An Effective Industrial Waste Water Management System by Machine Learning and IIOT

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ABSTRACT- Industrial waste water treatment is one of the challenging issues that Industry faces nowadays. The treated water is either recycled for Industrial use or discharged into water-bodies. If not properly treated, it may lead to severe environmental issues. Industries adopt different types of water treatment mechanisms for reducing the pollutants. Though modern day industries use PLC (Programmable Logic Controller) or SCADA (Supervisory Control And Data Acquisition) based Systems for waste water monitoring, many industries still need human intervention in the last stages of waste water treatment. In the proposed IIoT based system we introduce a new approach for the effective monitoring of Industrial waste water with the help of machine learning.

Index Terms—Industrial waste water, Internet of Things (IoT), Machine learning.

I. INTRODUCTION

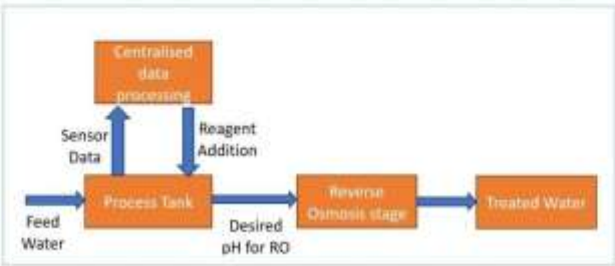
The goal of treating industrial waste water is to remove pollutants so that it can be recycled or fed back into water sources. This water may cause water sources to lose quality if it is not adequately treated. If industrial waste water is reused, improper waste water treatment will corrode the related machinery. Adding chemicals to waste water to neutralize its pH is one way to treat it.

In some water treatment facilities, the addition of reagents is not restricted to a pH of neutrality, but rather to a predetermined level, Which facilitates the effective removal of pollutants from industrial waste water by later stages such as reverse osmosis. IIoT is starting to be widely accepted in the industrial waste water management stages. Machine learning is a subfield of artificial intelligence that leverages data and algorithms to teach robots to think like people and then anticipate things based on incoming data. When machine learning is applied to industrial waste water treatment, human intervention will be reduced in the final stages of the procedure.

II. THE INDUSTRIAL INTERNET OF THINGS (IIOT) AND ITS USE IN THE MANAGEMENT OF INDUSTRIAL WASTE WATER

The Industrial Internet of Things (IIoT) emerged as a result of the extensive deployment and use of IoT-based devices in the industrial sector. Research in academia is now focused on improving the security aspects of important and sensitive data in industry over IoT. One of the main forces behind the fourth industrial revolution is IIoT. The International Data Corporation (IDC) has estimated that there would be over 41.6 billion IoT devices in use by 2025. IoT adoption in business is widespread because it lowers quality control costs and boosts operator efficiency. IoT has enhanced the industry's goals of decentralization, general connectivity, and interoperability. When comparing IIoT to IoT, the data volume is substantially larger and more real-time.

The process of treating waste water is intricate and involves several steps. Gathering sensor data at the treatment plant and sending it in real time are key components of integrating IIoT features into waste water treatment. The fundamental concept is illustrated in fig. 1.



A centrally located but remote facility processes this data. In this field, sensors are used to measure TDS, pH, temperature, pressure, and other variables. A computerized centralized system can be used to analyses this data. Actions at the treatment plant can be monitored and controlled based on the interpretation from this central station. We can raise the caliber of the treated water by adding more sensors to the facility.

III. THE USE OF MACHINE LEARNING IN THE INDUSTRY

These days, machine learning is becoming a crucial component of industry business. Machine learning is used to make predictions about plant maintenance, process optimization, quality control, supply chain optimization, and safety, in addition to financial and retail elements.

A. Predictive upkeep

Early plant maintenance can be carried out thanks to machine learning, which uses sensor and historical data.

B. Streamlining procedures

Machine learning can be used to optimize the production schedule by preventing bottlenecks in the production process. Additionally, it aids in waste reduction, which lowers expenses and boosts productivity.

C. Inspection of quality

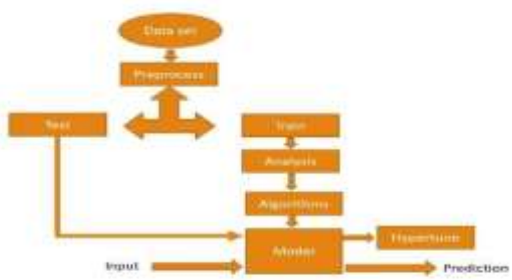
Real-time fault identification and root cause analysis are made possible by Machine learning through the analysis of sensor and historical data. As a result, the product's overall quality might be raised.

D. Optimization of the supply chain

Machine learning facilitates better delivery times, customer satisfaction, demand forecasting, inventory level optimization, and delivery time optimization.

E. Security

Workers' actions can be analyzed using machine learning to determine who is more likely to have accidents. It can therefore lower industry accidents. Figure 2 illustrates the general flow of events in a machine learning process.



IV. EXISTING WASTE WATER TREATMENT SYSTEM BASED ON IOT

The IoT-based real-time waste water monitoring and control system described in [1] is shown in Fig. 3. The waste water in the treatment plant provides the pH and temperature sensor data to the Internet of Things-based system. The gathered information is posted to a web server. The server-based system analyzes the data that is received and generates the necessary monitoring and controlling information Valves.

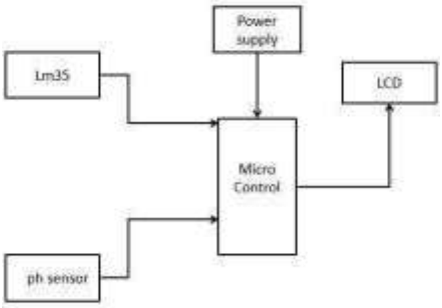


Fig 3 Existing System

The operator will be able to take corrective action thanks to the software installed in the monitoring equipment.

The following are some ways that the current system can be improved:

• More water parameters can be included for more thorough analysis.

• Strengthen wireless data security.

• The system's performance can be enhanced by integrating machine learning.

V. THE SUGGESTIVE SYSTEM

The system may incorporate machine learning characteristics to improve overall performance, as was covered in the preceding section. The demand from the industry to avoid human intervention in certain stages has grown recently. The suggested system incorporates machine learning capabilities to forecast the amount of reagent.

A. Overview of the System

A summary of the suggested structure for tracking industrial wastewater is shown in Figure 4. Temperature and pH readings are taken from the treatment facility. The gathered information is posted to the web server and is accessible from any distant location. There are four components to the suggested system:

1. PIC 16f887 and its corresponding sensors
2. A Google app script to move the gathered data to an online database.
3. Using Google Sheets to keep data
4. The section on machine learning

3) The temperature sensor, DS18B20, is a one-wire digital sensor with up to 9–12 bits of precision that

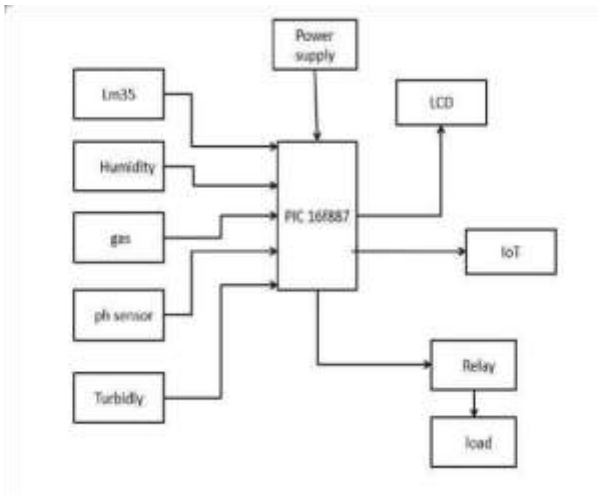


Fig 4 Proposed System

B. Architecture of the System

The waste water plant intake has temperature and pH sensors installed. The IoT module sends real-time temperature and pH measurements to the cloud server. The machine learning algorithm is implemented through the interpretation of the data. The next step is to anticipate the regent quantity when the algorithm has been precisely calibrated. The control signal for the control valve is derived from the anticipated quantity of reagent. It is necessary to allow enough time for the reagent to dissolve completely. The conclusion of a batch processing should be followed by the subsequent sample and reagent addition. In addition, a lookup database for the amount of additional reagent and the amount of time needed for complete reagent dissolution is kept on the cloud server. Thus, as indicated in fig. 6, the data from this look up table will serve as the basis for the batch processing.

C. The component hardware

1) PIC 16f887: The PIC16F887 is a popular 8-bit microcontroller from Microchip Technology, widely used in embedded systems and various electronic projects.

2) Analog pH Sensor Kit: The pH electrode and sensor interface are included in the pH sensor kit seen in Figure 8 It is an easy-to-use kit that works with any Arduino controller. This instrument measures the waste water's pH between 0 and 14 with an accuracy of about 0.01 pH.

is depicted in Figure 9. It can be used between -55 and 125 degrees Celsius. It gauges the waste water's temperature.

	Temperature	pH	Reagent_quantity	str_time
0	25.36	7.02	12	100
1	25.18	7.04	13	120
2	25.36	7.06	14	140
3	25.45	7.08	15	160
4	25.18	7.10	16	180
5	25.36	7.12	17	200
6	25.36	7.14	18	220
7	25.36	7.16	19	240
8	25.18	7.18	20	260
9	25.36	7.20	21	280
10	25.36	7.22	22	300

Fig 5 Look Up Table

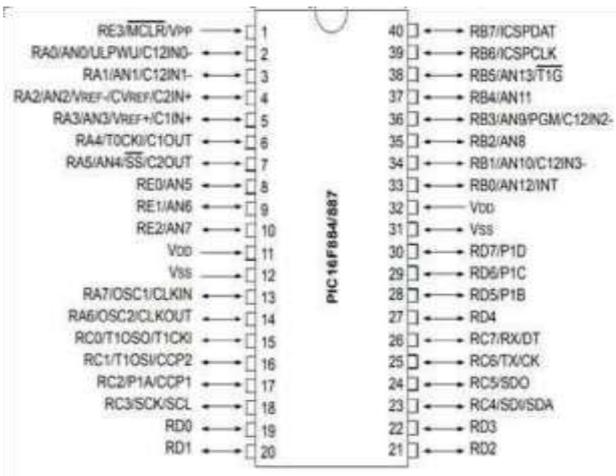


Fig 6 Pin Diagram of PIC16f887

Fig 7 pH Sensor

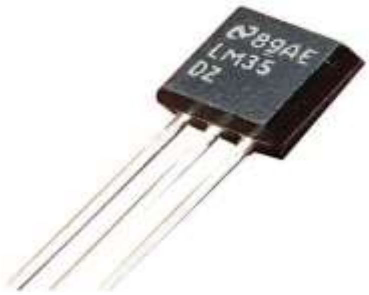


Fig 8 Temperature Sensor

D. The components of the software

The PIC 16F887 microcontroller, a popular choice for embedded systems and microcontroller projects, requires various software components for programming and development. Here are the essential software components typically used:

1) Integrated Development Environment (IDE):

IDEs like MPLAB X IDE or MikroC Pro for PIC provide a comprehensive platform for writing, compiling, and debugging PIC 16F887 firmware.

Compiler:

2) A C compiler (e.g., XC8) or assembly language tools are used to convert human-readable code into machine-readable code that the PIC 16F887 can execute.

3) C Language: The PIC 16F887 can also be programmed using the C language, which is a high-level programming language. Using C simplifies the development process compared to assembly language and makes the code more readable and maintainable. C abstracts away many hardware details, providing a more portable and easier-to-understand code structure. To program in C for PIC microcontrollers like the PIC 16F887, you typically use a compiler like XC8, which translates C code into machine-readable instructions compatible with the Microcontroller.

E. Results and Discussions of the Experiments

The experimental setup is shown in Fig. 10. Utilizing sensors

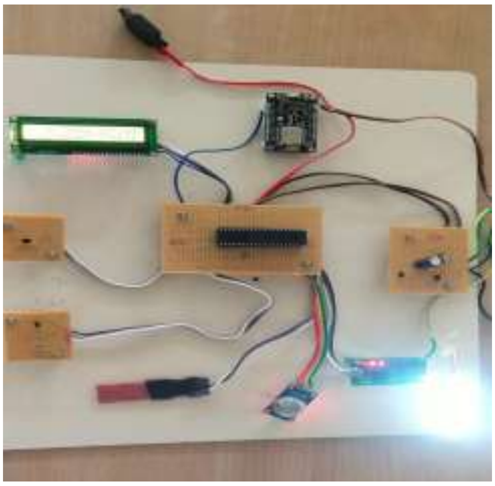


Fig 9 Hardware implementation of the proposed system.

Gather temperature and pH data. It is the PIC 16F887 IoT module that is gathering this data. Using Google App Script, the data is uploaded to a cloud-based Google sheet. The machine learning component uses the temperature, pH, and amount of reagent that were submitted. The data is divided 70:30 into training and test sets. After training is finished, the model can be applied to additional predictions. The controller sends the solenoid valve a control signal based on the anticipated value. Comparatively, three popular regression techniques are employed for forecasting. The models selected were Support Vector Regression, Random Forest, and Linear Prediction. The score () function from the sklearn library is used to assess the performance of three methods.

The optimal algorithm for our case study was determined to be linear regression, based on the accuracy findings shown below.

The sklearn library's linear regression function was employed. With the intention of incorporating several input factors and for improved

TABLE I COMPARATIVE DETAILS OF DIFFERENT ALGORITHMS

No	Algorithm	Accuracy score
1	Linear Regression	99.99
2	Random Forest	99.97
3	Support vector Regression	21.21

Precision, a different strategy was used. The cost function approach was used to approximate linear regression.

The total actions taken can be summed up as follows:

1. Normalization and scaling of features.
2. Doing the Cost Function Calculation.
3. Using gradient descent to find the cost function's minimum.
4. Forecasts

The superfluous data is eliminated through the use of feature scaling and normalization. It is necessary to identify the regression's best fit line. The vector form equation for the line with θ can be found by using the following formula:

$$h\theta(X) = [\theta X] \quad (1)$$

Where $h\theta(X)$ is the expected value and $[\theta X]$ term is the weighted sum of the input features X plus a constant known as the "intercept term" or "bias term." The regression line with the best fit will be found with the aid of the Cost function, J. The Cost function can be found by:

$$J = 1/2m\ Xm\ i+1\ [(h\theta(X) - y)\ 2\ ] \quad (2)$$

Where 'y' is the actual value, $h(X)$ is the predicted value, and 'm' is the length of the X vector. For more accuracy, the Cost function should be as small as possible. Thus, the Gradient Descent Method can be used to determine the least cost function. The derivative of the cost function is computed using the gradient descent method.

Next, it uses learning rate α to update the vectored form of the slope and bias terms. In fig.10, the Cost function as J versus iterations is clearly displayed.

Fig 10 Temperature Level Changed In Thing Speak

Fig 11 Ph Level Changed In Thing Speak

VI. CONCLUSION AND FUTURE WORK

The primary goal of the project is to use machine learning to remove human intervention from the last phases of industrial waste water treatment. In our case study, the linear regression technique proves to be the most effective approach. The amount of pollutants released into the treated water will be significantly decreased with the aid of a machine learning-enabled waste water treatment facility. The scale of the plant, the chemical makeup of the pollutants, and the type of water treatment process employed, and other factors all influence how well waste water treatment performs. More parameters added to the treatment plant's input side can lead to more accurate predictions. It matters how long it takes for the reagent to completely dissolve and achieve the appropriate pH. The creation of a neural network with these parameters is part of the project's future scope, which will enable the system to function like an expert technician in the field.

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