Forecasting of effluent from wastewater treatment industries using a novel Fuzzy logic system

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Abstract. Accurate modelling of the wastewater discharge parameters is necessary to lower the operational costs of such a wastewater treatment facility. The article presents a unique method for predicting the effluent prominence features for such an industrialized wastewater treatment facility. Artificial intelligence modelling is one such technique that enables analysis of the pollutant characteristics in treatment facilities and more effective regulation of them during processing. The study suggests using a fuzzy logic approach to regulate biological wastewater treatment. These computer programs are designed to forecast treatment issues in the future intervene promptly and efficiently in the facility, lessen or completely eradicate environmental pollution, enhance the ecosystem, and assess the wastewater treatment plant's treatment efficiency. The study intends to employ fuzzy logic models of artificial intelligence to accomplish the best treatment process, including O&G, BOD, COD, TSS, and TDS, while also assuring that the treated wastewater complies with regulations. Additionally, statistical analysis of the data was performed. The best value and the highest R^2 value were discovered; these numbers demonstrate that the expected and investigational performances are comparable, and that the plant's presentation could be correctly predicted utilizing a fuzzy logic model, allowing fuzzy logic to be employed to describe the method.

1 Introduction

The environment has recently emerged as one of the main objectives for corporate citizenship responsibility (CSR). Businesses are becoming more aware of environmental concerns and implementing sustainability management techniques to maximise their commercial development while also fulfilling their social responsibility. As a result, green innovation has piqued the interest of scholars and practitioners as a fresh model for environmental sustainability. Current research has identified several predecessors to green product creation, including technological benefits, the interchange of green knowledge, and market pressures [1]. As environmental issues worsen, there is a growing demand for firms, particularly those in the manufacturing sector, to be more environmentally responsible. This need drives firms and executives to embrace or develop creative techniques to addressing environmental threats. These approaches can be classified broadly as eco-innovations, which are innovations that "involve new or modified procedures, methodologies, structures, and product lines to avoid or minimize harm to the environment." The benefits of eco-innovation, such as lower carbon dioxide emissions and improved economic conditions, are repeatedly established. Researchers are paying more attention to the issues of what motivates eco-innovation and how organisations participate in it as a result of the growing desire for eco-innovation and understanding of its benefits [2].

Power and the atmosphere, especially the issue of environmental problems caused by synthetic greenhouse gases, seem to become such a severe worry in our civilization that practically everyone in the world is discussing it now. For outstanding efforts to global warming, and the United Nations–Intergovernmental Panel on Climate Change (IPCC) and current US Board Member Al Gore won the Nobel Peace Prize in 2007, Energy has undoubtedly been the lifeline of our industrial civilization, with per capita energy demand serving as a measure of a country's wealth. In the pre-industrial post-revolutionary period, mankind was mostly reliant on livestock and physical labor. The way of life was simple and uncomplicated, and the atmosphere remained pure during this great era. The steam engine, created in 1785, was the catalyst for Industrialization, ushering mankind into the mechanical age, or the age of machinery [3]. In the 1800s, the internal - combustion engine was invented, which propelled Industrialization. Industrialization swept across Europe, the US, and eventually the rest of the globe. The economical electricity supply throughout the mid-1880s ushered in the electric revolutionary or electronic century, which coincided with Nickola Tesla's invention of the commercial induction generator (1888). The transistors, invented by Bell Laboratory' in 1948, brought in the electronic breakthrough, or the period of contemporary sturdy devices. The thyristor was also

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designed by Bell Labs in 1956, and it has been widely commercialized by General Electric. We are now in the current era of solid-state electrical machines as a result of the electronic age [4].

While research on environmental economics emphasises the significance of regulations, research on creativity emphasises the crucial role of other variables in determining eco-innovations, particularly supply-side variables (such as businesses' organisational capacities) and demand-side processes (such as customer and societal requirements on corporate social responsibility) demonstrated that these characteristics are insufficient for spotting environmental opportunities. They conducted an econometric research to back up their assertion that people are more likely to recognise what they observe as their environmental attitude improves. Recently, a new exploratory study in entrepreneurship research has emerged. Recent study has focused specifically on environmental protection in business strategy. This emphasis does not neglect additional aspects (social and economic). However, regulating the negative effects of enterprises' economic activity on their local surroundings is given top priority. The goal is to create a long-term sustainable business model [5].

Battery production, electric power plants, chemical manufacturing, food production, iron and steel production, metalworking, nuclear energy production, mines and quarries, oil as well as gas production, petroleum refining and pharmaceutical production, petrochemical production, pulp, as well as paper production, industrial oil contamination, smelters, water treatment, textile mills, and wood preservation are specific of the industrial that yield industrial wastewater. Figure 1 depicts a few of the industries. Any wastewater produced by different industrial processes is referred to as industrial effluent. Receiving water sources are deteriorating as a result of the different industrial effluent/wastewater quality from one industry to another. In other words, it is highly desirable to treat all types of effluents coming from different sectors utilizing an industrial ETP/Effluent Treatment Plant [6]. Industrial effluent treatment is an efficient method for cleaning up wastewater that has been heavily contaminated by industrial pollutants so that it can be reused or discarded in or released back into the environment. Deterioration of the receiving water bodies stands produced by the condition of industrial wastewater wastes. This is owing to the possibility of soil pollution in receiving water bodies and also the creation of favourable conditions for microorganisms that produce toxins in waterborne industrial wastewater effluents that have either been improperly treated or left untreated. It is necessary to properly treat wastewater before release in order to adhere to the regulations and laws governing it. Appropriate treatment procedures for industrial wastewater sewages are obligatory to reduce the threat towards the environment as well as public health. Steady monitoring, appropriate and suitable management, cautious preparation, and relevant laws are counselled to ensure the unpolluted release of industrial wastewater through addicted to receiving water bodies [7]. The overall amount of rainfall integrated along a dewdrop clustering is a helpful metric of the disturbance's particle diameter, which is quantified as the rate of water mass loss or heat capacity generated, i.e., the disturbance's force.

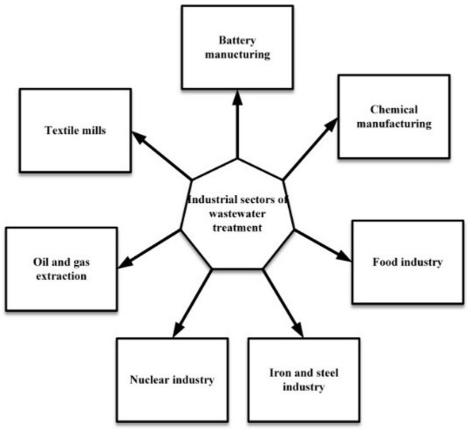

Fig. 1: Industrial sources of wastewater treatment

The prediction model multiplies actual cluster power statistics at both resolutions when low rain rates are eliminated by specifying a maximum rainfall intensity criterion while creating clusters. Because the most powerful downpour clusters occur in the tail, changes in tail behavior have a significant impact on the frequency among the most intense hurricanes. In calculations using specified ocean temperatures and greenhouse gases levels from a "standard operating procedure" climate warming assumption, the middle and end-of-century clustering power dispersion are examined in HIRAM [8]. Agriculture, health, and infrastructure are all affected by the size and change rate in the local hydrological processes. The variability of rainfall (in spacetime), especially at the limits, is critical in assessing the extent of destruction caused by specific occurrences. Components of these variations may be reflected in integration time methods of hydrodynamic parameters, particularly for the volume of water theoretically accessible for an area. The rise in international mean amounts, on the other hand, is not always relevant effects. Local predictions' robustness is questioned at best without an understanding of the motivating forces at the broadest temporal and geographic levels [9].

These designs have a broad range of applications for forecasting both municipal and commercial wastewater plants, but they have important shortcomings in many contexts, such as poor architectural and pragmatic recognisability, a lack of knowledge of sludge adequate provisions, and their measurement to very specific operational circumstances. Additionally, key model assumptions, such as the values of parameter estimation and model predictor variable, are needed for the correction of these representations for the modelling of wastewater treatment amenities. The variations in processing units, which significantly diminish the model's application, are another significant element. As a result, the use of linear/nonlinear-based designs to address the important dynamic nonlinear effects in wastewater treatment that are challenging to manage by traditional linear methodologies is encouraged by recent developments in soft calculating for modelling the variables of water treatment abilities [10].

Given the current exponential expansion of the business and the volume of wastewater that its procedures produce, it is critical that it have an effective organization for treating such effluents in order to minimize the influence of its releases and adhere to the ecological regulatory standards that raise their demand. This stimulates invention in the treatment facilities and the corresponding control as well as management of information technologies to produce a more effective procedure, whose benefits have indeed been demonstrated in various industrialized nations. The suggested method is an intelligent system that produces predictions about the behaviour of bioreactors using data from the biological phase of the process. This approach can increase decision-making on the operations of the treatment facility for wastewater and increase its efficiency and productivity. By implementing a continual prediction of out-of-range measurements, proactive actions can be taken when they are needed. As an outcome, gains were gained that resulted in operational cost reductions, including water of a higher quality than necessary and a decrease in bottlenecks due to microbial adaption [11]. To lessen the risk to the environment and human health, industrial wastewater effluents must be treated properly. To guarantee the uncontaminated release of industrial wastewater addicted to receiving water bodies, it is advised to use regular monitoring, effective and suitable treatment, prudent planning, and applicable laws. The remainder of this strategy is distributed in the following divisions: Section 2 presents relevant works and conducts a thorough study of them. Section 3 provides a full examination of the proposed fuzzy logic modelling and analysis for effluent prediction in wastewater treatment companies. Chapter 4 presents, examines, and critically evaluates the experiment's findings, as well as a comparison to industry norms. This section serves as the article's conclusion.

2 Related Works

Particularly, since the 1990s, the concept of eco-innovation has begun to be seen as a means of mitigating environmental harm. Eco-innovation is expected to reduce waste output, environmental damage, and the usage of manufacturing resources. The impact of eco-innovation on environmental and economic efficiency, however, has received little attention. Data was acquired for this aim by assembling questionnaires from 219 Turkish industrial firms. Using hierarchical linear modelling, researchers discovered that environmentalists appear to have a direct impact on pollution prevention, resource conservation, and recycling; also, they have an indirect positive impact on cost savings and, as a result, economic strength. For this exploratory case study, volunteers from BBC Prison Research were randomly assigned as guardians or inmates. This study investigates how therapies aimed at strengthening convicts' sense of shared social identity affect leadership processes. It provides psychometric, behavioural, and observational evidence to support the claims that (a) socialisation facilitates governance, (b) good leaders promote the formation of cultural identity, and (c) the effectiveness of uniqueness-related projects influences long-term achievement or lack thereof. The study also shows how identity loss influences both the emergence of authoritarian leadership in general and transformation in particular [12]. Climate change, environmental justice, and vulnerability are the subjects of a suggested exploratory geographical study [13]. Research shows that vulnerable groups, including disadvantaged persons of colour, tend to live in areas where socioeconomic and environmental concerns are more likely to affect them. As a result of climate change, these populations may experience higher rates of depression and environment disparities in health. The objective of the research was to examine the use of Geographic Information Systems (GIS) to analyse locations across the United States that may be sensitive to environmental changes. Using numerous social, environmental, and health factors, we used ArcGIS 9.3 to develop sensitivity ratings for places around the country that may be affected by global warming at the local state or federal level. The US Survey provided information on the racial group and socio-economic status. The United States Environmental Protection Agency provided information on the pollution effect of different levels. Health statistics were delivered by the National Centre for Health Statistics, the National Vital Statistics System, and the Behavioural Risk Factor Surveillance System. Researchers also used the Moran's I statistical to see whether there were any notable susceptibility groupings. The regions in the Southern, notably the Deep South, and metropolis centres in the Midwest and Northeast obtained the top ratings. Research researchers concentrated on which regions of the state may be particularly vulnerable to the significances of climate change. Further effort is necessary to enhance the geographic quality of the images and to add more physical parameters that would aid in identifying locations that ensure appropriate mitigation and adaptation. The biggest drawback of concentrating strictly on racial and ethnic disparities inequalities to assess demographic sensitivity to climate science and hazard is that it may exaggerate or distort district results.

Utilizing a novel combined linear-nonlinear approach, forecasting wastewater treatment plant quality characteristics were developed [14]. The most widely controlled wastewater discharge appearances are biochemical oxygen demand (BOD), total dissolved solids, chemical oxygen demand (COD), and total suspended solids (TSS). To evaluate the effectiveness and upgrading of sewage treatment facilities, various factors must be measured and predicted. The beneficial properties of effluent wastewater are modelled in this work using a new approach that associations a linear stochastic model (ARIMA) and also nonlinear outlier robust extreme learning machine procedure (ORELM) with different pre-processes (ARIMA-ORELM). A total of 144 unique (144 8 models) linear designs (ARIMA) are offered for every one of the researched variables, with the forecasting solution for each variable being chosen utilizing arithmetical indices. Additionally, 48 hybrid models (ARIMAORELM) and 48 nonlinear designs (ORELM) were taken into consideration. The hybrid designer's forecasts were more effective and accurate because it used both linear and nonlinear modelling techniques to represent the linear and nonlinear terms (collectively) of the every time - series data. With such a significant correlation coefficient of 0.95, the influent wastewater nonlinear TSS typical and the exhaust COD and BOD modelling techniques achieved the greatest efficiency. The ability to forecast all quality metrics was improved by the use of different models, with the wastewater BOD model achieving the best results.

In order to help decision-making regarding the management of the wastewater plant, the study suggests the creation of an intelligent design that analyses data from the system and predicts its behaviour. The implementation of such a multilayer perceptron neural network comprising two hidden layers including 22 neurons every, as well as process variable analysis, correlation, time-series decomposition, and autocorrelation approaches, allows for the construction of this technology. It is feasible to anticipate the chemical oxygen demand (COD) there at the input of the bioreactor with such a window as well as a mean complete percentage error, placing the work between the appropriate ranges for prediction. Scaling the system's prediction to other crucial process variables and gathering more data while taking into account recently discovered measurements are not taken into consideration in the on-going effort to enhance industrial wastewater treatment [15].

By merging an enhanced feed forward neural network and using an optimization technique, a machine learning system was created to enable real-time forecasting of wastewater treatment facility effluent quality of the water. Hourly influent flow rate, influent water quality parameters, and operational and also monitor parameters for WWTP processes were the data utilized as input variables for the feed forward neural network. The genetic algorithm GA-IFFNN framework could be a valuable method for the clear structure of monitoring reforms in WWTP processes since it was effective at apprehending complex non-linear interactions and extrapolation. The improved feed forward neural network model does not have an optimal control module to decrease WWTP operational expenses in real time although meeting effluent regulations, which poses a limitation for the investigation [16].

3 Materials and methods

3.1 Wastewater treatment

To create the characterization model that correlates to Waste Water Treatment, a database from the industry was used. In this facility, the organic load and different suspended solids carried by the raw wastewater are removed using the activated sludge method. The industry regularly collects the effluent and influent measurements of the wastewater parameters. The historical data that is readily available comprises a vast amount of data that corresponds to a thorough description of the plant. This data includes analytical research findings for the quality of the water and sludge, including pH, TSS, COD, BOD, TDS, and O&G.

3.1.1 pH analysis

Neutralization, coagulation, precipitation, and other biological treatment processes all depend on the pH analysis. The strength of the ionization of hydrogen in the solution is measured by pH. And Aimed at the removal of heavy metals as well as organic compounds during wastewater treatment, the pH must be measured. The wastewater sample's mean value for the metric was 7.32 + 0.91.

3.1.2 Biochemical Oxygen Demand

Dissolved oxygen (DO) differences between sample water prior to and after five days of spread serve as the primary indicator of BOD *[17]*. The dilution technique at 20˚C was used to evaluate the BOD on wastewater samples that were obtained from the business. The change in concentration of dissolved oxygen over course of five days demonstrates the oxygen demand again for inhalation even by aerobic natural microorganisms found in the illustration. By using the same method described above for the estimation ofDO_0, DO_5 were calculated. One blank solution was made in a clear bottle for DO_0 and yet another extra in an amber bottle aimed at DO_5, both of which were incubated alongside the sample which is calculated using eq. (1):

$$\mathrm{BOD_5(mgL^{-1})} = \frac{(\mathrm{DO_0}-\mathrm{DO_5})\times \mathrm{Vol.of\ BOD\ Bottle}}{\mathrm{Vol.of\ sample}} \quad (1)$$

3.1.3 Chemical Oxygen Demand

A wastewater sample's COD [18] serves as a measure for the amount of oxygen that must be dissolved in order to oxidize all soluble organic matter, especially non-biodegradable organic matter. There is only two to three hours are needed for this examination. It is a crucial factor in determining the calibre of effluent. The reaction with such a potent oxidizing agent, $K_2Cr_2O_7$ in concentrated H_2SO_4 (50%) has taken place to calculate the COD using eq. (2) in water.

$$\mathrm{COD(mgL^{-1})} = \frac{(\mathrm{D}-\mathrm{E})\times \mathrm{F}\times 8000}{\mathrm{Vol.of\ the\ sample\ (mL)}} \quad (2)$$

Where D is the amount of titrant needed to titrate the sample in millilitres; E is the amount needed to titrate the blank illustration in millilitres; and F is the normalcy of the ferrous ammonium sulphate solution.

3.1.4 Total Dissolved Solids

After being dried in an oven for about 100, the TDS there in the wastewater sample can be measured utilizing gravimeter analysis. The water sample was obtained into a pure conical flask after the wastewater specimen was processed using a pre-weight measured filter paper. The filtrate was held in a set volume there in petri dish, which was then heated to 180*˚C*. The succeeding equation (3) is employed to calculate the TDS:

$$TDS(mgL^{-1}) = \frac{(D-E)\times 1000}{Vol.of\ the\ sample\ (mL)} \quad (3)$$

Where E represents the mass of the evaporating dish in mg and D represents the mass of said dried residue as well as dish in mg.

3.1.5 Total Suspended Solids

The gravimeter technique was utilized to decide the TSS level in the wastewater sample. A typical glass fibre filter was used to filter the wastewater sample, and also the filtrate was then dried in an oven at about 103˚C to 105˚C degrees. In a desiccator, the filter paper remained chilled to room temperature. The final measurement of the filter's weight growth is utilised to determine the TSS value. The necessary equation is in (4):

$$\mathrm{TSS} = \frac{(\mathrm{D-E})\times 1000}{\mathrm{Vol.of\ the\ sample\ (mL)}} \quad (4)$$

Where D is the filter's mass in mg following filtration and E is its mass in mg prior to filtration.

3.1.6 Oil and Grease

Hexane was used as the extraction liquid for the processing of this parameter in the wastewater sample using the liquid-liquid extraction procedure. A conical flask was filled with the hexane (organic portion), as well as the tap on the separating funnel was used to separate the aqueous layer from the organic portion. In a fume cupboard, the solvent extracts are dried at about 20 ˚*C* to 25 ˚*C*.

The equation (5) reads as follows:

$$O\ and\ G(mgL^{-1}) = \frac{(D-E)(mg)\times 1000}{Vol.of\ the\ sample(mL)} \quad (5)$$

Where D is the rising mass in mg of the entire experimental sample, and E is the rising mass in mg of the blank.

3.2 Fuzzy logic model

Based on Zadeh's concept of fuzzy [19] sets, Mamdani became the first to develop fuzzy logic models (sometimes referred to as linguistic representations or fuzzy ifthen rules). These models can manage incredibly unexpected systems. Without the need for intricate mathematical equations, the concept of fuzzy sets, first presented by Zadeh in 1965, seems to be a useful technique for capturing information uncertainty and imprecision. By defining reasoning in the form of language instead of numerical values, these frameworks have the benefit of being capable to characterize non-linear functions in such a straightforward and intelligible manner. These offer a useful method to legibly define human knowledge through the use of fuzzy rules. The fuzzy logic model is shown in Figure 2.

Fuzzy controllers have a very straightforward conceptual basis. They consist of input, treating, and also output phases. In the input stage, thumbwheels, switches, and other input devices like sensors are mapped toward the applicable membership functions and also truth principles. Prior to combining the outcomes, the processing step invokes each pertinent rule and produces an outcome for each. The combined outcome is then transformed back into a specific control output value there in the output stage. While bells, as well as trapezoidal curves, are also utilized in the number of curves but also their order is more important when determining the form of membership functions.

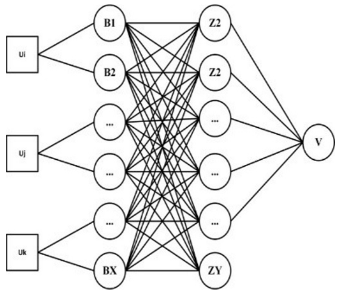

Fig. 2: Structure of fuzzy model

Since three towards seven curves were frequently sufficient to protection the necessary input value range, or what fuzzy mathematicians refer to as the "universe of discourse". The processing stage, as previously mentioned, is based on a set of logic rules expressed as IF-THEN statements, in which the IF part is referred to as the "antecedent" while the THEN portion is the "consequent." Numerous rules make up typical fuzzy control systems. Designing fuzzy control systems relies on empirical techniques, or, to put it another way, a methodical approach to trial-and-error.

A set having fuzzy bounds is a straightforward definition of a fuzzy set. Let Y represents the realm of speech and y represents its constituent parts. According to classical set theory, the distinguishing function of B, $f_B(y)$, is how the crisp set of that Y is defined in eq. (6).

$$f_{B(y):Y\rightarrow 0,1} \quad (6)$$

Where,

$$f_{B(y)=}\begin{cases}1, & if\ y\in B\\ 0, & if\ y\notin B\end{cases} \quad (7)$$

This set converts the universe Y into a pair of elements. Characteristic function fb(y) for each element y of universe Y is equivalent to 1 if y is an element of set B and equivalent to 0 if y is not an component of B. According to the fuzzy theory, the membership function of set B, function B(y), defines the fuzzy set A of the universe Y.

$$\mu_{B(y)}{:}Y\rightarrow[0,1] \quad (8)$$

Where,

$$\mu_{B(y)=}\ 1\ if\ y\ is\ totally\ in\ B;$$

$$\boldsymbol{\mu_B(y) = 0\ if\ y\ is\ not\ in\ B}$$

$$\boldsymbol{0 < \mu_B(y) < 1\ if\ y\ is\ partly\ in\ B}$$

There is a range of options available with this package. The degree to which y is a component of set B is characterized by the membership function B(y) for any component y of the universe Y. This degree, which has a value between 0 and 1, indicates the degree of involvement also recognized as the membership value of component y in set B. Fuzzy logic frameworks of artificial intelligence will be used in the study to achieve the optimal treatment method for O&G, BOD, COD, TSS, and TDS while also perhaps ensuring that the treated wastewater conforms to standards. The proposed methodology for predicting effluents from wastewater industry is shown in figure 3.

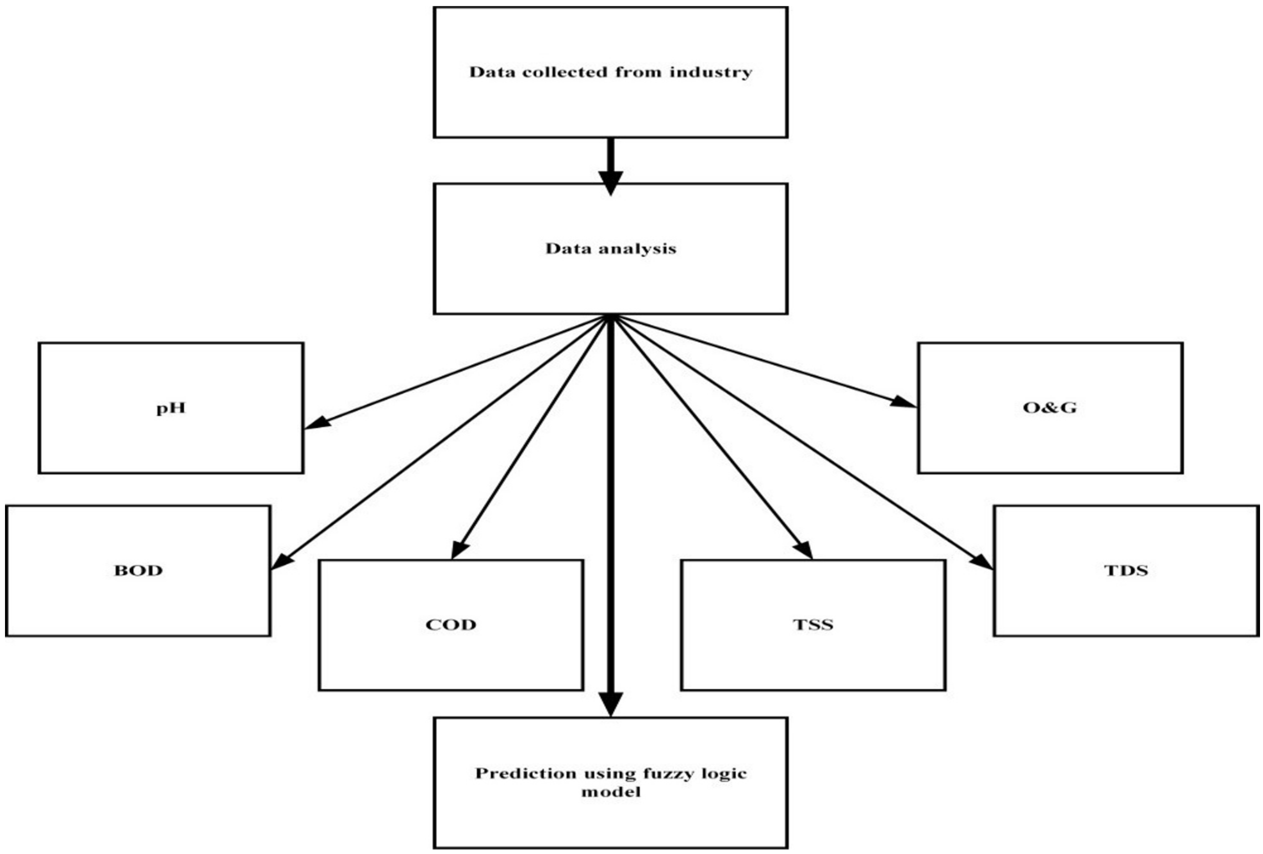

Fig. 3: Proposed methodology for prediction of effluent

4 Results and discussion

By using the test data in the produced data and comparing the yields as well as estimated values, the evaluation ability of the frameworks is evaluated. Additionally, the root mean square error and also the assurance coefficient (R^2)—all factual bounds—are used to analyse the anticipated and estimated benefits of flexible modulus. Eqn. (9) can be used to describe the RMSE [20].

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(z_{act_i}-y_{pred_i}\right)^2} \quad (9)$$

Additionally, Eqn. (10) can be used to get the determinant coefficient (R^2), which is obtained by:

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(z_{act_i}-z_{pred_i}\right)^2}{\sum_{i=1}^{m} z_{act_i}^2} \quad (10)$$

However, MAE [21], which is represented by Eq. (11) and is used to analyse the presentation and production of the anticipated models

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|z_{act_i} - z_{pred_i}\right| \quad (11)$$

The values of R^2 and MSE were used to assess how well the designed models performed. Whichever networking architecture has the highest value of R^2 and the lowest MSE is considered to be the best.

In order to properly evaluate every influent factor, which results in the effluent parameters COD, TSS, BOD, TDS, and O&G, the performance measurements of the Fuzzy Logic model for projecting every effluent eminence COD, TSS, BOD, TDS, and O&G were computed self-sufficiently.

4.1 Monitoring BOD outcomes

For every variable and training approach, the values of R^2, MSE, MAE, and RMSE were determined in the study. All of these findings were compared, and the constructed design was similarly encouraged for every input and output set of data. Table 1 and Figure 4 present a condensed and comparative analysis of all BOD monitoring results. R^2 value is high and MSE value is low when BOD has been monitored.

Table 1: Monitoring outcomes of BOD

	Fuzzy logic model Outcomes
R^2	0.9993
MAE	0.3318
MSE	0.2379
RMSE	0.4878

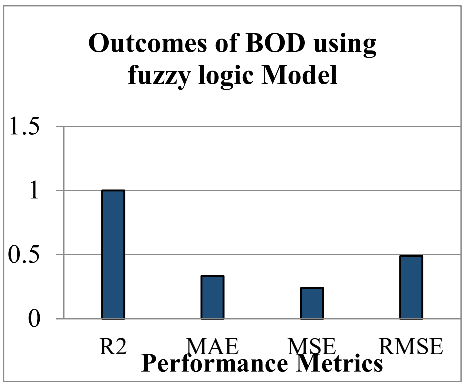

Fig. 4: Monitoring outcomes of BOD

4.2 Monitoring COD outcomes

The study determined the R^2, MAE, MSE, and RMSE values for each variable and training method. For every input-output set of data, the results were compared, and the built-in model was also encouraged. The findings of all COD monitoring are summarised and compared in Table 2 and Figure 5. When COD has been measured, R^2 value is high and MAE value is low.

Table 2: Monitoring outcomes of COD

	Outcomes(Fuzzy logic model)
R^2	9.9956
MAE	1.6079
MSE	5.5499
RMSE	2.3557

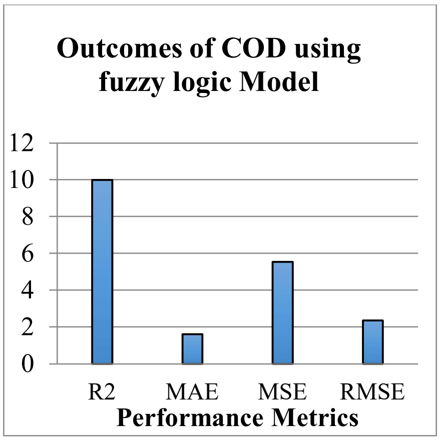

Fig. 5: Monitoring outcomes of COD

4.3 Monitoring TSS outcomes

Table 3: Monitoring outcomes of TSS

	Outcomes (Fuzzy logic model)
R^2	0.9992
MAE	0.4609
MSE	0.3599
RMSE	0.5981

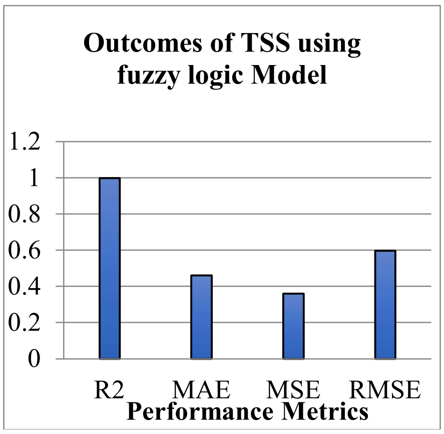

Fig. 6: Monitoring outcomes of TSS

The R^2, MAE, MSE, and RMSE values for each variable and training method were calculated. The outcomes were compared for each set of input-output data, and using the built-in model was also recommended. Table 3 and Figure 6 summarise and compare the results of all TSS monitoring. R^2 value is high and MSE value is low when TSS has been measured.

4.4 Monitoring TDS outcomes

Table 4: Monitoring outcomes of TDS

	Outcomes (Fuzzy logic model)
R^2	9.9981
MAE	2.8531
MSE	0.3628
RMSE	6.0252

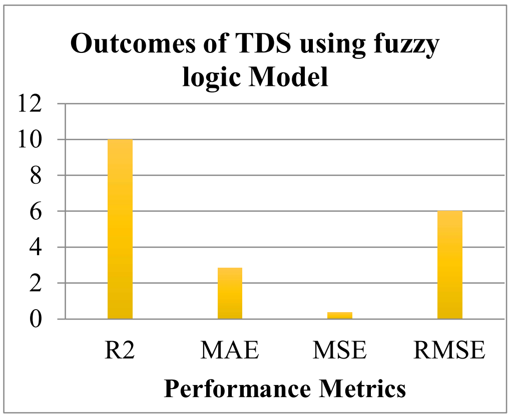

Fig. 7: Monitoring outcomes of TDS

The R^2, MAE, MSE, and RMSE values for each variable and training method were calculated. The outcomes were compared for each set of input-output data, and using the built-in model was also recommended. Table 4 and Figure 7 summarise and compare the results of all TDS monitoring. R^2 value is high and MSE value is low when TDS has been measured.

4.5 Monitoring of O&G outcomes

Table 5: Monitoring outcomes of O&G

	Fuzzy logic model Outcomes
R^2	0.9980
MAE	0.1213
MSE	0.0355
RMSE	0.1888

For each variable and training method, the R^2, MAE, MSE, and RMSE values were computed. For each set of input-output data, the results were compared, and it was also suggested that the built-in model be used. The findings of all O&G monitoring are summarised and contrasted in Table 5 and Figure 8. When O&G has been measured, the R^2 value is increased and the MSE value is low. Table 6 and figure 9 explains about the comparison between the proposed method and existing method.

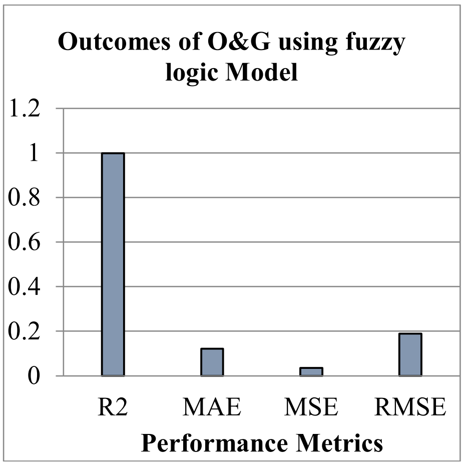

Fig. 8: Monitoring outcomes of O&G

Table 6: Comparison of R^2 with existing method

Technique	R^2
Proposed fuzzy logic model	0.99
ANN	0.98

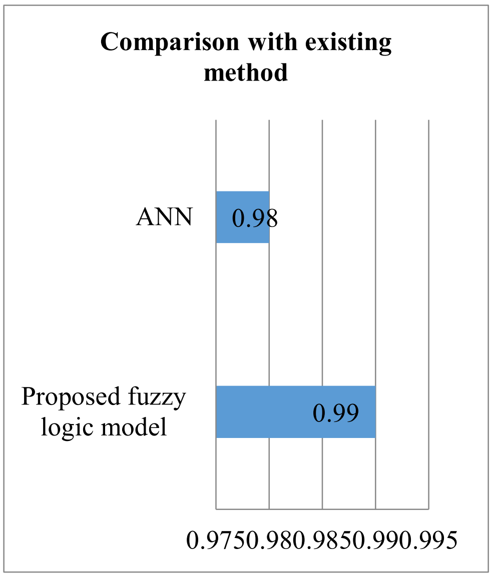

Fig. 9: Comparison with existing method

The amount to which the predicted and first measured values matched was investigated in the study. All of these findings show that, while the training techniques employed in this study produce good projected data sets, the fuzzy logic model performs significantly better than the others. The research that was done to compare all of the monitoring results is represented graphically. The fuzzy logic framework is preferred for great fit dataset for all parameters, according to a visual examination of the graph, and depending on the data set, it produces the best output for the task. In order to provide the best match for the data of the measured parameters, the training procedure of the fuzzy logic system may vary based on the data that is provided.

5 Conclusion

The determination of the research is to forecast the effluent water quality as it passes through wastewater treatment facilities. The study demonstrates that the COD, BOD, TDS, O&G, and TSS characteristics for the wastewater treatment industries may be predicted using fuzzy logic models. These conclusions imply that the research's supporting data stands reliable and that the framework is accurate, effective, and relevant for engineering management and references. Again then data become accessible, and the effectiveness of the frameworks developed in the study will be evaluated for long-term forecast. The study looked at how closely the initial measured values matched the predictions. All of these findings demonstrate that while the training methods used in this study create high-quality predicted data sets, the fuzzy logic method outperforms the others by a large margin. A graphic depicts the analysis that was performed to evaluate all of the ways of measuring. According to a visual inspection of the graph, the fuzzy logic framework is chosen for great fit datasets for all parameter, and based on the data set; it delivers the best result for the task. For additional research, the suggested methodologies can be expanded to the fuzzy logic models and Simulation systems.

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