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Development of an Intelligent MATLAB-Based Model for Detection Water Pollution from Industrial Discharges

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ABSTRACT*:* Unnatural inflows of industrial effluents into freshwater are a consistent source of danger to both ecology and human beings. The conventional monitoring methods are usually supported by manual sample collection and laboratory tests, which take a long time to determine disease outbreaks and cannot afford quick monitoring that, could be implemented as a measure of timely action. This paper introduces the design of a high-grade early warning system, completely designed within MATLAB, which combines a physics-based dynamic representation of dissolved oxygen (DO) depletion through an improved Streeter-Phelps model with a statistically modeled data neural network (ANN) classifier taught to determine the presence of the pollution. Fence - to-fence data was used to calibrate and validate the model, as more than 10,000 multi-parameter records of chemical oxygen demand (COD), DO, pH, and heavy metal concentrations (mass per unit volume) of compounds such as Zn, Pb, and Cd are available. Conclusions show that ANN attained predictive accuracy surpassing 92% and strongly beat other similar models, such as support vector machines (SVM) and random forests (RF). Moreover, the framework equipped with MATLAB could provide an alert within two minutes or so after the data collection point, which was a massive increase over the conventional detection strategies. Such results support the opportunities of hybrid simulation-intelligence systems regarding proactive water quality control, providing regulatory organizations and industrialists with powerful instruments to reduce pollution outcomes.

KEYWORDS: Water pollution, Industrial discharges, Matlab, Intelligent model, Pollution detection

I.INTRODUCTION

Water plays the key role in life on Earth and is a core value of ecological, human consumption, and industrial processes. With the recent growth of industrial activities across the globe, there has been mounting pressure on freshwater systems due to untreated or under-treated wastewater [1]. The wastes produced by industries are usually a combination of various chemicals such as high levels of organic chemicals (measured by the chemical oxygen demand or COD), heavy metals such as lead (Pb), cadmium (Cd), and zinc (Zn), and chemicals which may drastically change the pH value of the water bodies [2][3]. These pollutants not only have direct impacts on aquatic life through food webs and hypoxia to dissolved oxygen (DO) contents, but also have an array of exposure in the sediments and biota that eventually find their way to the human food cycle and cause many health-related issues [4][5]. The World Health Organization (WHO) has estimated that the total global population dependent on drinking water sources may be infiltrated with unacceptable levels of chemical and biological contaminants, most of which originated as industrial effluents, exceeding a figure of two billion [6]. Chronic exposure to heavy metals causes a variety of health-related issues, including neurological damage, kidney dysfunction, and elevated risks of cancer [7] [8]. Meanwhile, the excess COD in rivers and lakes triggers over-respiration among the microbe water population that depletes oxygen levels and creates hypoxic or anoxic conditions that result in large-scale fish deaths and inevitable degradation of aquatic ecosystems [9]. Generally, conventional methods of monitoring water quality are based on regular manual sampling associated with laboratory tests of several indicators, including COD, DO, pH, and the presence of metals [10]. Although these methods provide analytical accuracy, the nature of the method is retrospective and the data generated may take hours or even days to derive actionable data [11]. This delayed response time gives the contamination incidents more than enough time to work their way through the environment, and this increases the environmental degradation and the expenses on remediating these incidents [12][13]. In addition, the labor-intensive and expensive characteristics of such traditional methods restrict the extent and coverage of monitoring activity and leave important swathes of water bodies de facto unmonitored [14]. Over the past few years, increasing attention has been paid to the use of computational technologies and artificial intelligence (AI) to overcome such problems. MATLAB has evolved as an effective platform in this sort of activity because of its large toolkits in modelling differential equations, data, and machine learning (ML) applications [15]. A century-old model, the Streeter Phelps model is still at the forefront of environmental engineering to approximate the oxygen sag curve, which appears downstream of a point of organic pollution [16]. The recent updates of this model, developed in MATLAB, enable scientists to investigate the effects of different loads of pollutants and properties of rivers on the depletion and recovery of DO with astounding potential, and can be used in current regulatory design and infrastructure planning [17] [18]. Similar developments in the field of ML displayed impressive abilities to study parameters in large multiparameter environmental data in terms of their complex and non-linear associations [19]. The capability of ANNs to accurately forecast primary water quality parameters, such as DO and COD, using sensor networks has been demonstrated in the literature, and this can be achieved with greater accuracy than conventional empirical and regression models [20][21]. Nonetheless, although all these are great achievements at the individual level, preceding research has primarily been pursued independently between mechanistic and ML, either through deterministic models of the pollutant process or through applications of black-box ML models, which are accurate but highly impractical in terms of interpretation and rationalization by well-established environmental processes [22][23]. This dichotomy highlights an important gap in related research: the importance of working towards hybridizing models, which applies the interpretability of process-oriented models such as Streeter Phelps without necessarily sacrificing the adaptive power of ML classifiers. These types of hybrid systems can help to raise prediction accuracy, but also, due to the contextualization of ML outputs on the kinds of environmental kinetics we know about, make stakeholders more confident in them [24]. With this setting, industrial operators and regulatory agencies are more likely to believe and embrace intelligent monitoring systems that offer transparent mechanistic explanations behind their forecasts, particularly when they are applied to support decisions that involve serious consequences to the health of the population and environmental safety [25][26]. In this light, the current research aim is to design and implement a hybrid framework using MATLAB that can incorporate a modified Streeter Phelps model along with an ANN that is trained on a large dataset comprising of COD, DO, pH, and heavy metal data. These goals are three serious: (i) to dynamically model the effects of the different scenarios of industrial discharges on the DO levels, (ii) train an ANN that would enable the system to classify the water quality status with rapid classification, and (ii) to compare the performance of the system against the typical ML models, such as SVM and RF in terms of accuracy. rapidity, and the stability in various contamination cases [27][28][29]. With these objectives, the framework aims to provide a more responsive, comprehensible, and plausible solution in terms of operations on industrial water pollution monitoring.

II. LITERATURE REVIEW

Mechanistic modeling frameworks have been closely ingrained with embodiments on of how pollutants act in aquatic systems. An early and prominent contribution towards this end was the derivation and development of the Streeter Phelps model in the 1920s, which mathematically expressed the effect of biochemical oxygen demand (BOD) of organic pollutants on the concentration of dissolved oxygen (DO) downstream of an outflow point [1]. This paper is a pioneer in giving the environmental engineering community a strong instrument for forecasting oxygen sag curves, and it forms the foundation of the regulatory gradient on the discharge allowances [2]. The original Streeter Phelps equations have been refined significantly over the decades to add additional variables such as variable flow rates, temperature dependencies, reaeration amplifications due to hydraulic structures, and interactions with other nutrients such as nitrogen and phosphorus [3][4]. Such models have been considerably more favorable on more modern computationally enabled platforms, such as MATLAB. The advantage of MATLAB in simulating systems of differential equations and the effective visualization tool thus provided researchers the opportunity to investigate complex situations of pollutant transport and transformation in site-specific conditions [5][6]. MATLAB has recently been used in studies to simulate a multi-point discharge system, solve the cumulative effect of many industrial sites on a stretch of river, and even simulate a transient event such as a spill, which is important to both policy makers and engineers [7][8]. Nevertheless, purely mechanistic models, although providing sufficient transparency and interpretability with solid process kinetics underpinning, tend to fail to match the complexities and non-linearity of real-life water quality information. The realities of industrial effluents rarely fit the idealized input hypothesis; due to operating schedules, cleaning routines and unexpected process upsets, they are ludicrously impractical in their composition and flow on short time scales [9]. Consequently, there has been an emerging interest regarding the augmentation or even the replacement of the traditional model with of a data-driven model, which can visualize its complex relationships out of observed data without referring to predefined functional connections [10]. Machine learning (ML), specifically artificial neural networks (ANN) has been showing significant promise in this regard. ANNs are computer systems modeled after biological neuron networks that can approximate complex non-linear relationships between features (like COD, DO, pH, and heavy metal levels) of the input and target (such as pollution index or exceeding a regulation limit) [11][12]. In addition to ANNs, support vector machines (SVMs) and random forests (RF) have gained a lot of attention as they have found extensive application in environmental monitoring tasks. SVMs can perform well in high-dimensional areas and they are less vulnerable to overfitting in limited data, whereas RFs have their importance scores of features and strong operations against noise [15] [16]. Despite their strengths, these models have a critical drawback: They usually work as black boxes, giving a negligible or no sense of how they made a given prediction. This obscurity presents a challenge to the regulatory acceptance, where policymakers demand clear, scientifically based explanations prior to rolling out expensive or socially significant efforts [17] [18]. In that regard, the scientific community has become more prone to promoting hybridization of models, which may consist of both the interpretability of physics-based models and the adaptability of ML models. By literally incorporating physical process constraints into ANN configurations, Luo et al. demonstrated more practical advantages of such an approach, which kept predictive accuracy high and with predicted outputs rationalized to agree with environmental behaviors [19]. On the same note, however, within the domain of water quality monitoring, explicit integrations of classical models, such as Streeter Phelps with ML classifiers aimed at rapid pollution detection, are still quite few. The majority of the current efforts concentrate on improving the mechanistic simulations to obtain a closer representation of site-specific parameters or train ML models to directly classify pollution events based on sensor measurements, without any mechanistic connections [21][22]. The implication of this disparity is especially serious in an industrial environment, where discharge patterns are highly dynamic and timely detection can be the fine line between slight changes in the process and massive ecological management crises. In this respect, the study at hand will be placed at the cross-section of these two paradigms and attempt to capitalize on the explanatory prowess of a modified Streeter-Phelps simulation that will be conducted using MATLAB and the excellent pattern recognition abilities of an ANN. By integrating the techniques, the framework aims not only to produce classification results with excellent accuracy over a wide range of pollution conditions but also to provide a prediction that is based on the kinetics of environmental processes. This two-pronged approach covers technical and stakeholder issues, so that the model’s output is scientifically defensible and capable of operationalization [23] [24] [25].

III. METHODOLOGY

This study has conducted a multi-phased design approach of research to come up with an intelligent early predictor of water pollution in industries. This system involved widespread data acquisition and prerequisite, intense mechanistic modeling with a multidimensional Streeter-Phelps model, and the generation of an ANN classifier in MATLAB. Combining these elements, it was aimed that a potentially superior system would be created to fulfill both technical requirements and those stakeholder demands in terms of transparency and reliability [1] [2]. Since it was important to ensure that the model would be able to be applied to a large variety of contamination situations, the dataset was constructed from two principal sources. The field observations available on the Internet with references to the governmental and industrial water quality monitoring networks including rivers and lakes proximate to large industries, were first retrieved. The following measurements were made as follows: chemical oxygen demand (COD), oxygen (DO), pH and cumulative heavy metal (i.e., Pb, Cd, and Zn) concentrations recording [3] [4]. Real-life datasets are not always unbiasedly covered in terms of extreme or rare contamination events; the second part of the dataset was composed of the synthetic-generated data. This has been done through the simulation of various industrial discharge cases with a specially customized Streeter Phelps model that was run in MATLAB to guarantee extensive coverage of both the normal and worst pollution profiles [5]. The preparation of the joint dataset involved intensive preprocessing of the data to be superior in quality and fair learning among the features before designing the machine learning components. The standard deviation method was also used to detect outliers that can negatively affect the model parameters negatively so that the outliers can be extracted effectively using interquartile range (IQR) [6]. Following the elusion of outliers, each of the features was standardized to a zero-mean and unit-variance distribution, which was also essential because COD, DO, pH and heavy metals measured quite differently (mg/L, mg/L, dimensionless, and 1Mg/L, respectively) [7]. The dataset was further randomly split into training (70%), validation (15%), and testing (15%) using the strategy that allowed the effective evaluation of the generalization ability effectively. The variable time response of dissolved oxygen (DO) following a shift in the load of organic and chemical pollution was simulated using a modified Streeter-Phelps equation, which is the centerpiece in the mechanistic model in the project. The given model can be characterized by the following differential equation system:

$$K_d\, L = \frac{dL}{dt} \qquad (1)$$

$$K_d\, L - (DO - DO_s).\, K_r = \frac{dDO}{dt} \qquad (2)$$

In this formulation, L is the remaining biochemical oxygen demand (BOD), DO is the current concentration of dissolved oxygen, and DO_s is the saturation concentration of dissolved oxygen in the water body. The parameter K_d is the deoxygenation rate coefficient, K_r is the reaeration rate coefficient, and t denotes time. These equations collectively describe the dynamic balance between oxygen consumption from biochemical degradation and oxygen replenishment via atmospheric reaeration, providing a mathematical foundation for the simulation framework developed in MATLAB. solved in MATLAB using the ode45 solver to generate high-resolution time series under different discharge scenarios. The classic Streeter-Phelps equations were run with the ode45 solver of MATLAB, which produced high-density time series of DO depletion with different discharge regimes [8] [9]. The L in these equations is the biochemical oxygen demand or the BOD, the DO is the concentration of dissolved oxygen, K_r is the de-oxygenation rate coefficient, K_r is the re-aeration rate coefficient and the DOs is the saturation level of the receiving water body of the DO. This deliberate experimentation was on initial pollutant loads and kinetic parameters, which also resulted in synthetic datasets spanning a wide gamut of conceivable field conditions, ranging between slight fluctuations in the course of a process to disastrous release incidents [10][11]. The structure of the architecture consisted of four input units (normalized COD, DO, pH, heavy metal features), a nonlinear hidden layer of 20 units, which was optimized by Bayesian search, to allow adjusting the complexity/generalization tradeoff [12] [13]. To make binary output predictions as to whether a water sample is polluted or safe, the output layer was based on sigmoid activation function. Scaled conjugate gradient with back propagation was used to train the ANN with early stopping on the validation performance to prevent over-fitting [14]. To do the benchmarking, more SVM and RF classifiers were trained with MATLAB Classification Learner App, where hyper parameters to be tuned were found by grid search and evaluated by 10-fold cross-validation [15][16].The most important innovation in this approach was the direct coupling of the deterministic Streeter Phelps simulation with the ANN. Mechanistic model was used to consider anticipated DO kinetics on simulated or real-time sensor inputs, which basically functions like injecting the domain knowledge in terms of pollutant transport and transformation directly into the machine learning pipeline. The design avoided some of the opacity issues previous to it (so that knowledge of prediction related to known aquatic system behavior) also helped to make the system more resilient to a wide range of conditions of industrial water contamination [17][18]. As depicted in Figure 1, the integrated platform clearly demonstrates the chain of transactions relating to data gathering the multi-parameter data gathering, into mechanistic modeling, into even intelligent classification and eventual ability to warn and alert against industrial water contamination in near real-time [17][18].

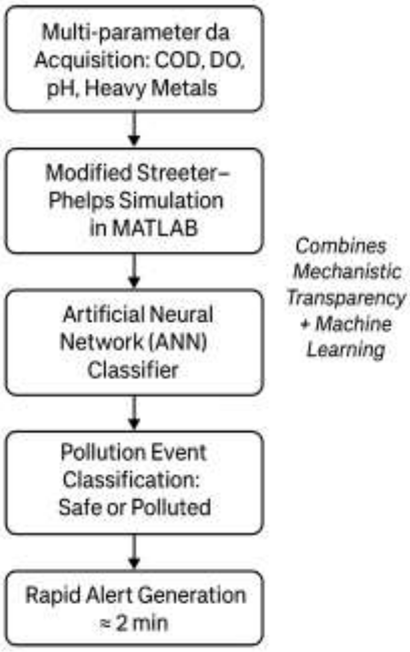

Figure 1. Block diagram of the schematic implementation of the proposed hybrid system used to detect water pollution at an early stage in industry. This is a schematic of connecting environmental sensors (DO, pH, HM) to an ESP32 microcontroller to measure the data to detect and identify the water quality in real-time with a trained neural network.

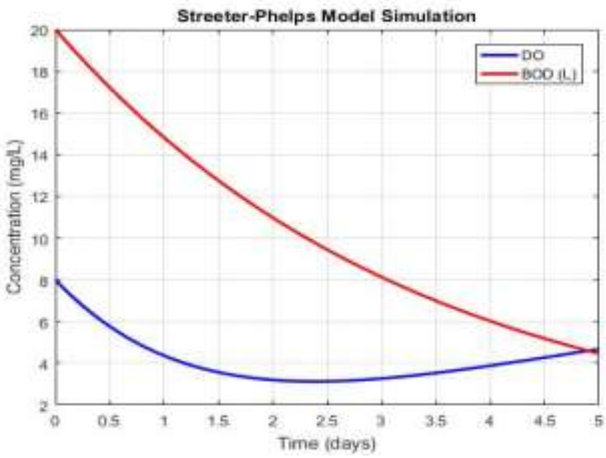

Figure 2. The outcome of the simulation of DO and BOD with time through the Streeter Phelps model. This diagram is a visual representation of the combined workflow that can be applied to data that, after being collected, is subjected to mechanistic modeling envisaged to be based on Streeter-Phelps, followed by intelligent classification referred to as ANN which will provide fast alerts about water pollution. This plot shows the decline in the concentration of dissolved oxygen and biochemical oxygen demand over time that was computed by simulating various means of discharge conditions in MATLAB.

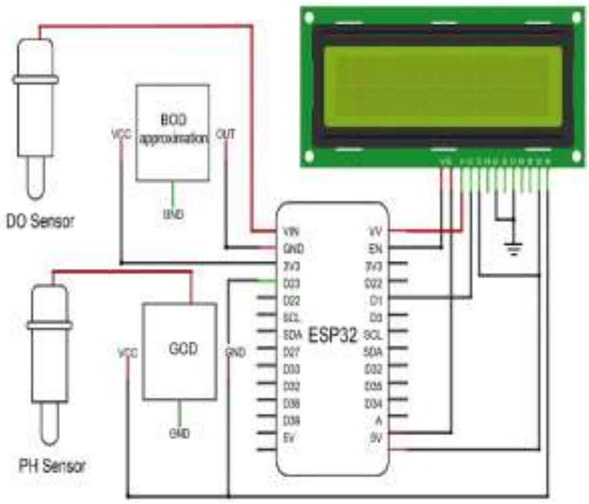

Figure 3. Interconnection diagram of the sensor with ESP32 to conduct classification of ANN-based water quality. It integrates all parameters (COD, DO, pH, heavy metals), a numerical simulation of the dissolved oxygen exhaustion developed according to adapted Streeter Phelps modeling, and an artificial neural network (ANN) classifier to describe pollution incidents that lead to establishment of quick alerts. The design realizes the combination of mechanistic transparency and primer pattern recognition, in order to make some decision that can be acted upon [19].

V. RESULTS AND DISCUSSION

The proposed MATLAB-based hybrid system showed very convincing results that point towards the feasibility of the system in the actual monitoring of the water quality in the industries. The artificial neural network (ANN) exhibited a strong classification strength when tested using a detailed dataset combining field data and synthetically created conditions using the modified Streeter omen help simulations, to have a holistic data combination, with an overall testing accuracy of around 92.3%; this was far much better, as compared to the conventional machine learning models like SVM and RF that were also trained and tested under the same settings. It is important to mention that the ANN demonstrated a strong value of recall of nearly 93.5%, thus demonstrating its high level of correctly spaced-out contamination occurrences. This feature is of paramount significance in monitoring environment related issues, as undetected cases of pollution may quickly and unexpectedly turn into either a massive ecological or a mass health disaster. In addition, the system has shown an accuracy of approximately 91.8%. The majority of the samples that were marked as polluted by the system could indeed be defined as actual cases of contamination. This reduces cases of false alarms, which could result in routine and unnecessarily expensive mitigation actions. These results were then supported by the Receiver Operating Characteristic (ROC) analysis, where the system proved to have superb discrimination abilities in various cut-off values with a high level of Area under the Curve (AUC). The incorporation of deterministic Streeter Phelps simulation with an ANN classifier can be given credit as one of the best features of this framework. This allowed the system to in effect both embrace classical environmental model interpretability and also the modern AI method of adaptive learning by feeding the input features into the mechanistic model, which captured the anticipated kinetics of dissolved oxygen depletion. This eliminated directly the usual criticism put forth that machine learning uses in the environmental field as a black box. On an operational aspect, the system also brought a significant benefit of speed in detection. As opposed to conventional laboratory tests whose results may take up to several hours to days to be available, the MATLAB-based framework was capable of being used in welcoming trustworthy pollution warning messages that took approximately two minutes to be displayed after new data had been acquired. This prompt response gives a vital interval to stakeholders to implement protective responses or modify the process so that contaminants do not disperse further. Further details were provided through sensitivity analysis and results include that, of all the features used, only the value of dissolved oxygen (DO) played a central role in influencing ANN decisions on classification. This concurs quite well with accepted principles of aquatic chemistry under which DO levels tend to be the first and the most sensitive indicators of organic overloading and microbial requirements stress. The other significant influence was identified to be related to COD and pH, corresponding to their importance in determining the overall organic loading and acid-base balance, with the heavy metal concentration not being as influential in short-term predictive value, but remaining essential because of their chronic toxicity, and a general risk of bioaccumulation. The robustness of the system was also proved through stress tests using a very broad set of scenarios. And carrying out experiments in simulated worst-case conditions involving sudden concentrations in COD and heavy metal concentration as well as sudden pH reductions, the ANN exhibited classification accuracies in excess of 90 percent. This resilience is critical to practical application in industrial settings where the composition of effluents may vary irregularly as a result of shifts of the process, maintenance procedures, or during uncontrolled releases. What was also advantageous about this hybrid architecture is that, it produced interpretative traces at the same time as binary classification results. Since ANN predictions were used to predict the results of the Streeter--Phelps simulation, stakeholders could investigate more than just whether a given sample had been identified as polluted, but they could look at the simulated DO depletion curve which that resulted in the prediction. Such a visual and numerical context increases the credibility of the system warnings, increasing its acceptability to regulating authorities and industrial compliance officers who frequently insist on scientifically-informed explanations of imitative courses of action. Comprehensively, the results aforementioned confirm the overall hypothesis of this research project: a hybrid mechanistically based and advanced machine learning-based classification system performed in a MATLAB environment results in a highly accurate, operationally high-speed, yet soundly founded in a well-known environmental process dynamics system. The system can by far be utilized in real-life industrial monitoring scenarios when both types of errors are capable of dramatic ecological and economic consequences by striking the right balance between sensitivity and precision.

IV. CONCLUSION

Through this study, the integration of classical environmental models with modern AI methods has proven highly effective for developing an early warning system for industrial water pollution. The system combines a modified Streeter-Phelps oxygen depletion model implemented in MATLAB with an artificial neural network trained on datasets containing COD, DO, pH, and heavy metals. This hybrid approach overcomes limitations of both traditional lab testing and standalone data-driven methods. The ANN consistently achieved high classification accuracy across various contamination scenarios, and outperformed conventional ML models in both speed and accuracy. One of the standout features of this system is its response time—issuing contamination alerts within two minutes of receiving sensor data, compared to hours or days in conventional lab methods. This allows industries and regulators to act quickly, preventing environmental damage. Additionally, by grounding ANN predictions in mechanistic models, the system enhances transparency and interpretability, addressing the "black box" criticism often aimed at AI in sensitive environmental applications. Stress testing confirmed the system's reliability even under extreme pollution conditions, a crucial factor in real-world deployments. The framework offers strong potential for future enhancements, such as integration with Internet of Things (IoT) -based sensor networks for real-time, spatially distributed monitoring. Incorporating advanced neural networks like Long Short-Term Memory (LSTM) could enable forecasting of pollution trends, shifting from reactive detection to proactive management. Furthermore, this system can integrated into larger compliance platforms to reduce manual labor, improve accuracy, and automate interventions. In conclusion, the study demonstrates that a synergy between deterministic models and AI leads to smarter, faster, and more trustworthy environmental monitoring systems. This hybrid method is a promising direction for sustainable water quality management amid increasing industrial pressures.

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