FORMULATION OF FITNESS FUNCTION TO PREDICT PH VALUE OF ADJACENT BLOCK VIA PH VALUE, WATER FLOW SPEED AND DIRECTION

NURUL NAJIHAH BINTI MOHD RADZI

B.ENG (HONS.) ELECTRICAL ENGINEERING (ELECTRONICS)

UNIVERSITI MALAYSIA PAHANG

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NURUL NAJIHAH BINTI MOHD RADZI

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Thank you.

ABSTRAK

Projek ini adalah berdasarkan penentuan kualiti air kerana kualiti air yang buruk juga boleh menimbulkan risiko kesihatan kepada ekosistem. Kualiti air diukur oleh beberapa faktor, seperti potensi hidrogen (pH), kepekatan oksigen terlarut (DO), tahap bakteria, jumlah garam (atau kemasinan), atau jumlah bahan terampai di dalam air (kekeruhan). Dalam projek ini, kami lebih menumpukan kepada pH air kerana ia memberi lebih impak dalam menentukan kualiti air. Dalam penyelidikan ini, kami memberi tumpuan kepada mengukur parameter kualiti air tasik utama Universiti Malaysia Pahang (3.5431680, 103.4355621). Kriteria kualiti air sedang diukur dan dianalisis untuk menentukan keadaan tasik. Semasa kami memantau pengukuran kualiti air terutamanya nilai pH, kami mendapati bahawa kelajuan aliran air juga memanipulasi nilai pH air. Untuk menyelesaikan masalah, kami mengumpulkan set data yang besar untuk diproses dan dianalisis. Untuk meramalkan kualiti air tasik, kami menggunakan fungsi kecergasan yang telah dirumus menggunakan Multi-Layer Neural Network (MLNN) dan membandingkan hasilnya. Terdapat dua proses yang perlu dilakukan dalam menganalisis data iaitu data latihan dan pengujian. Dalam proses latihan, data akan terus dimasukkan sehingga wajaran terbaik untuk setiap data diperolehi. Wajaran terbaik akan digunakan untuk menguji data dan mendapatkan nilai ramalan. Keputusan ramalan akan dibandingkan dengan nilai pH sebenar. Keputusan ramalan yang diperolehi oleh data ramalan pH dengan kelajuan 94.27% berbanding tanpa kelajuan iaitu 93.83%. Ini menunjukkan bahawa kelajuan merupakan salah satu faktor yang penting untuk menganggarkan pH.

ABSTRACT

This project is based on determining the water quality as poor water quality can also pose a health risk for ecosystems. Water quality is measured by several factors, such as potential of hydrogen (pH), the concentration of dissolved oxygen (DO), bacteria levels, the amount of salt (or salinity), or the amount of material suspended in the water (turbidity). In this project, we more focus on the pH of water as it given more impact on determine the quality of water. In this research, we focus on measuring water quality parameters of University Malaysia of Pahang main lake (3.5431680, 103.4355621). Water quality criteria are being measured and analyses to determine the state of the lake. As we monitor the water quality measurement especially the pH value, we notice that the speed of water flow also manipulates the value of pH water. Collect large set of data which comprises of five location, four of the locations pH are used to determine the fifth location pH. To predict the lake water quality, we are using fitness function that has been formulate using Multi-Layer Neural Network by Genetic Algorithm (MLNN-GA) and compare the results in terms of accuracy of prediction. The collected data is split into two which are training and testing data. The training data will keep being inserted until the best weightage for each data is obtained. The best weightage will be used to test the testing data and acquired the prediction value. The results of prediction will be compared with the actual pH value. The results of prediction obtained by predicted data pH with speed with 94.27% compared with predicted data without speed with only 93.83%. The result shown that speed is one of the factor that contribute to pH prediction.

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CHAPTER 1

INTRODUCTION

1.1 Overview

The potential of hydrogen (pH), the concentration of dissolved oxygen (DO), bacteria levels, the quantity of salt (or salinity), or the amount of material suspended in the water are all parameters that are used to determine the quality of water (turbidity). Water quality may also be determined by measuring the quantity of microscopic algae as well as the levels of pesticides, herbicides, heavy metals, and other toxins in specific bodies of water. Ecosystems may be endangered by poor water quality. [1]

We put a lot of emphasis on the pH of water in this project since it has a big influence on water quality. pH is a measured value that is based on a scale, like temperature. This implies that the pH of water cannot be measured as a concentration or a quantity. Instead, it's a number between 0 and 14 on a logarithmic scale that indicates how acidic or basic a body of water is. The lower the number, the lower the acidity of the water. The greater the number, the more fundamental the information is. A pH of 7 is considered neutral.

The aquatic species living in it will perish if the pH of the water is too high or too low. Chemicals and heavy metals in water can have their solubility and toxicity affected by pH. Although most aquatic species require a pH range of 6.5-9.0, some may survive in water with a pH outside of this range. [2]

Also, we take speed of flow water into account to determine the water quality as there are not many researches on this matter. There are many researches by using other factors, but speed of flow water is not considered. As water is flowing and not static, the speed might affect the pH and the water quality. In this research, we are more focus on the main lake of UMP only (3.5431680, 103.4355621). About 90 set of data had be collected and processed. The data will be used to formulate fitness function by using Genetic Algorithm (GA) as the learning algorithm for based neural network. Then, the data will be compared to the data taken without the speed of water factor.

1.2 Problem Statement

The common logarithm of the reciprocal of the concentration of hydrogen ions in moles per cubic decimetre of solution is the potential of hydrogen (pH), which is a measure of a solution's acidity or alkalinity. A pH of 7 indicates pure water, a pH of less than 7 indicates acid solutions, and a pH greater than 7 indicates alkaline solutions. The pH value will affect the chemical state of the water, as well as the availability of nutrients, biological functions, microbial activity, and overall water quality. So far, many studies have been conducted to determine the quality of water using the pH value; however, these studies do not limit themselves to this value.

In this research, we focus on measuring water quality parameters of University Malaysia of Pahang main lake. Water quality criteria are being measured and analyse to determine the state of the lake. As we monitor the water quality measurement especially the pH value, we notice that the speed of water flow also manipulates the value of pH water. Based on literature review that has been done shown that speed of water flow has not yet been used in any research to determine water quality by using pH water. Thus, in this research we will investigate whether the speed of flow water is manipulating the pH water.

1.3 Objective

The objectives of this project are:

i. To collect large set of data.
ii. To formulate fitness function to predict the lake water quality using speed of flow water and pH water using Multi-Layer Neural Network optimised Genetic Algorithm (MLNN-GA).
iii. Compare and analyse the result for pH water with and without speed of flow water.

1.4 Scope of Project

The scopes of this project are:

i. This project will be conducted at the main lake of University Malaysia of Pahang.
ii. Using GPS coordinate to change into the speed of flow water.
iii. Data will be taken using Wireless Passive Water Quality Catchment Monitoring System (WWM) and analyse using based propagation neural network.
iv. The project is conducted in sunny and cloudy condition only.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The main part of the topic itself can be separated into two part which is the hardware and software used to determine the quality of water. The literature review is going through the project process that already being conducted by other resources which can be adapted into this project.

2.2 Literature Overview

The usage of K-Chart below is to show overall studies on the regarding project. From the literature that has been made, it shown that there are two ways of predicting water quality which are by using hardware and software. There are different types of sensors used such as conductivity sensors, pH sensors, temperature sensors etc. All the data collected will be analysed by instrumentation equation as RMSE, MSE, MAPE.

Water quality also can be predict using software. There are difference of prediction, network, algorithms and data used in this way. The most common prediction used in overall studies are using Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Multi-Layer Neural Network (MLNN). In this project, we used MLNN-GA as there are same studies using the same prediction but using different data and get a better result of prediction.

There are used of difference network in water quality prediction such as Wireless Sensor Network (WSNs) using sensor nodes, unmanned ships and micro stations. There are also used of cloud server , GSM module, WIFI module to collect and saved the pH data. Using algorithm such as Levenberg-Marquardt, Random Forest Algorithm are the least used to find the water quality prediction. To find the water quality prediction, there are many factors that has been taken into accounts such as pH water, total dissolve solids, current temperature, and dissolve oxygen. In this study, we add two more factors that might affect the water quality which are speed and direction of flow water. All the details will be explained in the next subchapter. Figure 2.1 shown the K-Chart for Literature Review that has been done.

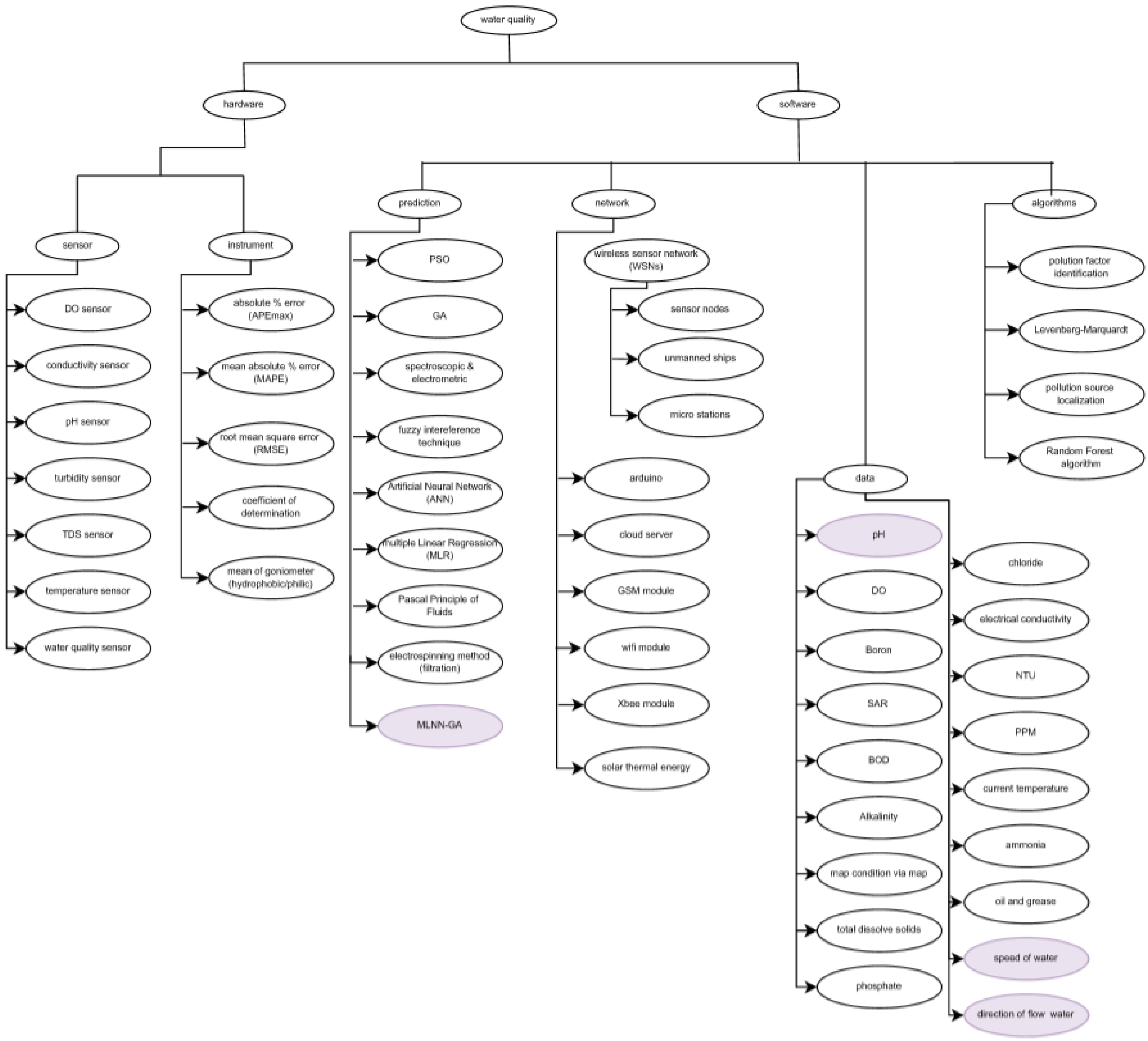

Figure 2.1 K-Chart

2.3 Hardware Usage

2.3.1 Water quality monitoring system in real time

A robotic fish with an onboard power system, sensing module, navigation, control, and wireless connection has been created thanks to developments in computer, communication, actuation technologies, and sensing. To measure the various properties of wastewater, a significant number of measuring instruments were employed. The pH was determined using the Hachr sension 3 (Cole-Parmer Instrument Company, USA). [14] The planned real-time water quality monitoring system keeps track of the water's quality.

The transmitter unit, shown in Figure 2.2, the reception unit, shown in Figure 2.3, and the motion controller make up the electrical component of the system. The power supply, sensors, and transmitter are all linked to the Arduino Nano in the Transmitter System. The Receiver System and Circuit consists of a power supply and a receiver coupled to a Node MCU, from which data may be transferred to the AWS Cloud for remote monitoring and quality analysis.

For continuous monitoring of the water body, the received data is shown in its current condition on the serial monitor. For underwater movement, the robotic unit's Motion Controller is made up of a battery, an RF controller, a buoyancy controller unit, a linear thrust motor, and a rotating thrust motor. [13]

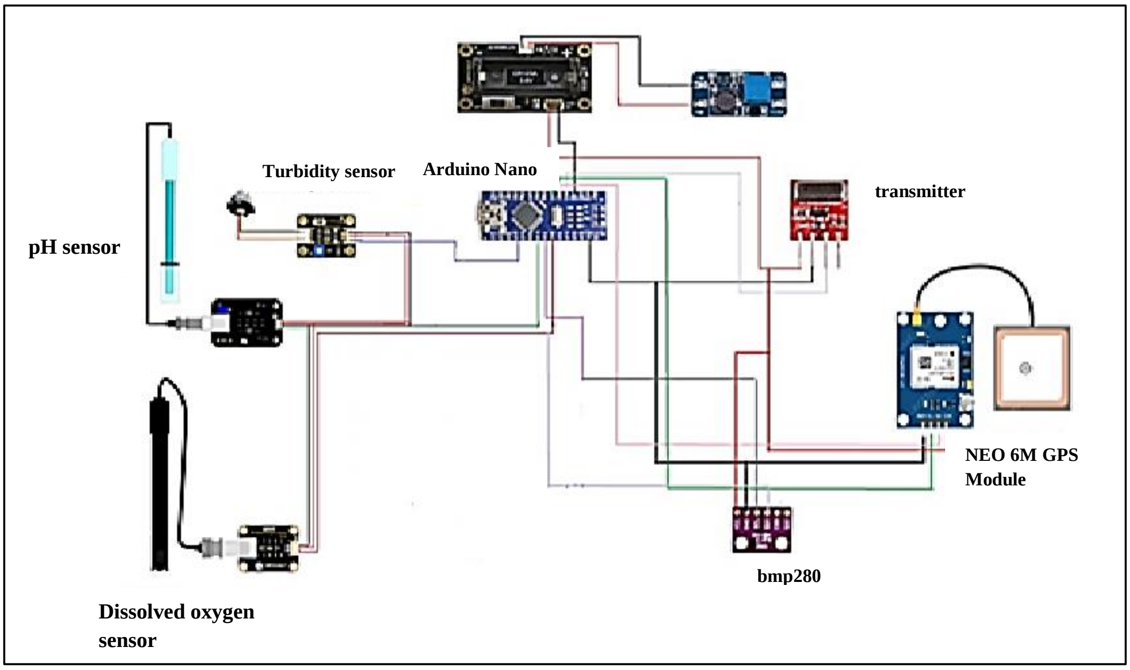

Figure 2.2 Transmitter Unit [13]

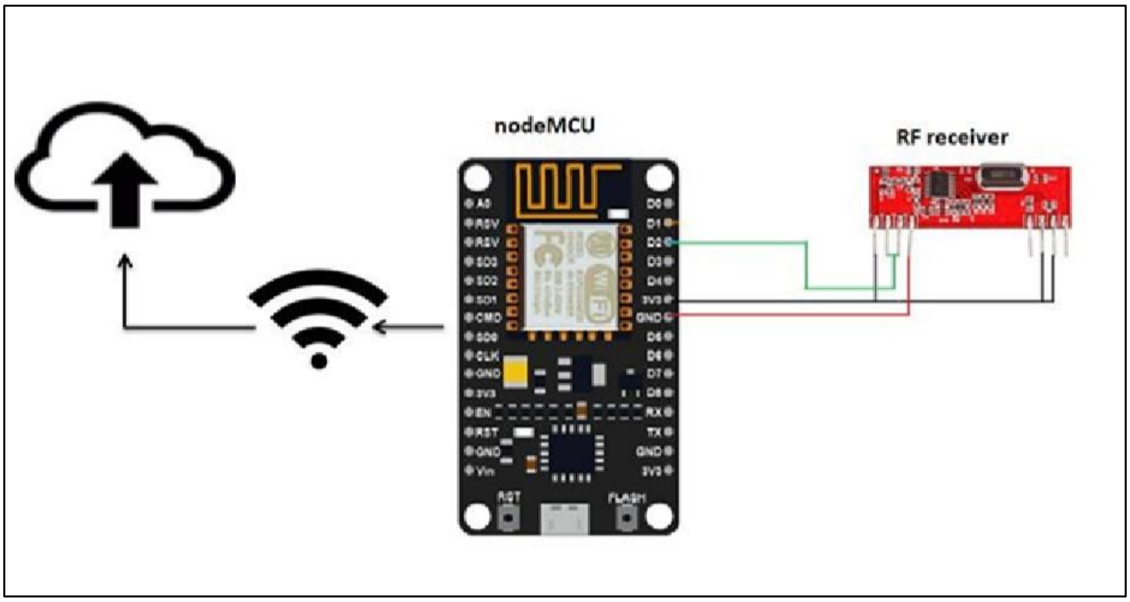

Figure 2.3 Receiver Unit [13]

2.3.2 Robot for monitoring quality of water based on IoT

Some research, such as the use of IoT (Internet of Things) technology, is carried out. The internet of things (IoT) is a technology that allows one item to interact with another over the internet. The implementation takes the form of a monitoring system that displays the value of sensors in ponds or aquaculture ponds via a mobile application to check water quality. [9] According to the Coordinator and Support Action for Global

RFID-related Activities and Standardization, IoT is described as a global network connection architecture that links real and virtual products through data collection, exploitation, and communication technologies.

As a result, a Remotely Operated Vehicle (ROV) has been used as a tool bearer to collect water quality data that can be monitored immediately through the Internet. The monitoring system programme flowchart is given in Figure 2.4.

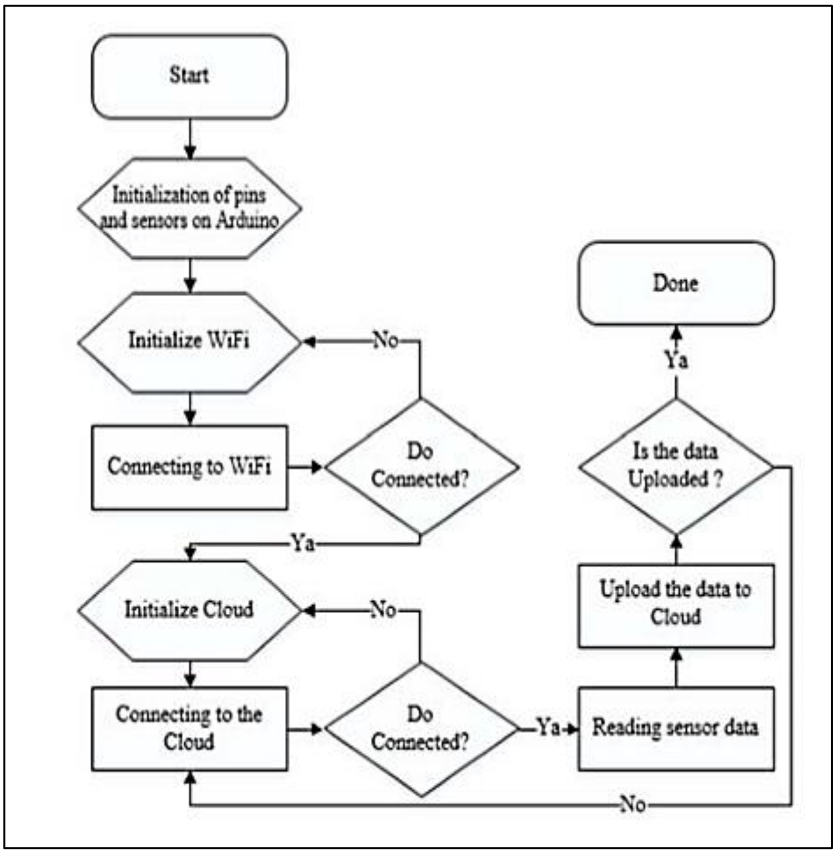

Figure 2.4 Flowchart Monitoring System Program [9]

The study employs robots as a carrier monitoring tool, monitoring pH, PPM, and NTU data in real time via the Internet of Things. ThingSpeak was utilised to conduct this study's IoT platform. A microcontroller called Arduino Nano is used in the robot system. A 2.4 GHz remote control will be used to guide the robot. The L298N motor driver is used to control the robot system's output, which is a DC motor. The Robot is made to float on the water. [6]

IoT has also been utilised for data visualisation on the Shrimp Pond Monitoring System based on temperature, pH, and dissolved oxygen (DO), in addition to ROV. An application to monitor ponds has previously been created as a monitoring system. The constructed monitoring system could only detect a number at a certain point in time, therefore it couldn't see the pond's general condition. The initial phase in this research's activity is data collecting through sensor reading. To determine each value of the parameter in the pool, temperature, pH, and DO sensors will be employed. The next step is to save the information in a database. The sensor's data is subsequently saved in a database to make processing easier. The mobile application, on the other hand, will be used to view the outcomes of prior data processing. Figure 2.5 show the pond sensor mapping design.

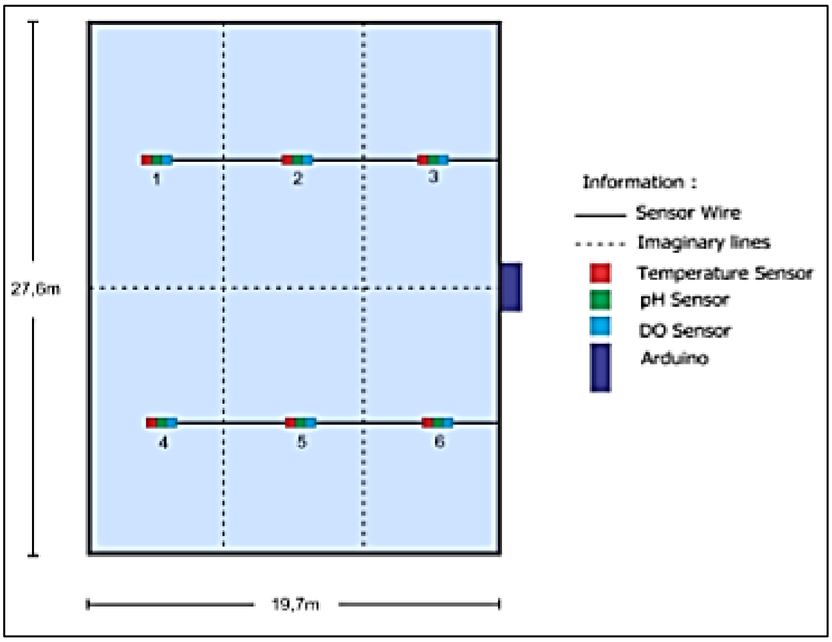

Figure 2.5 Pond Sensor Mapping Design [9]

The next stage is to construct a monitoring device. An Arduino Mega 2560, six DS18B20 temperature sensors, six DFRobot pH sensors, and six DFRobot DO sensors were utilised in one device. Each sensor will be at the mapping location. The purchase procedure may begin after everything is in place. Arduino is used to gather data. The data from the installed sensor will be sent to Arduino, which will then sample the value received by the sensor before sending it to the database. The sample limit is 30 data in 30 seconds. Following the collection of 30 data, an average search for sensors that have supplied 30 data to Arduino will be undertaken. [9]

2.3.3 Water pH Monitoring with a Smart Sensor Powered by a Thermoelectric Generator with a Phase-Change Material

This research describes the development of a smart pH sensor that uses solar thermal energy collected from the environment and stored in a PCM. The IEEE 1451 standard allows smart sensors to be integrated with other infrastructure elements, improving system integration and efficiency. The following are the four sections of this implementation:

i. Solar thermal energy harvesting
ii. Energy harvesting module
iii. Sensor networking following the IEEE1451 standard
iv. Smart sensor operation analysis

A solar concentrator, a hot source, a cold source, and an electrical energy storage device are required for the first section's thermal energy conversion to electrical energy. A thermoelectric generator produces voltage by using the Seebeck effect. Electric energy is controlled and stored by an energy harvest module. To monitor temperature at the hot and cold sources, two thermocouples are connected to an acquisition system that interacts with MATLAB. One header is for the gecko MCU, while the other is for the eZ430 system, in the energy harvest module. The IEEE1451 family of standards, which enables infrastructure parts to function together, supports transducer integration with other features of the transducer network.

There must be at least four TEDS present: A Transducer Channel TEDS characterises each transducer channel, while a User's Transducer Name TEDS records the transducer's identity; and lastly, the PHY TEDS specify the physical communications media used to link the TIM to the NCAP. The pH sensor gadget will require a signal conditioning circuit powered by 5V. An NCP1402-5 regulator is used to boost the 3.3V voltage from the power bus to 5V. A transistor controlled by a digital output port activates the voltage booster when a pH measurement is required. The ADC within the MCU converts the output signal from the conditioning circuit to digital domain. [15]

2.4 Studied based on Wireless Sensor Network (WSNs)

2.4.1 Intelligent Algorithms

Multiple sensors are installed in unmanned ships and micro stations, which are deployed on the sea and land, respectively, in the planned WSNs for water quality monitoring. TOC, nitrate nitrogen, turbidity, and other parameters are tested using UV-visible spectrometry sensors, which are combined with DO, conductivity, and pH sensors. A pollution factor identification method and a pollution source localization algorithm are both presented as intelligent algorithms.

To accomplish multi-sensor water quality data fusion, the pollution factor identification algorithm employs RBFN and entropy, taking into account multi-factor characteristics throughout the whole spectral range as well as the degree of disorder in the multi-factor water quality distribution. Additionally, among these various parameters, such as DO, conductivity, and pH, the pollution component that best indicates the water pollution source should be detected. The suggested technique reduces energy usage and saves energy in 20 iterations without compromising search performance significantly. Therefore, energy efficiency of pollution source localization is achieved. [2] Figure 2.6 and Figure 2.7 shown the convergence curves and total track lengths for the iterations.

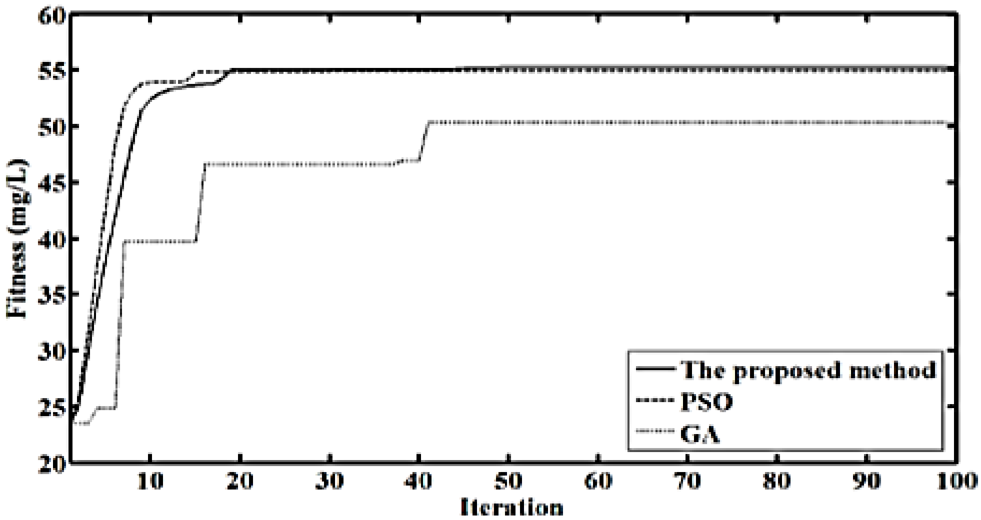

Figure 2.6 The Convergence Curves [2]

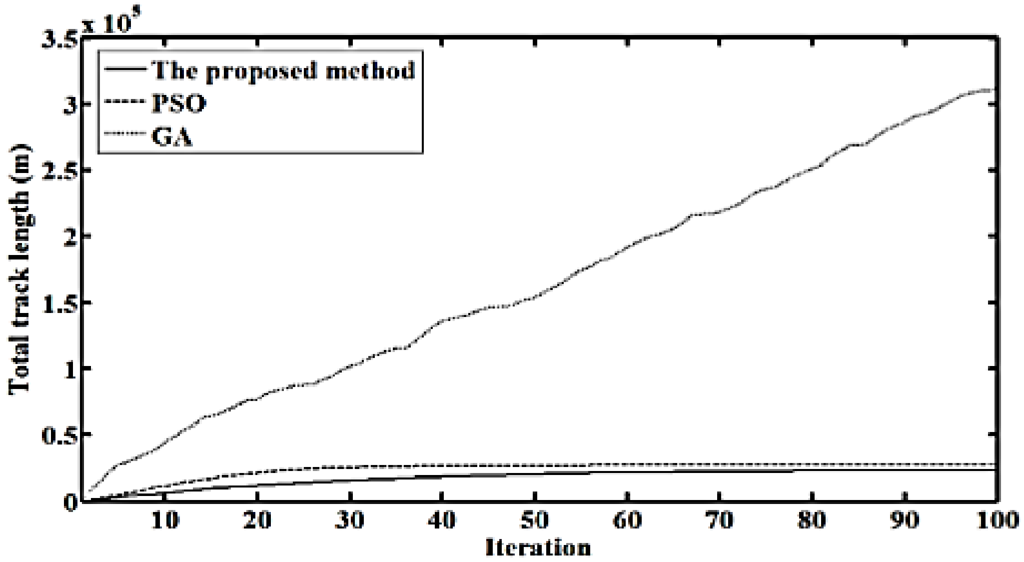

Figure 2.7 The Total Track Lengths [2]

2.4.2 WSNs interfaced with Arduino Controller

Each sensor node is made up of an Arduino microcontroller, an Xbee module, and water quality sensors. The sensor probes will continually monitor pH, temperature, and conductivity. Sensors detect the parameters in real time and relay the information to a data centre. The sensor data is processed and sent by the processing module. The Arduino microcontroller with atemega328p is chosen in this project because it is low cost, low power, more compatible, and has a large number of I/O ports that allow us to connect additional sensors. Zigbee technology is used to transmit data wirelessly between sensor nodes and coordinators because it is low-cost, dependable, and uses little power. Digi's XBee pro s2b modules are employed in this system because they are low-power and allow reliable data transfer between modules. Figure 2.8 depicts the proposed wireless sensor node architecture, which includes all three sensors as well as a wireless module that is connected to an Arduino microcontroller.

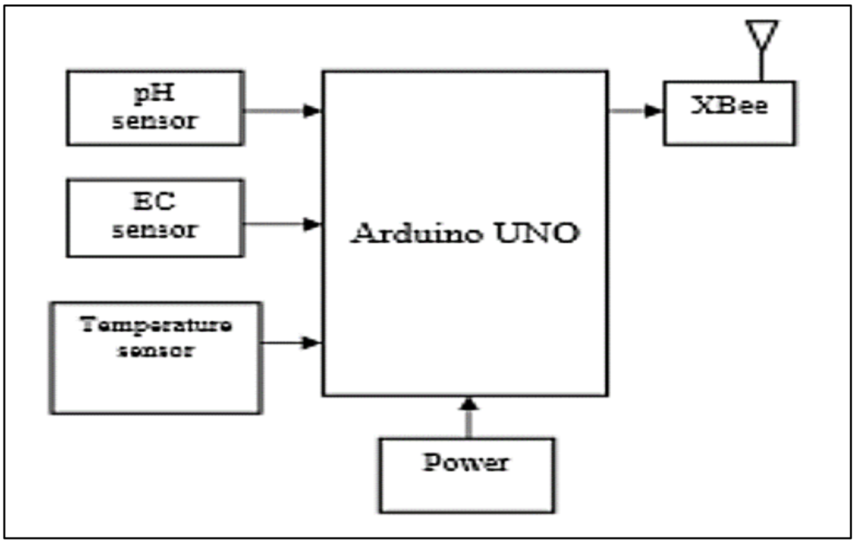

Figure 2.8 Block Diagram of Wireless Sensor Node [11]

GSM is used in addition to the Xbee module. [11] Many individuals are suffering from severe ailments nowadays as a result of contaminated water, according to the issue statement in the research. They are analysing a water quality monitoring system for their project, which provides data on water quality on a website. We can acquire data from remote and underdeveloped locations by using the WIFI module. The flowchart of sensor node is illustrated in Figure 2.9.

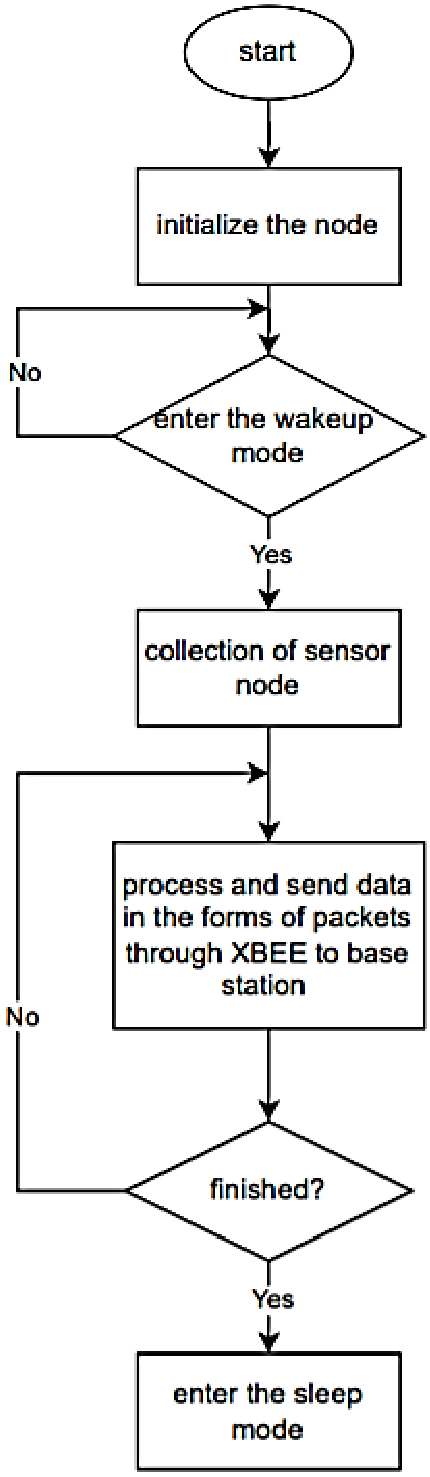

Figure 2.9   Flow Chart of a Sensor Node

This study shows a microcontroller-based water quality monitoring system that can determine numerous water parameters such as temperature, turbidity, and hydrogen potential with a high degree of precision (pH). The detection of those water characteristics is critical to living a healthy life, as many sources of water have been contaminated as a result of overcrowding. The constructed water quality monitoring system in this project-based research effort is portable and comprises of a microcontroller, a few basic sensors, and a display unit, all of which are highly beneficial for detecting the proper pH, temperature, and turbidity of water. Furthermore, the implemented system is extremely efficient and cost-effective, and as a result, the measuring device's precision is at an acceptable level.

The implemented device is made up of a microcontroller, LCD display, differential amplifier, power amplifier, thermistor, turbidity sensor, pH electrode, and other components that work together to perform depending on the electrical characteristics of water. The designed system for assessing water quality includes a microcontroller as a key component. The microcontroller's port A collects the voltage difference across the sensor, while port B is linked to the LCD display, which displays the value of the water parameter as a digital number. The microcontroller receives clock pulses from an oscillator. Figure 2.10 depicts the block diagram of the designed water quality measurement system. [10]

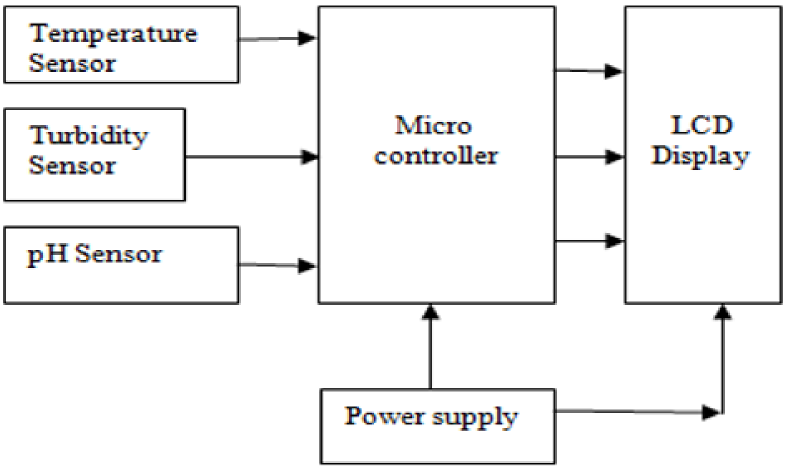

Figure 2.10 Block Diagram of the System to Measure Water Quality [10]

2.5 Optimized Algorithm

2.5.1 Prediction using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) method

The outcomes of the study show that a model based on PSO and GA to enhance the BP neural network can reliably predict water quality parameters, indicating that the model may be used to estimate lake water quality. Since the water quality features of the test come from a variety of Internet of Things (IOT) collecting devices and time data intervals, as well as a significant amount of data being manually input, the original data is insufficient. Furthermore, water parameters often have distinct dimensions and orders of magnitude, and data may be translated to the same order of magnitude without dimension using a normalised processing technique. Using PSO to optimise the BP neural network speeds up convergence and reduces the chance of sliding into local extremum. The mean square error (MSE) is used as the objective function to determine the fitness value of the initial particle swarm. In this study, the PSO-GA-BPNN method is used. The flow chart of the PSO-GA-BP neural network prediction model is shown in Figure 2.11.

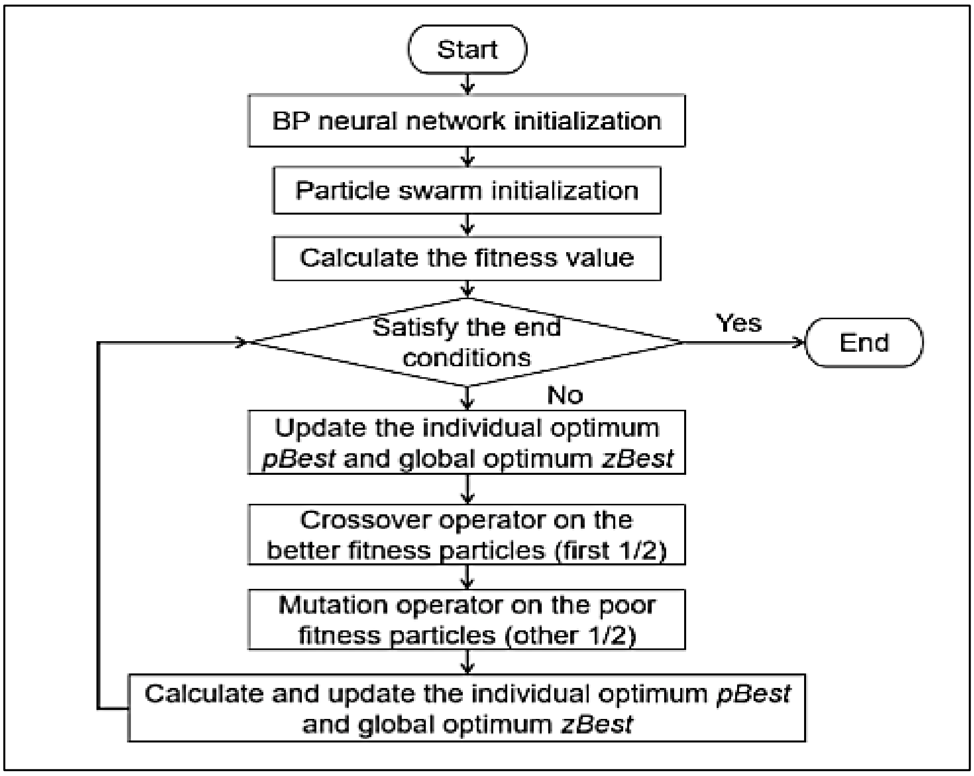

Figure 2.11 Flow Chart of PSO-GA-BP Neural Network Prediction Model [1]

A time series data set was split into two subsets for training and testing the models in this study; the first 70% of the data set was used to train the models, while the remaining 30% was utilised to test them. The following comparison standards were used to assess the method's effectiveness:

$$\mathrm{APE} = \frac{|y-\hat{y}|}{y} \times 100\% \qquad 2.1$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{|y-\hat{y}|}{y} \times 100\% \qquad 2.2$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(y-\hat{y})^2}{n}} \qquad 2.3$$

$$R^2 = \frac{\left(\sum_{t=1}^{n}(y-\overline{y})(\hat{y}-\overline{\hat{y}})\right)^2}{\sum_{t=1}^{n}(y-\overline{y})^2\sum_{i=1}^{n}(\hat{y}-\overline{\hat{y}})^2} \qquad 2.4$$

Where APE stands for absolute percentage error, MAPE for mean absolute percentage error, and RMSE for root mean square error. y is the observed quality parameter in period t, whereas y is the anticipated quality parameter, and n is the total number of periods in the equations. The coefficient of determination is R, and the average of the measured quality parameter across time is y(bar). The closer R2 is near 1, the better the fitting result. MAPE and RMSE are commonly used to assess model accuracy, whereas APE and R2 are better suited to assess model robustness. [1]

2.5.2 Using Spectroscopic and Electrometric method for pH measurement

The most common method for measuring pH is electrometric. To detect the pH of aqueous samples at relevant temperature and pressure conditions, many types of high pressure and high temperature glass electrodes are commercially available. Particularly during depressurization, these glass and reference electrodes must be handled with care. For accurate pH monitoring in C02-brine-mineral systems, spectroscopic methods are an option. However, for both calibration and testing samples, this procedure necessitates the addition of a amount of dye indicator to the aqueous phase. In addition, each dye indicator has a restricted pH range; however, combinations of dye indicators at concentrations can be created to span the desired pH range. In contrast to the electrometric technique, the spectroscopic method does not require calibration of the instrument for pH measurement each time before employing buffer solutions. A pH metre with a glass electrode and an Ag/AgCl probe as an internal reference was used to measure the pH of all the buffer solutions with varying ionic strengths at atmospheric pressure and at the test temperatures. [3]

2.5.3 Analysed Water Quality based on pH using Fuzzy Inference System

The fuzzy inference approach is used to evaluate water quality since the data is ambiguous and unclear. The Mamdani method is the most widely used fuzzy inference approach. This approach employs a set of fuzzy rules given by a skilled human operator. In four phases, the strong Mamdani-style fuzzy inference process is carried out:

i. Fuzzification of the input variables
ii. Rule evaluation
iii. Aggregation of the rule outputs
iv. Defuzzification.

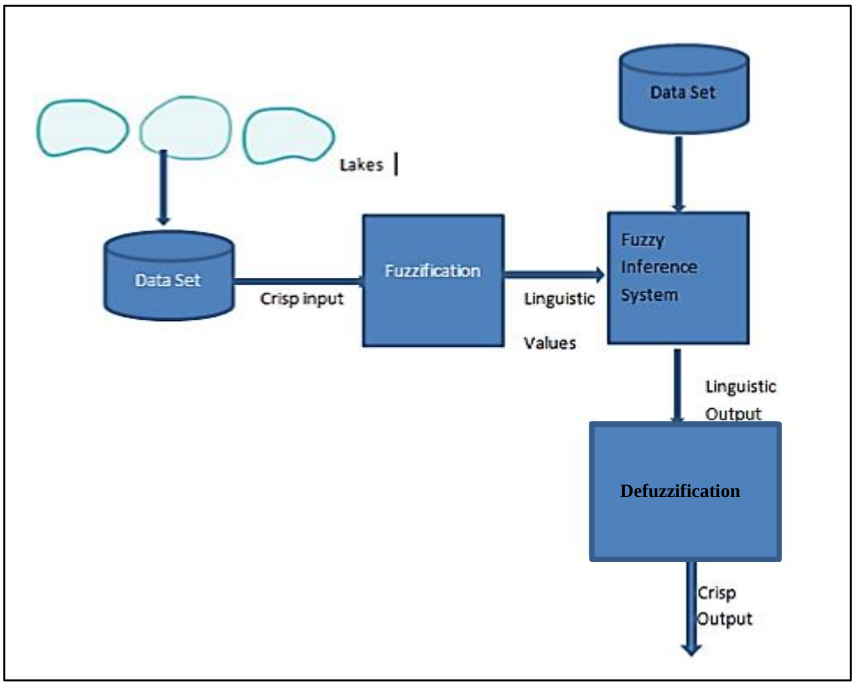

Figure 2.12 Basic System Architecture

Figure 2.12 shown the basic system Architecture of fuzzy inference approach. The first stage in the fuzzy inferencing approach is fuzzification. Crispy inputs are turned into fuzzy inputs referred to as linguistic variables by a domain conversion. Crisp inputs, such as pH, DO, and TC, are ideal. The second phase is to consider the fuzzed inputs and link them to the fuzzy rules' antecedents. When a fuzzy rule contains a lot of antecedents, fuzzy operators like AND and OR are employed to get a single integer that represents the antecedent assessment result. The membership function is then applied using this number's truth value. In a fuzzy system, aggregation is a crucial phase. It's an approach for combining all rules' outputs. Find the membership functions of all rules that have been cut or jumbled in the past and merge them into one fuzzy set. In a fuzzy inference system, defuzzification can be the last module. A crisp number is the final result of a fuzzy system. [4]

2.5.4 Artificial Neural Network (ANN)

The present approach is a laboratory process in which samples are gathered from bodies of water and tested in laboratories. This technology is both cost-effective and replaces the chemical way of analysing water quality criteria. This paper presents a brief methodology for predicting unknown parameters such as alkalinity, chloride, and sulphate values using known parameters such as pH, electrical conductivity, and TDS, among others, using the Levenberg–Marquardt algorithm, which aids in the classification of water bodies for various applications. An artificial neural network is essentially a collection of neurons or nodes. It's also known as neuronal interconnection. Artificial neural networks, in general, need many data sets to train. For training, 876 values of each parameter were utilised, which were collected from various locations. Pollution Control Board provided the data.

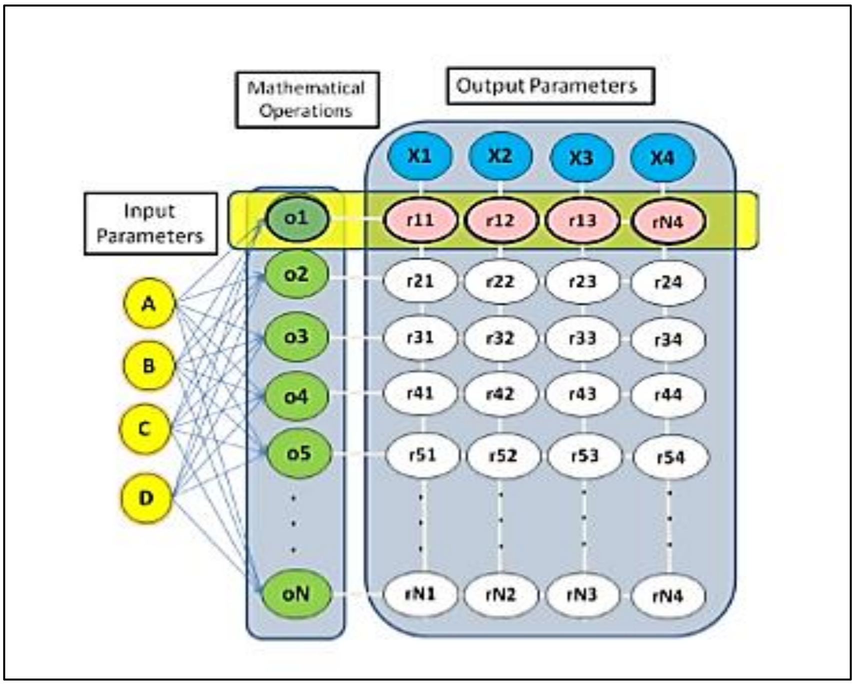

Figure 2.13 Pre-processing of Dataset [5]

Figure 2.13 above is the pre-processing of dataset, where A, B,C and D represents the input parameters. o1, o2, o3 .... oN represents the mathematical operations that are done before training the neural network. The mathematical operations can be sum, product, square, square root, logarithmic etc. X1,X2,X3 and X4 represents the output parameters which are to be predicted. r11,r12 ....rN4 represents the correlation coefficient between mathematical operation and the corresponding output parameter. To train the neural network, a mathematical process is performed that selects the output parameter with the highest correlation coefficient. The rationale for this is because the best correlation means that the predicted parameter is more accurate. Until the local curvature is appropriate to construct a quadratic approximation, the Levenberg–Marquardt algorithm is employed to transition to the steepest descent technique. When there is an average number of parameters, the Levenberg Marquardt technique is applicable. It has a higher memory need, but it is the quickest. Finally, testing entails assessing the Mean Absolute Percentage Error (MAPE), which is a statistical measure of a forecasting method's prediction accuracy. In percentage notation, it shows accuracy. [5]

2.5.5 Random Forest Algorithm

The goal of this study is to develop a low-cost, multi-function device that uses machine learning algorithms such as Decision Tree, Decision Forest, and Multi-layer Perceptron to determine the value of DO level using hydrological modelling of water parameters such as temperature, pH, and conductivity. When compared to the other two strategies, the Random Forest strategy generated the most accurate metrics. The algorithm is shown in Table 1 below. After then, the data is filtered in a number of methods to remove errors, fragmented data, and faulty sensor inputs, among other things. The filtering accepts only complete data and non-erroneous values, which can only be achieved if all sensors record their observed parameters.

The sample size of the acquired data is 1,019,189. Minute, 5-minute, 10-minute, 30-minute, and 60-minute periods are resampled from the filtered dataset. This is done to determine which interpolation would result in the best model, as determined by the evaluation. On the basis of various combinations of pondwater characteristics, many prediction models were developed. To evaluate these models, the R Square, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were utilised (RMSE). A larger R Square value denotes less error or unexplained variation, signifying improved DO level prediction and precision. MAE evaluates how big errors affect the model's accuracy. MSE is kept to a minimal minimum to ensure that the predicted DO level matches the actual DO level. A smaller RMSE is desirable to minimise large variations in forecast and real DO levels.

Table 1   Random Forest Regression Algorithm

RANDOM FOREST REGRESSION ALGORITHM				
Trial No.	Time	Predicted DO	Actual DO (Atlas Scientific)	Percent Error
1	11:10:31	15.83	16.55	4.350
2	13:36:03	19.29	19.26	0.156
3	14:51:38	19.68	20.98	6.196
4	14:56:42	19.68	19.22	2.393
5	15:12:20	21.24	21.19	0.236
6	15:21:21	21.21	22.36	5.143
7	15:23:20	21.24	21.39	0.701
8	15:25:21	18.5	18.27	1.259
9	15:28:21	21.17	21.97	3.641
10	15:29:47	18.5	18.13	2.041
			AVERAGE:	2.612

Table 2   Decision Tree Regression Algorithm

TABLE II. DEVICE EVALUATION – DECISION TREE

DECISION TREE REGRESSION ALGORITHM				
Trial No.	Time	Predicted DO	Actual DO (Atlas Scientific)	Percent Error
1	11:01	17.84	15.95	11.850
2	12:09	18.21	14.84	22.709
3	12:11	18.21	16.67	9.238
4	12:15:50	18.21	16.37	11.240
5	12:18:50	18.21	20.01	8.996
6	12:26:50	18.21	20.34	10.472
7	13:21	18.24	17.85	2.185
8	13:50:31	18.24	17.98	1.446
9	14:42:48	19.5	20.03	2.646
10	14:55:12	15.1	14.89	1.410
			AVERAGE:	8.219

Based on the Top 6 Key Parameters (time when data was taken, pH, temperature, Electric Conductivity, Total Dissolved Solids, and salinity), it can be inferred that the top performing models are built from Per Minute Sampling, using Random Forest and Decision Tree algorithms as shown in Table 2, based on the following Top 6 Key

Parameters (time when data was taken, pH, temperature, Electric Conductivity, Total Dissolved Solids, and salinity). [12]

2.5.6 Utilizing Multiple Linear Regression (MLR)

pH, TDS, and conductivity are the WQPs examined in this research. To estimate the WQPs of the materials under consideration, standard tests were carried out in a laboratory setup. The pH, TDS, and conductivity sensors were initially calibrated by comparing the measured WQPs of pure drinking water to WHO guidelines. The sensors were then submerged in distilled water for a few minutes. Adding 0.25 mg of K2Cr2O7 to one litre of clean drinking water yielded a contaminated sample of K2Cr2O7. The colour of the sample quickly turned to yellow. The pH, TDS, and conductivity of tainted drinking water (K2Cr2O7 + H2O) were then determined. By adjusting the concentration of K2Cr2O7 from 0.25 mg/litre to 2.75 mg/litre, the aforesaid procedure was repeated in stages. Furthermore, this procedure was repeated for other hexavalent chromium compounds, namely Na2CrO4, Na 2Cr2O4·2H2O, and PbCrO4.

MLR was used to model the interdependencies between WQPs. The correlation coefficients between pH and TDS, TDS and conductivity, and conductivity and pH were calculated (r1, r2, r3). To confirm the correctness of the suggested MLR model, the difference between measured and estimated WQPs was calculated. [7]

CHAPTER 3

METHODOLOGY

3.1 Introduction

This project explored the challenges faced by simulation. The project will go through a three phase in total which is collect data of the pH water, speed and direction of flow water at UMP main lake, processing data and test the fitness function on it. This is in order to obtain the full view on how the project will be conducted. The phases are being discussed in this chapter.

3.2 Project Flow

Figure 3.1 below shown the flow of the project. The project begins with doing some research on the project title. Next, continue to collect data pH and speed at UMP's main lake by using hardware named Wireless Passive Water Quality Catchment Monitoring System (WWM). About 90 data had been collected. Processing data is done at the same time by using EXCEL AND MATLAB software. Next, after all the data have been processed, a model to predict pH value was developed by using MLNN-GA. To develop a suitable model, we need to decide on how many layer and neuron need to be used. Using this model, best weight for each set of data was selected based on GA optimization. After the best weight was established, analyse the performance of the model. Using the model, we get the pH value for the middle point. The data then being compared to the other data that exclude speed of flow water as the factor of changing pH water.

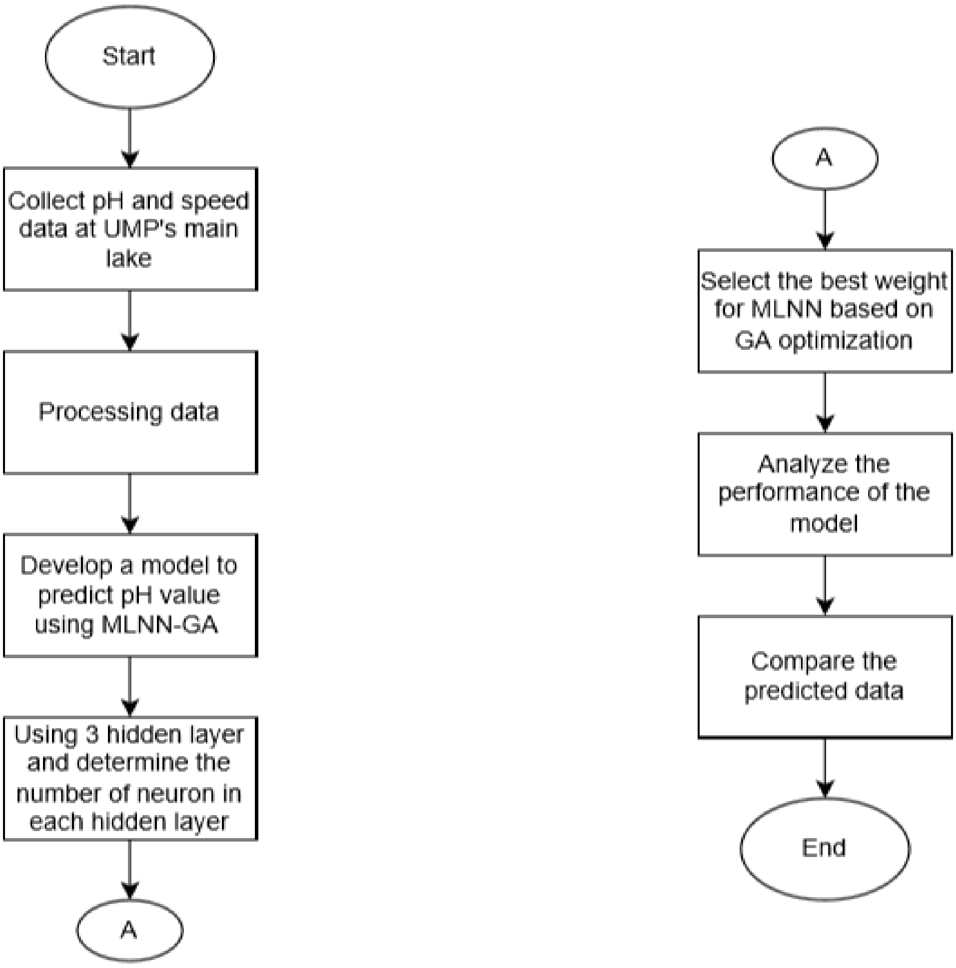

Figure 3.1 Project Flow

3.3 Collecting Data

In this research, data is collected at UMP main lake area. To assure the accuracy of the data, there are 90 set of data that had been collected. For each set of data, five different point need to be taken of their pH water and speed data. There is some time that has been set for each data point to be taken, which are five minutes each. The time set is to allow the data collected being stable and accurate.

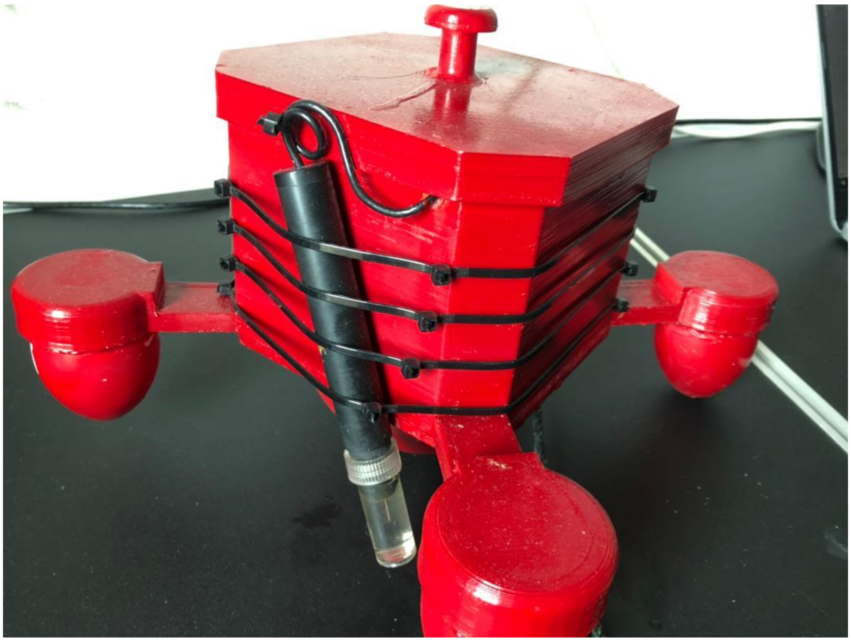

Figure 3.2 Wireless Passive Water Quality Catchment Monitoring System

The data of the lake is collected using Wireless Passive Water Quality Catchment Monitoring System (WWM) as shown in Figure 3.2. WWM is used to collect data of pH water and GPS. Basically, in WWM, there are few components used. They are pH sensor and LoRa GPS tracker. These two components are connected by Arduino UNO and powered by eight battery AA. Figure 3.3 shown the component inside of the WWM hardware.

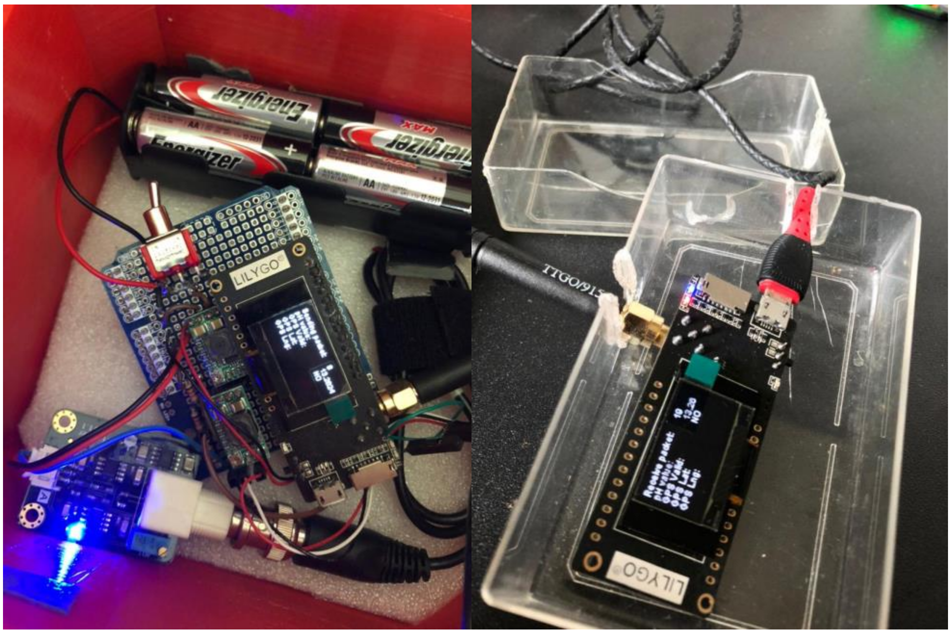

Figure 3.3 Component inside the WWM

To collect data, WWM is connected to laptop and data collected can be monitored using serial monitor in the Arduino Software. WWM is put at each point with five-meter distance apart from another point as can be seen in Figure 3.4 below. After five minutes and data is stable, it will be transferred to excel to ease the data processing.

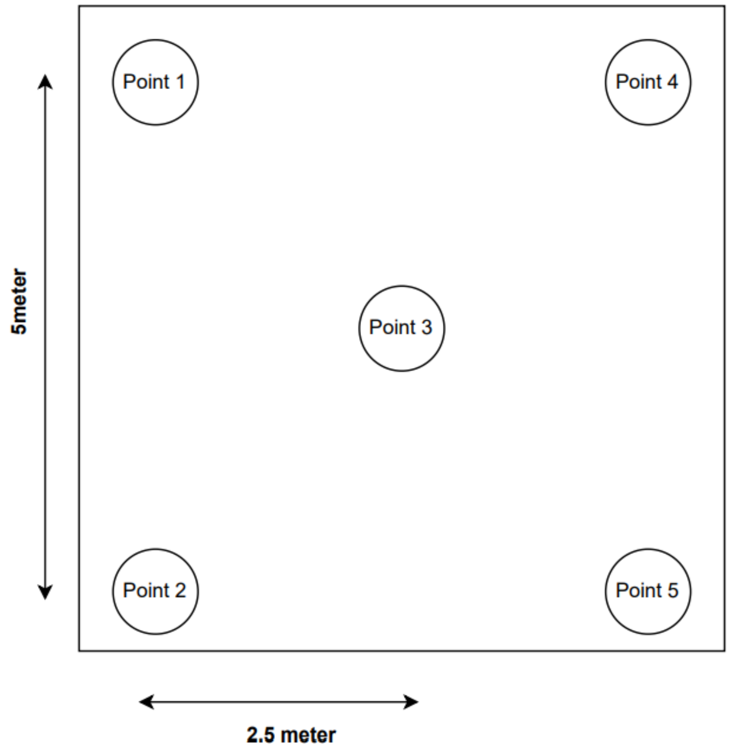

Figure 3.4 Location of Five Point of Data

The scope of collecting data is limit to sunny and cloudy day only where data that had been taken during rainy day are not acceptable. The reason on why the data are not acceptable and invalid during rainy days as rain water will affect the value of pH water due to its surrounding.

3.4 Data Processing

Data processing is needed as the data collected might have errors and become invalid due to some measurement factors. In this project, EXCEL and MATLAB software is used to process the data. From the WWM device, the data will be transferred to Arduino

Software and to ease the data processing, it will be transferred to EXCEL file. The data that are needed from each set of data are pH water, latitude and longitude value.

Latitude and longitude value are needed to get the speed of water flow at each point on every second.

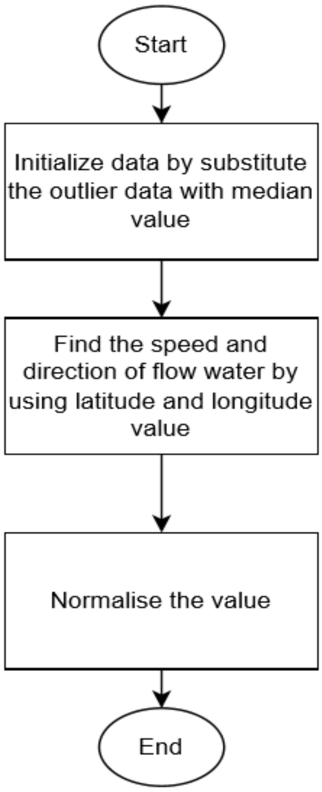

Figure 3.5 Overall Process Flow of Processing Data

Figure 3.5 shown the overall process flow of processing data. First step was to initialized data by substitute the outlier data with median value. Outlier data here means the data that might lead to errors data when being simulated. Next, find the speed and direction of flow water by using the latitude and longitude value. Last, normalise all the value by dividing all the value with the highest value of speed, angle and pH.

In order to find the value of water flow speed, there are few steps that need to be done in EXCEL:

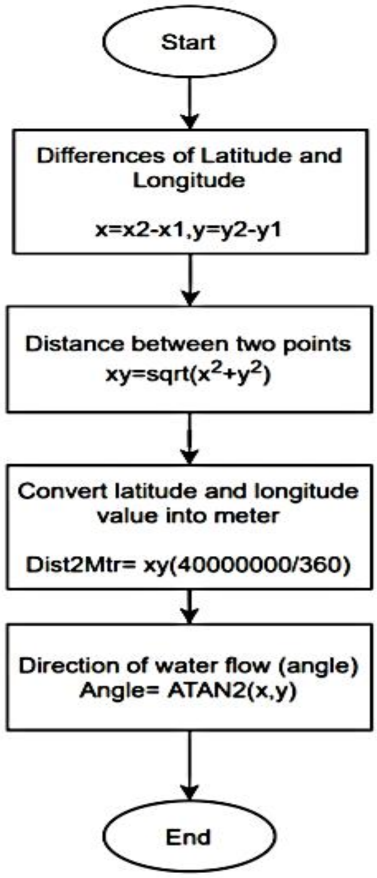

Figure 3.6 Flowchart to Find the Direction of Water Flow

As shown in the Figure 3.6, from the first step, differences of latitude and longitude need to be calculated as we need to know how much the hardware move on every five minutes. Converting latitude and longitude into meter measurement to ease the calculation to find the angle. Angle is needed to find the direction of the hardware move from its initial place.

After getting all the data needed, the data that has been processed in EXCEL will be exported to MATLAB to be simulated. In MATLAB, a coding to find its velocity is developed to make it easy to read the data. Also, from the data that has been processed, boxplot is constructed to see whether the data is valid or not. If there are outlier, the data will be replaced with the median value.

3.5 Develop a Model to Predict pH Value using MLNN-GA

As refer to previous study, Multi-Level Neural Network (MLNN) was used and introduced new prediction method which are four input, three hidden layer and single output where the inputs are pH value at 4 different point. In this study, we are adding two more input that we considered as new factor that manipulate the pH value which are the speed and direction of the flow water. Thus, new prediction method is introduced, which is twelve input, three hidden layer and one output. We had twelve value as input since we need to take two parameter value at each point which are the pH value, speed value and the direction.

In this study, we decided to use the same number of neurons used in previous study for each hidden layer which are 20 neurons for the first and second layer, and ten for the third layer. We used the same number as it is proven that with these number of neurons, it will produce the lowest penalty value, and root mean square (RMSE).

The flowchart of MLNN-GA is shown in Figure 3.7. The process starts with initializing the input that we get from WWM system. To create an accurate model, there are two phase which are training and testing data. These two phases were using different set of data. The process of modelling will start with training the data. There are two set of data that need to be train which are data pH with speed and data pH without speed. The data were kept being train and compute error until the optimized weight achieved.

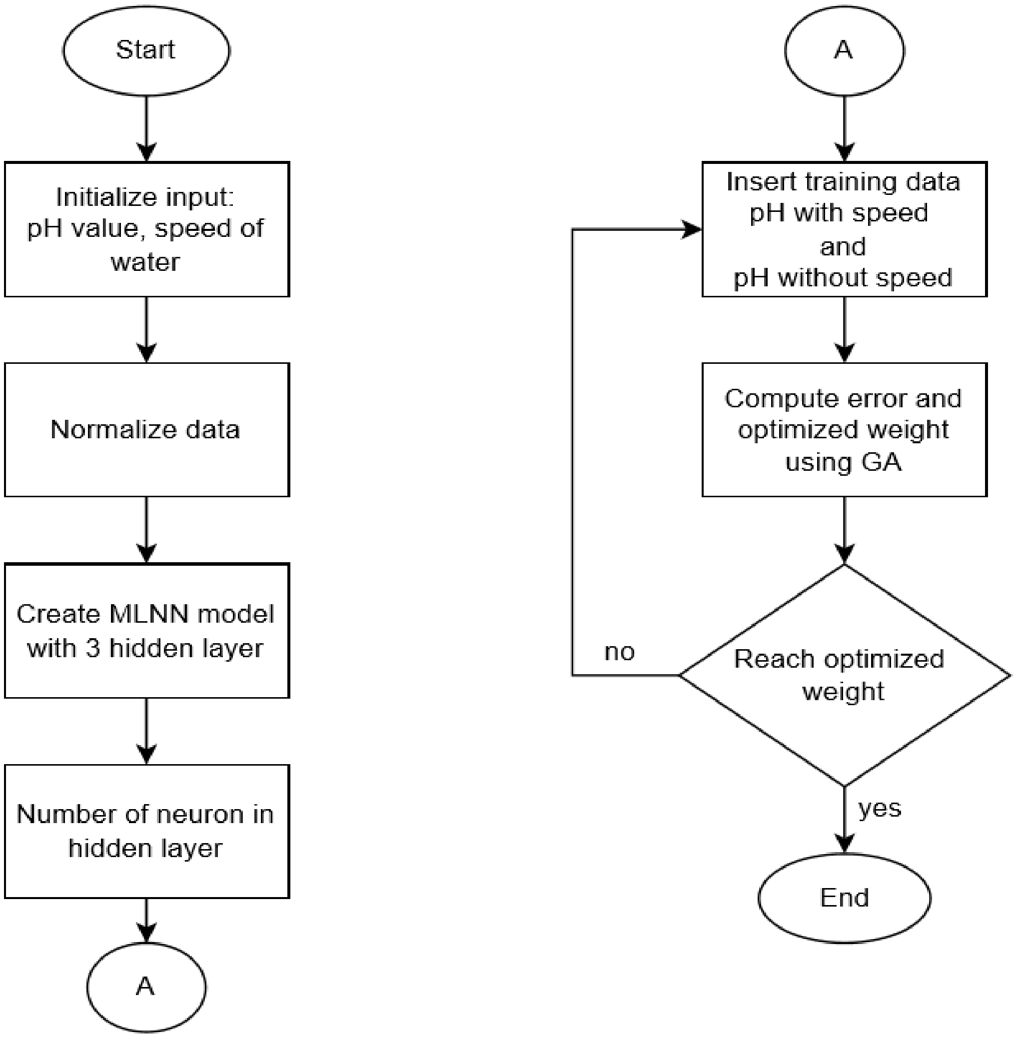

Figure 3.7 Flowchart of MLNN-GA

3.6 Analyse the Performance of the Model

When the optimized weight achieved, insert the testing data. In this project, optimized weight is achieved on the computation of 40 training data for data pH with speed and 25 training data for data pH without speed. By testing the data, we get the predicted data for the pH value. In analysing the predicted data, the actual value will be compared to the two predicted data. Four formula are used to compare between predicted data and the actual data; to obtain the error value, percentage error, RMSE value, and accuracy of prediction.

$$\text{Error Value} = |Actual\ output - predicted\ output| \qquad 3.1$$

$$\text{Percentage Error \%} = \left|\frac{Actual\ ouput - Predicted\ output}{Actual\ Output}\right| \times 100\% \qquad 3.2$$

$$\text{RMSE} = \sqrt{\left(\frac{1}{n}\sum_{i}^{n}(Actual\ Output - Predicted\ output)^2\right)} \qquad 3.3$$

$$\text{Prediction Accuracy} = 100\% - Percentage\ Error\% \qquad 3.4$$

Equation 3.1 until 3.2 will be used to obtain the value used to compare the accuracy of the prediction value.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter will briefly explain the result from the develop coding that have been studied. Which is by create MLNN-GA model to predict the pH value data to be compared with the actual value.

4.2 Training Data

During the training process, GA will optimize the optimum weight of the network until it reached the stopping criteria. The input will be changed continuously by different set of data until it reaches the best weight. These weightages will be used to test the data and get the predicted value of pH water.

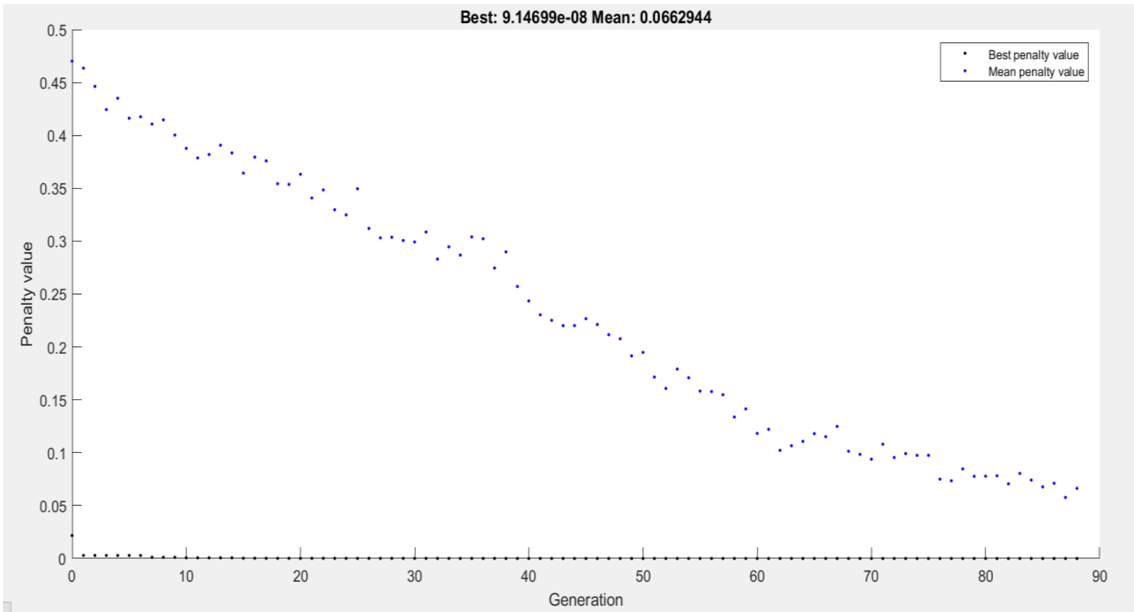

Figure 4.1 Training Process for Data Set pH Without Speed

Figure 4.1 above shown the results of training process for data set pH without speed. Training process was stop at data set 25 but the best weightage was obtained at data set 24 as overlearn occur which the accuracy of data was higher at data set 24 than data set 25.

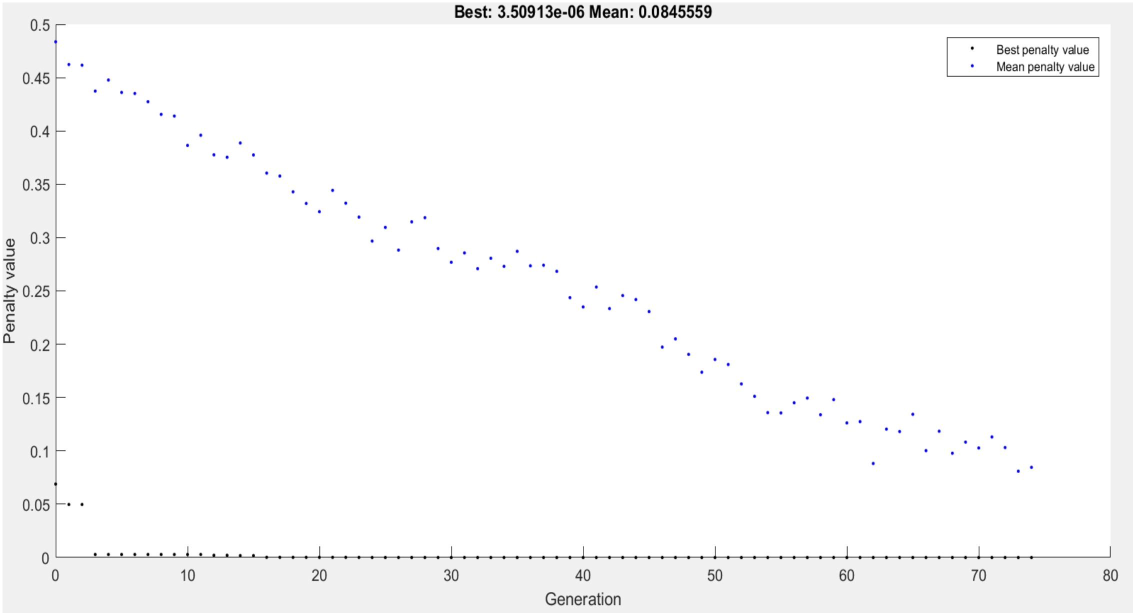

Figure 4.2 Training Process for Data Set pH With Speed

Meanwhile, Figure 4.2 above shown the results of training process for data set pH with speed where it stops at training data set 40. Overlearn also occur during this training process and training data set 38 was chosen as the best weightage to test the remaining data.

4.3 Result of pH Prediction Based on MLNN optimised by GA

The best weightage obtained from the training process was being used to get the prediction data. Testing data which were the data pH with and without speed were insert one by one to get the predicted pH data.

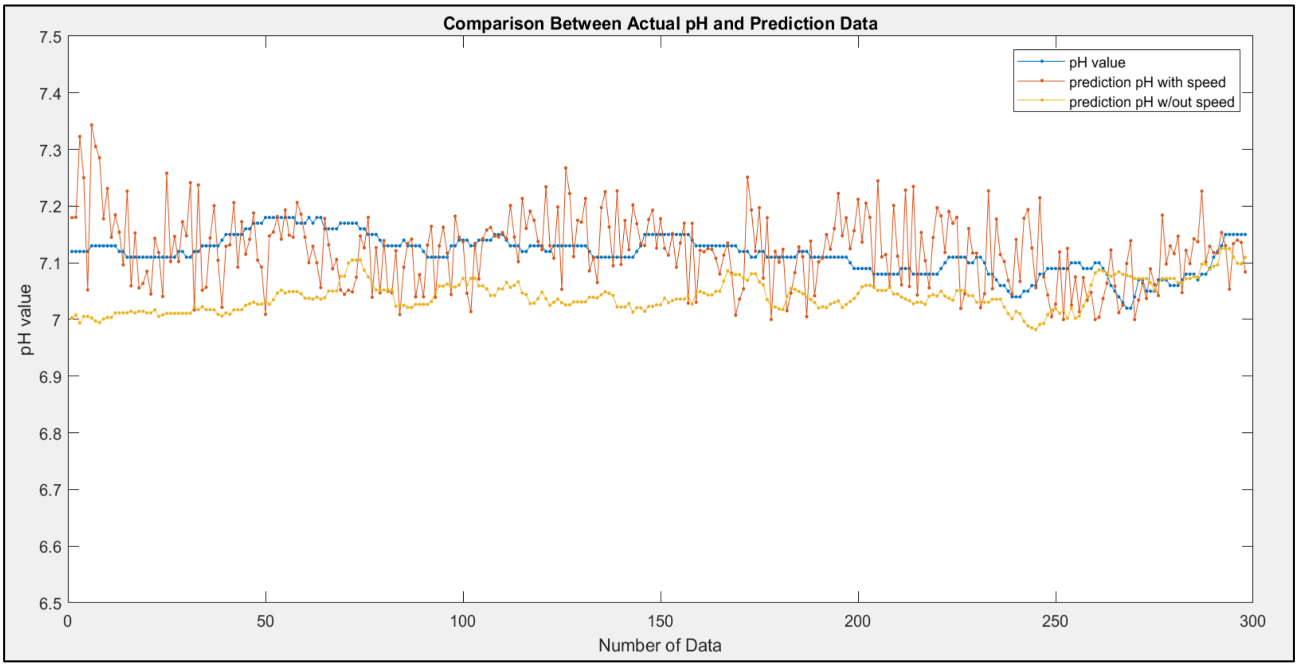

Figure 4.3 Comparison of Data pH for All Data in One Set

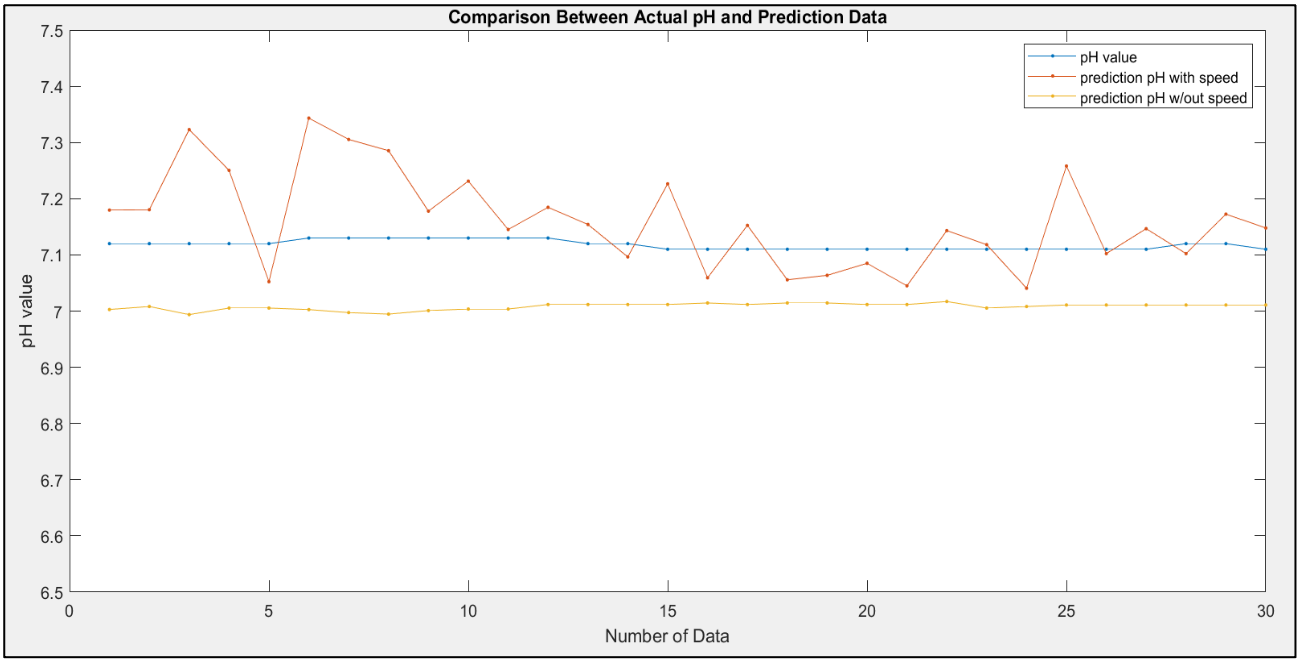

Figure 4.4 Comparison of Data pH for 30 Data in One Set

Figure 4.3 shown the comparison of the actual value with the predicted data pH with and without speed for all the data for set data 42. Meanwhile, Figure 4.4 shown only 30 data in one set to ease the comparison. For other data set can be seen in the Appendix.

4.4 Comparison of Actual Value of pH with pH Data with and without Speed

In this subchapter, the accuracy of the predicted value was being obtained by comparing the value of error, percentage error, RMSE and last the accuracy of the prediction.

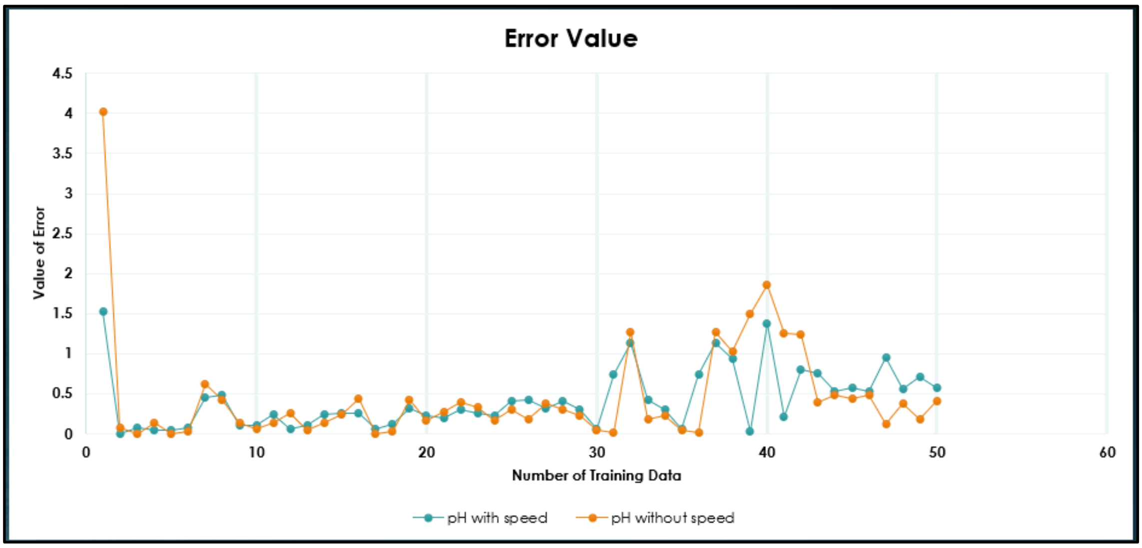

Figure 4.5 Error Value for Predicted Data

Figure 4.5 indicates the error value obtained for each data set. Based on the values obtained, data pH without speed records the highest error value by 4.02 while for data pH with speed records 1.53 error values.

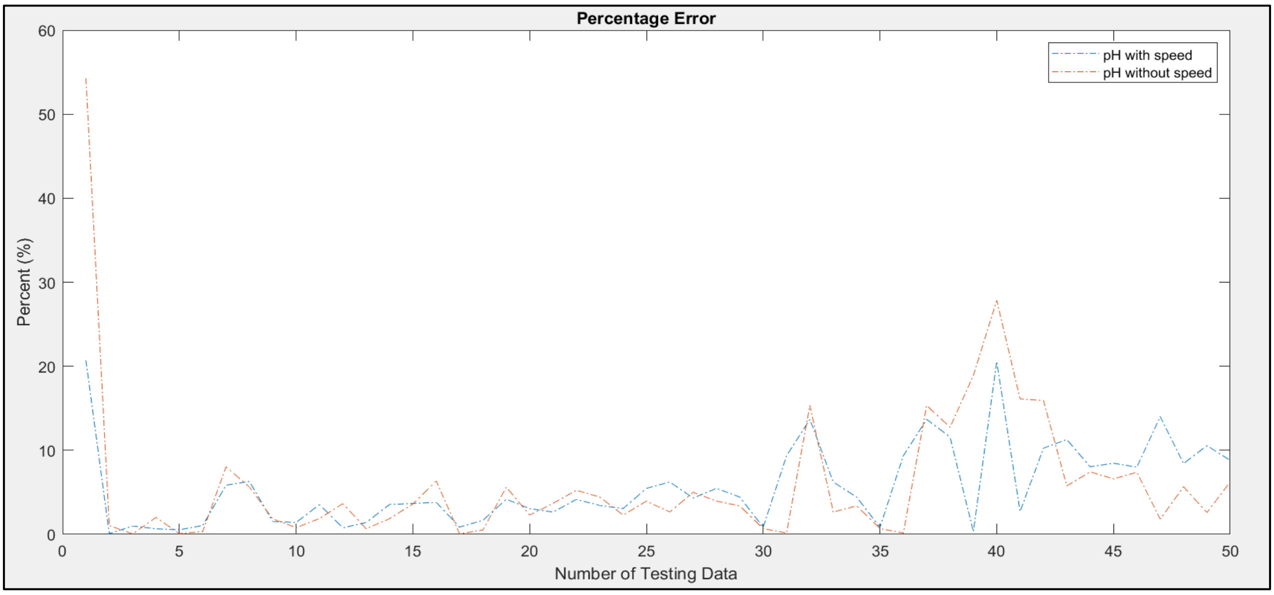

Figure 4.6 Percentage Error for Predicted Data

Figure 4.6 shown the percentage error for all 50 set of testing data. Based on the values obtained, data pH without speed had the higher percentage overall which were 54.26% while for data pH with speed obtained 20.69%.

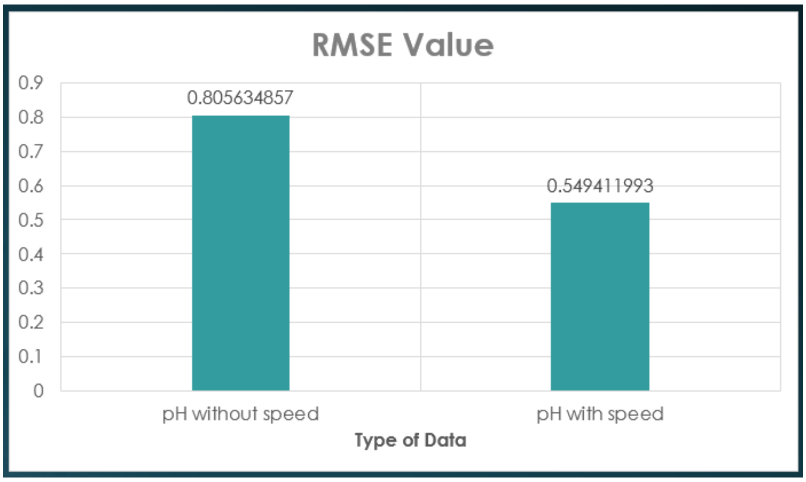

Figure 4.7 RMSE Value for Predicted Data

Next, Figure 4.7 indicates the average RMSE value obtained by each type of data. Data pH with speed has a lowest RMSE value from the other data with value of 0.5494. Overall, the average prediction accuracy at UMP Main Lake for two types of data has been summarised. Based on results shown in Figure 4.8, data pH with speed obtained a highest prediction accuracy with average value of 94.27% while the data pH without speed obtained a least prediction accuracy value with 93.83% as the prediction pH value with speed is more accurate and closed to the actual value of pH.

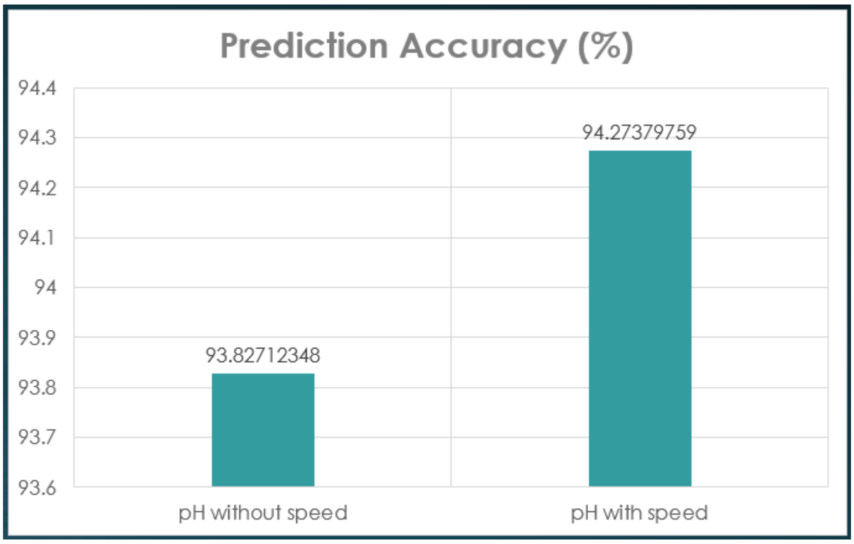

Figure 4.8 Prediction Accuracy for Predicted Data

CHAPTER 5

CONCLUSION

5.1 Conclusion

To conclude, by the end of this project, we managed to collect large data set of pH water required to complete this study. We also succeed in creating fitness function using MLNN-GA to predict the lake water quality using speed of flow water and pH water. Data direction of water flow was also has been tested and the result that we obtained did not increased the prediction accuracy but led to errors prediction data. For future research, we might suggest investigating more about the direction of flow water parameter that will be able to become new parameter of water quality. Using the prediction value, we analyse few parameters to predict the accuracy. We get error value of 4.02 and 1.53 for both data pH without and with speed, percentage error of 54.26 for data pH without speed and 20.69 for data pH with speed, RMSE value of 0.8056 and 0.5494 for data pH without and with speed. Using these parameters, we obtained the prediction accuracy for each type of data which are 93.83% for prediction data pH without speed and 94.27% for prediction data pH with speed. To summarize, speed of flow water is proven to be one of the factors that manipulate the value of pH water as the data predicted using speed is more accurate than the data without it.

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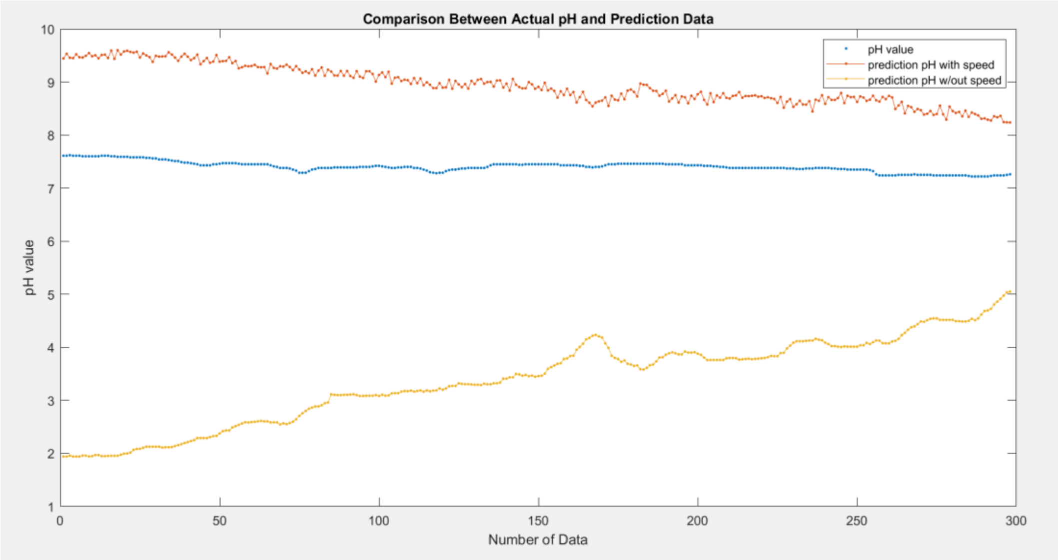
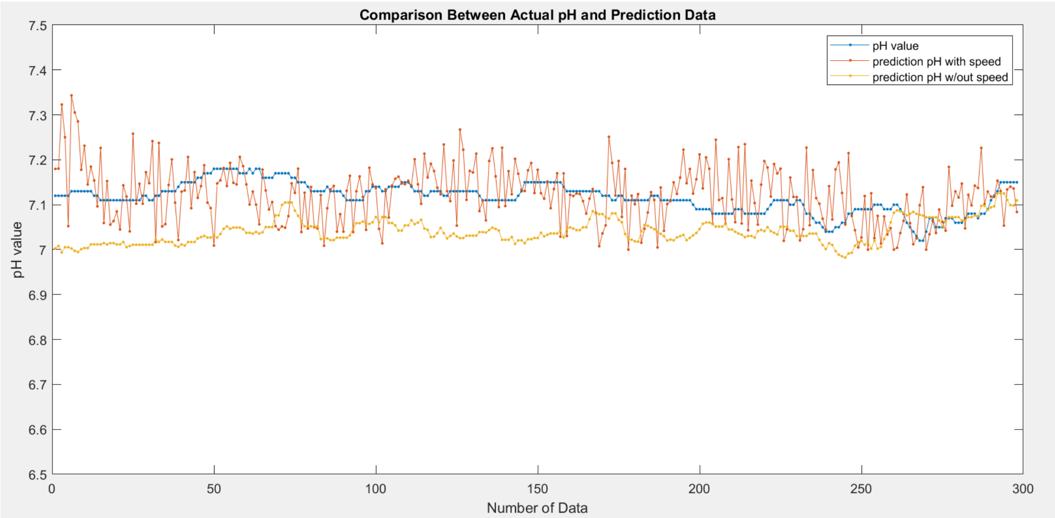
APPENDIX

Comparison of Actual Value with the Predicted Data for All Data Set

Data Set 41



Data Set 42



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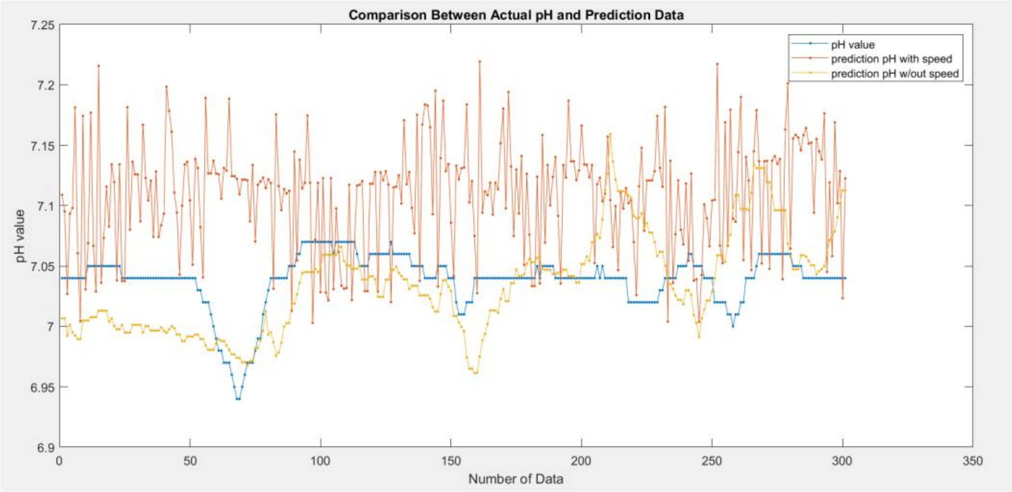

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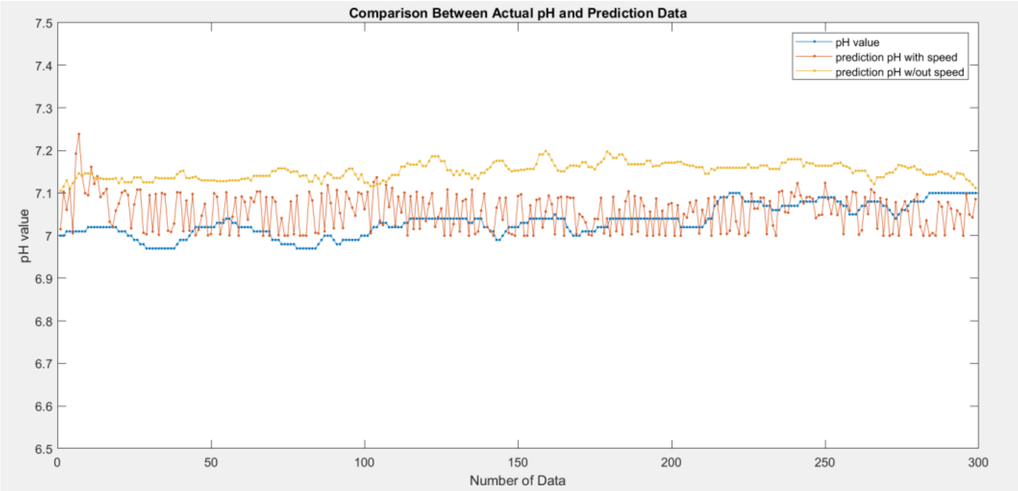

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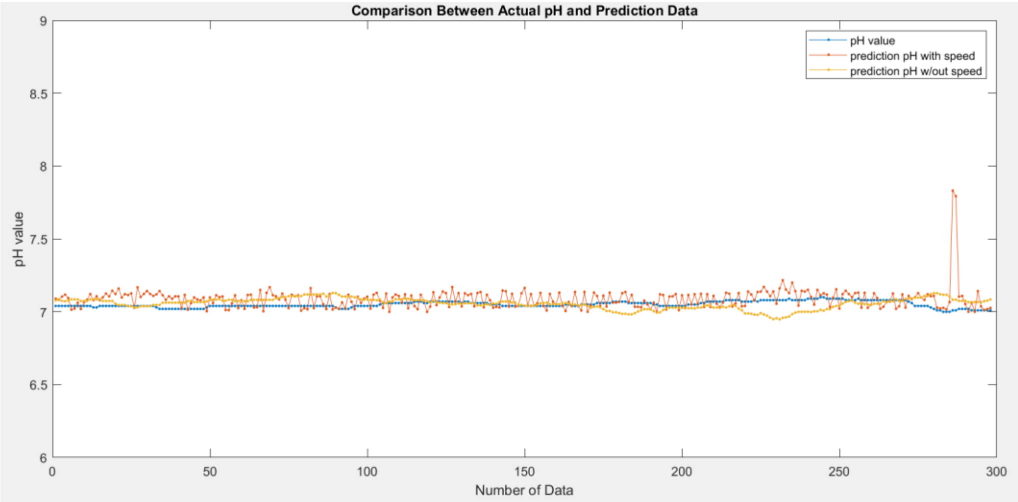

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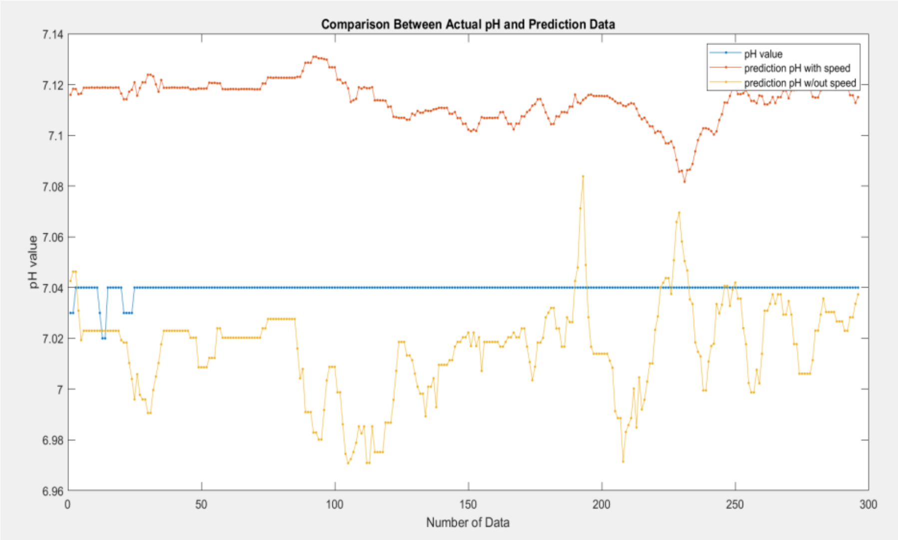

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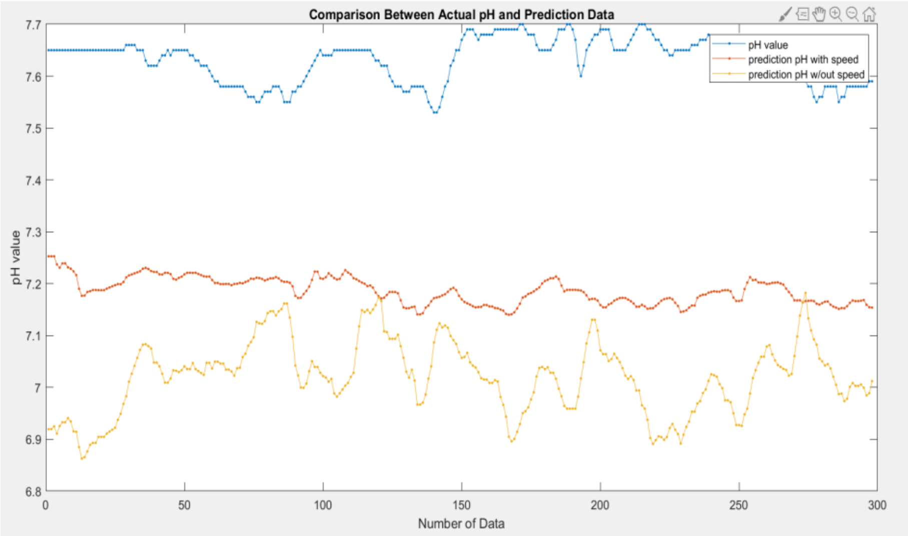

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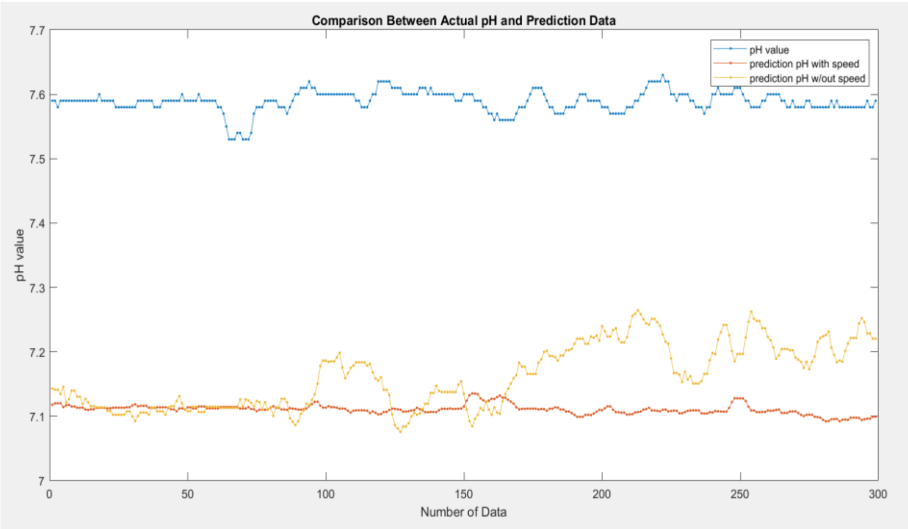

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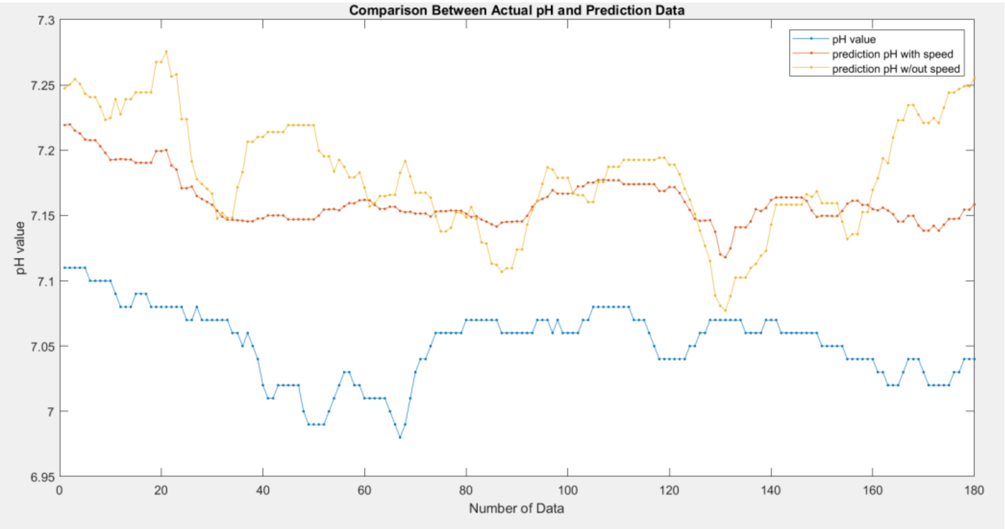

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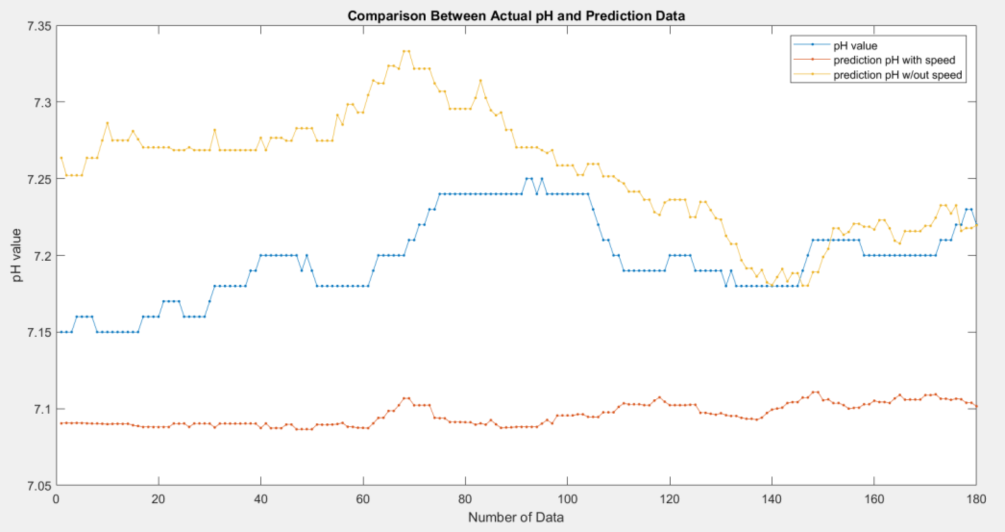

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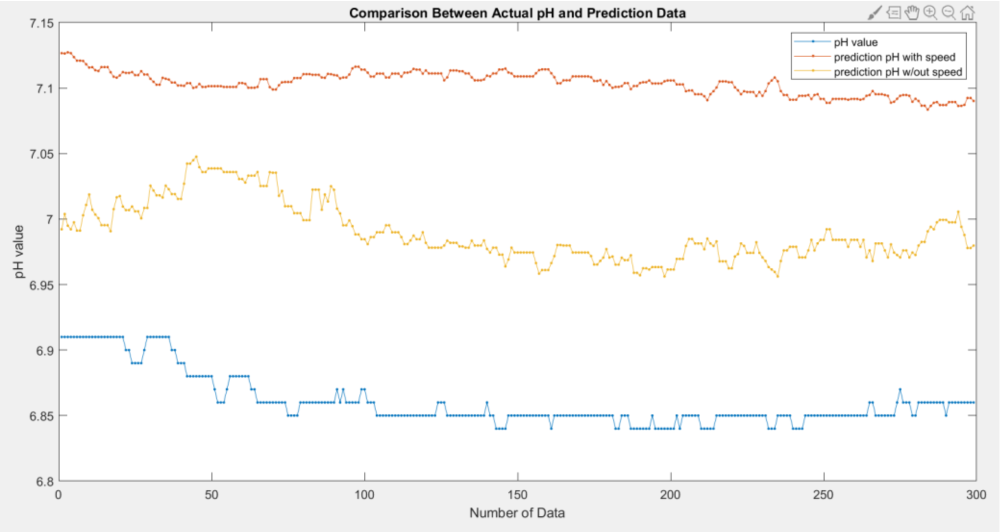

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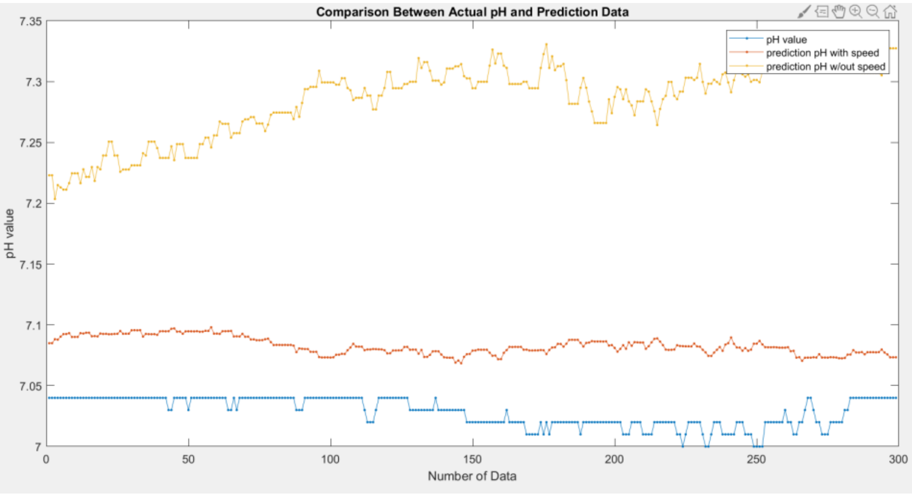

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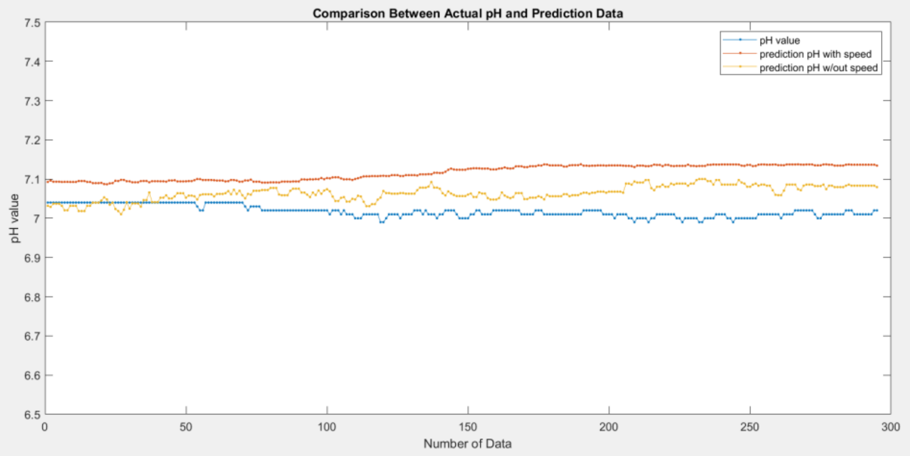

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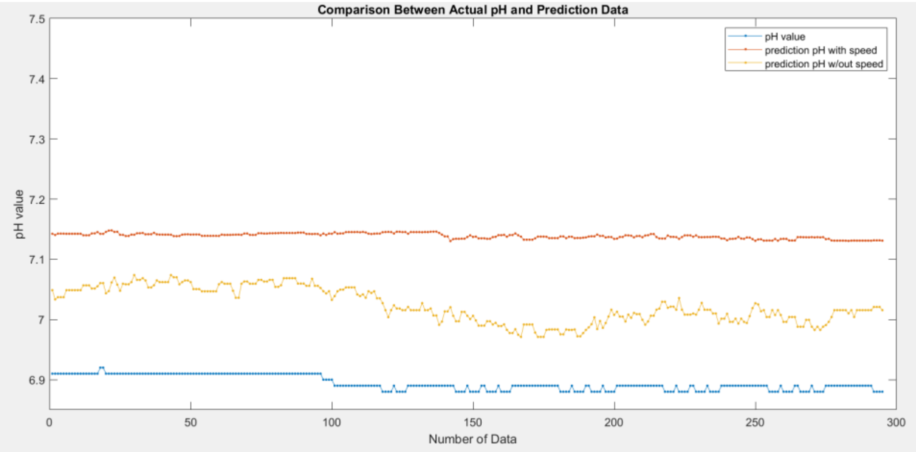

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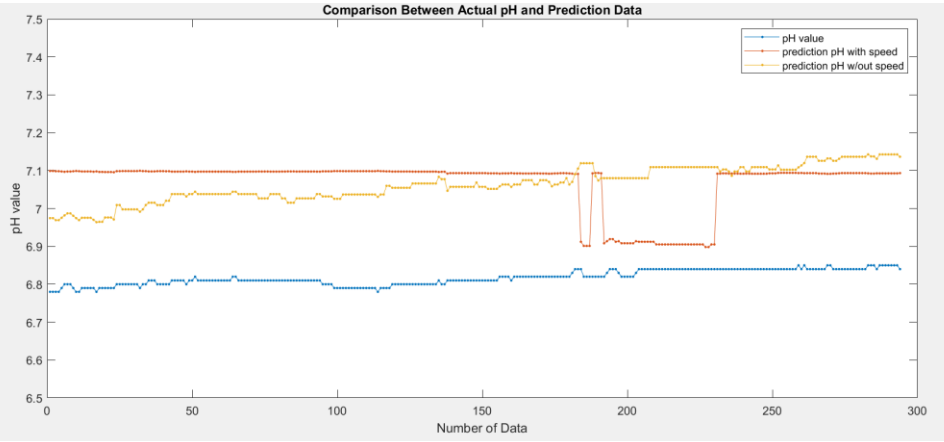

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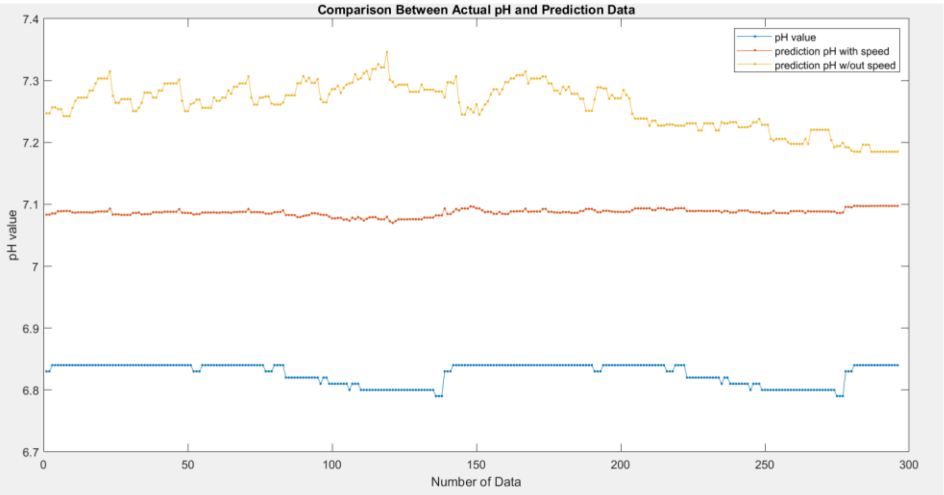

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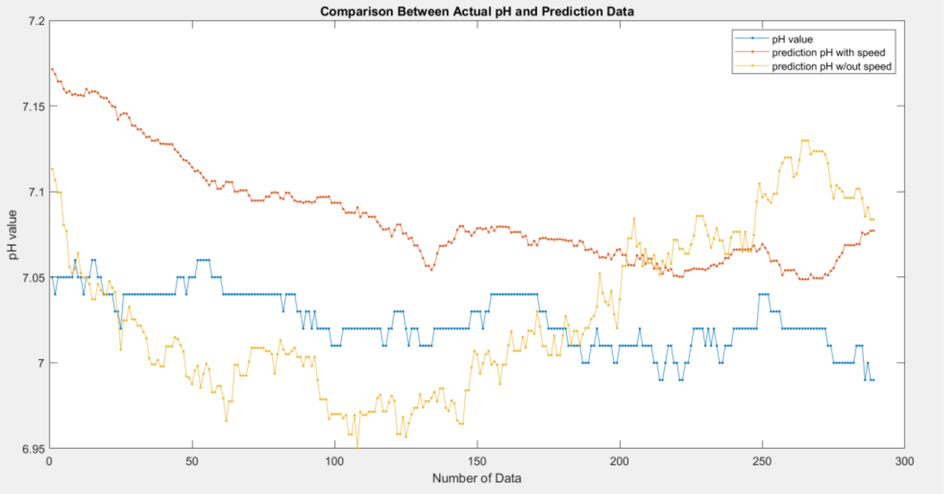

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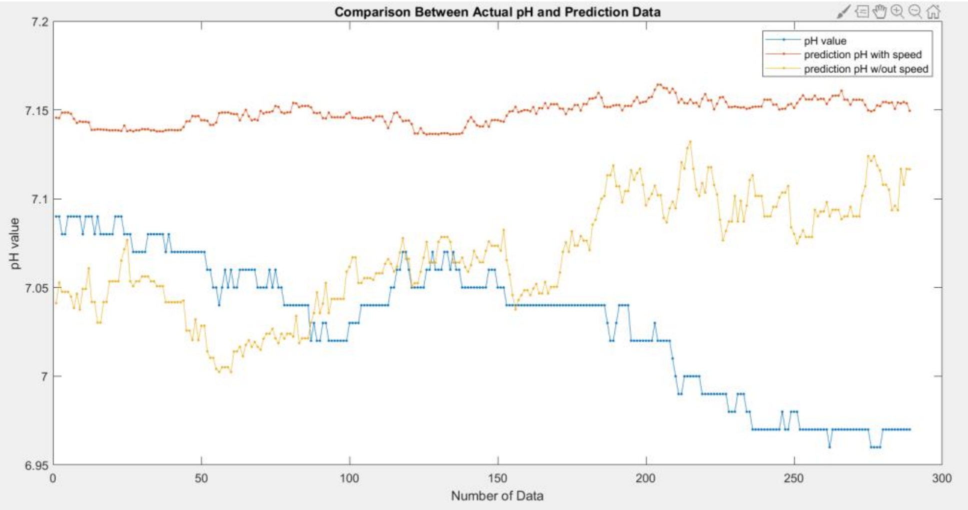

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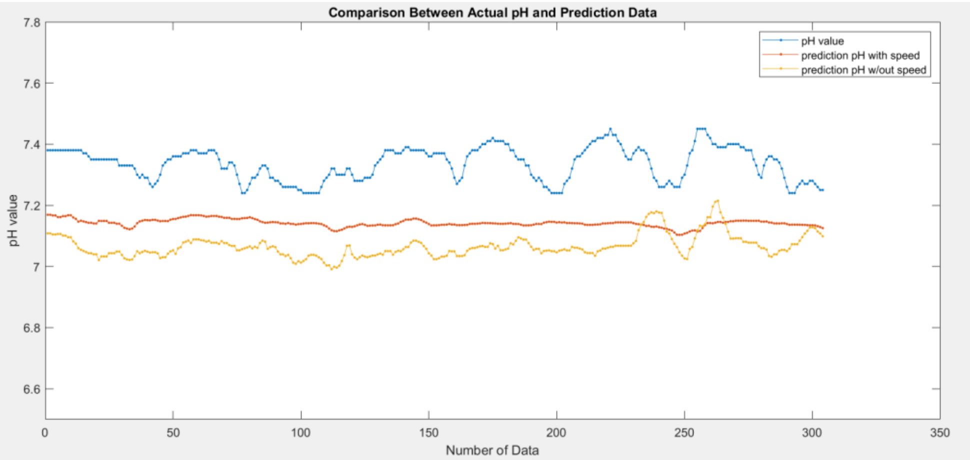

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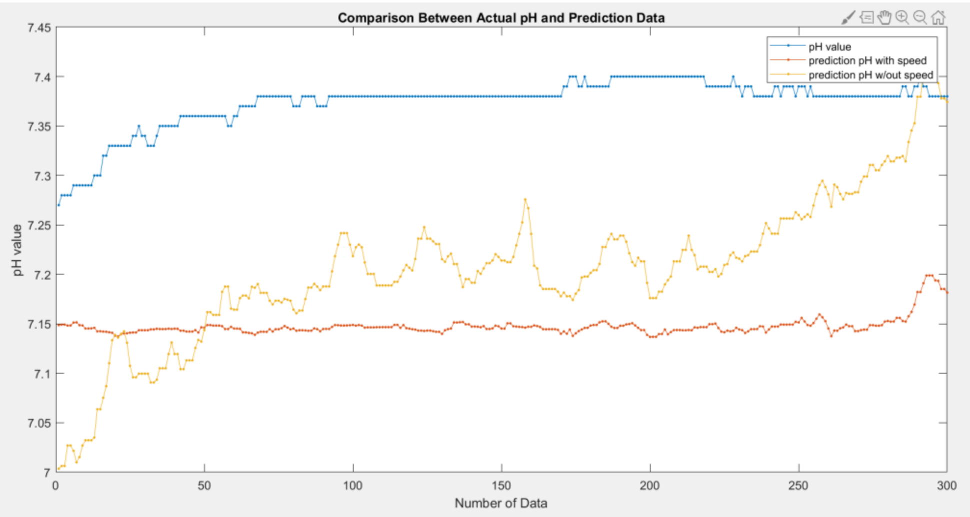

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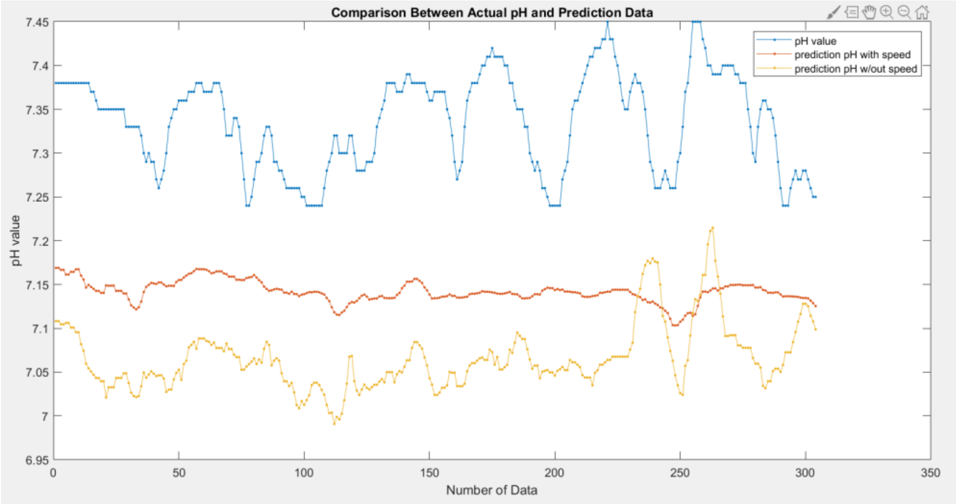

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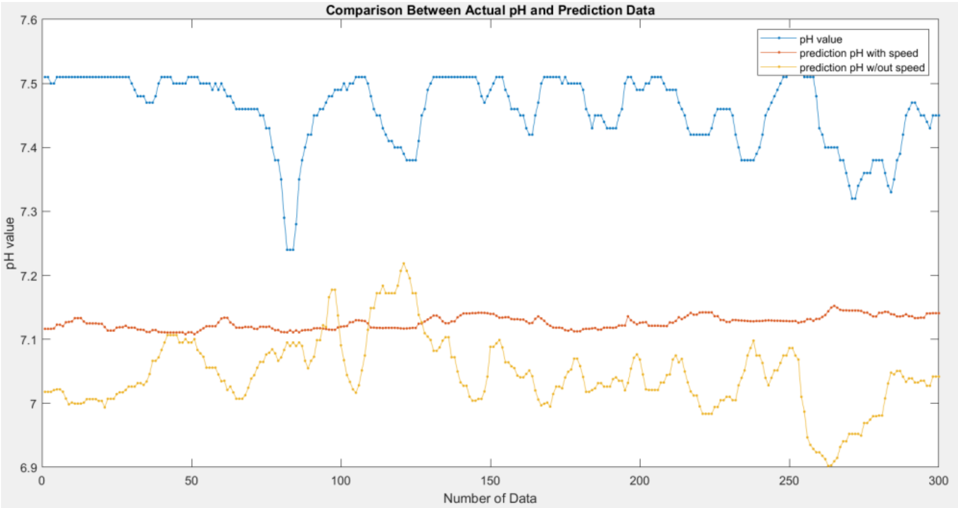

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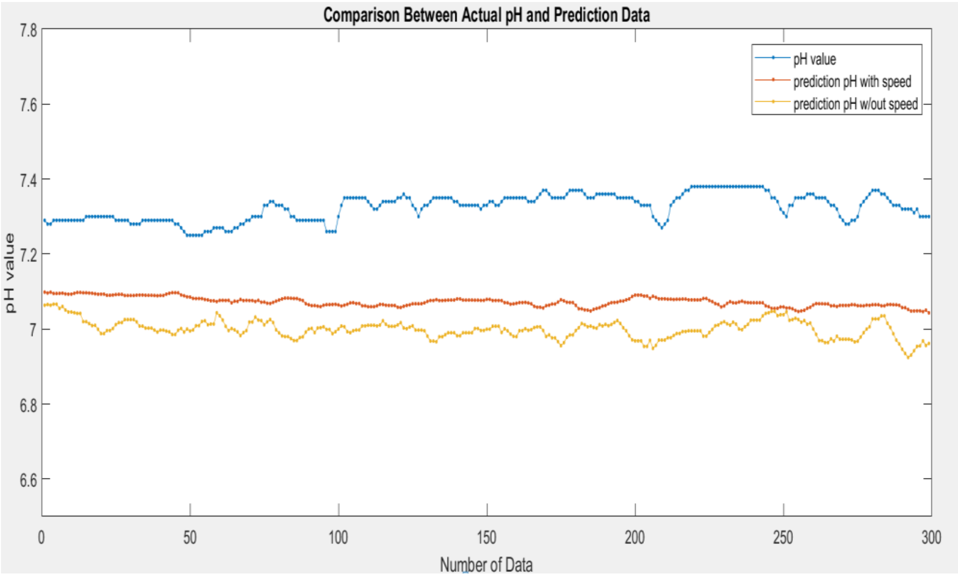

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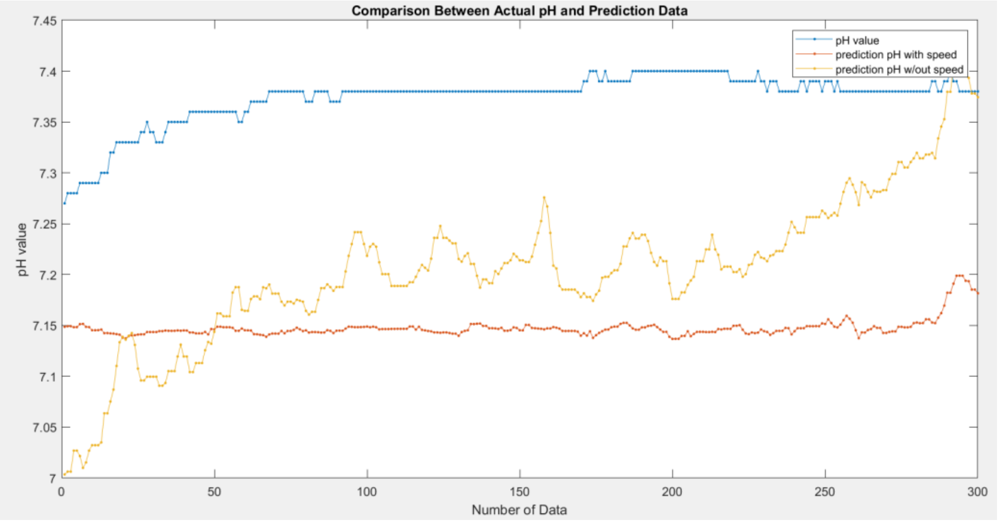

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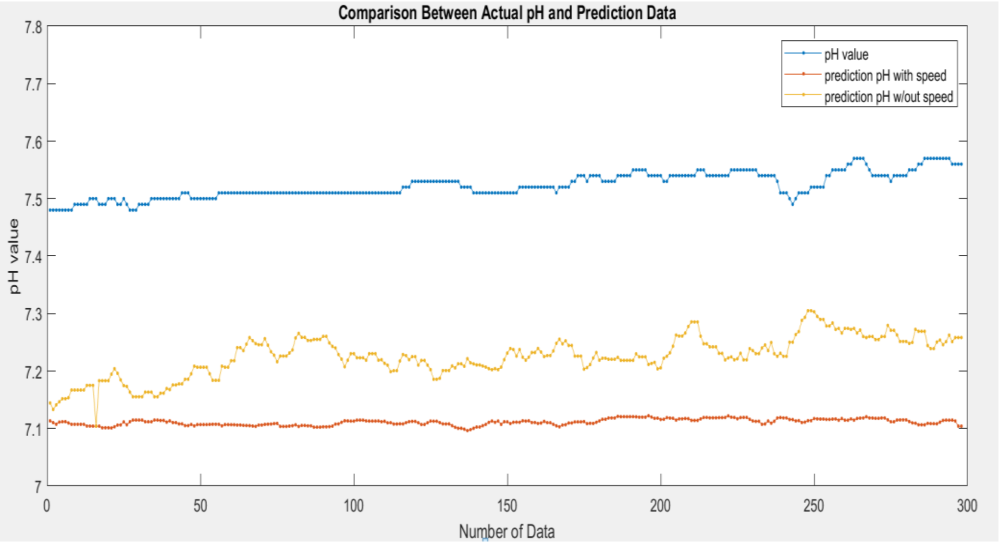

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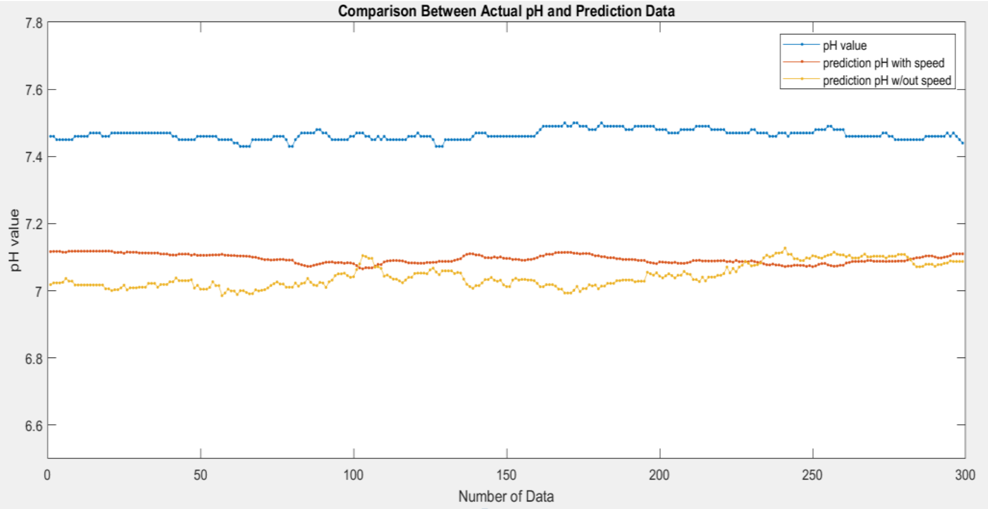

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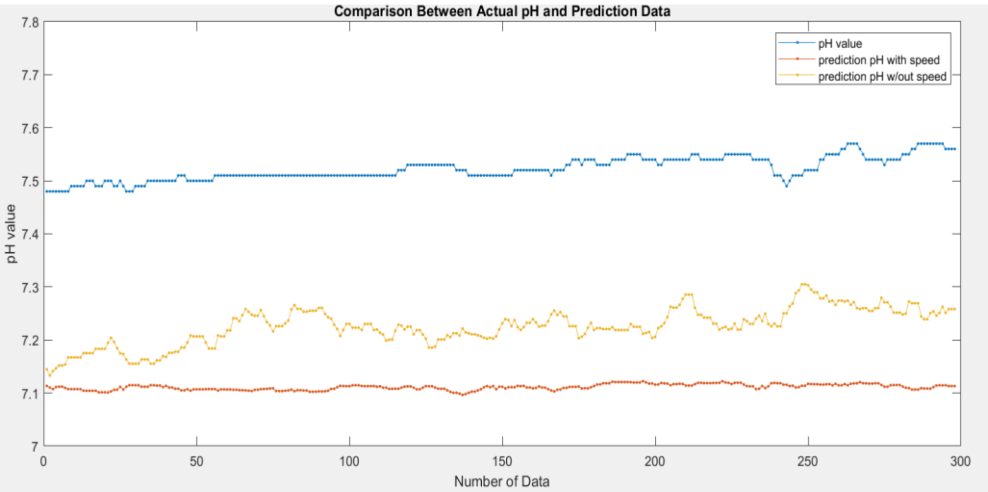

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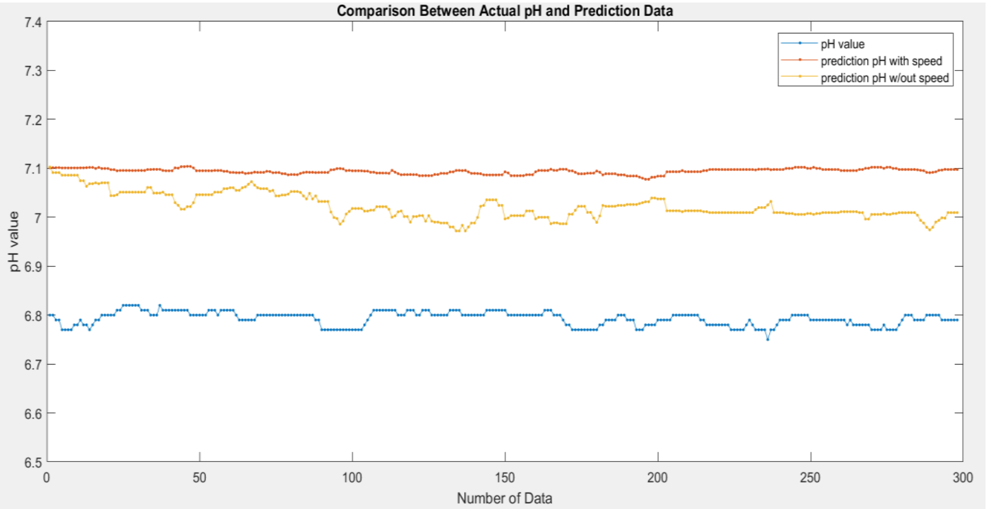

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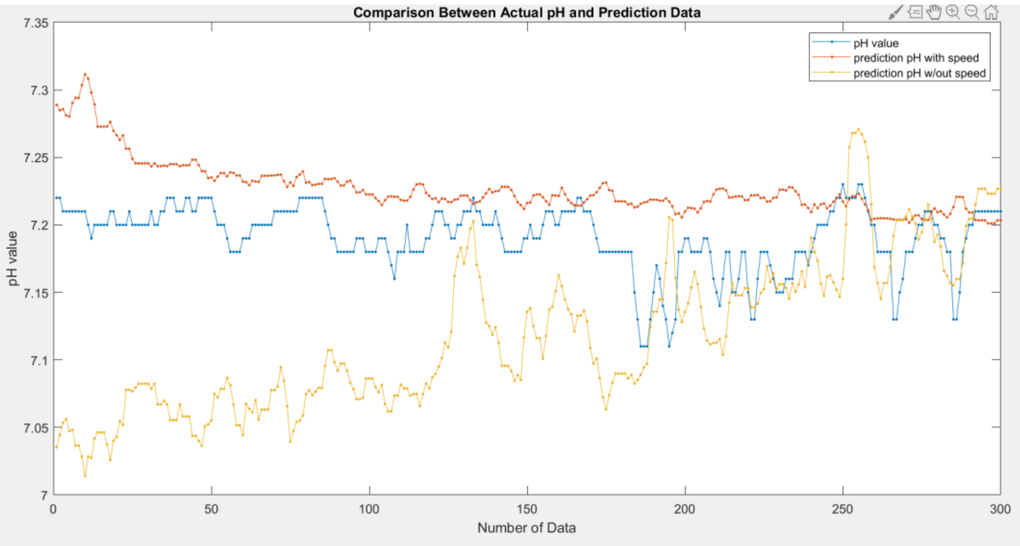

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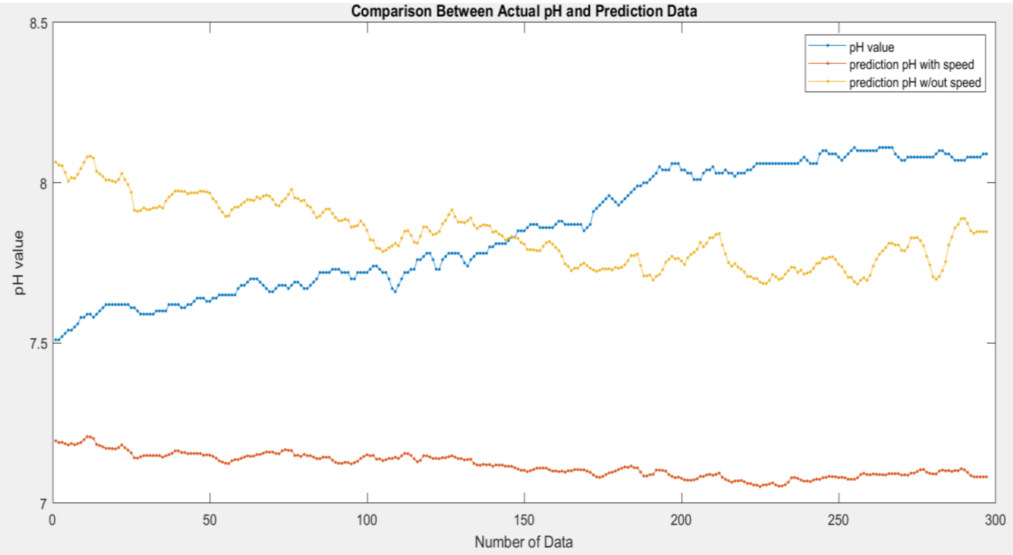

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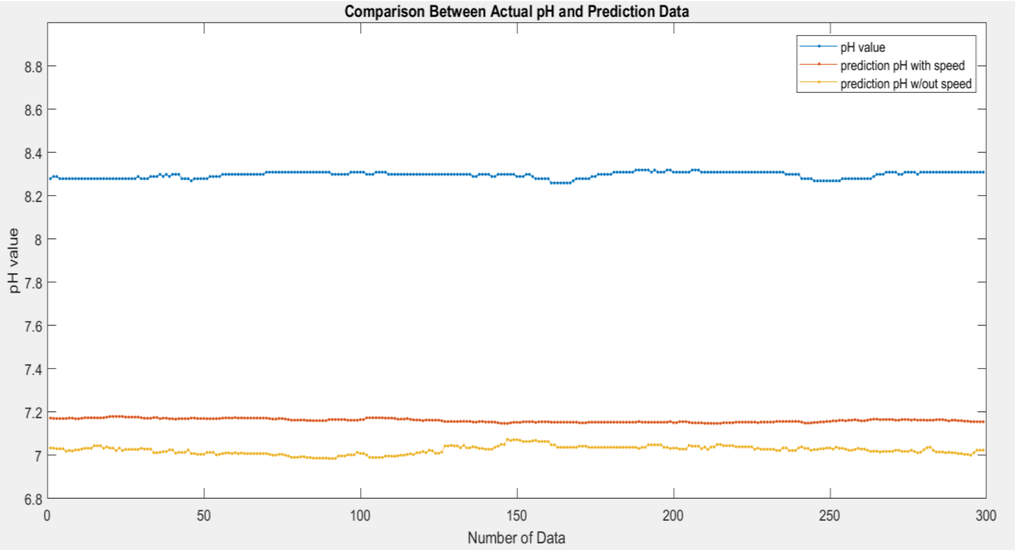

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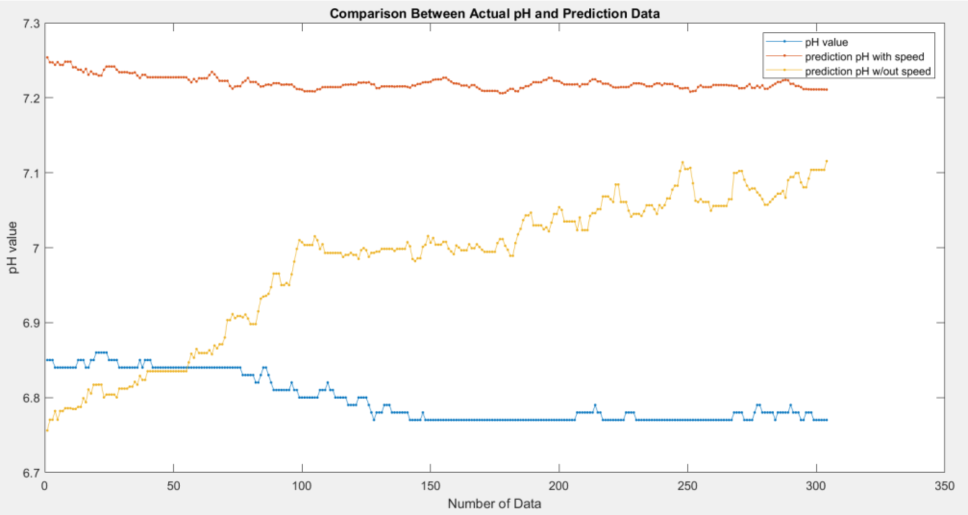

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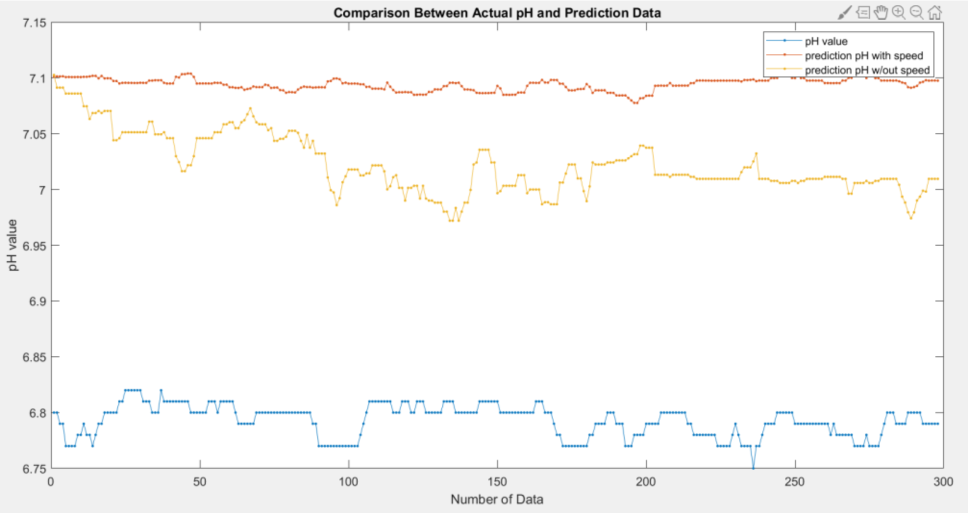

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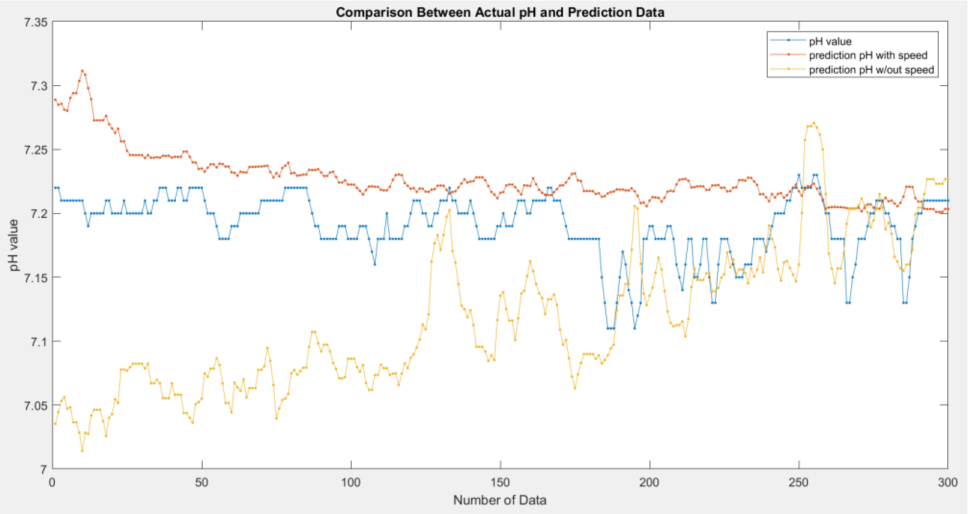

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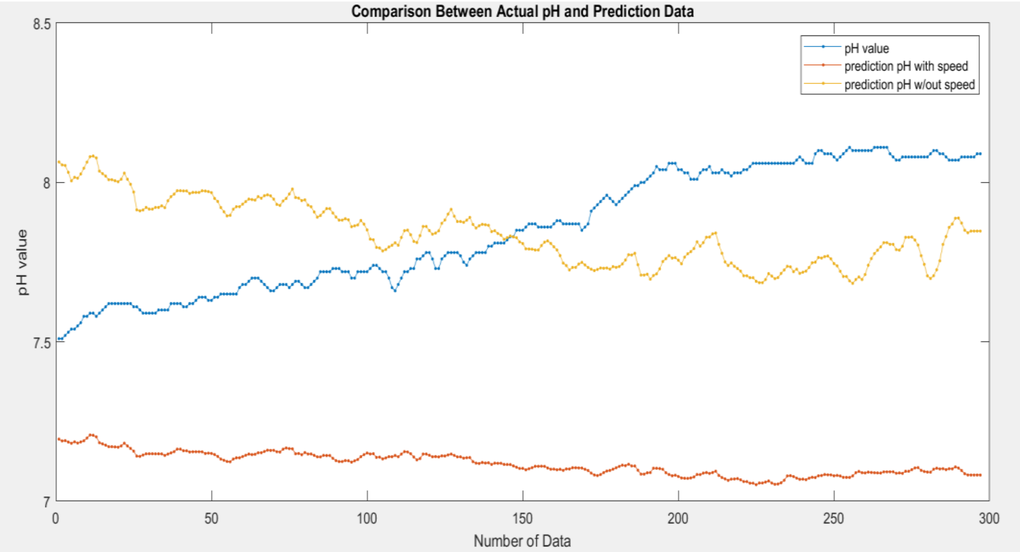

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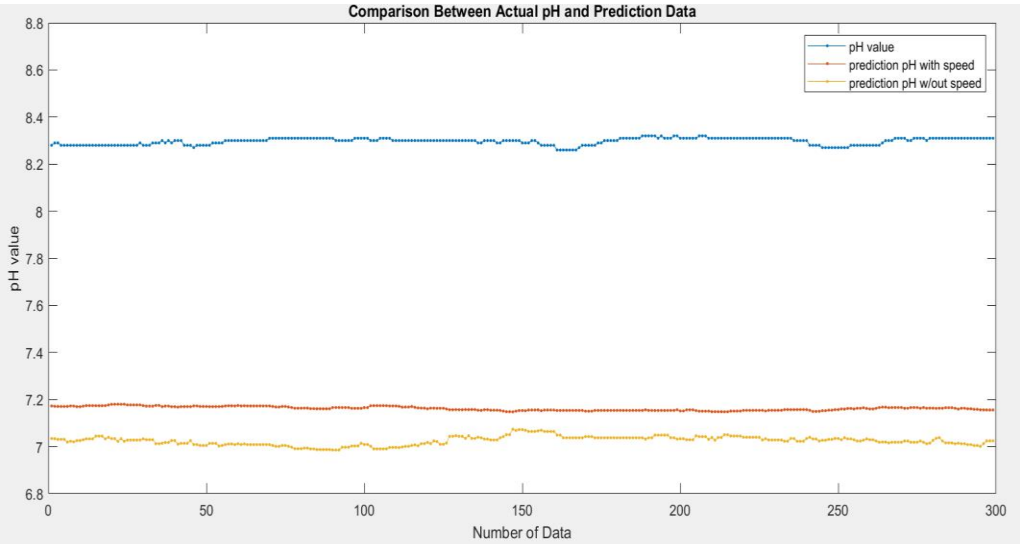

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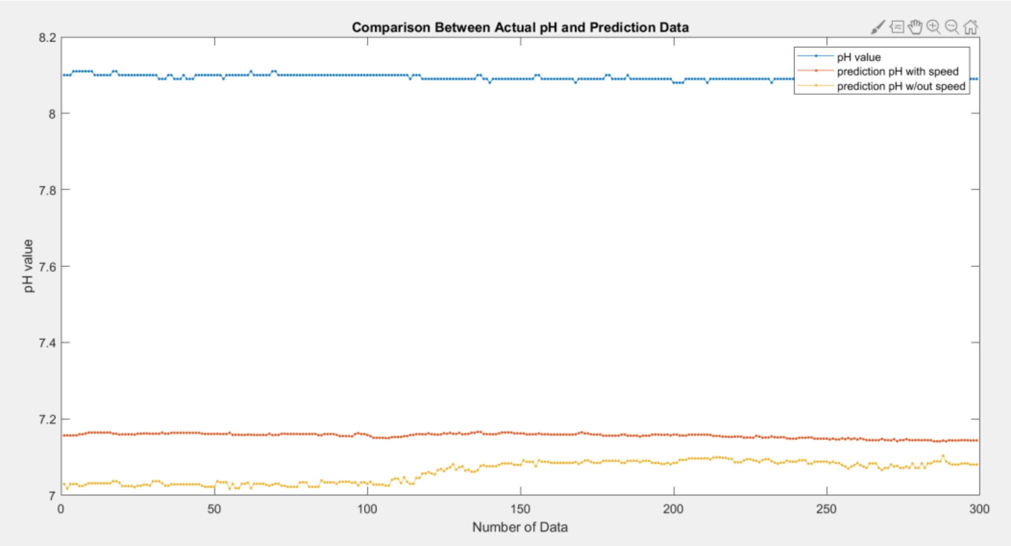

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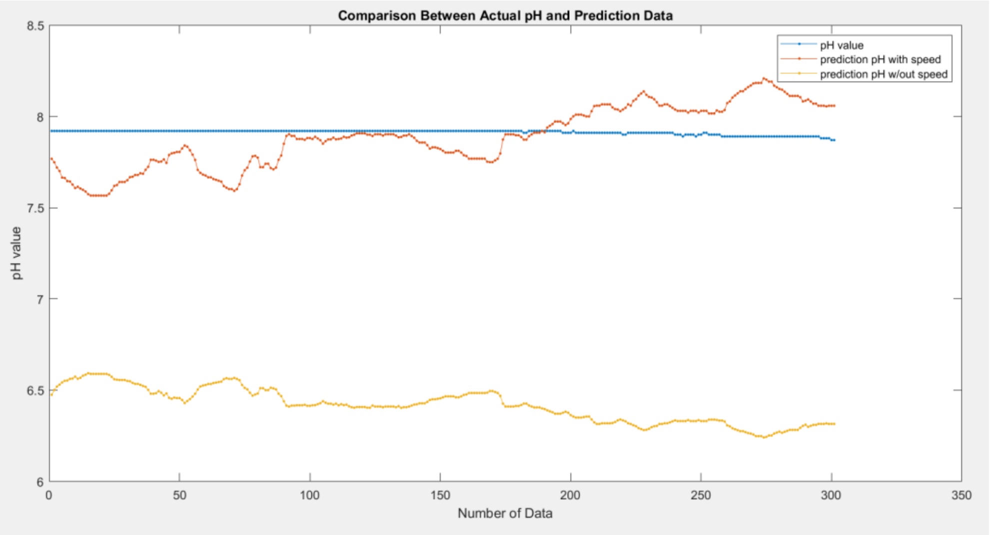

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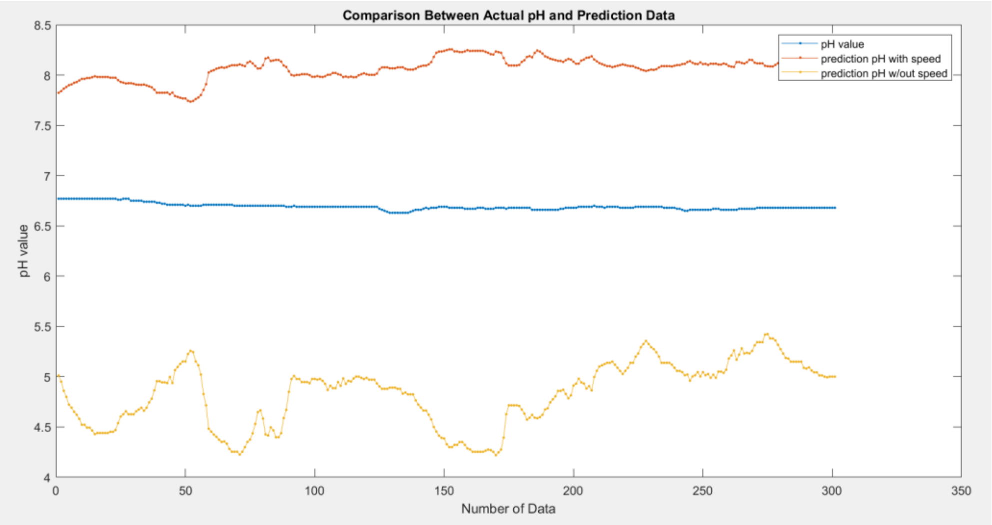

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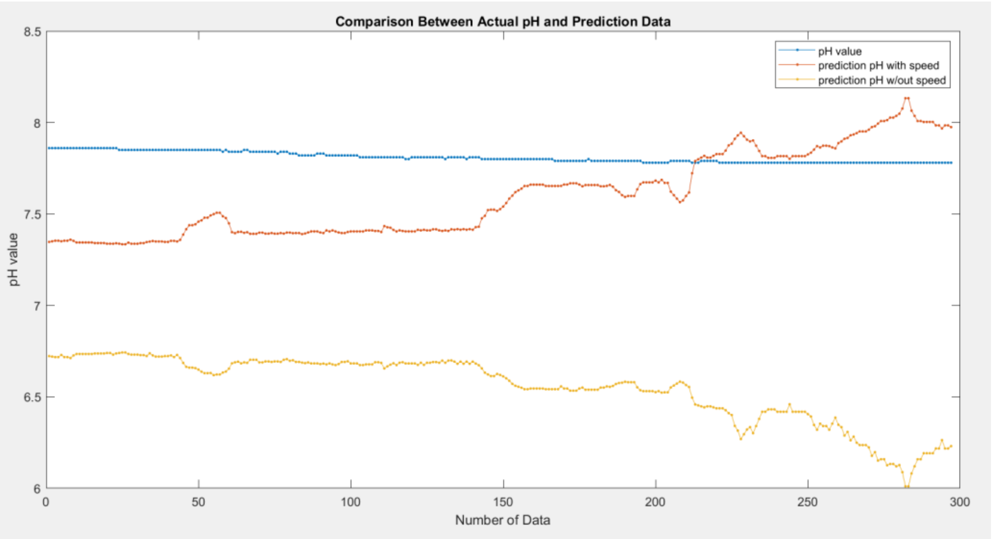

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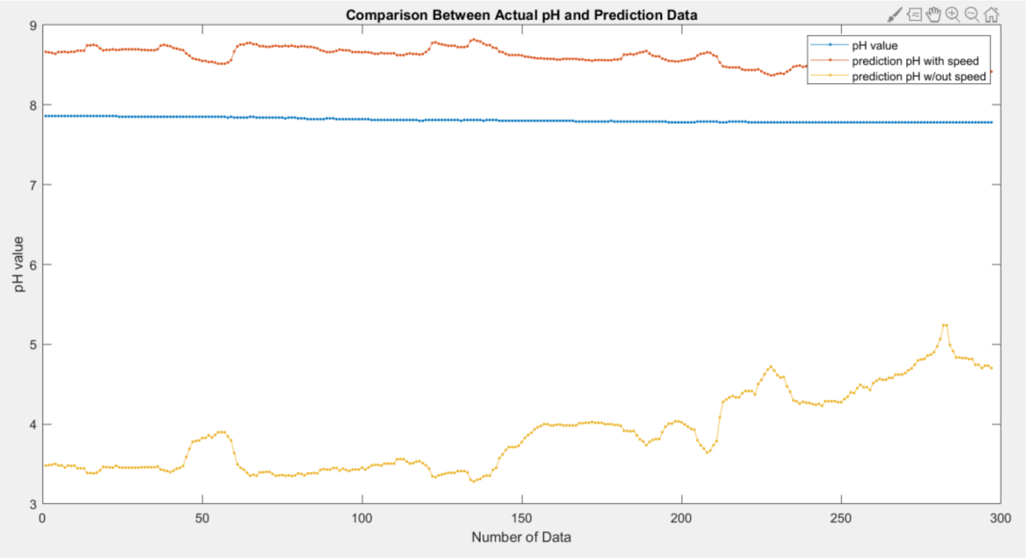

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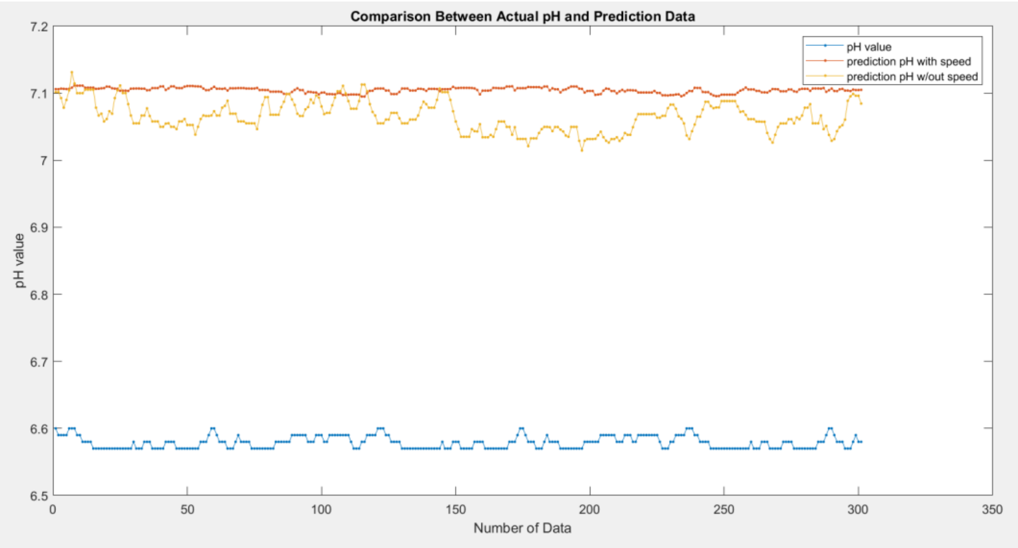

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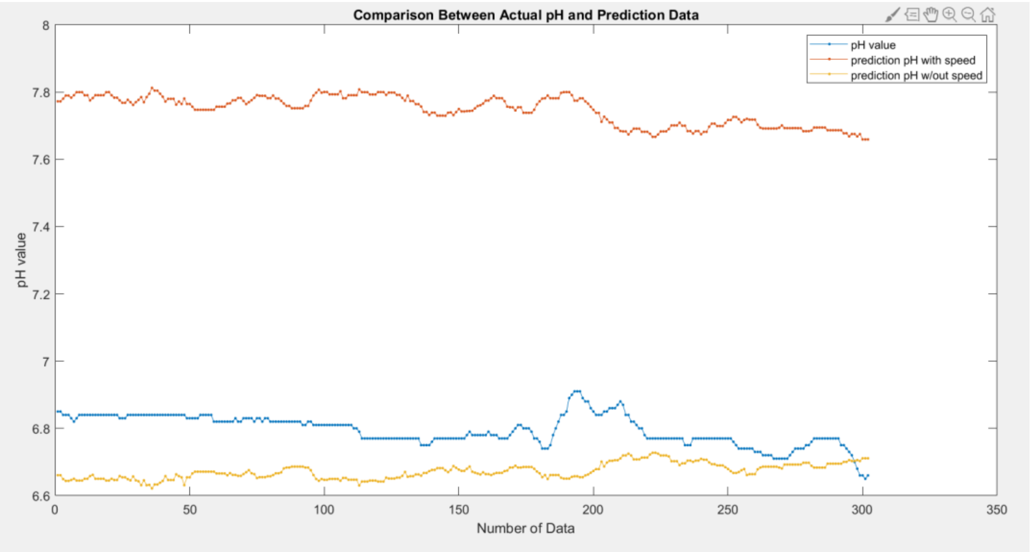

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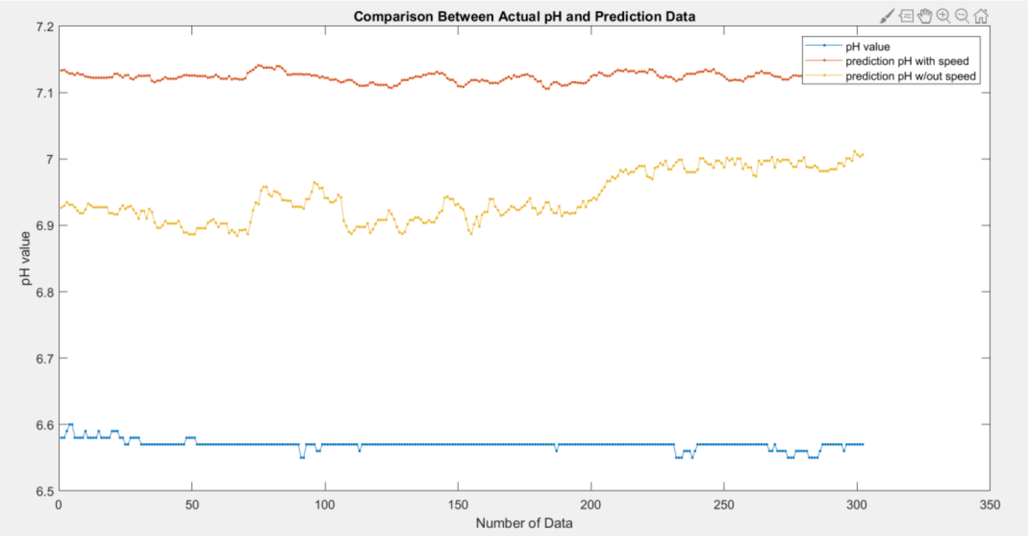

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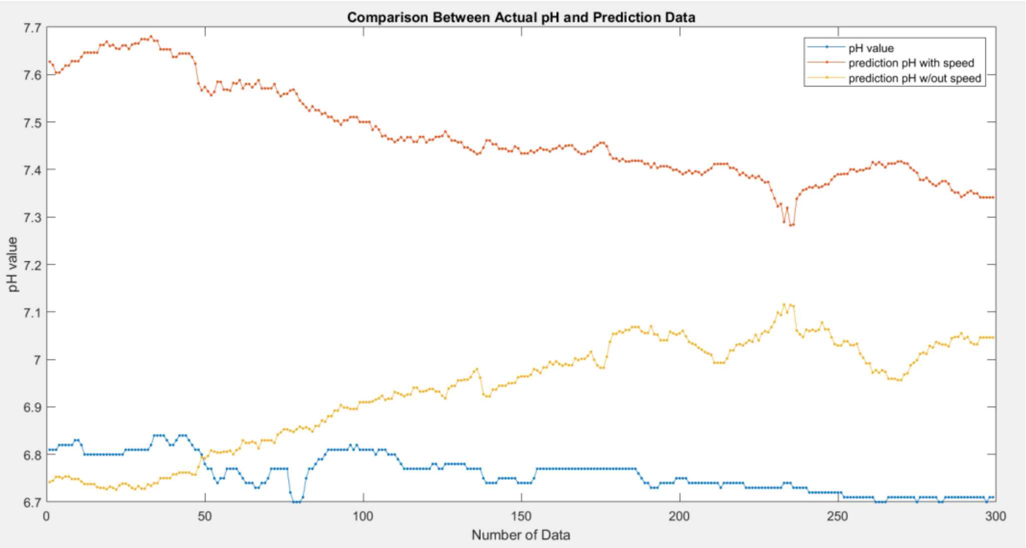

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