a coagulant, and the effectiveness of removing turbidity and petroleum materials was studied. The doses of coagulants and initial pH levels were varied for this purpose. The pH values were 5, 5.5, 6, 6.5, 7, 7.5, 8, 8.5, 9, 9.5, 10, 10.5, 11, 11.5, 12, and 12.5. Figure (4) shows the effect of pH values on turbidity removal at a fixed dosage of alum (200 mg/L). We note that the turbidity value of the sample (70.5 NTU) gradually decreases with increasing pH, reaching its lowest value at pH 8.5, reaching 1.02, indicating that the coagulation process is at its most efficient at this pH. Then, turbidity begins to gradually increase with increasing pH, which means that the turbidity removal efficiency declines. From this trend, it is clear that there is an optimum pH to achieve the lowest possible turbidity level, and this value is approximately between (7-10), where turbidity is at its lowest levels, indicating that the coagulation process is effective within this range due to the stability of the electrical charge of the alum molecules and their ability to interact with impurities.

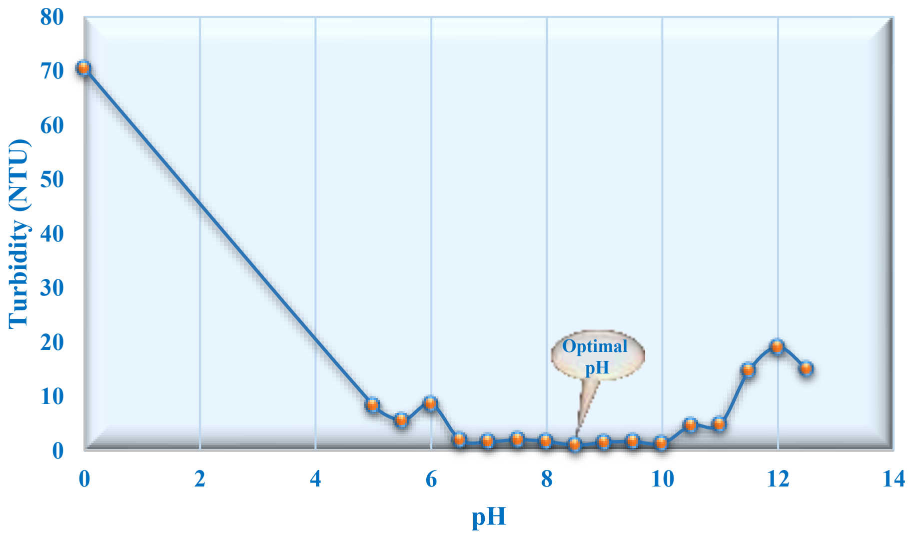

Fig. 4. Relationship between pH and turbidity at a fixed dosage (200 mg/L

As for the dosage of the coagulant (sodium aluminum sulfate) used, 200, 400, 800, 1500, 2000 and 4000 mg/L, Figure (5) shows the relationship between the amount of alum added (in mg/L) and the resulting turbidity when the pH was set to 8.5, which is one of the optimal values . Turbidity was highest when no alum was added (70.5 NTU), then decreased sharply when 200 mg/L of alum was added to 1.02 NTU, which is the lowest turbidity level recorded. When the dose was increased to 400 mg/L, the turbidity increased slightly to 1.42, then fluctuations in the values appeared as they did not continue to decrease, but increased again at higher doses, such as 800 mg/L (8.76 NTU) and 2000 mg/L (1.64 NTU). This behavior indicates that exceeding the optimal dosage of alum may lead to the phenomenon of restabilization, where the excess positive charge causes the suspended particles to re-stabilize rather than sediment. Therefore, it can be said that the optimal dosage for turbidity removal at pH = 8.5 is approximately 200 mg/L of alum, which achieves the lowest turbidity value. The oil content of the sample was measured before treatment at 9.8 mg/L, and after treatment with alum prepared from waste, it decreased to 0.1 mg/L, with a removal rate of up to 98.97%.

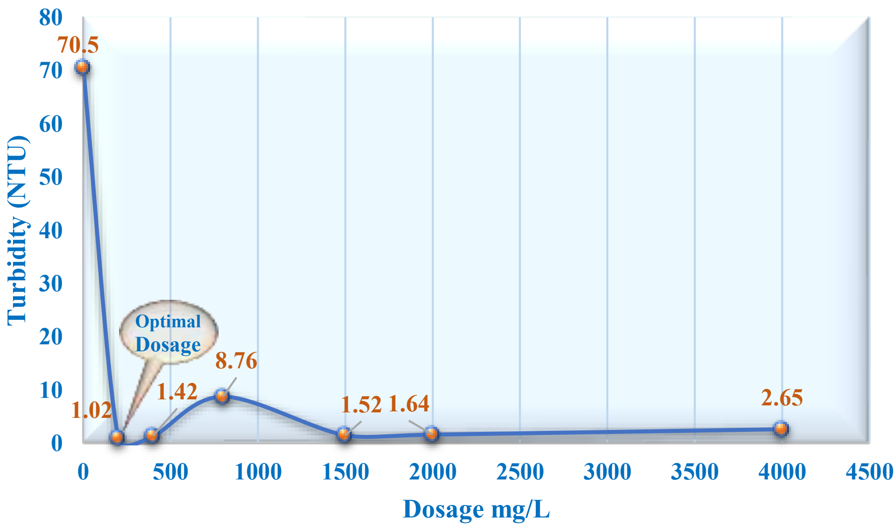

Fig. 5. The relationship between the dosage of coagulant used and turbidity

After removing the oil contaminants, the treated water was re-evaluated for irrigation purposes, particularly for non-food plants. This approach is in line with the concept of water reuse, which has become essential in light of water scarcity in many regions, particularly the study area. According to the standards of the Food and Agriculture Organization and the World Health Organization (WHO), the use of treated water for irrigation of non-food plants requires adherence to certain limits in terms of the concentration of organic matter, suspended matter, dissolved salts, and hazardous pollutants such as petroleum hydrocarbons. With petroleum concentrations as low as 0.1 mg/L, the water falls within the permissible limits for indirect irrigation, especially if the soil is well-aerated and does not allow these compounds to accumulate in the roots or be transferred into the food chain. These plants include Linum usitatissimum (used in the flax fiber industry), Cannabis sativa L. (textile industry), Eucalyptus spp. (timber production), and Jatropha curcas (diesel fuel production), etc[29-31].

III. Water Evaluation for Irrigation

Table (2) shows that the electrical conductivity values for the five sites ranged between 1.71 and 4.52 dS/cm. Sites 1, 2, and 3 were higher than the standard irrigation limits, which negatively impact plant water uptake and reduce productivity, especially for salinity-sensitive plants. Sites 4 and 5 were lower than the standard irrigation limits, making them relatively suitable for irrigation. Figure (6) shows the spatial distribution of electrical conductivity. The values increase towards the north, indicating higher salinity, which may be unsuitable for irrigation[1].

Table 2: Irrigation parameter values for industrial drainage in the Kwashe area

Parameters	Site No.						Standards
		1	2	3	4	5	
EC_{25}	Min	1.65	0.67	0.79	1.06	1.05	2.225
	Max	10.97	8.76	7.59	3.27	2.47	
	Mean	4.52	3.00	2.78	1.90	1.71	
	SD	3.48	2.97	2.46	0.75	0.51	
Na%	Min	10	3	6	28	16	60
	Max	63	74	82	78	51	
	Mean	33	32	45	38	35	
	SD	18	27	26	16	13	
SAR	Min	0.9	0.1	0.3	1.8	1.2	9
	Max	11.3	14.7	16.7	16.3	5.0	
	Mean	3.9	3.8	5.3	4.2	3.0	
	SD	3.2	4.8	4.9	4.5	1.6	
MAR	Min	2	9	17	30	34	50
	Max	34	74	70	61	60	
	Mean	16	34	40	48	49	
	SD	10	20	15	9	8	
RSC	Min	-35.2	-12.4	-10.8	-12.4	-6.8	2.25
	Max	6	-4	5.2	-1.6	-0.8	
	Mean	-18.1	-7.8	-5.2	-5.5	-3.8	
	SD	12.6	3.1	5.4	3.7	1.9	
KR	Min	0.1	0.0	0.1	0.4	0.2	1
	Max	1.7	3.0	5.4	3.5	1.1	
	Mean	0.6	0.8	1.5	0.9	0.6	
	SD	0.5	1.0	1.7	1.0	0.3	
PI	Min	15	13	18	37	32	75
	Max	76	80	95	83	65	
	Mean	41	43	56	52	50	
	SD	20	25	27	14	12	
PS	Min	6.2	2.8	3.9	4.4	5.3	10
	Max	22.9	19.4	24.3	26.2	11.2	
	Mean	14.2	10.4	11.8	9.7	7.8	
	SD	6.0	6.7	7.2	6.5	2.3	
Oil pollutants	mg/l	43.3	4.7	1.3	20.9	1.3	0.1

High Na% leads to soil degradation (soil compaction), which reduces water permeability and negatively affects root growth. Na% levels varied between (33-45), and were within the standard limits for irrigation. 86% of the values were within the standard limits for irrigation. The spatial distribution in Figure (6) shows the deterioration of water quality for irrigation in the southern part of the study area[32].

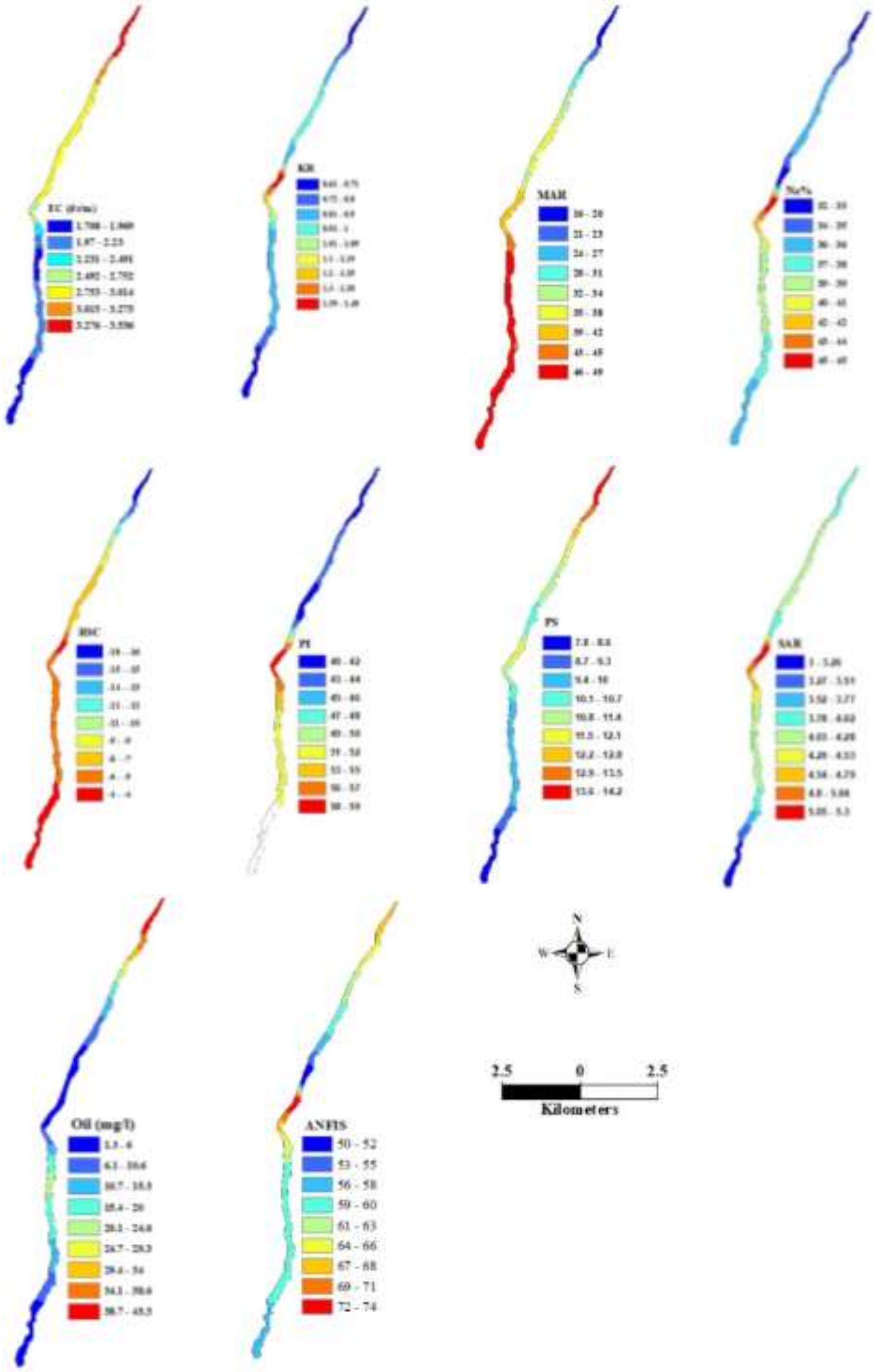

Fig. 6. Spatial distribution of industrial wastewater values in the Kwashe area

The SAR (sodium absorption ratio) is a key indicator for assessing irrigation water quality in terms of its impact on soil properties. A high SAR value indicates a higher proportion of sodium relative to calcium and magnesium, leading to soil structure disintegration and deterioration of water and air permeability. This deterioration impedes root nutrient uptake and negatively impacts plant growth and productivity.

Alkaline soils resulting from high SAR are more susceptible to hardening, requiring agricultural interventions such as periodic water leaching or the use of soil amendments such as agricultural gypsum to adjust the ionic balance. SAR values for the study area ranged from 0.1 to 16.7, with 92% and 100% of the values and rates falling within the standard irrigation limits, respectively[33].MAR values showed significant variation between sites, ranging from about 2 to over 60, reflecting significant variations in magnesium concentration between sites. Site 1 showed relatively low values in most samples, while Sites 2, 4, and 5 recorded relatively high values in several readings, indicating a possible magnesium excess in those sites. High magnesium disrupts the ionic balance in the root zone, inhibiting the activity of beneficial microorganisms, such as nitrogen-fixing bacteria and beneficial fungi (mycorrhizae). Negative RSC values indicate a good chemical balance between carbonates and other cations. Negative values indicate that water does not pose a threat to the soil structure[34].A high KR value (greater than 1) indicates an increase in sodium content, which has direct and indirect negative effects on plants and soil. It leads to soil alkalinity, as well as a deficiency in plant nutrients. KR values varied between (0.0 and 5.4) for the studied sites, and 78% and 80% of the values and rates were within the permissible limits for irrigation, respectively. The spatial distribution indicates a deterioration in the quality of irrigation water in the central part of the study area[35].High PI values lead to the deposition of calcium and magnesium in the soil in the form of carbonates, causing an actual deficiency in the availability of Ca^{2+} and Mg^{2+} to the plant despite their presence in the water, and leading to an imbalance in the nutritional balance of the plant, which affects many cellular and regulatory functions. PI values varied between (13-95) for the study area, and 86% of the studied values were within the standard limits for irrigation, while all rates were suitable for irrigation[36, 37].Forty-four percent of all PS values studied were unsuitable for irrigation due to high concentrations of chloride and sulfate ions in the water, which negatively impact water quality for irrigation. High PS values in irrigation water lead to high osmotic potential, which hinders water absorption from the soil. This causes water stress even when the soil is moist. Furthermore, the toxicity of elements such as chloride and sodium causes leaf margin burn and yellowing, and hinders physiological processes within the plant, such as photosynthesis and respiration. The spatial distribution shows a significant improvement in water quality for irrigation compared to the northern part of the study area[38].

VI. Water Evaluation for Irrigation Using Artificial Intelligence

Treated surface water for non-food plant purposes was evaluated using artificial intelligence. The inputs were EC_{25}, Na%, SAR, MAR, RSC, KR, PI, and PS for the five sites, using five layers as shown in Figure (2). Table (3) shows that the water quality ranged from good to excellent. The main reasons for the results were the PI values, which are the most influential in determining water quality in this model. This is logical because permeability is very important for soil irrigation; water with good PI promotes salt drainage and prevents salt accumulation. KR and SAR values also play a secondary role, indicating the importance of assessing the sodium and calcium/magnesium balance. EC_{25} and Na% have a limited effect, which may indicate that the ANFIS model handles water with greater flexibility with high salinity as long as the other parameters are good. Finally, slightly negative values, such as MAR, are not significant, but may play a role in extreme cases.

Table 3: Water quality assessment results using WQI and ANFIS methods

Site No.	ANFIS	Water quality
1	67	Good
2	50	Excellent
3	74	Good
4	60	Good
5	57	Good

Pearson analysis in Table (4) showed that the relationship between EC_{25} and MAR was very strongly negative (approximately -0.94), while the relationship between Na% and KR and PI was strongly positive (over 0.89), indicating that higher sodium concentrations are associated with an increased risk of deteriorating water quality for irrigation, as measured by KR (sodium content) and PI (permeability index). The relationship between SAR and Na, and KR was also strongly positive, reinforcing the notion that these variables are linked by convergent chemical behavior that affects the suitability of water for irrigation, especially in areas with alkaline soils.The relationship between the variables and the ANFIS model relies on learning from the complex relationships between the variables. A moderate to strong positive relationship was observed between ANFIS and Na%, SAR, KR, PS, and PI, indicating that these variables significantly influence model predictions. The relationship between ANFIS and EC_{25} was relatively weak (around 0.28), which may indicate that EC_{25} alone is not a critical variable in determining model outputs, or that it has a nonlinear effect that is not easily captured by the Pearson coefficient. The weak negative relationship between ANFIS and MAR may reflect that the model accounts for rainfall as a mitigating factor for salt accumulation, but it is not the most important factor in determining water quality.

Table 4: Pearson analysis of irrigation and ANFIS coefficients

	EC_{25}	Na	SAR	MAR	KR	PI	PS	ANFIS
EC_{25}	1							
Na	-0.206	1						
SAR	0.317	0.809	1					
MAR	-0.938	0.394	-0.073	1				
KR	0.101	0.894	0.919	0.193	1			
PI	-0.609	0.899	0.518	0.751	0.699	1		
PS	0.849	0.118	0.532	-0.845	0.232	-0.308	1	
ANFIS	0.280	0.740	0.725	-0.235	0.618	0.444	0.666	1

CONCLUSION

The results of this study demonstrate that using aluminum waste and spent battery fluid to prepare alum represents an innovative and environmentally effective approach to industrial wastewater treatment. The prepared material demonstrated its high efficiency in removing turbidity and oil contaminants under specific operating conditions, demonstrating its potential as a sustainable, economical alternative to conventional materials. Evaluation of the treated water quality using an adaptive neuro-fuzzy inference system confirmed the accuracy of this model in predicting the suitability of water for irrigation, especially for non-food plants with high pollutant tolerance. These results highlight the importance of combining recycling, water treatment, and artificial intelligence technologies to build integrated water resource management systems that support the principles of the circular economy and contribute to achieving sustainable development in emerging industrial environments.

RECOMMENDATIONS

1. Encouraging the use of industrial waste, such as aluminum waste and battery fluids, in the production of innovative treatment materials (such as alum), as an efficient and cost-effective method that contributes to reducing pollution and supporting the circular economy.
2. Expanding the application of the ANFIS (Adaptive Neuro-Fuzzy Inference System) model to include water quality assessment in other industrial areas, given its high accuracy in predicting the suitability of irrigation water based on complex indicators.
3. Adopting water treatment using alum prepared from waste as a sustainable alternative to commercial chemicals, especially in areas suffering from resource scarcity or high treatment costs.
4. Reusing treated water to irrigate non-food plants, such as flax and industrial hemp, which are less sensitive to pollutants and have high economic value, reduces pressure on freshwater resources.
5. Raise institutional and environmental awareness about the feasibility of innovative environmental solutions in water treatment, particularly in the context of sustainable urban and industrial planning in developing and semi-arid countries.

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