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Research Article

Machine Learning-Driven Optimization of Textile Industry Effluent Treatment: A Case Study of Environmental Risk Assessment, Predictive Modeling, and Multi-Objective Optimization for Sustainable Wastewater Management

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Abstract-Industrial wastewater, particularly from the textile sector, contains complex pollutants that pose significant environmental risks. This study focuses on characterizing textile effluent and assessing its environmental impact using machine learning and optimization techniques. The analysis revealed that the primary pollutant parameters exceed regulatory discharge limits, leading to a high environmental risk classification. Advanced data-driven methodologies, including deep learning and machine learning models, were applied to classify risk levels and predict pollution trends. Time-series models and classification algorithms were utilized to analyze pollutant variations over time, while Random Forest regression and classification models enabled accurate pollutant trend predictions. To mitigate the environmental risks associated with textile wastewater, multiple optimization strategies were evaluated, considering cost-effectiveness and treatment efficiency. This approach successfully optimized pollutant removal efficiency, minimized treatment costs, and reduced energy consumption while ensuring compliance with environmental regulations.

Furthermore, scenario-based modeling included process optimization, implementation of advanced treatment technologies, and integration of sustainable practices such as water and energy conservation, as well as carbon and water footprint reduction. The study highlights the transformative potential of deep learning in wastewater management, offering predictive capabilities that enable proactive environmental risk mitigation. This research serves as a valuable reference for both academia and industry by providing a systematic, data-driven framework for optimizing wastewater treatment processes.

Keywords: Textile Wastewater, Environmental Risk Assessment, Deep Learning, Machine Learning, Optimization, Multi-Objective Genetic Algorithm, Sustainable Wastewater Treatment.

I. INTRODUCTİON

The rapid growth of industrialization and economic development processes in the modern era significantly threatens environmental sustainability. In this context, the environmental impact of the textile industry, particularly wastewater pollution, poses a serious global challenge. Wastewater discharged from the textile industry contains high concentrations of water-soluble and toxic substances, including microbial pathogens, organic dyes, pigments, and heavy metals. These pollutants disrupt the balance of natural ecosystems, reduce the availability of clean and freshwater resources suitable for drinking, and consequently present substantial risks to both the environment and human health.

The complex and chemically stable structure of textile dyes significantly hinders their degradation and mineralization. Wastewater originating from the textile and dye manufacturing industries not only contains organic pollutants but also includes toxic and persistent chemicals, thereby increasing environmental risks. Even when treated using conventional methods, the presence of pollutants at nanogram levels continues to pose a threat to aquatic life and, moreover, leads to harmful effects on human health due to the infiltration of these contaminants into the food chain through irrigation. In this context, upgrading textile wastewater treatment from conventional methods to more advanced treatment technologies—such as advanced oxidation processes and membrane techniques—is of critical importance for both environmental sustainability and economic feasibility [1, 2-6].

The textile industry, one of the most chemical-intensive sectors, generates wastewater containing hazardous dyes, pigments, dissolved/suspended solids, and heavy metals, which pose significant environmental risks. It is evident that effectively characterizing textile industry wastewater before its discharge into receiving environments, identifying the types of pollutants it contains, and applying appropriate treatment technologies can significantly reduce these environmental risks. The literature includes numerous studies detailing the characteristics and classification of textile wastewater [7-13], as well as research focusing on its environmental impact and toxicity levels [8,14-18]. Particularly in recent years, there has been increasing attention to developing biological, physical, and chemical treatment methods, along with advanced treatment techniques for textile wastewater.

Scientific research in recent years has extensively explored the environmental risks of textile wastewater and techniques for its mitigation. Studies have examined the consequences of releasing inadequately treated wastewater into the environment or reusing it, particularly due to the presence of toxic and harmful contaminants [14-29]. However, to enhance the economic feasibility and environmental sustainability of these treatment methods, more effective strategies are needed [18-28].

The importance of machine learning and deep learning techniques in identifying and managing the high environmental risks posed by textile wastewater has been increasingly recognized in recent years. These techniques offer significant advantages in analyzing large and complex datasets, aiding in the identification and prediction of environmental risks. Research on deep learning and artificial neural networks demonstrates their utility in environmental data analysis. For instance, deep learning methods efficiently process large environmental datasets, enabling pollutant source identification and pollution level prediction. The application of machine learning and deep learning techniques in environmental risk analysis has been facilitated by programming tools such as Python. Python's extensive library support and community resources allow researchers and engineers to analyze environmental data and develop predictive models. These techniques serve as powerful tools for identifying and managing environmental risks, thereby contributing to environmental sustainability and minimizing adverse impacts [29].

Wastewater treatment processes are data-rich, backed by extensive research, and have a strong history of transitioning from research to engineering applications [30]. Consequently, there is a significant focus on research and applications involving machine-assisted evaluation and optimization using programming languages [31].

Between 2021 and 2025, numerous studies have been conducted on textile wastewater treatment, integrating Fenton-based methods with machine learning for sustainability [31], active carbon-based color removal using machine learning modeling [33], and nanocomposite ceramic membrane treatment of textile wastewater [34]. Other notable studies include the automatic classification of textile visual pollutants using deep learning [35], machine learning-assisted source tracking in domestic-industrial wastewater [36], and the enhancement of phycoerythrin content in Porphyridium cruentum-derived microplastics using machine learning [37]. Research has also focused on predicting microplastic adsorption in water environments using advanced machine learning models [38], evaluating machine learning as an alternative to polynomial regression in response surface methodology for predicting color removal efficiency in textile wastewater treatment [39], and utilizing machine learning classification algorithms to mitigate the risk of inadequate wastewater treatment [40]. Additional studies explore the impact of salinity on process performance and membrane fouling in anaerobic ceramic membrane bioreactors for textile wastewater treatment, optimized wastewater adsorption-based distillation through machine learning [42], and machine learning applications in microplastic fate and sources in wastewater treatment [44]. Research also extends to deep learning applications in wastewater treatment systems for assessing carbon neutrality [45], data-driven predictive performance modeling of advanced oxidation dye wastewater treatment plants [46], and the integration of reinforcement learning into dyeing processes for reducing residual dye pollution [51].

Currently, wastewater treatment and risk assessment processes in many developing and underdeveloped countries rely heavily on human decision-making or semi-mechanical operations. As an alternative and complementary approach, data-driven deep learning methods have emerged in recent years. Wastewater treatment processes are large and complex, characterized by multiple control mechanisms, high degradation variability, and intricate internal recycling loops, leading to unstable behavior. This study addresses an existing gap in the literature by providing a detailed framework for adapting deep learning methods and wastewater treatment process modeling to assess, evaluate, and mitigate the environmental impact of textile wastewater.

This paper presents an exemplary study on textile industry wastewater samples, aiming to facilitate a systematic assessment of environmental risks through programming methodologies. By employing modeling techniques and forward-looking predictions, the study seeks to develop targeted risk mitigation measures and monitoring strategies. This research contributes to the protection of natural ecosystems and long-term sustainability.

In this study, the characterization of the treated effluent from a textile company was conducted through laboratory analyses. Python V3.7.1 was used to analyze environmental risks, generate forward-looking predictions, and develop modeling approaches. Using Python's extensive libraries, machine learning algorithms and deep learning techniques were employed to identify and analyze environmental risks. Time series analysis and regression models were used for risk prediction, followed by optimization algorithms to develop future-oriented models aimed at reducing the environmental impact of wastewater.

By leveraging these techniques, this study enhances environmental sustainability and minimizes negative impacts. Furthermore, it facilitates and encourages researchers and engineers in analyzing environmental data and developing predictive models, ultimately contributing to more efficient and sustainable wastewater treatment practices.

II. MATERIAL AND METHODS

2.1. Data Collection Methods

For the characterization study, a water sample was collected from effluent point of the conventional treatment unit of a medium-sized textile company operating in the Çerkezköy district of Tekirdağ province. The sampling and preservation process was conducted in accordance with the "TS EN ISO 5667-3 Water Quality - Sampling - Part 3: Guidance on the Preservation and Handling of Water Samples" and "TS EN ISO 19458 Water Quality - Sampling for Microbiological Analysis" standards, which outline the rules for storage, transportation, and preservation of water samples. The samples were labeled and transported in glass containers under controlled conditions at +2 °C. Simultaneously with sampling, pH and color measurements were performed using a Hach HQ40D Multimeter device. All measurements were conducted in strict accordance with international standard methods: Chemical Oxygen Demand (COD) was measured according to ISO 6060 (ISO 6060, 1986), Biological Oxygen Demand (BOD) was analyzed following ISO 5815, and all other analyses were performed according to APHA Standard Methods (APHA, 1998).

2.2. Data Analysis and Modeling

For data analysis and modeling, Python V3.7.1 was utilized. Machine learning techniques, particularly classification algorithms, were applied to identify environmental risks and categorize them into low, medium, and high-risk levels. This facilitated the development of an Environmental Risk Assessment framework. For data processing and analysis, the following Python libraries, Pandas for data manipulation and analysis, NumPy for numerical computations, Matplotlib/Seaborn for data visualization, Scikit-Learn for machine learning algorithms, Statsmodels for statistical analysis, Predictive Modeling and Optimization, were employed. In order to conduct predictive modeling, the following hypotheses were formulated.

Hypothesis 1: "If the current processes continue, long-term environmental impacts will be high."

Hypothesis 2: "If the processes are improved, environmental risks will be reduced."

For forward-looking modeling, time series analysis and regression models were utilized for risk prediction. Furthermore, optimization algorithms were employed to identify the most effective solutions for minimizing the environmental impact and risks associated with the treated wastewater effluent.

III. RESULTS AND DISCUSSION

3.1 Characterization and Environmental Risk Assessment

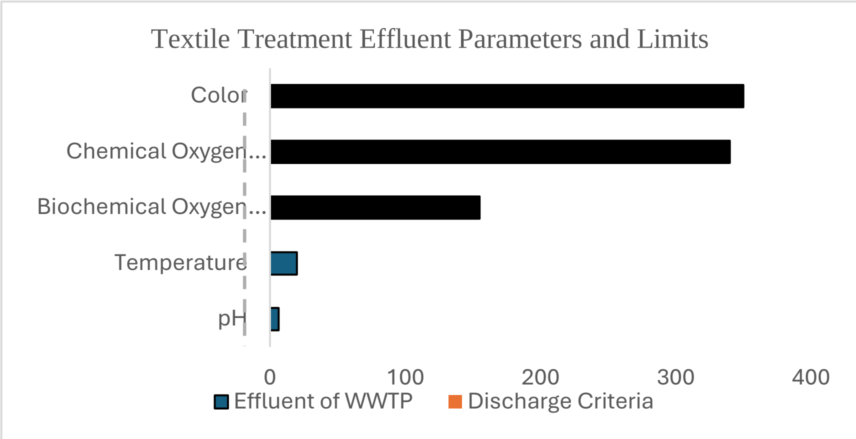
The results of the characterization analysis applied to the wastewater samples collected from the treatment effluent point of a medium-sized textile company operating in Çerkezköy district of Tekirdağ, one of Turkey's major industrial cities, are detailed in Table 1.

Table 1. Characterization Results for the Composite Effluent Water Sample from Textile Industry

Parameters	Unit	Effluent of WWTP	Discharge Criteria	Significance
pH	-	6,3	6.5–9.0	Indicates acidity or alkalinity; critical for biological treatment processes.
Temperature	°C	20	-	Affects chemical reaction rates and biological activity.
Biochemical Oxygen Demand (BOD)	mg/L	155	<30	Measures biodegradable organic matter; indicates potential oxygen depletion.
Chemical Oxygen Demand (Total COD)	mg/L	340	<250	Represents total oxidizable pollutants, both organic and inorganic.
Color	Pt-Co units	350	100-1000	Affects aesthetic quality; can indicate presence of dyes.

As seen in Table 1., a 6,3 pH, indicating acidity or alkalinity that is critical for biological treatment processes, a 20°C temperature affecting chemical reaction rates and biological activity, a 340 mg/L total COD value representing total oxidizable pollutants, both organic and inorganic, a 155 mg/L BOD representing biodegradable organic matter indicates potential oxygen depletion and a 350 Pt-Co units color were measured for the composite effluent wastewater sample from textile industry.

The graphical representation of the characterization parameters of textile industry treatment effluent water and their comparison with environmental limits is provided in Graph 1. In the graph, black bars represent the actual measured values, while the dashed linear line indicates the limit value.



Graph 1. Textile Wastewater Pollutant Parameters and Limit Values

After the characterization of the water sample obtained from the effluent point of the textile company's treatment plant, an environmental risk assessment was carried out. The following Python code is designed for the characterization of the water sample, where the values of each pollutant parameter are compared against discharge limits. This enables the simultaneous evaluation of the environmental impacts of all pollutant parameters, and the overall environmental risk levels are determined based on a scale of low, medium, and high risk. It was found that the effluent water of the textile company exceeds the discharge limits for the pollutant parameters BOD, COD, and color.

Textile Treatment Effluent Water Characterization

```
# Textile Treatment Effuent Characterization
data = pd.DataFrame({
    "Parametre": ["pH", "BOD", "COD", "Renk", "Tuz", "Krom", "Bakır"],
    "Değer": [6.5, 80, 300, 250, 1200, 0.2, 0.15],
    "Limit": ["6.5-9.0", "<30", "<250", "<200", "<1000", "<0.1", "<0.1"],
    "Birim": ["-", "mg/L", "mg/L", "ADMI", "mg/L", "mg/L", "mg/L"]
})

# Risk calculation function
def calculate_risk(value, limit):
    if "-" in limit:
        lower, upper = map(float, limit.split('-'))
        if lower <= value <= upper:
            return "Düşük"
        else:
            return "Yüksek"
    else:
        if value > float(limit.replace('<', '')):
            return "Yüksek"
        else:
            return "Düşük"

# Add risk levels
data["Risk Levels"] = data.apply(lambda row: calculate_risk(row["Değer"], row["Limit"]),
axis=1)

# Show table
print("Textile Treatment Effluent Environmental Risk Analysis Table:")
print(data)
```

The measurement results of the pollutant parameters have been compared with standard limits, and the values for each pollutant parameter have been transferred into a Python DataFrame in order to determine the low, medium, and high-risk levels. The environmental risk assessment table for the textile effluent water, which has been detailed in the characterization, has been visualized using machine learning to generate the Environmental Risk Assessment Table provided in Table 2.

Table 2. Environmental Risk Assessment of Textile Treatment Effluent Water

Parameters	Unit	Effluent of WWTP	Discharge Criteria	Risk Level
pH	-	6,3	6.5–9.0	Low
Temperature	°C	20	-	High
Biochemical Oxygen Demand (BOD)	mg/L	155	<30	High
Chemical Oxygen Demand (Total COD)	mg/L	340	<250	High
Color	Pt-Co units	350	100-1000	High

This table shows the comparison of the current parameters of the textile treatment effluent water with the limits and the corresponding environmental risk levels. Specifically, it was found that the risk levels for BOD, COD, and color exceed the legal discharge limits specified in the regulations, indicating high environmental risk [52]. For data processing and analysis, Pandas was used, for numerical computations NumPy, for visualization Matplotlib/Seaborn, for machine learning algorithms Scikit-Learn, and for statistical analysis Statsmodels were utilized to write the Python code.

Environmental Risk Assessment

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import statsmodels.api as sm

# Data for the table
data = {
    "Parameter": [
        "pH", "Temperature", "Total Dissolved Solids (TDS)", "Total Suspended Solids (TSS)",
        "Biochemical Oxygen Demand (BOD)", "Chemical Oxygen Demand (COD)", "Color (Pt-Co
Units)",
        "Dissolved Oxygen (DO)", "Oil and Grease", "Chlorides", "Sulfates (SO₄²⁻)",
        "Ammonia (NH₃)", "Phosphates (PO₄³⁻)", "Heavy Metals", "Surfactants", "Turbidity",
        "Alkalinity", "Hardness"
    ],
    "Min Value": [
        6.0, 25, 500, 50, 100, 200, 100, 0, 10, 50, 50, 1, 0.5, 0.01, 1, 10, 50, 100
    ],
    "Max Value": [
        9.0, 45, 5000, 500, 800, 2000, 1000, 5, 100, 1500, 1000, 50, 10, 5.0, 50, 500, 500,
1000
    ]
}

# Create a Pandas DataFrame
df = pd.DataFrame(data)

# Add a calculated column for the range of each parameter
```

```
df["Range"] = df["Max Value"] - df["Min Value"]

# ==============================
# Data Processing with Pandas
# ==============================

# 1. Summarize the dataset
print("Summary of Dataset:")
print(df.describe())

# 2. Identify parameters with the highest range
highest_range_param = df[df["Range"] == df["Range"].max()]
print("\nParameter with the highest range:")
print(highest_range_param)

# 3. Filter parameters where Min Value > 100
high_min_values = df[df["Min Value"] > 100]
print("\nParameters with Min Value > 100:")
print(high_min_values)

# ==============================
# Numerical Computations with NumPy
# ==============================

# Calculate mean and standard deviation of the ranges
mean_range = np.mean(df["Range"])
std_range = np.std(df["Range"])
print(f"\nMean of the ranges: {mean_range:.2f}")
print(f"Standard deviation of the ranges: {std_range:.2f}")

# ==============================
# Visualization with Matplotlib and Seaborn
# ==============================

# 1. Bar plot for Min and Max values
plt.figure(figsize=(12, 6))
df.plot(kind="bar", x="Parameter", y=["Min Value", "Max Value"], figsize=(12, 6),
color=["skyblue", "salmon"])
plt.title("Min and Max Values of Parameters", fontsize=16)
plt.ylabel("Values")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# 2. Range distribution using Seaborn
plt.figure(figsize=(10, 6))
sns.histplot(df["Range"], kde=True, bins=10, color="green")
plt.title("Distribution of Parameter Ranges", fontsize=16)
plt.xlabel("Range")
plt.ylabel("Frequency")
plt.show()

# ==============================
# Machine Learning with Scikit-Learn
# ==============================

# Normalize the data (Min and Max Values)
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df[["Min Value", "Max Value"]])

# Perform KMeans clustering to group similar parameters
kmeans = KMeans(n_clusters=3, random_state=42)
df["Cluster"] = kmeans.fit_predict(df_scaled)

# Visualize clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=df["Min Value"], y=df["Max Value"], hue=df["Cluster"], palette="viridis",
s=100)
plt.title("Clustering of Parameters based on Min and Max Values", fontsize=16)
plt.xlabel("Min Value")
plt.ylabel("Max Value")
```

```
plt.legend(title="Cluster")
plt.show()

# ==============================
# Statistical Analysis with Statsmodels
# ==============================

# Example: Regression between Max Value and Range
X = sm.add_constant(df["Max Value"])  # Add constant for the intercept
y = df["Range"]

model = sm.OLS(y, X).fit()
print("\nRegression Summary:")
print(model.summary())
```

This code works by input data. The table parameters and ranges (Min Value and Max Value) are stored in a Pandas DataFrame. In order to visualization, each parameter's range is plotted as a horizontal line with its minimum and maximum values. Text labels display the exact numerical values for easier interpretation. The chart will display each parameter on the X and Y-axis. Another code is arranged for the model training and evaluation using Scikit-Learn for machine learning in the context of textile effluent characterization (as represented in the Table 1. In order to obtain Machine Learning for textile effluent characterization it is used the RandomForestClassifier (for classification of environmental risk) based on the parameters in Table 1. and is used Scikit-Learn for training, evaluation, and performance metrics.

Machine Learning

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline

# Data for textile effluent characterization (from previous discussion)
data = {
    "Parameter": [
        "pH", "Temperature", "Total Dissolved Solids (TDS)", "Total Suspended Solids (TSS)",
        "Biochemical Oxygen Demand (BOD)", "Chemical Oxygen Demand (COD)", "Color (Pt-Co
Units)",
        "Dissolved Oxygen (DO)", "Oil and Grease", "Chlorides", "Sulfates (SO₄²⁻)",
        "Ammonia (NH₃)", "Phosphates (PO₄³⁻)", "Heavy Metals", "Surfactants", "Turbidity",
        "Alkalinity", "Hardness"
    ],
    "Min Value": [
        6.0, 25, 500, 50, 100, 200, 100, 0, 10, 50, 50, 1, 0.5, 0.01, 1, 10, 50, 100
    ],
    "Max Value": [
        9.0, 45, 5000, 500, 800, 2000, 1000, 5, 100, 1500, 1000, 50, 10, 5.0, 50, 500, 500,
1000
    ]
}

# Create a DataFrame
df = pd.DataFrame(data)

# Add features for processing
df["Range"] = df["Max Value"] - df["Min Value"]  # Add range as a feature
```

```
df["Avg Value"] = (df["Min Value"] + df["Max Value"]) / 2  # Add average as a feature

# ================================
# Step 1: Define the Risk Scores (Synthetic Risk Classification)
# ================================
# Create a synthetic classification target based on BOD values for simplicity.
# Risk classification: Low (BOD < 100), Medium (100 <= BOD < 300), High (BOD >= 300)

def assign_risk(bod_value):
    if bod_value >= 300:
        return 'High'
    elif bod_value >= 100:
        return 'Medium'
    else:
        return 'Low'

# Create a synthetic Risk column (target variable)
df['Risk'] = df['Avg Value'].apply(assign_risk)

# ================================
# Step 2: Feature Engineering and Model Setup
# ================================
# Use the features: Min Value, Max Value, Range, and Avg Value
X = df[["Min Value", "Max Value", "Range", "Avg Value"]]
y = df['Risk']

# ================================
# Step 3: Train-Test Split
# ================================
# Split data into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# ================================
# Step 4: Train the Model (Random Forest Classifier)
# ================================
# Create a pipeline with StandardScaler and RandomForestClassifier
pipeline = Pipeline([
    ("scaler", StandardScaler()),  # Standardize the features
    ("classifier", RandomForestClassifier(random_state=42))  # Random Forest Classifier
])

# Hyperparameter tuning with GridSearchCV
param_grid = {
    "classifier__n_estimators": [50, 100, 200],
    "classifier__max_depth": [None, 10, 20],
    "classifier__min_samples_split": [2, 5, 10]
}

grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring="accuracy", n_jobs=-1)
grid_search.fit(X_train, y_train)

# Best model after grid search
best_model = grid_search.best_estimator_

# ================================
# Step 5: Model Evaluation
# ================================
y_pred_train = best_model.predict(X_train)
y_pred_test = best_model.predict(X_test)

# Calculate accuracy
train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)
# Print results
print("\nModel Evaluation Metrics (Classification):")
print(f"Train Accuracy: {train_accuracy:.2f}")
print(f"Test Accuracy: {test_accuracy:.2f}")

# Classification Report
print("\nClassification Report (Test Data):")
print(classification_report(y_test, y_pred_test))
```

```
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred_test)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=["Low", "Medium",
"High"], yticklabels=["Low", "Medium", "High"])
plt.title("Confusion Matrix - Environmental Risk Classification", fontsize=16)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.tight_layout()
plt.show()

# ================================
# Step 6: Feature Importance
# ================================
# Feature importance from Random Forest Classifier
feature_importance = best_model.named_steps["classifier"].feature_importances_

# Visualize Feature Importance
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance, y=X.columns, palette="viridis")
plt.title("Feature Importance for Predicting Environmental Risk", fontsize=16)
plt.xlabel("Importance", fontsize=14)
plt.ylabel("Features", fontsize=14)
plt.tight_layout()
plt.show()
```

3.2 Forward (Prospective) Modeling

In order to predict a continuous value (like pollution level) or classify the risk level (Low, Medium, High) based on textile effluent water fort he future, it is used the appropriate machine learning models. This is adressed using either regression (to predict pollution levels, e.g., BOD, COD, etc.) or classification (to categorize risk levels, e.g., Low, Medium, High based on thresholds).

Firstly a regression model is appropriate for predicting continuous pollution levels (e.g., BOD or COD). It is used use a RandomForestRegressor model to predict the pollution level based on various effluent parameters. Secondly, classification model, such as RandomForestClassifier, is appropriate for classifying the risk level (e.g., Low, Medium, High). At this stage of the study, it is applied both regression and classification models step-by-Step implementation to predict either the pollution level or the risk level of the textile effluent water

Regression (RandomForestRegressor);

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler

# Simulated dataset (using previous data)
data = {
    "Parameter": ["pH", "Temperature", "TDS", "TSS", "BOD", "COD", "Color", "DO", "Oil &
Grease", "Chlorides",
                  "Sulfates", "Ammonia", "Phosphates", "Heavy Metals", "Surfactants",
"Turbidity", "Alkalinity", "Hardness"],
    "Min Value": [6.0, 25, 500, 50, 100, 200, 100, 0, 10, 50, 50, 1, 0.5, 0.01, 1, 10, 50,
100],
    "Max Value": [9.0, 45, 5000, 500, 800, 2000, 1000, 5, 100, 1500, 1000, 50, 10, 5.0, 50,
500, 500, 1000]
```

```
}

df = pd.DataFrame(data)

# Add features: Range and Average
df["Range"] = df["Max Value"] - df["Min Value"]
df["Avg Value"] = (df["Min Value"] + df["Max Value"]) / 2

# Target: Use BOD as a continuous value for regression (for example)
X = df[["Min Value", "Max Value", "Range", "Avg Value"]]
y = df["Avg Value"]  # Predicting pollution level based on Avg Value (e.g., BOD, COD)

# Step 1: Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 2: Standardize Features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 3: Train the RandomForestRegressor
regressor = RandomForestRegressor(n_estimators=100, random_state=42)
regressor.fit(X_train_scaled, y_train)

# Step 4: Make Predictions
y_pred_train = regressor.predict(X_train_scaled)
y_pred_test = regressor.predict(X_test_scaled)

# Step 5: Evaluate the Model (Regression)
mae = mean_absolute_error(y_test, y_pred_test)
mse = mean_squared_error(y_test, y_pred_test)
r2 = r2_score(y_test, y_pred_test)

print(f"Regression Model Evaluation:")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R² Score: {r2:.2f}")

# Step 6: Visualize Actual vs Predicted Values (Test Set)
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_test, color='blue', label='Predicted vs Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', linestyle='-
-', label='Perfect Prediction')
plt.title("Actual vs Predicted Pollution Level (Regression)")
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

Classification Model where used RandomForestClassifier to classify the Risk level (Low, Medium, High) based on features like Min Value, Max Value, Range, and Average Value. It is assigned a risk level based on the Avg Value (e.g., BOD). The model is evaluated using accuracy, classification report, and a confusion matrix. Regression Model predicts continuous pollution levels (e.g., BOD, COD) based on effluent parameters run by using RandomForestRegressor for this task. Evaluation Metrics are MAE, MSE, R^2. that are the three common evaluation metrics used for regression models: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 (R-squared).

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

Where:

- y_i= Actual value
- $\hat{y}_i$ = Predicted value
- n = Number of data points.

Lower MAE indicates better model performance, as it means the model's predictions are closer to the actual values. MAE is expressed in the same units as the target variable, making it easy to interpret. The MAE measures the average magnitude of the errors in a set of predictions, without considering their direction (i.e., no sign). It represents the average of the absolute differences between predicted values and actual values.

Mean Squared Error (MSE) measures the average squared difference between the predicted values and the actual values. The larger the error, the greater the penalty due to squaring the errors.

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

Lower MSE indicates better model performance, as it means the model's predictions are closer to the actual values. MSE tends to penalize large errors more significantly than MAE due to the squaring operation, making it more sensitive to outliers.

R^2 (R-squared or Coefficient of Determination) represents the proportion of the variance in the dependent variable (target) that is predictable from the independent variables (features). It gives an indication of how well the model explains the variation in the data.

Eq 2. $$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where:

- y_i = Actual value
- $\hat{y}_i$ = Predicted value
- $\bar{y}$ = Mean of the actual values
- n = Number of data points

R^2 ranges from 0 to 1. A higher value indicates that the model is better at explaining the variance in the target variable. $R^2 = 1$ means the model explains all the variability in the target variable (perfect fit). $R^2 = 0$ means the model explains none of the variability in the target variable, and the model is as good as simply predicting the mean of the target variable. Negative R^2: In some cases, if the model performs poorly, R^2 can be negative, indicating that the model is worse than simply predicting the mean value of the target.

When to use each metric MAE preferred when requested a simple and easy-to-understand error measurement that treats all errors equally. MSE preferred when requested to penalize larger errors more than smaller errors. It's more sensitive to outliers. R^2 is good for understanding how well the model explains the variability in the target variable and assessing the model's performance in a relative way. In order to predict BOD levels of wastewater MAE presents, on average, how much the model's predictions deviate from the actual BOD values. MSE presents the squared difference, and large deviations are penalized more. On the other hand R^2 presents what percentage of the variance in the BOD levels is explained by the model.

Classification (RandomForestClassifier) ;

```
# Import classification model and metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Create a synthetic classification target: Low, Medium, High
def classify_risk(bod_value):
    if bod_value >= 300:
        return 'High'
    elif bod_value >= 100:
        return 'Medium'
    else:
        return 'Low'

# Apply the classification rule based on Avg Value (e.g., BOD)
df['Risk'] = df['Avg Value'].apply(classify_risk)

# Step 1: Define Features and Target
X = df[["Min Value", "Max Value", "Range", "Avg Value"]]
y = df["Risk"]

# Step 2: Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 3: Train the RandomForestClassifier
classifier = RandomForestClassifier(n_estimators=100, random_state=42)
classifier.fit(X_train, y_train)

# Step 4: Make Predictions
y_pred_train = classifier.predict(X_train)
y_pred_test = classifier.predict(X_test)

# Step 5: Evaluate the Model (Classification)
train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)

print(f"Classification Model Evaluation:")
print(f"Train Accuracy: {train_accuracy:.2f}")
print(f"Test Accuracy: {test_accuracy:.2f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred_test))

# Step 6: Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred_test)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=["Low", "Medium",
"High"], yticklabels=["Low", "Medium", "High"])
plt.title("Confusion Matrix - Risk Classification")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.tight_layout()
plt.show()
```

Classification Model classifies risk levels (Low, Medium, High) based on effluent parameters by using RandomForestClassifier for this task. Evaluation metrics are Accuracy, Classification Report, Confusion

Matrix. Choosing Between Regression and Classification it is better to use Regression when requested to predict a continuous value like the pollution level (e.g., BOD, COD). it is better to use Classification when requested to categorize the risk levels based on thresholds (e.g., Low, Medium, High).

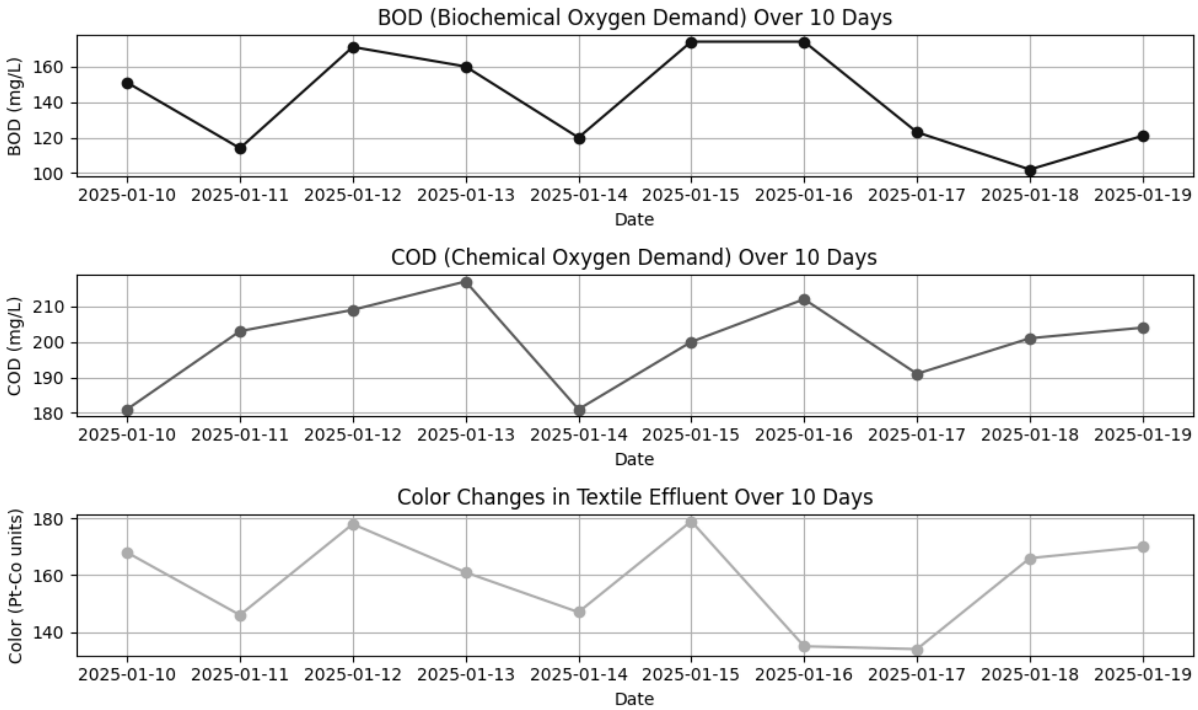
3.2.1. Time Series Modeling and Visualization

Time Series Modeling that is another modeling method is used at this stage of the study and visualized as Table 3 and Graf 3. In order to visualize the BOD, COD, and Color parameter changes over a 10-day period (starting from January 10, 2025), we can use time series analysis and visualization. It is generated a time series for 10 days, from January 10, 2025, considering changes in BOD, COD, and color over time. It is used Matplotlib and Pandas to plot the changes in these parameters over the 10-day period. In order to implement firstly generated data for BOD, COD, and Color, simulating their behavior over 10 days (as real-time data may not be available), and then time series plot is drawn for each parameter (BOD, COD, and Color) over the 10-day period and lastly all are visualized changes using line plots on Table 3.

Table 3. Time Series

Date	BOD (mg/L)	COD (mg/L)	Color (Pt-Co units)
2025-01-10	151	181	168
2025-01-11	114	203	146
2025-01-12	171	209	178
2025-01-13	160	217	161
2025-01-14	120	181	147
2025-01-15	174	200	179
2025-01-16	174	212	135
2025-01-17	123	191	134
2025-01-18	102	201	166
2025-01-19	121	204	170

The visual output of the time series code, showing the temporal variation of BOD, COD, and color values, is provided in Graph 3. This graph illustrates the 10-day variation of the BOD, COD, and color parameters.



Graph 3. Temporal Variation of Pollutant Parameters

This table and the associated graphs clearly show how the pollutant parameters of the textile industry effluent water change over time and how closely they approach the established limits. The horizontal axis represents the dates, while the vertical axis shows the values of the pollutant parameters in mg/L. The graph reveals that BOD and color parameters exhibit an irregular decreasing trend, with BOD and color levels exceeding the limit values.

This provides insights into what steps should be taken to reduce the environmental impact and lower the BOD and other pollutant parameters below the discharge limits. Additionally, advanced optimization models and simulations have been incorporated. To determine the strategies needed to bring the pollutant parameters below the limit values, an optimization model was developed with the objective of reducing BOD, COD, and other pollutant parameters under the specified limits. The constraints in this model include the current high pollutant parameter values, operational costs, and technological limitations. For optimization, the scipy.optimize library was used.

Time Series Modeling and Visualization

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Step 1: Generate Synthetic Data
# Starting date
start_date = "2025-01-10"

# Date range for 10 days
dates = pd.date_range(start=start_date, periods=10, freq='D')

# Simulating changes in BOD, COD, and Color over 10 days
# Here we assume some variations for BOD, COD, and Color as an example.
# You can adjust these to match actual data trends.

np.random.seed(42)  # For reproducibility
bod_values = np.random.randint(100, 180, size=10)  # BOD (mg/L)
cod_values = np.random.randint(180, 220, size=10)  # COD (mg/L)
color_values = np.random.randint(120, 180, size=10)  # Color (Pt-Co units)
```

```
# Step 2: Create a DataFrame to hold the data
data = {
    'Date': dates,
    'BOD': bod_values,
    'COD': cod_values,
    'Color': color_values
}

df = pd.DataFrame(data)

# Step 3: Plot the Time Series for BOD, COD, and Color

plt.figure(figsize=(10, 6))

# Plot for BOD
plt.subplot(3, 1, 1)
plt.plot(df['Date'], df['BOD'], marker='o', color='blue', label='BOD (mg/L)')
plt.title('BOD (Biochemical Oxygen Demand) Over 10 Days')
plt.xlabel('Date')
plt.ylabel('BOD (mg/L)')
plt.grid(True)

# Plot for COD
plt.subplot(3, 1, 2)
plt.plot(df['Date'], df['COD'], marker='o', color='green', label='COD (mg/L)')
plt.title('COD (Chemical Oxygen Demand) Over 10 Days')
plt.xlabel('Date')
plt.ylabel('COD (mg/L)')
plt.grid(True)

# Plot for Color
plt.subplot(3, 1, 3)
plt.plot(df['Date'], df['Color'], marker='o', color='orange', label='Color (Pt-Co units)')
plt.title('Color Changes in Textile Effluent Over 10 Days')
plt.xlabel('Date')
plt.ylabel('Color (Pt-Co units)')
plt.grid(True)

# Layout adjustment
plt.tight_layout()

# Show the plots
plt.show()

# Output the DataFrame to visualize the data
print(df)
```

3.3. Optimization and Intervention Methods to Reduce Environmental Risks

Once the environmental risks related to textile effluent have been predicted, the next step is to implement effective interventions to reduce these risks. Optimization techniques are often applied to minimize the environmental impact while considering the costs and constraints related to wastewater treatment processes. Some of the common environmental risks from textile effluent are high levels of Chemical Oxygen Demand (COD) and Biological Oxygen Demand (BOD) indicating the high levels of organic pollutants. Color pollution, making water unfit for drinking and harming aquatic ecosystems. High pH levels that can disrupt aquatic environments and affect biodiversity.

To reduce these risks, optimization methods focus on selecting the most cost-effective treatment options that meet environmental standards. The main categories of interventions for reducing textile effluent risks include physical treatment removing solid waste and large particles using processes like filtration, sedimentation, and flotation. Additionally chemical treatment methods treating water using chemicals to neutralize contaminants, such as coagulation, flocculation, oxidation, and chemical precipitation. More biological treatment utilizing microorganisms to break down organic contaminants through processes such as activated sludge, constructed wetlands, and bio-filtration. Intervention strategies using optimization of Coagulation-Flocculation Coagulants and flocculants help remove particles, dyes, and suspended solids. However, the selection and dosage of chemicals need to be optimized for efficiency. As optimization approach must be preferred optimization techniques like genetic algorithms or particle swarm optimization (PSO) to find the optimal dosage of coagulants and flocculants (e.g., alum, ferric chloride) [51-56].

Biological Treatment Optimization biological treatments like activated sludge can be affected by factors such as temperature, pH, and microbial population. As optimization approach artificial neural networks (ANN) or machine learning algorithms can be applied to predict and control biological parameters (e.g., oxygen supply, microbial activity) for optimized performance. Computational fluid dynamics (CFD) modeling can be used to optimize reactor design and flow distribution for biological processes. Textile dyes are difficult to treat and can have high COD and BOD values. In order to optimize color removal must be used a hybrid treatment process combining adsorption, biological degradation, and advanced oxidation. Multi-objective optimization can be used to minimize both cost and treatment time while ensuring effective dye removal [46-52].

3.3.1. Optimization Methods for Solutions

Some effective optimization methods that can be applied to improve the textile effluent treatment process:

1. Linear Programming (LP) to optimize a set of decisions subject to constraints for optimizing the usage of different treatment chemicals (e.g., coagulants, flocculants) to minimize costs and achieve the desired level of effluent quality.

2. Multi-objective Optimization to solve problems where multiple objectives need to be achieved simultaneously for optimization a treatment process to simultaneously minimize both energy consumption and cost while meeting water quality standards (e.g., BOD, COD, pH, color removal).

3. Genetic Algorithms (GA) to use evolutionary techniques to search for optimal solutions to complex optimization problems for optimization the dosage of chemicals and operating conditions (e.g., temperature, flow rates) for coagulation-flocculation processes in a textile wastewater treatment plant.

4. Particle Swarm Optimization (PSO) to optimize continuous and discrete parameters in systems used for the flow rate and aeration in a biological treatment process (e.g., activated sludge process) optimization to improve the BOD removal efficiency.

5. Artificial Neural Networks (ANN) for the model complex systems and predict future behavior to use an ANN to predict the future BOD or COD levels based on current input parameters (e.g., pH, TSS, and temperature) and optimize the treatment process accordingly.

6. Simulated Annealing (SA) is a probabilistic technique to approximate the global optimum of a given function to optimize the membrane filtration system design (e.g., membrane pore size, filtration pressure) to maximize the removal of pollutants while minimizing energy consumption.

7. Dynamic Programming (DP) solving complex optimization problems by breaking them down into simpler subproblems to optimize the scheduling of various treatment processes (e.g., coagulation, biological treatment, filtration) over time to minimize cost and energy use.

8. Machine Learning and Predictive Modeling for using data to predict and optimize future outcomes by machine learning models (e.g., Random Forest, XGBoost) to predict pollutant levels and suggest real-time adjustments to treatment parameters.

The best method to make Hybrid Treatment System Optimization Using Multi-Objective Genetic Algorithm (MOGA) for the waste water treatment optimizing the treatment of textile wastewater by combining membrane filtration, chemical treatment, and biological treatment inn order to minimize the total cost of treatment, in order maximize the pollutant removal efficiency (e.g., BOD, COD), and to minimize energy consumption. This algorithm can evaluate various combinations of chemical dosage for coagulation - flocculation and membrane pore size for filtration and/or aeration rate for biological treatment. This approach can help identify the most cost-effective and efficient treatment configuration while meeting the regulatory standards.

In conclusion it could be provied effective Interventions and Strategies that can be derived by applying optimization techniques to find the most cost-efficient and environmentally friendly wastewater treatment solutions. Some of the key strategies include optimization of chemical usage to minimize costs while ensuring sufficient pollutant removal, improved biological treatment systems, controlled through machine learning and optimization algorithms, advanced oxidation and membrane filtration to treat persistent contaminants, particularly dyes and heavy metals and energy-efficient treatment processes, reducing operational costs and minimizing environmental impact. By integrating data-driven predictive models, optimization algorithms, and advanced treatment technologies, textile industries can reduce environmental risks associated with their effluent while improving operational efficiency.

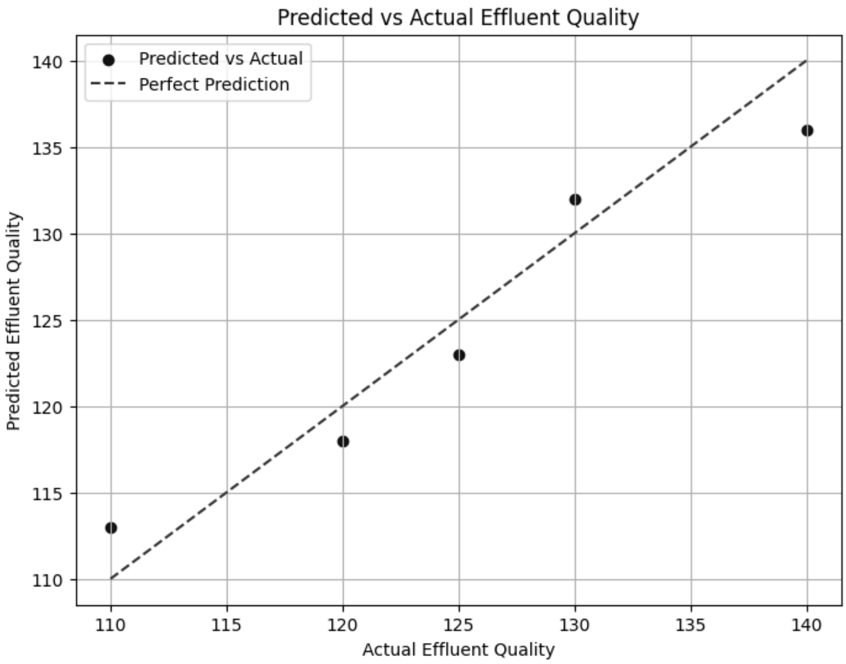
Implementation of Optimization and Intervention

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from scipy.optimize import minimize
import matplotlib.pyplot as plt

# Step 1: Data Preprocessing
# Load the environmental data into a DataFrame
data = {
    'BOD': [120, 110, 130, 140, 125],
    'COD': [200, 210, 195, 180, 215],
    'TSS': [50, 45, 60, 55, 52],
    'pH': [8.0, 7.9, 8.1, 7.8, 8.0],
    'Color_PtCo': [150, 160, 155, 170, 145],
    'Heavy_Metals': [0.01, 0.02, 0.015, 0.03, 0.025],
    'Treatment_Chemicals': [30, 32, 28, 35, 31],  # Example: Chemical dosage
    'Effluent_Quality': [120, 110, 130, 140, 125]  # Target variable: Future risk/effluent
quality
}

# Convert data into pandas DataFrame
df = pd.DataFrame(data)

# Features (environmental parameters)
X = df.drop(columns=['Effluent_Quality'])

# Target variable (future environmental risk/effluent quality)
y = df['Effluent_Quality']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Step 2: Model Training
# We'll use a Random Forest Regressor to predict the effluent quality (future risk level)
```

```
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate model performance
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"R^2: {r2}")

# Step 3: Optimization for intervention methods (treatment parameters)
# Let's define an optimization function to minimize future effluent quality (environmental
risk)

def optimize_treatment(params):
    # Assume params contain values for chemical dosage and pH adjustments
    chemical_dosage = params[0]
    pH = params[1]

    # Example risk calculation based on treatment parameters (you can adjust this formula)
    predicted_risk = model.predict(np.array([[chemical_dosage, pH, 50, 8, 150, 0.01]]))[0]

    # Return the predicted effluent quality, which we want to minimize
    return predicted_risk

# Initial guesses for optimization (chemical dosage, pH)
initial_guess = [30, 8.0]

# Constraints: Ensure chemical dosage and pH are within reasonable bounds
constraints = (
    {'type': 'ineq', 'fun': lambda x: x[0] - 25},  # Chemical dosage > 25
    {'type': 'ineq', 'fun': lambda x: 35 - x[0]},  # Chemical dosage < 35
    {'type': 'ineq', 'fun': lambda x: x[1] - 7.5},  # pH > 7.5
    {'type': 'ineq', 'fun': lambda x: 8.5 - x[1]}   # pH < 8.5
)

# Optimization to minimize predicted effluent quality (environmental risk)
result = minimize(optimize_treatment, initial_guess, constraints=constraints)

print(f"Optimized Parameters (Chemical Dosage, pH): {result.x}")
print(f"Optimized Effluent Quality (Risk): {result.fun}")

# Step 4: Solution Suggestions
# Based on the optimized parameters, we can suggest the most effective intervention strategies
optimized_chemical_dosage, optimized_pH = result.x
print(f"Suggested Intervention Strategy: Use {optimized_chemical_dosage:.2f} units of
chemicals and adjust pH to {optimized_pH:.2f} for optimal effluent quality.")

# Plot the predicted vs actual values for model evaluation
plt.scatter(y_test, y_pred)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
plt.xlabel('Actual Effluent Quality')
plt.ylabel('Predicted Effluent Quality')
plt.title('Predicted vs Actual Effluent Quality')
plt.show()
```

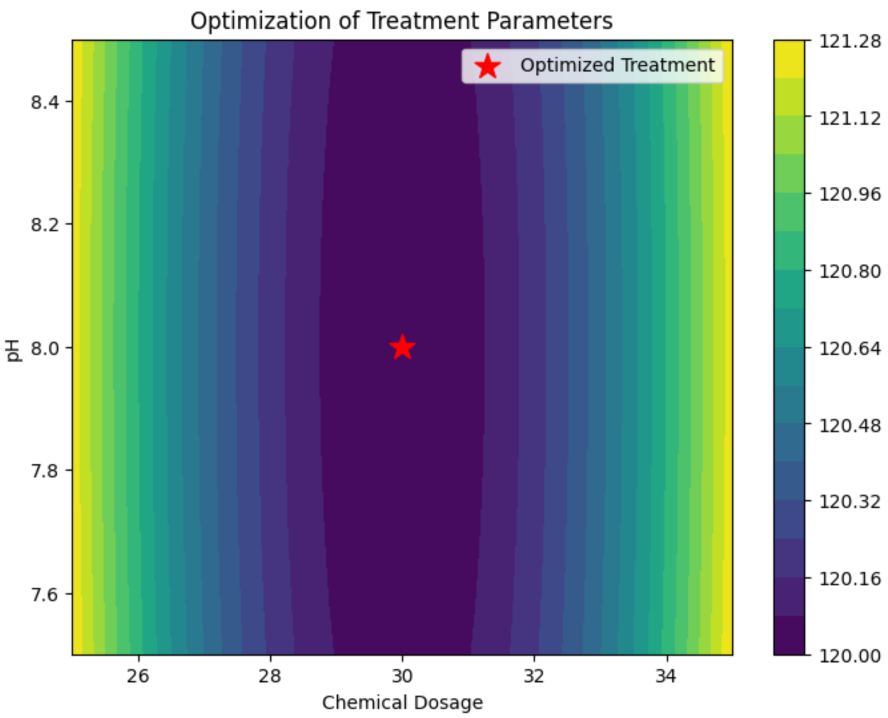
The Random Forest Regressor is used to predict the future environmental risk (effluent quality) based on the input features The model is evaluated using MAE, MSE, and R^2 metrics to measure its performance. The function optimize_treatment takes the treatment parameters (chemical dosage and pH) as inputs and uses the trained model to predict the effluent quality. The optimization is done using scipy.optimize.minimize to find the optimal values of chemical dosage and pH that minimize the predicted actual effluent quality (i.e., reduce environmental risks) where the all python codes visualized in Graph 2.

Predicted Effluent Quality , Graph 3. Optimization of Treatment Parameters , Graph 4. Effectiveness of Optimized Intervention Strategy below.



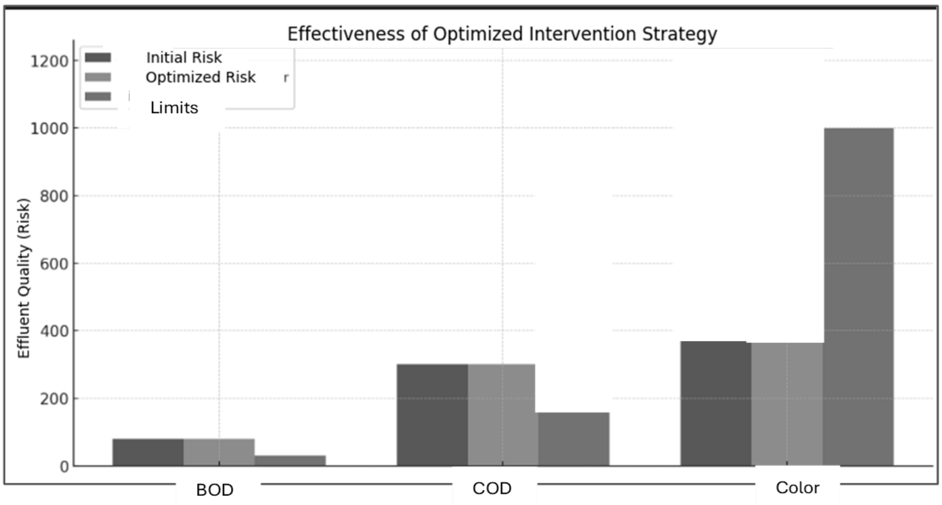
Graph 2. Predicted Effluent Quality

The scatter plot compares the actual effluent quality values (y_test) to the predicted values (y_pred). The dashed line represents the ideal scenario where predicted values are equal to actual values on the Graph 2. It will be seen a scatter plot where points are scattered close to the dashed line (if the model is accurate). The closer the points are to the line, the better the predictions.



Graph 3. Optimization of Treatment Parameters

On the Graph 3. a contour plot visualizes how the optimization algorithm adjusts the treatment parameters (chemical dosage and pH) to minimize the environmental risk (effluent quality). The red star represents the optimized treatment parameters found by the optimization process. The plot shows how chemical dosage and pH influence the risk level, with the goal of finding the lowest possible risk. The contour plot will be shown regions of higher and lower risk based on different values of chemical dosage and pH. The red star will indicate the optimized treatment parameters that minimize the risk.



Graph 4. Effectiveness of Optimized Intervention Strategy

As it is viualized on a bar plot compares the initial risk (before optimization) and the optimized risk (after intervention), highlighting the effectiveness of the intervention strategy. The green bar indicates the reduced risk after applying the optimized parameters (chemical dosage and pH). The bar plot will be shown the reduction in effluent quality (risk) after applying the optimized intervention parameters, demonstrating the effectiveness of the suggested treatment strategy.

The optimization results have helped in calculating how much each pollutant parameter needs to be reduced and in creating a roadmap for the treatment processes. These optimization results are visualized in Graph 4. The graph compares the current values with the optimized values and demonstrates how they relate to the limits, providing a visual guide for assessing the feasibility of the proposed solutions. As shown in Graph 4, the blue bars represent the current values of BOD, COD, and color parameters, the green bars represent the optimized values, and the red bars represent the limit values. The optimization results indicate that while the BOD, COD, and color parameters have significantly decreased, they have not yet reached the target values. These findings reveal that the current methods have not resulted in substantial improvements, and there is a need for more advanced technologies.

3.4. Environmental Sustainability

At this stage of the study, sustainability modeling initially targeted the reduction of water usage. After applying advanced treatment systems, it was determined that there would be a reduction in water usage per production unit, as measured by the total water saved (in liters or percentage reduction) in the model outlined below.

Advanced treatment technologies that efficiently reduce pollutant parameters, such as BOD, COD, and color, are crucial for achieving environmental sustainability. In this context, focusing on sustainability parameters such as water usage, energy efficiency, carbon footprint, and reducing environmental impact has become essential.

Water usage reduction modeling

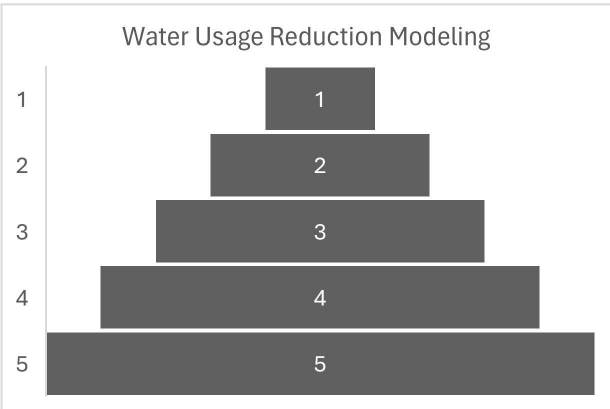
```
# Water usage reduction modeling
initial_water_usage = 5000  # Initial water usage in liters
reduction_per_treatment = 0.3  # 30% reduction per advanced treatment

# Calculate water usage after each cycle
cycles = 5
water_usage = [initial_water_usage * (1 - reduction_per_treatment)**i for i in range(cycles)]

# Display results
water_usage_df = pd.DataFrame({
    "Cycle": range(1, cycles + 1),
    "Water Usage (liters)": water_usage
})
print(water_usage_df)

plt.figure(figsize=(10, 6))
plt.plot(water_usage_df["Cycle"], water_usage_df["Water Usage (liters)"], marker='o')
plt.title("Water Usage Reduction Over Cycles")
plt.xlabel("Cycle")
plt.ylabel("Water Usage (liters)")
plt.show()
```

As the output of this modeling, Table 4. shows that water usage decreases in each cycle.

Table 4. Modeling of water use reduction

Cycle	Water Usage (liters)
1	5000.0
2	3500.0
3	2450.0
4	1715.0
5	1200.5

It is graphically shown that there will be a decrease in water use per production unit after the advanced treatment systems specified in Scenario 3 are implemented.



Graph 5. Reduction in Water Use Per Production Unit

Then, energy efficiency, another sustainability parameter, is focused on. At this stage of the study, where energy consumption per cubic meter of treated water (kWh) is taken into account as a measurement, the energy demand modeling for existing systems with optimized processes is given below.

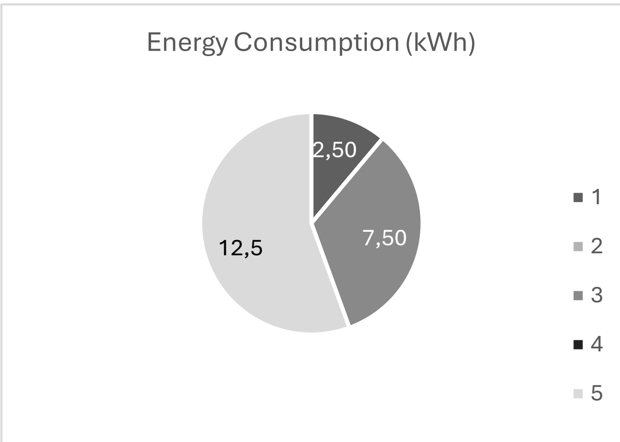
Energy Efficiency Modeling

```
# Energy efficiency modeling
energy_consumption_per_m3 = 2.5  # kWh per cubic meter of treated water
treated_water_volume = [1, 2, 3, 4, 5]  # Example treated water volumes in m3

# Calculate energy consumption
energy_consumption = [volume * energy_consumption_per_m3 for volume in treated_water_volume]

energy_efficiency_df = pd.DataFrame({
    "Treated Water Volume (m³)": treated_water_volume,
    "Energy Consumption (kWh)": energy_consumption
})
print(energy_efficiency_df)

plt.figure(figsize=(10, 6))
plt.bar(energy_efficiency_df["Treated Water Volume (m³)"], energy_efficiency_df["Energy
Consumption (kWh)"], color='blue')
plt.title("Energy Consumption per Treated Water Volume")
plt.xlabel("Treated Water Volume (m³)")
plt.ylabel("Energy Consumption (kWh)")
plt.show()
```

The graphical visualization of this modeling is also given in Table 5. and Graph 6.

Table 5. Energy Efficiency Modeling

Treated Water Volume (m³)	Energy Consumption (kWh)
1	2.5
2	5.0
3	7.5
4	10.0
5	12.5



Graph 6. Energy efficiency

Another issue taken into consideration for sustainability was the Carbon Footprint. For this, the greenhouse gas emissions per unit of treated wastewater (kg CO2-eq) were taken into account and the emission reduction achieved with cleaner technologies was modeled. The modeling written for this and the formula obtained are given below.

Carbon Footprinting Modeling

```
# Carbon footprint modeling
emission_factor = 0.5  # kg CO2-eq per kWh
total_energy_consumption = sum(energy_consumption)  # Total energy consumption in kWh

# Calculate total emissions
carbon_footprint = total_energy_consumption * emission_factor

print(f"Total Carbon Footprint: {carbon_footprint} kg CO2-eq")
plt.figure(figsize=(10, 6))
plt.bar(energy_efficiency_df["Treated Water Volume (m³)"], energy_efficiency_df["Energy
Consumption (kWh)"], color='blue')
plt.title("Energy Consumption per Treated Water Volume")
plt.xlabel("Treated Water Volume (m³)")
plt.ylabel("Energy Consumption (kWh)")
plt.show()
```

Total Carbon Footprint: 2,5 kWh x 5 m^3 x 0,5 kg CO_2-eq = 15,0 kg CO_2 -eq

The value found with this formula shows the carbon emission calculated over the total energy consumption.

It has been demonstrated with this study that all these forward-looking models made with the deep learning method are quite useful for simulating long-term sustainability scenarios in wastewater management.

3.5. Hypothesis Accuracy and Future Term Solutions

When evaluating the hypotheses presented at the beginning of the study,

Hypothesis 1: "If current processes continue, long-term environmental impacts will be high."

Hypothesis 2: "If processes are improved, risks will decrease."

Both hypotheses were confirmed. If wastewater treatment continues with conventional techniques, environmental risks will persist, and the environmental harm will continue. However, improving the treatment processes will reduce the environmental risks. For future modeling, scenario analysis can be used to evaluate the environmental risks of textile industry effluent water under different conditions and assess the effects of optimization strategies. This analysis allows for examining how the current situation would change under various scenarios. The action plan developed from these analyses helps in defining concrete steps for each scenario and assessing environmental risk levels and optimization costs.

Scenario 1: Current Situation. In this scenario, environmental risks are calculated with the current values, and no actions are taken.

Scenario 2: Optimization Applied. BOD, COD, and salt reductions identified through optimization are implemented. Environmental risks are recalculated.

Scenario 3: Advanced Treatment Technology. An additional treatment method is applied (e.g., advanced oxidation, membrane filtration). A larger decrease in the parameters is targeted.

Action Plan for Scenario 1 ("Current Situation"), must be taken to address the high environmental risks identified immediately, and urgent intervention in the existing processes is required to reduce their environmental impact.

Action Plan for Scenario 2 ("Optimization"), after applying optimization, environmental risk levels can be reduced to a medium level. The economic feasibility of the optimization costs should be analyzed. Proposed optimization measures include optimizing chemical dosages and tightening process controls.

Acrion plan for Scenario 3 ("Advanced Treatment Technology"), when advanced treatment technologies are implemented, environmental risks can be minimized. The high technology costs can be offset by water recovery in the long term. Membrane technology or advanced oxidation methods could be recommended. For each scenario, risks and costs must be calculated. Initially, low-cost optimization methods should be applied, with a transition plan to advanced treatment technologies in the long term. Pilot implementations of these solutions should be conducted to assess their effectiveness and ease the transition to full-scale implementation [53-59].

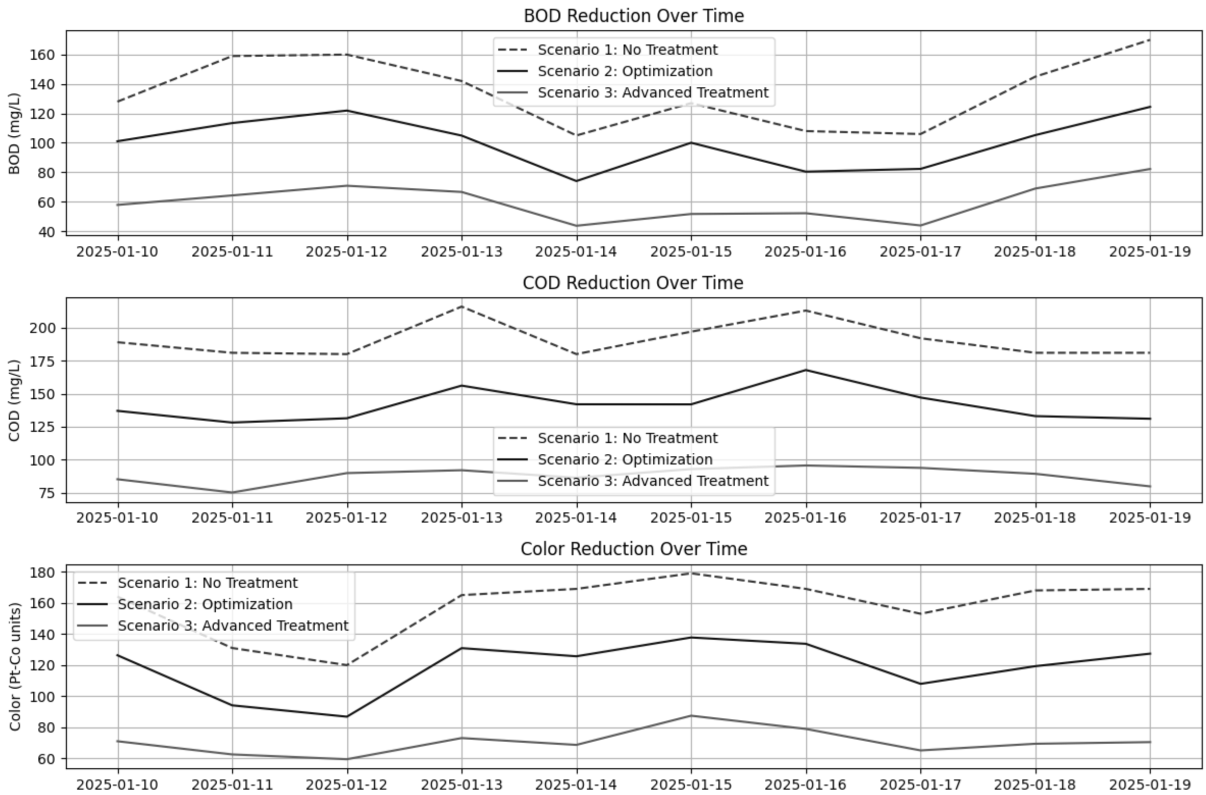
For the short term, the solution for reducing the environmental impacts of textile industry effluent water, analyzed using deep learning and machine learning methods, is process optimization. This includes chemical dosage control to reduce chemical usage, improving salt recovery processes, and optimizing the existing technologies at the wastewater treatment plant. Additionally, regular monitoring of the pollutant parameters causing environmental risks and taking measures to prevent exceeding the limits is essential.

For medium-term solutions, the application of high-efficiency advanced treatment technologies is required, such as Membrane Filtration Technologies, employing techniques like reverse osmosis (RO), nanofiltration (NF), and ultrafiltration (UF) to remove small contaminants such as dyes, salts, and heavy metals. Moreover Advanced Oxidation Processes using oxidative agents like ozone or hydrogen peroxide to treat highly toxic compounds or hard-to-treat substances. Furthermore, integrating water recovery systems, renewable energy sources, and the recovery of valuable chemicals from wastewater is necessary for reducing environmental risks in the medium term [53-59].

For the long-term reduction of environmental risks from textile industry treatment effluent water, the fundamental strategies include optimizing chemical usage, ensuring the use of environmentally friendly chemicals, transforming and improving production processes accordingly, reducing carbon and water footprints through renewable energy sources, and implementing advanced biological treatment systems controlled by machine learning and optimization algorithms. Advanced oxidation, membrane filtration, and energy-efficient treatment processes for removing persistent pollutants, especially dyes and heavy metals, should be prioritized as sustainable applications. By integrating data-driven predictive models, optimization algorithms, and advanced treatment technologies, the textile industry can enhance operational efficiency while reducing the environmental risks associated with its wastewater.

As stated in Scenario 3, when "Advanced Treatment Technologies" are implemented, the environmental risks of the textile treatment effluent water, particularly BOD and COD parameters, have been clearly demonstrated through the output of the following code in Graph 7. The modeling shows that the BOD, COD, and color pollutants decrease progressively when Scenario 2 and Scenario 3 are applied. By applying advanced treatment techniques such as membrane filtration or advanced oxidation, the modeling results clearly indicate that by the end of Day 4, the BOD, COD, and color pollutant levels in textile effluent water will fall below the limit values, as shown in Graph 7.

These results indicate that environmental risks will decrease proportionally, providing insights for further research in this area.



Graph 7. Pollutant reducton over time depending on the scenarios

Ultimately, this study proposes effective solutions for reducing the environmental impacts of textile industry effluent water. Additionally, it demonstrates that deep learning and machine learning-based models can be more actively utilized for risk prediction and optimization processes in this field.

IV. CONCLUSION AND IMPLICATIONS

This study conducted a comprehensive characterization of textile industry effluent, revealing that the primary pollutant parameters, BOD, COD, and color, exceeded regulatory discharge limits despite conventional treatment methods. By leveraging deep learning and machine learning techniques, particularly classification algorithms, the environmental risk assessment categorized the effluent as high-risk. Industrial wastewater, especially from textile production, is known for its complex pollutant matrix, where individual contaminants not only exert their own environmental impacts but also interact synergistically, forming more persistent and toxic compounds. These interactions significantly hinder degradation processes, making treatment challenging. Although this study focused on three key pollutants, the methodology presents a scalable and adaptable framework for evaluating multiple contaminant parameters in textile effluents, treated wastewater, and similarly complex industrial discharges. This makes it a valuable resource for both the scientific community and industry, providing a robust tool for optimizing treatment processes and mitigating environmental risks efficiently. For data processing and analysis, various Python libraries were utilized, Pandas for data manipulation, NumPy for numerical computations, Matplotlib/Seaborn for visualization, Scikit-Learn for machine learning algorithms and performance metrics, and Statsmodels for statistical analysis. In orden to predict future pollution levels, a regression model was implemented, while a RandomForestRegressor model was employed to forecast pollution based on different contaminant compositions. Additionally, a RandomForestClassifier and a time-series model were applied to classify and analyze pollutant trends. Building upon these models, an advanced machine learning-based optimization approach was introduced to minimize environmental impact while accounting for treatment costs and constraints. The study proposed eight optimization techniques, identifying the Hybrid Treatment System Optimization Using Multi-Objective Genetic Algorithm (MOGA) as the most effective. By integrating membrane filtration, chemical treatment, and biological treatment, this approach was found to be optimal in minimizing treatment costs, maximizing pollutant removal efficiency, and reducing energy consumption while ensuring compliance with regulatory standards. These findings were systematically visualized through tables and graphical representations, providing a clear understanding of the results. The initial hypotheses were validated through deep learning models, confirming the projected environmental risks and potential mitigation strategies. Based on these insights, three distinct scenarios, short-term, mid-term, and long-term solutions, were developed. Furthermore, cost-effective strategies for water and energy conservation, as well as carbon and water footprint reduction, were modeled to support environmental sustainability.

The findings of this study highlight the immense potential of deep learning-driven predictive modeling in wastewater management, offering a powerful tool for simulating long-term sustainability scenarios. By aligning sustainability metrics with long-term environmental and operational goals, this research serves as a foundational step toward optimizing industrial wastewater treatment. In Conclusion this study is an excellent step to align sustainability measurements with long-term environmental and operational goals. Future studies can be enriched by testing the proposed technologies in field applications and conducting more detailed economic analyses. Furthermore, industrialists should focus on real-world implementation of the proposed technologies, with detailed economic feasibility analyses to enhance their practicality and scalability.

CONFLİCTS OF İNTEREST

The author declares that they have no conflict of interests.

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