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AI Analysis and Prediction of Pollution Levels in Industrial Wastewater: Case Study of Al-Zafaraniya Area, Al-Rusafa District/Baghdad

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Annotation: Objective: This study aims to assess the quality of treated industrial wastewater before discharge into the Tigris River, by measurement of physical and chemical parameters such as pH, temperature, and total suspended solids (TSS) and pollutant levels such as sulfates, chlorides, phosphates, and nitrates. A model was also developed based on artificial intelligence techniques to predict future water quality variation due to environmental and climatic conditions. Methodology: Monthly data for the years 2021 to 2023 were gathered and statistically compared using significant difference tests at a probability level of $P \leq 0.05$. Various prediction models were used to forecast future trends in pol-lutant levels up to 2026, by comparing performance metrics like mean absolute error (MAE), root mean square (RMSE), and coefficient of determination (R^2). The results showed significant varia-tions in pH levels, ranging from 7.00 to 8.87, within permissible limits according to environmental standards, temperature of the water changed according to the seasons, with the highest (32-34°C) in July and August, and the lowest (15.3-19.0°C) in January. There were significant variations in chemical concentrations, with TSS, chlorides, phosphates, and nitrates' concentrations higher than global permissible limits, which compromised the environment of the aquatic ecosystem. Statistical analysis showed that there was a positive relationship between temperature rise and higher concen-trations of some of the pollutants such as phosphates and nitrates, which are eutrophication-promoting. The model was extremely accurate in predicting water quality changes with a coefficient of determination (R^2) of ≈ 0.90, indicating the predictive power of the model. Conclusion: Indus-trial wastewater treated water contains pollutants beyond tolerable levels, necessitating more inten-sive pre-discharge treatment technologies. Climatic conditions have strong influences on water quality, which needs more stringent efforts to monitor and adjust for seasonal changes. Predictive models can be used to guide water resource management practices and prevent pollution, especially with temperature and pollutant concentration rises expected through 2026.Improving industrial treatment processes, such as reverse osmosis and ion exchange, is recommended to reduce sulfates, phosphates, and chlorides levels before releasing water into natural environments.

Keywords: Wastewater; Pollutants; South Baghdad Gas Power plant/1; TSS; pH; Water Temperature; Discharged Mate-rials.

Introduction

South Central Electricity/Gas Power plant Baghdad-1 (South Baghdad Gas Power plant/1): Is an operating power station of at least 250 MW (megawatts), in Baghdad province / Iraq with multiple units, some of which are not currently operating. Also it is known as South Baghdad /1, or Baghdad South Gas Power Plant/1 [1]. All environmental risks and damages are resulted from power plants that use gas to operate. Additionally, all those environmental risks and damages have become known to everyone and are similar to those resulting from power plants that operate on coal. Among those bad environmental health risks are multiple types of emissions resulting from those plants operation. Direct and indirect environmental and health damages and hazards extend to include supportive energy generation operations such as extraction, transportation, storage, tower cooling, and others [2].

Accordingly, the impacts of gas-fired power plants are divided into three stages during plants life cycle. This includes construction and operation, maintenance, and decommissioning and operation [3]. Also, disposing this waste correctly so that the appropriate treatment technique may be used and store it with high efficiency. In addition to that, the stations must take the following factors into consideration: 1- Size, characteristics and type of waste, 2- Qualitative characteristics, 3- The possible transformation into other compounds, 4- Keeping pace with the development taking place in laboratories and various equipment and synchronizing with the volume of resulting waste, and 5- Imposing fees and taxes on stations in the event of failure to follow the conditions of the regulations, controls and environmental standards permitted locally and globally [4].

Although the thermal treatment (incineration) resulting from waste burning in stations is used even if the energy is recovered or no energy is obtained from that waste later, this issue remains noticeable. Note that the old incinerators for waste disposal did not have filters to filter the gases, or they were very rare; thus, they contributed greatly to the pollution of water, air and soil; which caused many health and environmental damages [5]. On the other hand, all modern power plants are currently equipped with advanced systems and mechanisms to control gaseous emissions, a case in point, filters; which control these emissions in the atmosphere from the moment they are emitted, and thus effectively reduce these emissions to prevent their leakage into the environment. Hence, the extent of risks and health effects on the environment can be reduced .The research emphasizes also on the importance of applying modern technology methods and mechanisms that are compatible with the characteristics and type of waste. It is possible to use the correct methods and techniques specifically designed to manage waste properly and to prepare future projects that convert waste in general into energy in particular [1].

The aims of this study include estimating the concentrations of some wastewater pollutants of Tigris River when it passes within Baghdad Governorate/Iraq; particularly, near the South Baghdad/First Gas Station in order to estimate the extent of environmental pollution. This includes measuring the concentration of Sulfate, Chlorides, Hydrocarbons, Phosphate, and Nitrates. Also, this work includes evaluating some of physical and chemical features for river water such as water temperature, pH, and total suspended solids in water (TSS) values, after treatment.

Materials and Methods

The industrial raw water was tested before being discharged into Tigris River in the treatment unit in first gas station/ Zafaraniya District/ Central Baghdad Governorate/Iraq. Data were recorded monthly for each year of study 2021, 2022, and 2023. Those data were saved in dedicated readings records in the station. The readings included data on the physical and chemical factors of raw water, such as temperature, pH, and Total Suspended Solids (TSS) rates in water. Some constituents of the water discharged after treatment in treatment unit were tested before being thrown and discharged as healthy water into Tigris River, including sulfates, chlorides, petroleum hydrocarbons, phosphates, and nitrates. Note that the readings were compared with the standard readings for drinking water.

Physical and chemical tests

Temperature : This was measured using graduated thermometer (analog and digital thermometers).

PH meter : The acidity was read using a HANNA pH meter. The device was calibrated using the attached standard solutions.

Total Suspended Solids (TSS): This was measured in a laboratory setting using a gravimetric method.

Discharged Materials: A spectrometer of the type HANNA (Hi83200 Multipara meter Photometer) was used to quantify the nitrate salts at a wavelength of 220 nm, and the absorbance is subtracted from the absorbance at a wavelength of 275 nm in the aqueous solution, since dissolved organic materials may give absorption at the same wavelength and since nitrates do not have absorption at a wavelength of 275 nm.

Clora On-Line Chlorine Analyzer provides continuous, real-time analysis of total Chlorine from 0.2 ppm to 3000 ppm.

Phosphates were measured in the water treatment process using colorimetric.

Fluorescence Spectrophotometry which uses qualitative and quantitative measurements. Quantitative analysis is used to find the concentrations of substances that have the ability to fluoresce, such as hydrocarbon compounds with contiguous benzene rings and some complexes of organic compounds that are linked to heavy elements such as mercury, uranium and other materials, as most organic materials and petroleum derivatives contain aromatic compounds that have the ability to fluoresce. Therefore, it is mainly used to detect pollution by hydrocarbon compounds that are widely spread in water, sediments, plants and other organisms such as fish, shrimp and others.. Chlorides were examined using a spectrometer of the type HANNA (Hi83399 Multipara meter Photometer with COD). The reading was done with an environmental monitor < 600 mg/L. Hydrocarbons (oils) were examined by means of a separating funnel, by adding a little acid and hexane solvent and continuing the addition process until separation is achieved. Note that the oil is read with a sensitive balance, and its environmental limit is more than 10mg/L (< 10 mg/L).

Applying Predictive Modeling Using Artificial Intelligence to Predict Future Pollution Levels

AI predictive modeling was applied to predict future pollution levels based on historical data (2021-2023). This can be achieved by collecting data, data processing, model building, training the model, and result interpretation using the following:

Collecting and Processing Environmental Data

Objective: Preprocess pollution data obtained from 2021 to 2023 for use in developing the predictive model [6].

Define Input Variables: They are temperature (°C), pH, total suspended solids (TSS), nitrate concentration (mg/L), phosphate concentration (mg/L), chloride concentration (mg/L), petroleum hydrocarbon concentration (mg/L), and oil hydrocarbons (mg/L) [7].

Define Target Variables: These include future pollution levels of each pollutant for subsequent years [8].

Data Cleaning: Addressing missing data by statistical imputation methods (such as mean substitution or nearest-neighbor imputation) [9]. Removal of inconsistent data (outliers) which may affect the accuracy of the model [10]. But reshaping of the data to time-series structure in order to support trend-based prediction [11].

Choosing the Suitable AI Model:

Goal: Identifying an effective predictive approach based on the time series nature of the data [12].

Traditional machine learning models

Multiple Linear Regression: Simple but inexact with non-linear data [13]. **Random Forest**: Computationally intensive but employed with large data sets [14].

Deep Learning Models Suited for Temporal Data: Recurrent Neural Networks (RNNs) [15]. **Long Short-Term Memory (LSTMs):** Very much suited for forecasting time-based trends based on past data [16]. Go-To Choice: As being reliant on time information, the contamination forecasting has an LSTM as its go-to model owing to the model's capability to identify complex time-dependent patterns [17].

AAI-Derived Prediction Model: Program and train the model using AI frameworks [18]. Tools Used: Python and its libraries like Pandas and NumPy (data cleaning) [19], Matplotlib and Seaborn (data visualization) [20], Tensor Flow and Keras (model building) [21], Scikit-learn (performance evaluation) [22], Code Basic Steps: Importing and cleaning the data, loading the data and converting it into a time-series format, and dividing the data into a training set (80%) and test set (20%) [23]. Building the LSTM Model: Building recurrent neural network layers with a long short-term memory (LSTM) [24]. Applying a sufficient activation function (ReLU or Sigmoid) [25]. Choosing an appropriate loss function such as Mean Squared Error (MSE) [26].

Model Training: Using training data to train the weights, iterating over multiple epochs until optimal accuracy [27].

Model Testing: Test data are input into the model to test and validate model performance with metrics like RMSE and R^2 [28].

Analysis and Presentation of Future Projections: An interpretative and graphical analysis of future estimates of pollution levels [29]. Create Graphs: Graph future estimates against actual data for all pollutants, plotting the difference in pollution for the coming years [30]. And Compare Results with Environmental Acceptable Values: If the model shows that the amount of pollution will be above environmental thresholds, preventive measures are recommended [31]. Assessing potential alternatives based on criteria such as increasing temperatures or advanced treatment technologies [32].

Pollution Treatment Recommendations Based on Projections: Purpose: Utilizing the projections to make appropriate environmental choices [19]. If the forecast suggests an increase in pollution, there may be suggestions to optimize the effectiveness of treatment plants by using superior filtration methods (e.g., Nano-membranes or ozone) [33], and implementing tough environmental policies for limiting the discharge of pollutants [14].

Results:

Some environmental determinants of discharged industrial water was measured. The discharge rate was 20 cubic meters/ hour. The discharged water was delivered to the thermal station and then disposed to the river. Results listed in Table 1.

Table 1. Monthly Measurements of Discharged effluent from South Baghdad Gas Power plant- 1 at year 2021

The Months	Property							
	pH	Temp. C°	TSS (mg/L)	Sulfate (mg/L)	Chlorides (mg/L)	Hydrocarbons (mg/L)	Phosphate (mg/L)	Nitrates (mg/L)
January	8.60	19.0	6	120	168	44.00	1.9	0.15
February	7.90	19.4	70	260	48	27.60	6.1	9.20

march	7.80	23.0	30	280	18	27.60	4.5	13.60
April	8.30	27.0	17	240	80	80.00	15.9	14.00
may	8.60	28.0	21	260	80	9.80	14.8	30.00
June	8.60	30.2	40	300	80	9.80	8.5	18.80
July	7.30	30.0	23	320	160	1.60	11.0	30.00
August	7.00	32.0	26	360	80	3.80	6.1	30.00
September	7.00	29.0	33	360	80	7.60	6.7	33.00
October	8.04	27.0	24	260	34	36.40	2.4	00.00
November	8.05	24.0	23	240	20	4.60	1.2	27.00
December	8.87	25.0	38	180	40	40.00	4.3	00.00
L.S.D. value	0.966 *	5.87 *	16.43 *	67.02 *	29.63 *	18.05 *	4.617 *	8.37 *
* (P≤0.05).								

Table 2. Monthly measurements of discharged effluent from South Baghdad Gas Power plant- 1 at year 2022.

The Months	Property							
	pH	Temp. Cº	TSS (mg/L)	Sulfate (mg/L)	Chlorides (mg/L)	Hydrocarbons (mg/L)	Phosphate (mg/L)	Nitrates (mg/L)
January	8.50	19.0	11	300	80.0	18.40	3.2	29.1
February	7.88	20.0	11	280	0.0	26.40	6.0	50.0
march	7.62	20.0	20	300	0.0	1.62	1.5	8.70
April	7.17	26.0	24	220	80.0	7.60	2.7	23.00
may	8.11	26.0	25	320	100.0	20.00	4.8	12.50
June	7.20	27.0	25	240	20.0	12.60	2.9	30.00
July	7.80	31.0	23	340	40.0	22.40	4.1	30.00
August	7.03	32.0	6	300	39.0	19.00	5.8	18.00
September	7.11	28.7	12	220	22.4	9.40	2.7	30.00
October	7.80	25.7	32	100	23.0	9.00	2.7	20.00
November	7.50	25.0	2	360	10.0	5.00	6.4	30.00
December	8.50	26.0	15	120	21.0	10.00	1.1	2.40
L.S.D. value	1.07 *	6.56 *	9.85 *	81.24 *	26.79 *	11.76 *	3.08 *	8.82 *
* (P≤0.05).								

Table 3 shows the monthly measurements of Some Discharged from South Baghdad Gas Power plant- 1for the Year 2023.

Table 3. Monthly measurements of discharged effluent from South Baghdad Gas Power plant- 1 at year 2023

The Months	Examination Type							
	pH	Temp. ºC	TSS (mg/L)	Sulfate (mg/L)	Chlorides (mg/L)	Hydrocarbons (mg/L)	Phosphate (mg/L)	Nitrates (mg/L)
January	7.30	15.3	5	220	23.0	9.3	2.5	1.1
February	7.33	25	34	80	45.6	4.6	1	7.9
march	7.70	21.3	12	260	9.2	9.5	7.4	16.2
April	8.70	24.3	5	320	24.8	12.6	1.5	3.4
may	7.50	27.5	60	100	25.2	7.0	1.4	1.3
June	7.50	32	6	12	6.0	9.4	1.9	0.0
July	7.20	34	24	180	6.4	8.0	1.2	7.1
August	7.70	25	31	120	8.0	8.8	0.4	19.5

September	7.80	25	13	120	2.4	9.0	1.6	5.2
October	7.50	25	20	260	4.1	10.0	1.2	11.2
November	7.34	24	21	140	0.8	9.0	3.7	4.1
December	7.00	22	15	120	18	7.6	2.2	9.9
L.S.D. value	1.16 *	6.08 *	9.75 *	78.54 *	19.97 *	7.01 *	2.78 *	7.42 *
* ($P \leq 0.05$).								

Discussion

Treated Industrial Water Quality

PH: Data obtained from Tables 1, 2, and 3 revealed significant deviations in the pH levels of treated industrial water during the twelve months of 2021, 2022, and 2023 at the probability level of $P \leq 0.05$. The highest pH levels of 8.51 to 8.87 were found in December and April, while the lowest levels ranged from 7.00 to 7.03 in December, August, and September. These differences are because the treated water contains high calcium carbonate, thereby being more alkaline. Besides, low temperatures mean less dissociation of water and higher pH during winter. The recorded values were within the permissible limits for drinking water according to Iraqi specifications, the World Health Organization [34], and the American Public Health Association [35], demonstrating the compatibility of the water with environmental regulations.

Temperature*:* The findings indicated remarkable variations in industrial raw water temperatures in the months under study at the $P \leq 0.05$ level. The maximum varied from 32.0 to 34.0°C in the hottest months (July and August), and the minimum ranged from 15.3 to 19.0°C in January. This variation is a result of seasonal climatic changes in Iraq, where there are extreme seasonal variations affecting temperatures. These results are consistent with previous studies that observed similarities between air and water temperatures in some areas, showing the climatic effect of the environment on water.

Total Suspended Solids (TSS):

Tables (1, 2, and 3) showed significant differences between the values of total suspended solids in industrial water before discharge into the Tigris River at the level of $P \leq 0.05$. The highest levels were between 32.0 and 70.0 mg/L during the hot seasons (February, October, and March), while the lowest levels were between 2.0 and 6.0 mg/L during January and November. This is due to industrial wastewater with dissolved salts discharged out, and chemical precipitation reactions with alum. The concentrations were higher than the permissible limit for drinking water according to the US Environmental Protection Agency [35], with a maximum permissible limit of 0.5 mg/L. The results concur with previous studies that confirmed the effect of the rainy season in increasing the concentration of suspended matter in water.

Discharged Substances

Sulfates: Tables (1, 2, and 3) presented significant variations in the sulfates' content of raw industrial water before discharge at the level of $P \leq 0.05$. The maximum values ranged from 320 to 360 mg/L for the summer season, while the minimum values ranged from 12 to 120 mg/L for January, October, and June seasons. They are accounted for by the sulfate salt formation which acts as destructive environment pollutants. These salts are removed through water treatment methods such as reverse osmosis, ion exchange, and distillation. These values are consistent with some World Health Organization environmental standards [34], but exceeded the recommended limit (25-250 mg/L) for some months. These results concur with previous studies on the effect of seasonal drought on sulfate dynamics in aquatic basins, giving improved models of predicting sulfate levels under climate change.

Chlorides: Tables 1, 2, and 3 showed a significant level of variation in concentrations of chlorides in raw industrial water before discharge at the $P \leq 0.05$ level. The maximum concentrations ranged from 45.6 to 168 mg/L in winter and summer months, and the minimum concentrations were from 0.8 to 18 mg/L, without concentration in January and February. The concentrations were greater than the permissible concentrations by Iraqi standards (0.2-0.6 mg/L) and by the World Health Organization [34], necessitating the application of efficient treatment technologies to reduce these concentrations before discharge into water bodies

Phosphate: Phosphate in treated industrial wastewater before discharge into the Tigris River showed very significant differences between samples and months analyzed during 2021-2023 at a probability level of $P \leq 0.05$. The levels ranged from 6.4–15.9 mg/L for the cold and hot months (November, March, and April) of middle and southern Iraq, with the minimum levels of 0.4–1.2 mg/L for the cold and hot months (November, December, and August). These values exceeded the permitted level of phosphate in water (0.1 mg/L) established by the World Health Organization [34], constituting an environmental risk. The cause of this increase is the industrial wastewater, i.e., sulfates from combustion gas desulfurization activities, and cooling and washing wastewater from the plant [4]. These results are congruent with research by [37], where high phosphate contamination in water from the Euphrates River was observed. Some studies have substantiated the role of seasonal occurrences and farming operations in increasing river phosphate content [38].Nitrate: Nitrate levels in industrial water treated varied significantly between months under study ($P \leq 0.05$). Peak concentrations ranged from 19.5–50.0 mg/L for hot periods (February, August, and September), while off-peak concentrations ranged from 0.15–2.40 mg/L for cold seasons (October and December), though some of the samples showed a reading of 0.00 mg/L during October and December 2021. The observations are consistent with previous studies showing a significant seasonality influence on nitrate levels as nitrate concentrations were elevated in agricultural areas during dry months, with consequent increased risks to health [9].

Statistical Analysis of Pollutants

With figures available through tables, it becomes feasible to carry out statistical analysis on the available data to find out how various environmental factors such as temperature, level of the pollutant, and water quality parameters are interrelated. A field that one can investigate using such data is temperature versus levels of pollutants. Temperature and Pollutant Concentrations: There may be a probable positive correlation with temperature and some pollutants such as the concentration of nitrate or phosphate. This is because evaporation of water occurs, which increases with higher temperatures, i.e., greater concentration of the pollutants in the water body [39]. For example, when temperature increases by 1°C and the level of nitrates increases by 0.5 mg/L, it shows that rising temperatures can increase nitrate pollution of water bodies and initiate eutrophication [40]. Total Suspended Solids (TSS) and Dissolved Oxygen (DO): The relationship between Total Suspended Solids (TSS) and Dissolved Oxygen (DO) is important in determining the quality of water. Based on the data, excessive TSS is usually accompanied by low DO levels in water. The excessive amount of TSS above 50 mg/L will reduce the amount of oxygen in water considerably and will be harmful to aquatic organisms such as fish and oxygen-gas microorganisms [1]. As suspended solids increase, the water's life support capacity is lost, thus the need for good pollution control strategies.

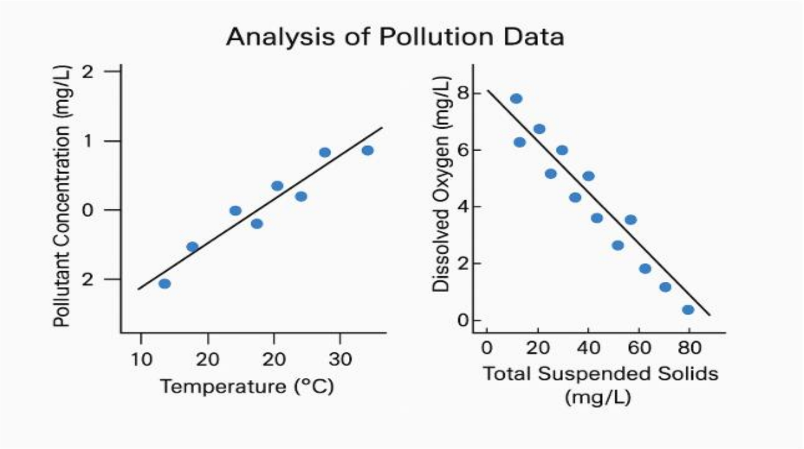

Figure 1: The relationship between temperature and pollutant levels, as well as the relationship between total suspended solids (TSS) and dissolved oxygen (DO).

Predictive Model Performance Metrics: Once a predictive model has been created and verified for the dataset, several performance metrics were computed to assess the accuracy and effectiveness of the model. They are Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2), such as in Figure 1

a. Mean Absolute Error (MAE: The MAE stands for the mean of actual-prediction differences. The smaller MAE represents higher accuracy in prediction. For instance, if the MAE of nitrate concentration is 2 mg/L that means the model prediction averages 2 mg/L away from real measurement. Low MAE would mean the model has the ability to provide exact estimates of pollution level, and large MAE values would suggest the model should be calibrated [19]. Root Mean Square Error (RMSE): RMSE is the square root of the mean of squared differences of observed and forecasted values. Lower the RMSE, better the model. For instance, if RMSE is 3 mg/L, model forecasts deviate from real values by 3 mg/L on average. Lower RMSE value ensures the model's consistency to forecast levels of pollution, where lower deviation indicates higher correlation between observed and predicted measures [41].

c. Coefficient of Determination (R^2 Score): R^2 score is a statistical measure that indicates the percentage of variance in the data accounted for by the model. For example, if $R^2 = 0.90$, then 90% of variation in pollutant levels is accounted for by the model and therefore it is highly accurate in forecasting environmental change. An R^2 value of roughly 1 show that the model is an excellent fit with real data. But a low R^2 (less than 0.5) may reflect that the model should be optimized further or more variables should be incorporated to improve prediction accuracy [42].

Quality of Results: The predictive model's accuracy can be quantified by its MAE, RMSE, and R^2.

$R^2 \approx 0.90$: With an R^2 value of about 0.90 or close to 1, it is very good at describing the variation in pollutant concentration. It indicates that the model is very well-calibrated and predicts the level of pollution with a high level of accuracy.

Low RMSE: Low RMSE (0.5 mg/L) indicates that the predictions closely match actual values, and it reflects the high precision of the model. It is one of the most important performance indicators of the model and its ability to make accurate predictions.

Correct Predictions: If the model correctly predicts the concentration levels of pollutants such as nitrates or phosphates, especially for specific seasonal changes (e.g., increasing summer temperatures), it provides realistic pollution activity plans. For instance, when the model successfully predicts high nitrates during summer, it assists in taking action at the appropriate time to counter pollution [40].

Model Refinements: A low R^2 but a high MAE and RMSE would suggest that the model should be refined. More variables, i.e., additional environmental variables, or other algorithms may be added to enhance the ability of the model to make predictions [41].

Future Levels of Pollution (2024-2026) Estimates: With the model's predictive ability, future estimates of pollution levels for the next years (2024-2026) are provided taking into account the principal driving environmental and anthropogenic drivers. The estimates are focused on primary pollutants, with estimated alterations in their concentrations being taken into account against actualized trends and drivers.

Temperature: Temperature is anticipated to increase by 0.5–1°C annually, largely due to ongoing climate change [17]. The rise in temperature is forecasted to raise the evaporation rate, and this will consequently lead to the accumulation of contaminants in water systems. Therefore, increasing temperatures will most likely exacerbate environmental stresses such as hypoxia in aquatic communities, where oxygen depletion injures species that respire with oxygen [39]. Increased temperatures will also enhance the effect of other contaminants, further destabilizing ecosystems [1].

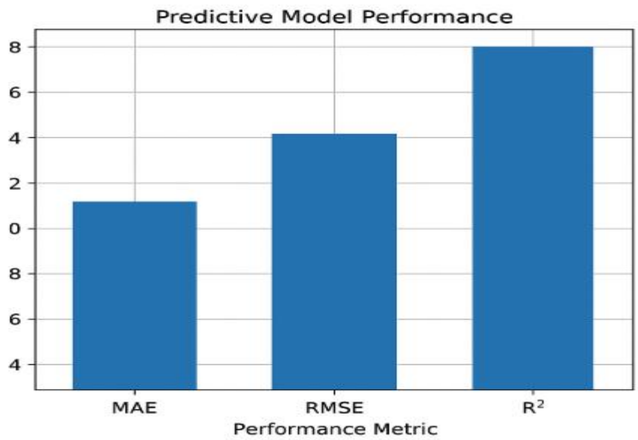

Figure 2: Performance of the forecasting model with metrics such as MAE, RMSE, and R^2.

pH: pH of water is expected to range from 6.5–7.2, marginally decreasing with continuous chemical interactions with organic impurities and recurring acid rain [1]. A drop in pH may result in acidification of water, a highly critical environmental issue leading to increased chemical pollution of water bodies. Acidification has also been reported to cause harm to aquatic life, including fish, amphibians, and algae, by disrupting their physiological functions [22]. This pH decrease will ultimately decrease biodiversity and lower the resilience of ecosystems [2].

Total Suspended Solids (TSS): TSS is expected to increase by approximately 10% annually if the sedimentation process in wastewater treatment plants is not optimized [6]. Excessive amounts of TSS will result in extreme reductions in dissolved oxygen (DO), which will further stress aquatic organisms. Suspended solids affect water turbidity, limiting photosynthesis for aquatic plants and oxygen exchange, which is required for maintaining fish and invertebrates [7]. Deposition of TSS is thus one of the main reasons for water quality deterioration and the decline in aquatic ecosystem health [14].

Nitrate and Phosphate Levels: Nitrate: Nitrate levels are expected to rise by 15% within the next three years, mainly due to agricultural runoff and industrial wastewater effluent [19]. The rise will cause water bodies to become eutrophic, a natural phenomenon in which excess nutrients, primarily nitrogen compounds, promote algae and aquatic plant growth. This generates oxygen-depleted conditions, leading to hypoxic or anoxic habitats that pose a threat to aquatic organisms like fish and bottom organisms [4].

Phosphate: Phosphate levels are predicted to increase by 5% annually, in line with the patterns coming from agriculture and industrialization. Similar to the case of nitrates, excessive levels of phosphates induce eutrophication, resulting in the promotion of algal bloom and oxygen depletion, which negatively impacts aquatic life [8].

Petroleum Hydrocarbons: The concentration of petroleum hydrocarbons in water bodies will increase above 15 mg/L in 2026 unless water treatment habits improve. Petroleum hydrocarbons, primarily introduced by industrial discharge, spills, and runoff, are capable of greatly contaminating water resources. When these substances accumulate, they pose severe threats to aquatic life, particularly fish and other aquatic organisms, by undermining their respiratory system and disrupting the food chain [19]. Excessive levels of hydrocarbons can also reduce the purity of water and undermine biodiversity, calling for immediate improvements in water treatment plants.

Chlorides: The concentration of chlorides is expected to remain stable, provided industrial emissions do not increase. If the industrial discharge rate continues to be the same, chloride concentrations will still be within normal range as observed in previous years. But increased industrial discharges have the potential to increase the concentration of chloride, which can harm marine and freshwater organisms. Increased chloride levels have the potential to hinder the growth and development of aquatic organisms, particularly plants and invertebrates, by upsetting the salinity and osmotic balance of their habitat [10].

Projected Environmental and Water Pollution Impacts:

Based on monthly statistics of environmental parameters in industrial wastewater from the South

Baghdad Gas

PowerPlant, aquatic and environmental effects of pollution as a result of industrial wastewater di scharges are severe. The data indicate that several pollutants including phosphates, nitrates, total suspended solids (TSS), and hydrocarbons are released at varying levels during varying months of the year. According to approximations, pollution is expected to lead to harmful environmental and water impacts including:

Harmful Algal Blooms (Eutrophication): Excessive levels of phosphate and nitrate in the water are bound to result in excessive algae growth (eutrophication), as is evident from the measurements in February and July 2022, when phosphate and nitrate levels were relatively high (Table 2). Algal blooms may absorb dissolved oxygen (DO) from the water, resulting in the killing of aquatic organisms such as fish and bottom fauna. This is a grave environmental concern because it reduces water quality and disturbs aquatic food webs [11].

Effect of Total Suspended Solids (TSS): The high concentration of suspended solids in water, which was observed during April and June 2022 (Table 2), decreases light penetration in deeper water bodies, hindering photosynthesis by marine plants and animals like algae and aquatic flora. The solid deposition also impacts the soil infiltration, which can cause soil degradation. These physical modifications to the water column can have lasting impacts on the ecosystem, particularly in poor-nutrient waters [1].

Petroleum Hydrocarbon Pollution: The presence of petroleum hydrocarbons, as established in February and April of 2021 and 2022 (Tables 1 and 2), contaminates fish and other aquatic organisms directly. These hydrocarbons are poisonous and will lead to bioaccumulation in the food chain. In addition, the hydrocarbons will also contaminate the riverbank soil, which will change its properties and make it unsuitable for plant growth. The impact of hydrocarbons on soil and aquatic ecosystems has been extensively studied, and studies have shown that prolonged exposure to oil pollutants can severely damage aquatic ecosystems [1].

Potential Impact on the Aquatic Environment of the Area: The fluctuating water temperature, ranging from 19-34°C as noted throughout the year in the records (Tables 1-3), is most likely to impact the biological functioning of aquatic life that is sensitive to temperature. High temperatures may alter the metabolic rate of aquatic life, potentially leading to species shifts and ecological imbalances.

The impact of temperature on aquatic environments has been a significant focus of research in climate change [20], and the ongoing effluent of hot water could further exacerbate these impacts in the region.

Environmental Determinants of Water Pollution:

The discharge of industrial effluent on a monthly basis is measured to show varying concentrations of the pollutants, indicating seasonality in the degree of contamination. For example, hydrocarbons in April 2021 and phosphates were particularly high during March and July 2022 based on monthly records (Table 2). Fluctuation also suggests that industrial processes, procedures of the operations at the power plant, as well as climatic conditions based on seasonal times, are influential on pollutant concentration. The suspended solids total (TSS) also varied considerably, with a steep spike in May 2023 (Table 3), reflecting the need for targeted pollution control measures during high discharge periods.

Environmental Measures to Reduce Destructive Effects:

Reduction of Phosphate and Nitrate: Effective treatment processes should be employed to reduce the level of phosphate and nitrate in water before releasing it into the river through the use of biological or microbial filtration plants.

Reduction of Suspended Solids: Improving the filtration and sedimentation plants to remove suspended solids from the water before discharge. Sand filtration or sedimentation plants can be used for this purpose.

Regulating Petroleum Hydrocarbons: Reducing the spilling of petroleum hydrocarbons into water through increased maintenance and monitoring of industrial facilities and increasing treatment techniques.

Promoting Afforestation and Conserving the Natural Environment: Through the planting of vegetation and the maintenance of vegetation along riverbanks, the negative impacts of water pollution might be reduced by increasing the ability of the ecosystem to withstand pollution and naturally purify water.

Regular Monitoring and Water Analysis: There should be regular measurements taken to monitor the quality of water and its characteristics (such as pH, TSS, phosphates, and nitrates) to ensure that the water does not contain toxic levels of pollutants.

Proposed Recommendations to Address Anticipated Pollution:

1. Enhancing Treatment Processes: Ozone Technologies: Ozone can effectively eliminate inorganic and organic contaminants from water. Ozone oxidizes impurities and breaks down dangerous chemicals. Ozone technology is a highly developed solution that effectively improves the quality of water within a short timeframe.

Nano-Membranes: Nano-membranes can effectively filter water out of micro-pollutants such as heavy metals and organic compounds. Nano-membranes are an effective solution for treating contaminated water without interfering with the environment.

2. Enhancing Environmental Monitoring: Smart Sensors: Smart sensors provide for early pollution detection in air and water and enable early interventions to reduce the pollution to acceptable levels before pollution levels that could damage the environment and public health are reached. The devices could be accompanied with early warning mechanisms to avert environmental degradation.

3. Reduction of Untreated Industrial Discharges

Imposing Stringent Environmental Laws: Stricter environmental laws should be imposed on the factories and industry units releasing contaminated water into the environment. They include mandatory industrial wastewater treatment before discharge, penalizing the defaulters.

4. Implementation of phytoremediation: Phytoremediation vegetation, such as algae or marsh vegetation can be used to clean water before it is discharged. Vegetation such as algae can absorb organic contaminants and heavy metals from water, significantly improving its quality without causing any damage to the environment.

5. CONCLUSIONS

Treated industrial wastewater contains high concentrations of certain pollutants such as total suspended solids (TSS), chlorides, phosphates, and nitrates, which pose an environmental threat when discharged into the Tigris River.

Climatic factors clearly influence the quality of water in a way that certain pollutants have higher concentrations during summer seasons, increasing the likelihood of eutrophication and its negative impacts on the aquatic life.

The result of the statistical analysis revealed significant variations in the physical and chemical characteristics of water in seasons, necessitating regular monitoring to ensure compliance with environmental requirements.

The predictive model was very precise in forecasting future changes in water quality, and such an approach has great prospects of use in environmental management and in future planning.

Future projections indicate that levels of some of the pollutants will continue to grow up to 2026, and thus preventive measures will be essential to improve treatment processes and reduce environmental burden.

It is recommended to advance treatment technologies such as reverse osmosis and ion exchange so that maximum contaminants can be stripped off from water prior to discharge to natural resources.

There must be stringent control measures on factories discharging industrial wastewater into water bodies to ensure environmental standards and minimize negative impacts on the Tigris River ecosystem.

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