

EVALUATION OF TURBIDITY MEASURING USING IOT BASED SENSORS

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DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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This thesis is the result of my own investigation, except where otherwise stated.

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TABLE OF CONTENT

DECLARATION	ii
ACKNOWLEDGEMENT	iii
TABLE OF CONTENT	iv
LIST OF FIGURES	vi
LIST OF TABLES	ix
LIST OF ABBREVIATIONS	xi
ABSTRAK	xii
ABSTRACT	xiii
CHAPTER 1 INTRODUCTION	1
1.1 Project Background.....	1
1.2 Problem Statement.....	5
1.3 Project Objectives.....	5
1.4 Scope of Project.....	6
1.5 Thesis Outline.....	6
CHAPTER 2 LITERATURE REVIEW	8
2.1 Water Quality Standard in Malaysia.....	8
2.2 IoT water quality monitoring system.....	10
2.3 Water Quality Prediction.....	13
2.4 Turbidity measurement.....	14
2.5 Fouling effect on the sensors.....	15
CHAPTER 3 METHODOLOGY	17
3.1 Overview.....	17
3.2 Deriving New Turbidity-Voltage Conversion Formula for Turbidity Sensor ...	17
3.3 Repetitive Turbidity Measurement on Calcium Carbonate Solution.....	20
3.4 Repetitive Turbidity Measurement on Pure Water.....	23
3.5 Time-Based Turbidity Measurement on Calcium Carbonate Solution.....	23
3.6 Time-Based Turbidity Measurement on Oil Emulsion.....	24
3.7 Time-Based Turbidity Measurement on Dye Solution.....	25
3.8 Time-Based Turbidity Measurement on Protein Emulsion.....	25

CHAPTER 4 RESULT AND DISCUSSION.....	26
4.1 Deriving New Turbidity Voltage Conversion Formula for Turbidity Sensor....	26
4.2 Repetitive Turbidity Measurement on Calcium Carbonate Solution	32
4.3 Repetitive Turbidity Measurement on Pure Water	38
4.4 Comparison between Turbidity Sensors	45
4.5 Time-Based Turbidity Measurement on Calcium Carbonate Solution	47
4.6 Time-Based Turbidity Measurement on Oil Emulsion	52
4.7 Time-Based Turbidity Measurement on Dye Solution	63
4.8 Time-Based Turbidity Measurement on Protein Emulsion.....	74
CHAPTER 5 CONCLUSION AND FUTURE WORK.....	87
5.1 Conclusion.....	87
5.2 Future Work	89
REFERENCES.....	90
APPENDIX A	94
APPENDIX B	96
APPENDIX C	97

LIST OF FIGURES

Figure 1.1: Arduino UNO Wi-Fi Rev.2 board.....	4
Figure 2.1: Composition for each class of water (Part 1).....	8
Figure 2.2: Composition for each class of water (Part 2).....	9
Figure 2.3: Water classes and their uses	10
Figure 3.1: Hanna Instruments HI98703 Precision Turbidity Portable Meter.....	19
Figure 3.2: Arduino coding for obtaining the output voltage of the turbidity sensor	20
Figure 3.3: Arduino coding for obtaining output voltage and turbidity value from turbidity sensor.....	22
Figure 3.4: Setup for time-based turbidity measurement on calcium carbonate solution	23
Figure 3.5: Setup for time-based turbidity measurement on oil emulsion.....	24
Figure 4.1: Graph of turbidity meter reading against volume of CaCO_3 (deriving formula)	27
Figure 4.2: Graph of turbidity sensor A output voltage against volume of CaCO_3 (deriving formula).....	28
Figure 4.3: Graph of turbidity sensor B output voltage against volume of CaCO_3 (deriving formula).....	28
Figure 4.4: Graph of turbidity sensor C output voltage against volume of CaCO_3 (deriving formula).....	29
Figure 4.5: MATLAB script to compute the gradient and coefficient (Part 1)	30
Figure 4.6: MATLAB script to compute the gradient and coefficient (Part 2)	31
Figure 4.7: Result from the computation	31
Figure 4.8: Graph of turbidity meter reading against volume of CaCO_3 (validation)	34
Figure 4.9: Graph of turbidity sensor A against volume of CaCO_3 (validation)	34
Figure 4.10: Graph of turbidity sensor B reading against volume of CaCO_3 (validation)	35
Figure 4.11: Graph of measured turbidity reading against actual turbidity reading	35
Figure 4.12: Turbidity bottle for the turbidity meter	37
Figure 4.13: Distribution graph for output voltage from Sensor A (pure water).....	38
Figure 4.14: Distribution graph for turbidity from sensor A (pure water).....	39

Figure 4.15: Distribution graph for output voltage from Sensor C (pure water).....	40
Figure 4.16: Distribution graph for turbidity from Sensor C (pure water).....	40
Figure 4.17: Distribution graph for output voltage from Sensor D (pure water).....	41
Figure 4.18: Distribution graph for turbidity from Sensor D (pure water).....	42
Figure 4.19: Boxplot for output voltage measured from the turbidity sensors (pure water)	45
Figure 4.20: Boxplot for turbidity measured from the turbidity sensors (pure water)	46
Figure 4.21: Graph of turbidity sensor A output voltage against time (calcium carbonate)	47
Figure 4.22: Graph of turbidity sensor A turbidity against time (calcium carbonate).....	48
Figure 4.23: Graph of turbidity sensor B output voltage against time (calcium carbonate)	48
Figure 4.24: Graph of sensor B turbidity against time (calcium carbonate).....	49
Figure 4.25: Graph of mean output voltage against volume of oil	52
Figure 4.26: Graph of turbidity against volume of oil	53
Figure 4.27: Graph of output voltage against time on oil emulsion (Set A).....	54
Figure 4.28: Graph of turbidity against time on oil emulsion (Set A).....	55
Figure 4.29: Graph of output voltage against time on oil emulsion (Set B).....	56
Figure 4.30: Graph of turbidity against time on oil emulsion (Set B)	56
Figure 4.31: Graph of output voltage against time on oil emulsion (Set C).....	57
Figure 4.32: Graph of turbidity against time on oil emulsion (Set C)	58
Figure 4.33: Graph of mean output voltage against volume of dye.....	63
Figure 4.34: Graph of turbidity against volume of dye	64
Figure 4.35: Graph of output voltage against time on dye solution (Set A).....	65
Figure 4.36: Graph of turbidity against time on dye solution (Set A)	66
Figure 4.37: Graph of output voltage against time on dye solution (Set B).....	67
Figure 4.38: Graph of turbidity against time on dye solution (Set B)	67
Figure 4.39: Graph of output voltage against time on dye solution (Set C).....	68
Figure 4.40: Graph of turbidity against time on dye solution (Set C)	69

Figure 4.41: Graph of mean output voltage against volume of protein	74
Figure 4.42: Graph of mean output voltage against volume of protein	75
Figure 4.43: Formation of bubbles when mixing albumin with water	76
Figure 4.44: Graph of output voltage against time on protein emulsion (Set A).....	77
Figure 4.45: Graph of turbidity against time on protein emulsion (Set A).....	78
Figure 4.46: Graph of output voltage against time on protein emulsion (Set B).....	79
Figure 4.47: Graph of turbidity against time on protein emulsion (Set B).....	80
Figure 4.48: Graph of output voltage against time on protein emulsion (Set C).....	81
Figure 4.49: Graph of turbidity against time on protein emulsion (Set C).....	82

LIST OF TABLES

Table 1.1: Details of sensors used in IoT water quality monitoring system.....	3
Table 3.1: Ratio for calcium carbonate liquid solutions.....	18
Table 3.2: Ratio for calcium carbonate liquid solutions (validation).....	21
Table 3.3: Ratio for oil emulsion liquid solutions (validation).....	24
Table 3.4: Ratio for dye solution liquid solutions (validation).....	25
Table 3.5: Ratio for protein emulsion liquid solutions (validation).....	25
Table 4.1: Turbidity meter reading (deriving formula).....	26
Table 4.2: Turbidity sensor reading (deriving formula).....	27
Table 4.3: Turbidity meter reading (validation).....	32
Table 4.4: Turbidity sensor A reading (validation).....	32
Table 4.5: Turbidity sensor B reading (validation).....	33
Table 4.6: Average for turbidity sensors' output voltage and turbidity reading.....	33
Table 4.7: Percentage error between the actual turbidity and measured turbidity (validation).....	36
Table 4.8: Statistical analysis for Sensor A (pure water).....	39
Table 4.9: Statistical analysis for Sensor C (pure water).....	41
Table 4.10: Statistical analysis for Sensor D (pure water).....	42
Table 4.11: Transition process of the calcium carbonate liquid solution.....	50
Table 4.12: Overview for time-based turbidity measurement on oil emulsion.....	52
Table 4.13: Statistical analysis for Set A (oil emulsion).....	55
Table 4.14: Statistical analysis for Set B (oil emulsion).....	57
Table 4.15: Statistical analysis for Set C (oil emulsion).....	58
Table 4.16: Transition process of the oil emulsion liquid solution.....	60
Table 4.17: Overview for time-based turbidity measurement on dye solution.....	63
Table 4.18: Statistical analysis for Set A (dye solution).....	66
Table 4.19: Statistical analysis for Set B (dye solution).....	68
Table 4.20: Statistical analysis for Set C (dye solution).....	69

Table 4.21: Transition process of the dye solution liquid solution.....	71
Table 4.22: Overview for prolong turbidity measurement on protein emulsion	74
Table 4.23: Statistical analysis for Set A (protein emulsion)	78
Table 4.24: Statistical analysis for Set B (protein emulsion).....	80
Table 4.25: Statistical analysis for Set C (protein emulsion).....	82
Table 4.26: Transition process of the protein emulsion liquid solution	84

LIST OF ABBREVIATIONS

IoT	Internet of Things
TDS	Total dissolved solids
DO	Dissolved oxygen
EC	Electrical conductivity
NTU	Nephelometric Turbidity Unit
IQR	Interquartile Range
ESN	Echo state network
PP	Polypropylene

ABSTRAK

Air memainkan banyak peranan yang penting dalam kehidupan seharian kita. Oleh itu, pemantauan kualiti air kita adalah penting. Terdapat banyak cara untuk memantau kualiti air kita dan sistem pemantauan kualiti IoT adalah salah satu kadah yang paling popular kerana sistem ini menawarkan pemantauan masa nyata terhadap kualiti air, kebolehan untuk mengakses data air daripada media penyimpanan dalam talian dan kebolehan untuk menjadi alat kawalan jauh bagi sistem air. Untuk memastikan sistem ini menyampaikan fungsinya, ketepatan penderia adalah penting. Dalam kajian ini, keupayaan penderia untuk mengukur kekeruhan akan dinilai. Disebabkan bukti baharu ditemui, formula yang disediakan oleh pengilang adalah tidak tepat dan formula penukaran voltan-kekeruhan baharu diperlukan. Untuk mendapatkan formula baharu, penderia kekeruhan akan diuji dengan cecair yang mempunyai nilai kekeruhan yang diketahui. Selepas itu, dengan menggunakan formula baharu, prestasi penderia kekeruhan akan diuji dengan emulsi minyak, larutan pewarna, emulsi protein, kalsium karbonat dan air tulen. Selain itu, pengukuran kekeruhan berulang pada larutan kalsium carbonate dan air tulen berjaya dijalankan. Di samping itu, pengukuran kekeruhan berasaskan masa pada larutan kalsium karbonat, emulsi minyak, larutan pewarna dan emulsi protein telah dijalankan.

ABSTRACT

Water serves many important roles in our daily life. Thus, it is essential to monitor our water quality. IoT water quality monitoring system is one of the most popular method to track the water quality as it offers real-time monitoring and accessibility of data through cloud. To ensure the system delivers its function, the accuracy of the sensors is the key element that we must focus on. In this study, the turbidity sensor measuring capability is evaluated. Owing to new data attained, the formula provided by the manufacturer yielded poor accuracy and a new voltage-turbidity conversion formula is needed. The turbidity sensor will be tested with solution with known turbidity value and a new formula will be derived. After that, the turbidity sensor with the new formulation will be put under various turbidity measurements using oil emulsion, dye solution, protein emulsion, calcium carbonate solution and pure water to validate its performance. Besides that, the repetitive turbidity measurement on calcium carbonate solution and water is successfully carried out. Time-based turbidity measurement on calcium carbonate solution, oil emulsion, dye solution and protein emulsion are carried out.

CHAPTER 1

INTRODUCTION

1.1 Project Background

Water is crucial to our daily life. From keeping us alive to flushing our toilet, water plays many important roles in our life. Therefore, monitoring and maintaining the water quality is essential in sustaining the health of the ecosystem and population livelihood. To ensure the water is up to good standard, water quality measurement must be carried out from time to time at water system to allow authorities to study and treat the water accordingly in making sure the water is usable.

Water quality measurement extracts water quality parameter from the water to determine its water quality. Some example for these water quality parameters are turbidity, pH, total dissolved solid (TDS), dissolved oxygen (DO), electrical conductivity (EC) and so on. Turbidity is the amount of solid matter (particles or colloids) suspended in water that obstruct light transmission. In simple words, it measures the cloudiness of the water. pH is defined as the effective hydrogen-ion concentration in the water. The lower the pH, the more acidic the water is said to be. TDS is the amount of inorganic salt and small organic matter present in the water. DO is the amount of dissolved oxygen in the water. EC is the ability of an aqueous solution to transfer an electric current. [1]

These water quality parameters are very useful as variation of these parameters over the normal level indicates that there might be some problems with the water. For instance, water might have excessive algae growth if DO of the water is too high. [2] Besides that,

if there is sudden increase in the water turbidity, this might indicate that the water has been contaminated with bacteria [3]. Therefore, it is important that the water quality measurement can be carried out as frequent as possible and at the same time making sure that the result obtained is accurate.



There are many ways where the water quality measurement can be carried out. There are traditional lab-based methods and deployment of water quality monitoring system. In today's world, the deployment of water quality monitoring system becomes the much more favourable way to measure the water quality. This is because traditional lab-based methods such as UV Measurement, Mass Spectrometry and Ion Sensitive Electrodes require authorities to carry out water sampling on site and bring the samples back to the lab for testing [2]. It is time-consuming, technical training required and does not offer real time data. Thus, deployment of water quality monitoring system becomes the most popular method recently as it can carry out real-time monitoring on the water quality and less labour intensive [4]. Water quality monitoring system relies on various sensors to collect the essential water quality parameter and feedback to the main system.

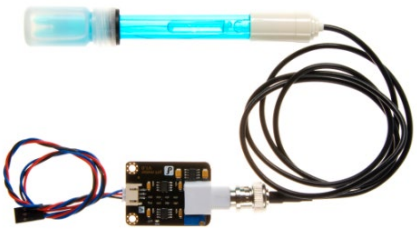

As good as the water quality monitoring system seems to be, there are still some limitations such as it requires physical presence of workers to control the system and the water data can only be accessed at the place where the water quality monitoring system is installed. Therefore, to further improve the capabilities of these water quality monitoring system, various researchers have tried to integrate Internet of Things (IoT) into these systems and the result is quite promising. The addition of IoT enables the water quality monitoring system to be controlled remotely and the data collected can be accessed

remotely. Although the outcomes are promising, there are a lot of efforts to be carried out in making sure the system works perfectly while still maintaining a good accuracy.

In this project, the IoT water quality monitoring system that is selected for this project is the IoT water quality monitoring system developed in the collaboration research project of various researcher from NICT and ASEAN IVO which is “IoT system for Water Reuse in Developing Cities” [5]. It consists of water level sensor, turbidity sensor, pH sensor and EC sensor to collect the water quality parameter. Table 1.1 below shows the sensor used and the specification of these sensors are attached in Appendix A.

Table 1.1: Details of sensors used in IoT water quality monitoring system

Sensor	Details
Water Level Sensor	<p data-bbox="558 968 1406 1003">DFRobot SEN0204 Non-Contact Liquid Level Sensor XKC-Y25-</p> <p data-bbox="922 1041 1040 1077">T12V [6]</p> 
Turbidity Sensor	<p data-bbox="721 1419 1243 1455">DFRobot SEN0189 Turbidity Sensor [7]</p> 

pH Sensor	<p style="text-align: center;">DFRobot SEN0161 pH meter [8]</p> 
EC Sensor	<p style="text-align: center;">DFRobot DFR0300 Gravity Analog Electrical Conductivity Sensor Meter V2 (K=1) [9]</p> 

All these sensors are connected to a microcontroller board which is Arduino UNO Wi-Fi Rev.2 board [10] that reads, processes and uploads the sensor data to ThingSpeak. The specification of this microcontroller is attached in Appendix B.



Figure 1.1: Arduino UNO Wi-Fi Rev.2 board

ThingSpeak is an IoT cloud platform where user can send sensor data to the cloud as well as analyse and visualize the data with MATLAB or other software [11]. However, the focus

of this study is only on the turbidity sensor. Throughout this experiment study, the turbidity measuring capability of this IoT water quality monitoring system will be evaluated.

1.2 Problem Statement

Water quality monitoring system is a crucial system in any water system as it monitors water parameters (i.e., turbidity, EC, etc.) and feedbacks to the authorities. It is important for the system to provide accurate readings on these water parameters as these water parameters determine the water quality. Based on the study done by Wong et al. [12], it is found that the turbidity sensor used in the IoT water quality monitoring system should exhibit linear behaviour for the relationship between average voltage readings and average NTU readings. However, based on the manufacturer's claim, this relationship is supposed to be non-linear [7]. This inconsistency might cause the sensor to produce incorrect reading for the water and compromise the aim of this IoT water quality monitoring system.

1.3 Project Objectives

- i. To derive new voltage-turbidity conversion formula for the turbidity sensor
- ii. To evaluate the performance of the turbidity sensor with new formula

1.4 Scope of Project

This study will be focused on evaluating the turbidity measurement on the IoT water quality monitoring system developed for the “IoT system for Water Reuse in Developing Cities” project. Due to the new evidence found, new voltage-turbidity conversion formula for the turbidity sensor will be derived using experiment method. The turbidity sensor will be tested with solution with known turbidity value and a new formulation will be derived based on the voltage value obtained from the turbidity sensor and the known turbidity value. Next, the turbidity sensor with the new formulation will be put under various turbidity measurements to validate its performance with the new formulation. The liquid solutions used for the turbidity measurements are oil emulsion, dye solution, protein emulsion solution, calcium carbonate solution, and pure water. The sensor data will then be analysed.

1.5 Thesis Outline

The organization of this thesis is arranged into 5 chapters.

Chapter 1

- Introduces the importance of water, the need for water quality measurement system, water parameters, the need for IoT water quality monitoring system, IoT water quality monitoring system used for the project
- States the problem statement, objectives and scope of the project

Chapter 2

- Reviews the water quality standard in Malaysia, IoT water quality measurement system, turbidity measurement, turbidity sensing working mechanism, fouling effect on sensor

Chapter 3

- Describes the methodology of the project

Chapter 4

- Discuss the new turbidity sensor formulation and the turbidity sensor data from the experiment

Chapter 5

- Conclude about the project and future work to further improve the project

CHAPTER 2

LITERATURE REVIEW

2.1 Water Quality Standard in Malaysia

In Malaysia, the Department of Environment of Malaysia has established its own standards for water quality [13]. There are 5 classes for the water quality standard which are Class I, Class IIA/IIB, Class III, Class IV and Class V. Each class is split based on the tolerance for each of the water parameter. Due to different tolerance in water parameters, each class of water has different usages. Figures 2.1, 2.2 and 2.3 below show the complete details of the water quality standards implemented in Malaysia.

NATIONAL WATER QUALITY STANDARDS FOR MALAYSIA (cont.)

PARAMETER	UNIT	CLASS					
		I	IIA	IIB	III	IV	V
Ammoniacal Nitrogen	mg/l	0.1	0.3	0.3	0.9	2.7	> 2.7
Biochemical Oxygen Demand	mg/l	1	3	3	6	12	> 12
Chemical Oxygen Demand	mg/l	10	25	25	50	100	> 100
Dissolved Oxygen	mg/l	7	5 - 7	5 - 7	3 - 5	< 3	< 1
pH	-	6.5 - 8.5	6 - 9	6 - 9	5 - 9	5 - 9	-
Colour	TCU	15	150	150	-	-	-
Electrical Conductivity*	µS/cm	1000	1000	-	-	6000	-
Floatables	-	N	N	N	-	-	-
Odour	-	N	N	N	-	-	-
Salinity	ppt	0.5	1	-	-	2	-
Taste	-	N	N	N	-	-	-
Total Dissolved Solid	mg/l	500	1000	-	-	4000	-
Total Suspended Solid	mg/l	25	50	50	150	300	300
Temperature	°C	-	Normal + 2 °C	-	Normal + 2 °C	-	-
Turbidity	NTU	5	50	50	-	-	-
Faecal Coliform**	count/100 ml	10	100	400	5000 (20000) ^a	5000 (20000) ^a	-
Total Coliform	count/100 ml	100	5000	5000	50000	50000	> 50000

Notes :

N : No visible floatable materials or debris, no objectional odour or no objectional taste

* : Related parameters, only one recommended for use

** : Geometric mean

a : Maximum not to be exceeded

Figure 2.1: Composition for each class of water (Part 1)

NATIONAL WATER QUALITY STANDARDS FOR MALAYSIA

PARAMETER	UNIT	CLASS				
		I	IIA/IIIB	III*	IV	V
Al	mg/l	↑	-	(0.06)	0.5	↑
As	mg/l		0.05	0.4 (0.05)	0.1	
Ba	mg/l		1	-	-	
Cd	mg/l		0.01	0.01* (0.001)	0.01	
Cr (VI)	mg/l		0.05	1.4 (0.05)	0.1	
Cr (III)	mg/l		-	2.5	-	
Cu	mg/l		0.02	-	0.2	
Hardness	mg/l		250	-	-	
Ca	mg/l		-	-	-	
Mg	mg/l		-	-	-	
Na	mg/l	-	-	3 SAR	↓	
K	mg/l	-	-	-		
Fe	mg/l	1	1	1 (Leaf) 5 (Others)		
Pb	mg/l	0.05	0.02* (0.01)	5		
Mn	mg/l	0.1	0.1	0.2		
Hg	mg/l	0.001	0.004 (0.0001)	0.002		
Ni	mg/l	0.05	0.9 [#]	0.2		
Se	mg/l	0.01	0.25 (0.04)	0.02		
Ag	mg/l	0.05	0.0002	-		
Sn	mg/l	-	0.004	-		
U	mg/l	-	-	-	↓	
Zn	mg/l	5	0.4 [#]	2		
B	mg/l	1	(3.4)	0.8		
Cl	mg/l	200	-	80		
Cl ₂	mg/l	-	(0.02)	-		
CN	mg/l	0.02	0.06 (0.02)	-		
F	mg/l	1.5	10	1		
NO ₂	mg/l	0.4	0.4 (0.03)	-		
NO ₃	mg/l	7	-	5		
P	mg/l	0.2	0.1	-		
Silica	mg/l	50	-	-	↓	
SO ₄	mg/l	250	-	-		
S	mg/l	0.05	(0.001)	-		
CO ₂	mg/l	-	-	-		
Gross-α	Bq/l	0.1	-	-		
Gross-β	Bq/l	1	-	-		
Ra-226	Bq/l	< 0.1	-	-		
Sr-90	Bq/l	< 1	-	-		
CCE	μg/l	500	-	-		
MBAS/BAS	μg/l	500	5000 (200)	-		
O & G (Mineral)	μg/l	40; N	N	-		
O & G (Emulsified Edible)	μg/l	7000; N	N	-		
PCB	μg/l	0.1	6 (0.05)	-		
Phenol	μg/l	10	-	-		
Aldrin/Dieldrin	μg/l	0.02	0.2 (0.01)	-		
BHC	μg/l	2	9 (0.1)	-		
Chlordane	μg/l	0.08	2 (0.02)	-		
t-DDT	μg/l	0.1	(1)	-		
Endosulfan	μg/l	10	-	-		
Heptachlor/Epoxide	μg/l	0.05	0.9 (0.06)	-		
Lindane	μg/l	2	3 (0.4)	-		
2,4-D	μg/l	70	450	-		
2,4,5-T	μg/l	10	160	-		
2,4,5-TP	μg/l	4	850	-		
Paraquat	μg/l	10	1800	-		

Notes:

* - At hardness 50 mg/l CaCO₃

- Maximum (unbracketed) and 24-hour average (bracketed) concentrations

N - Free from visible firm sheen, discoloration and deposits

Figure 2.2: Composition for each class of water (Part 2)

WATER CLASSES AND USES

CLASS	USES
Class I	Conservation of natural environment. Water Supply I – Practically no treatment necessary. Fishery I – Very sensitive aquatic species.
Class IIA	Water Supply II – Conventional treatment required. Fishery II – Sensitive aquatic species.
Class IIB	Recreational use with body contact.
Class III	Water Supply III – Extensive treatment required. Fishery III – Common, of economic value and tolerant species; livestock drinking.
Class IV	Irrigation
Class V	None of the above.

Figure 2.3: Water classes and their uses

2.2 IoT water quality monitoring system

Flynn et al. [14] has worked on Smart Coast, a wireless sensor network for water quality monitoring. Due to the increasing importance of water quality and implementation of Water Framework Directive (WFD), authorities at the water system are forced to abandon the traditional method of testing the water quality, which is analyzing the water samples at the laboratory and look for new method to do so. SmartCoast was one of the possible solutions to these water system managers. The aim of SmartCoast is to create a wireless sensor network that can carry out real-time water quality monitoring and enable users to access the data via internet. It features plug and play sensor interface and uses lower power communication protocol, Zigbee. Temporally, the SmartCoast is still under development and the water quality parameters that it can monitor are temperature, pH, conductivity, water depth, turbidity, phosphate content and dissolved oxygen in the water.

Lakshmikantha et al. [15] has noticed pollution of water is getting more serious these days and wanted to solve it by creating a IoT based smart water quality monitoring system that allows early detection of water pollution. With this early warning, suitable

countermeasures can be carried out to fix the pollution and water quality can be retained. They have proposed a cost effective IoT system that can measure pH, turbidity, temperature, conductivity, humidity, and carbon dioxide content in the water. This system is controlled Arduino ATMEGA328 and it will read the sensor data, compare it with the standard values and send the values to the authorities via the Wi-Fi module. If the sensor detects abnormal values from the water, a warning signal will be sent via the Wi-Fi module to the authorities so that further action can be taken. The developed model is tested with three different water samples.

Pasika et al. [16] has created a low-cost smart water quality monitoring system using IoT. They have discovered that there is a need to develop this system as the pollution and contamination in water becoming a very serious issue. Besides that, they also highlighted that the conventional water quality measurement is time-consuming and tedious as the water must be manually sampled and sent for examination in the laboratories. Therefore, they have created a system that integrates pH sensor, turbidity sensor, ultrasonic sensor and DHT-11 sensor to measure the water pH, turbidity of water, water level, and surrounding temperature and humidity. All these sensors are controlled by Arduino Mega, a microcontroller unit and the data are uploaded to cloud server, ThingSpeak via the data transmission module ESP8266 Wi-Fi module.

Shafi et al. [17] have proposed a surface water pollution detection using IoT. They have found out that Pakistan was facing serious declination of water quality due to the increasing activity in modernization and industrialization. As frightening as the issue seem to be, this problem continues worsen as Pakistan still relies on traditional systems which cannot provide real time water quality measurement. Therefore, Shafi et al. [17] have

proposed an IoT based water quality system that is capable of real-time monitoring on the water quality, store and transfer the water data to cloud as well as controlling the water flow through a mobile app. pH sensor, turbidity sensor and temperature sensor have been integrated into this system to collect important water quality parameter. Furthermore, they have created a predictive model for the system so that it can classify the water quality based on the collected data. Through their testing, deep neural network surpasses all other machine learning algorithms with an accuracy 93%.

Jerom B et al. [18] have proposed an IoT based smart water quality monitoring system using cloud. They have highlighted the current water problem and the ineffectiveness of the conventional water quality measurement process which does not provide real-time result. Thus, they have designed a low-cost IoT based system that allows real-time monitoring of water quality. The system comprises of a controller unit, battery and various sensors that can detect dissolved oxygen, temperature, humidity, pH, carbon dioxide, and soil moisture. The controller unit used here is NodeMCU and all components are encapsulated in a watertight buoy container. This floating buoy design allows easy deployment of the system and diverse extension. As it is floating on water surface collecting water data, it can communicate with other neighbour nodes via the wireless communication module on the controller unit, forming a huge network of water quality monitoring system. The data is stored in the cloud and machine learning techniques are used as a decision layer to predict the usability of the water.

2.3 Water Quality Prediction

Lessels et al. [19] have proposed a linear mixed model to estimate water quality using stream discharge and turbidity. Constantly extracting water parameters to determine water quality is extremely expensive. Therefore, estimation-based water quality monitoring becomes the more preferable way to determine the water quality. Lessels et al. [19] have assessed the ability of a linear mixed model to estimate the total phosphorus and nitrogen content of the catchments using stream discharge and turbidity data collected using non-probabilistic sampling. Through their effort, they have found that the prediction accuracy has been raised by 15% if the model is fed only with the turbidity data. However, they also found that the prediction will be more accurate when using both turbidity and stream discharge data in event based cross validation. They have highlighted more work have to be done to validate their results.

Zhou et al. [20] have worked on a water quality prediction method which based on multi-source transfer learning. Traditionally, water prediction method uses data from one monitoring data, ignoring data from nearby monitoring points. Therefore, Zhou et al. [20] have designed this water quality prediction method that can utilize the data from multiple nearby monitoring points. By doing so, the prediction accuracy can also be increased. Using feature extraction and alignment, the common water quality parameters from the desired monitoring point and its nearby monitoring point are obtained and aligned. Using the aligned features and disturbed computing, the prediction model is created which is based on Echo state network (ESN) on multiple nearby monitoring point. Optimization is

carried out on the prediction parameter and testing is carried out using the actual water quality dataset.

2.4 Turbidity measurement

Parra et al [21] has designed and developed a low-cost smart turbidity sensor that is able to differentiate the different types of turbidity for monitoring the water quality in fish farms. Based on Beer -Lambert law, the sensor is designed and houses 4 LEDs with different wavelength as the light sources. A photodiode and photoresistor are used as the light detector for this turbidity sensor and it is placed at 180° of the light sources. Calibration was carried out using different algae and sediments and an algorithm is derived for the turbidity sensor to characterize the turbidity samples based on the resistance on the light detector.

Lambrou et al. [22] has proposed a turbidity system to monitor the household drinking water quality. The working principle of this turbidity system is based on the concept that the intensity of light scattered by the suspended matter is proportional to its concentration. The designed turbidity system is portable, battery powered, user friendly and relatively cheaper than existing product in the market. Extensive testing has been carried out by Lambrou et al. [22] to make sure it is comparable to the device available in the market. The final turbidity system is capable of measuring turbidity in the range of 0-100 NTU with precision of 0.2 NTU.

Kitchener et al. [23] has reviewed the principle of turbidity measurement. They have re-examined the physics of light scattering in water. The turbidity measurement can be split

into two basic methodologies: turbidimetry in which the degree of transmission of light is determined and nephelometry in which the degree of light scattering is evaluated. Nephelometry can be subdivided into 3 categories which are forward-scattering, side-scattering, and back-scattering. Different instruments use different measurement angles and these values are not always reported. Therefore, they proposed all turbidity-measuring devices should be calibrated with precise optical attenuators which allows every turbidity-measuring device to be cross-comparable with any other instrument that is calibrated the same way.

Wang et al. [24] has proposed a low-cost turbidity sensor that can be integrated with IoT freshwater monitoring system. They have found out that the current turbidity measuring device in the market is expensive and has limited functionality. As a result, it is unsuitable and economically unfeasible to deploy such system widely. Therefore, Wang et al. [24] has designed a turbidity sensor by incorporating an 850nm infrared LED as the light source and two orthogonal photodetectors. The proposed design is capable of measuring 0-200 NTU with high resolution and accuracy sensing and 0-1000 NTU low resolution and accuracy sensing.

2.5 Fouling effect on the sensors

Fouling is defined as the unwanted buildup of material on a surface [25]. The development of fouling is perceived as a multistage process of which adhesion of fouling agents to surface is an essential step. Fouling occurs when solid objects are submerged under flowing fluid for a long period of time [26]. Since the sensors for the water quality

monitoring system must be immersed in water 24/7, fouling become one of the most prominent problems when deploying water quality monitoring system.

There are many types of fouling, inorganic fouling and biofouling. Inorganic fouling is the formation of inorganic precipitate on the surface [27]. Biofouling is referred to as the unwanted adhesion and growth of organism on the surface, forming biofilms. Inorganic fouling can be prevented by reducing the foulant concentration in the feedwater. However, biofouling is difficult to control just by reducing the number of microorganisms in the water [28]. Bacteria are ubiquitous and can easily adhere, accumulate and multiply in water system even their number is initially diminished. When bacteria grow on a surface, it results in the formation of a gel-type layer known as biofilm.

Biofilm is a surface-attached gelatinous matrix composed of microorganism, the extracellular polymers substances (EPS) and foreign substances such as adsorbed molecules and small abiotic particles. Such a matrix is highly hydrated, often containing more than 90% water (mass percentage) and its properties depend on three kinds of factors: biological (microbial species), chemical (fluid composition in contact with the biofilm), and physical (hydrodynamic and thermal conditions under which the biological layer is formed). The thickness of biofilm layers can reach a few millimeters, or even centimeters, but typically ranges from 10 micron to 1 mm [29].

Although from the biofilm is not as thick it seems to be, it is thick enough to cause the sensitive water quality measurement sensors to give false reading or even malfunction.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter describes the methodology used to perform this study. This includes the method used to derive the new turbidity-voltage conversion formula for the turbidity sensor and to carry out various turbidity measurements using various liquid solutions (i.e., calcium carbonate solution, oil emulsion, dye solution, protein emulsion, and pure water) to investigate the turbidity measurement using the turbidity sensor via proposed formulation. The coding written for the turbidity sensor is also attached in this section.

3.2 Deriving New Turbidity-Voltage Conversion Formula for Turbidity Sensor

To gain the new formulation, the turbidity sensor will be used to measure different liquid solutions with known turbidity. The voltage yielded by the turbidity sensor are recorded. Then, a correlation formula will be derived based on the known turbidity and the voltage attained from the turbidity sensor.

The liquid solutions are prepared using 5 wt.% calcium carbonate solution (CaCO_3) and it is diluted with distilled water to form 20 different liquid solutions. Pure distilled water (PW) is used as the benchmark sample. The dilution is carried out using the ratio method which is based on the ratio of calcium carbonate solution to distilled water. Table 3.1 shows the ratio for all the calcium carbonate liquid solutions.

Table 3.1: Ratio for calcium carbonate liquid solutions

Set	Ratio (CaCO₃ to Water)	
A	1	4.00
B	1	4.50
C	1	5.00
D	1	5.50
E	1	6.00
F	1	6.50
G	1	7.00
H	1	7.50
I	1	8.00
J	1	8.50
K	1	9.00
L	1	9.50
M	1	10.00
N	1	10.50
O	1	11.00
P	1	11.50
Q	1	12.00
R	1	12.50
S	1	13.00
T	1	13.50
PW	0	1.00

For simplicity, the volume of distilled water is fixed at 100ml and the volume of calcium carbonate solution is varied. Below shows the sample calculation to compute the volume of calcium carbonate solution needed for the dilution ratio of 1:4:

$$\frac{\text{Volume of distilled water}}{\text{Volume of calcium carbonate}} = \frac{4}{1}$$

$$\frac{100}{\text{Volume of calcium carbonate}} = \frac{4}{1}$$

$$\text{Volume of calcium carbonate} = \frac{100}{4}$$

$$\therefore \text{Volume of calcium carbonate} = 25 \text{ ml}$$

Same calculation is applied to rest of the liquid solutions.

Next, 10ml of each liquid solutions are taken out and measured with turbidity meter. The turbidity meter used is the HI98703 Precision Turbidity Portable Meter from Hanna Instruments [30] and its specification is attached in Appendix C. It is measured 3 times and the average value is calculated. This average value is assumed to be the exact turbidity value for the liquid solutions.



Figure 3.1: Hanna Instruments HI98703 Precision Turbidity Portable Meter

After that, the liquid solutions will be measured again using the turbidity sensor and the output voltage from turbidity sensor is recorded. It is measured 3 times and the average value is calculated. Figure 3.2 shows the Arduino coding to obtain the output voltage from the turbidity sensor.

```
//Turbidity sensor

//Define the variables used
float voltage;

void setup() {
  Serial.begin(9600); //Baud rate: 9600
}
void loop() {
  // read the input on analog pin:
  int sensorValue = analogRead(A0);

  // Convert the analog reading (which goes from 0 - 1023) to a voltage (0 - 5V):
  float voltage = sensorValue * (5.0 / 1024.0);

  Serial.print("Voltage= ");
  Serial.print(voltage);

  delay(2000);
}
```

Figure 3.2: Arduino coding for obtaining the output voltage of the turbidity sensor

The data is then analyzed and a new correlation formula based on the known turbidity and output voltage attained from the turbidity sensor is derived.

3.3 Repetitive Turbidity Measurement on Calcium Carbonate Solution

Using the new turbidity-voltage correlation formula, repetitive turbidity measurement on calcium carbonate liquid solutions using the turbidity sensor is carried out

to validate the performance of the new formulation. As a benchmark, turbidity meter is used to measure the exact turbidity for the calcium carbonate liquid solutions.

Using the same dilution method stated in Section 3.2, 10 different liquid solutions are prepared using 5 wt.% calcium carbonate solution and pure distilled water (PW). Table 3.2 shows the ratio for all the liquid solutions containing calcium carbonate.

Table 3.2: Ratio for calcium carbonate liquid solutions (validation)

Set	Ratio (CaCO₃ to Water)	
A	1	4.00
B	1	5.00
C	1	6.00
D	1	7.00
E	1	8.00
F	1	9.00
G	1	10.00
H	1	11.00
I	1	12.00
J	1	13.00
PW	0	1.00

For validation purpose, 10ml of each liquid solutions are taken out and measured with turbidity meter. The turbidity meter used is the HI98703 Precision Turbidity Portable Meter from Hanna Instruments. It is measured 3 times and the average value is calculated. This average value is assumed to be the exact turbidity value for the liquid solutions.

By inserting the new turbidity-voltage correlation formula, the liquid solutions will be measured again using the turbidity sensor. The maximum and minimum output voltage

and turbidity measured from turbidity sensor are recorded. It is measured twice and the data is tabulated. Figure 3.3 shows the Arduino coding for obtaining the output voltage and turbidity value from the turbidity sensor.

```
//Define the variables used
float voltage;
float NTU;

void setup() {
  Serial.begin(9600); //Baud rate: 9600
}
void loop() {
  // read the input on analog pin
  int sensorValue = analogRead(A0);

  // Convert the analog reading (which goes from 0 - 1023) to a voltage (0 - 5V)
  float voltage = sensorValue * (5.0 / 1024.0);

  // Convert voltage to NTU value
  NTU = 835*(4.46-voltage);

  // Upper limit and lower limit
  if(NTU < 0)
  {
    NTU = 0;
  }
  if(NTU > 3000)
  {
    NTU = 3000;
  }

  Serial.print("Voltage= ");
  Serial.print(voltage);
  Serial.print(" NTU = ");
  Serial.println(NTU);

  delay(2000);
}
```

Figure 3.3: Arduino coding for obtaining output voltage and turbidity value from turbidity sensor

The data is then analyzed by comparing the value obtained from the turbidity meter and the turbidity sensor.

3.4 Repetitive Turbidity Measurement on Pure Water

By using the new turbidity-voltage correlation formula, repetitive turbidity measurement on pure water samples using the turbidity sensor is carried out to validate the performance of the new formulation. Distilled water is used to represent the pure water samples. 60 turbidity measurement is carried out on the pure water samples for each sensor.

3.5 Time-Based Turbidity Measurement on Calcium Carbonate Solution

By using the new turbidity-voltage correlation formula, time-based turbidity measurement on calcium carbonate solution using the turbidity sensor is carried out. Using the same dilution method stated in Section 3.2, a liquid solution is prepared using 5 wt.% calcium carbonate solution and distilled water. The ratio used here is 1:13.

Next, the turbidity sensor is dipped into the calcium carbonate liquid solution and the turbidity measurement is carried out continuously for 20 minutes. The output voltage and turbidity value measured from the turbidity sensor are recorded every 2 seconds. The Arduino coding used here is the same as the Arduino coding used in Section 3.3. The setup for this experiment is shown in Figure 3.4.

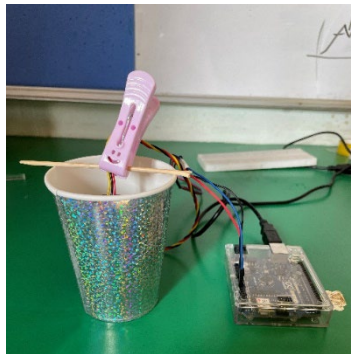


Figure 3.4: Setup for time-based turbidity measurement on calcium carbonate solution

3.6 Time-Based Turbidity Measurement on Oil Emulsion

Similarly, time-based turbidity measurement on oil emulsion using the turbidity sensor is carried out. Using the same dilution method stated in Section 3.2, three different liquid solutions are prepared using corn oil and distilled water. Table 3.3 shows the ratio for all the liquid solutions containing oil.

Table 3.3: Ratio for oil emulsion liquid solutions (validation)

Set	Ratio (Oil to Water)	
A	1	7.00
B	1	8.00
C	1	11.00

Next, the turbidity sensor is dipped into the oil emulsion liquid solutions and the turbidity measurement is carried out continuously for 60 minutes. The output voltage and turbidity value measured from the turbidity sensor for Set A are recorded every 10 seconds while for Set B and Set C are recorded every 1 minute. The setup for this experiment is shown in Figure 3.5.



Figure 3.5: Setup for time-based turbidity measurement on oil emulsion

These procedures are adopted for all time-based turbidity measurements for other liquid solutions.