The Study of Interrelationships Between Dissolved Oxygen Level and Other Pond Water's Physical Properties

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***Abstract*— The study involves gathering a bulk of data from a pond, consisting of measurements of pH, temperature, conductivity, dissolved oxygen, and turbidity. These data were then processed using data visualization in Python. The constructed graphs illustrate the direct relationship between DO and the considered parameters, albeit in differing degrees. The gathered data (totaling 1,109,190 data) has shown that out of the considered parameters, pH yielded the highest correlation with DO, with turbidity following suit. The temperature values in the gathered data also were directly proportional to the DO measurements, although less than the previously-mentioned parameters. The least seen connection was with conductivity. The study proves that indeed, water parameters are interconnected. The diversity of the data gathered has shown the researchers how much one parameter is closely-connected to the dissolved oxygen level, since it is the primary focus in maintaining the water's aquatic life, and therefore has a more justified understanding of the said parameter. It follows, ultimately, that maintaining the ample DO level entails maintaining the values of the parameters closely correlated to it.**

***Index Terms*— water parameters. dissolved oxygen, Python, machine learning, hydrological modelling**

I. INTRODUCTION

It could easily be said that water has vast potential in many aspects, such as livelihood. However, although water is abundant as a resource, it follows that we do not fully understand its properties and attributes. This hinders us from harnessing its full potential, especially for people who rely on it as livelihood, wherein dissolved oxygen, one of the key parameters in waters supporting aquatic life, is very crucial.

It immediately follows that understanding the implications of water parameters and how they move with respect to one another is important. This is because it would allow for an immediate remedy of a certain parameter, if one knew which parameter affected the DO levels the most. One could prioritize maintaining the levels of one parameter and allow another to move naturally, all while keeping the most important parameter in check. Ultimately, this leads to a more efficient maintenance of a body of water. This provides the most advantage to fish farmers who look after ponds; keeping the DO levels of a fish pond translates directly to the status of their livelihood.

Dissolved oxygen (DO) is the most critical indicator of a body of water's health and water quality [1]. This refers to the presence of free, non-compound oxygen found in water. The amount of dissolved oxygen present in a body of water influences the growth and survival of the aquatic organisms living in it [2]. As fish, algae, and other aquatic organisms depend on the oxygen levels to thrive, it is considered a very important parameter. Dissolved oxygen is also a factor in considering the power of the water treatment process [3-4]. On this note, it is highly relevant to measure the dissolved oxygen level of aquaculture to ensure its capacity to support aquatic life. The dissolved oxygen level, however, depends on many factors such as temperature, salinity, oxygen depletion, oxygen sources, and others [5].

In this study, the researchers considered the water's temperature, pH level, conductivity, salinity and total dissolved solids in order to construct a predictive model that obtains the dissolved oxygen (DO) level of a body of water, using machine learning.

It is expected that the output of this study would show relevant data that can be used to interpret how the parameters are related to one another.

II. METHODOLOGY

A. Data Acquisition

A sensor node equipped with various sensing devices was deployed to obtain measurements of temperature, pH level, conductivity, salinity and total dissolved solids. It was deployed in a pond to gather data on the mentioned water parameter. Installed with the formulated program, Arduino will process the gathered data. It will, in turn, send this information to a laptop accessible to the researchers. Based from the determined degree of correlation between the considered water parameter and DO level, the researchers will form different suitable input combinations. This is to assess which of combination will provide a relative accurate prediction of DO, utilizing minimal cost of resources. The level of accuracy of each input combination will be taken into consideration. The input combination which will meet these criteria will become the so-called optimum combination.

Fig. 1 illustrates the flowchart of the data gathering process of the buoy. The study mostly relied on the physical construction of the buoy for the data acquisition. From this, the researchers analyzed the data and come up with the most practical and cost-effective solution for the development of the DO meter.

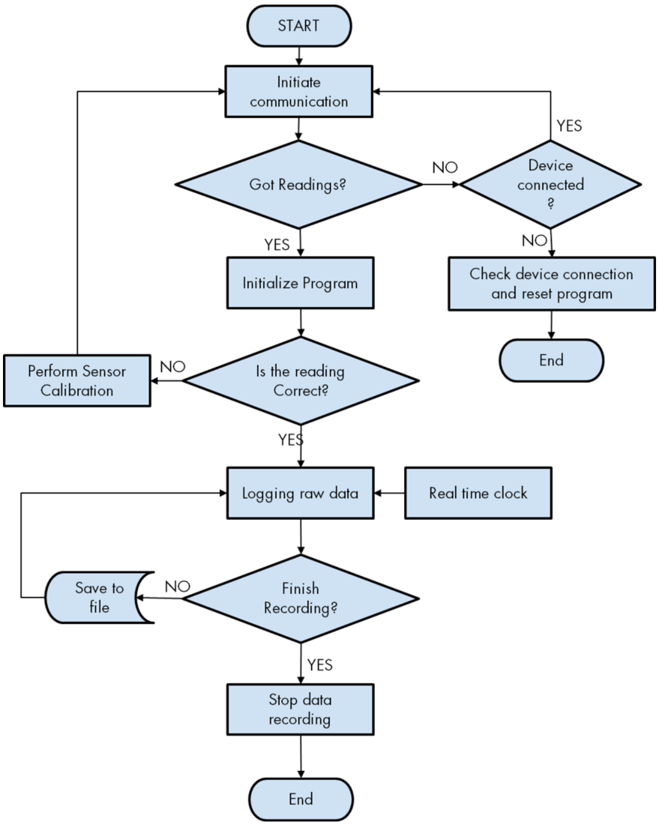

Fig. 1 Buoy's Data Gathering Flowchart

B. Construction of Data-Gathering Buoy

The data-gathering buoy that was developed mainly consisted of the five sensors (DO, temperature, turbidity, pH, and conductivity) which gathers measurements from the water each second. The inner circuit included an SD card, and a real-time clock for the logging of the gathered data, and to include the time and date it was measured, respectively.

The buoy itself is designed in consideration of the specifications observed and described by the beneficiary, consolidated with design considerations from past researches and industry standards. The buoy is cylindrically-shaped, as this is one of the accepted standards in the design of buoys, and because it is a stable shape in terms of its buoyancy [7]. There is also the factor of the size of the device, to ensure that it won't be attacked by the fishes in the pond. According to the University of Wisconsin Sea Grant Institute, fish typically attack prey that are smaller than them and avoid those that are significantly larger than them. Thus, as the fishes of the beneficiary's pond are only ornamental koi fishes (Cyprinus carpio), the buoy's size as of the design should not be a problem, as it is significantly larger than most typical koi fishes. For safety precaution, however, the researchers have installed a plastic wire mesh around the device. Figure 2 shows the final data-gathering buoy.


Fig. 2. Data-gathering buoy

C. Data Acquisition, Filtering, and Processing

Following the construction of the data-gathering buoy, the researchers had then sought the help of the Philippine Council for Agriculture, Aquatic, and Natural Resources Research and Development (PCAARRD), in search for a possible pond the buoy can gather data from. This led them to the Bureau of Fisheries and Aquatic Resources (BFAR) in Ambulong, Batangas, where the buoy was then deployed for the data-gathering process.

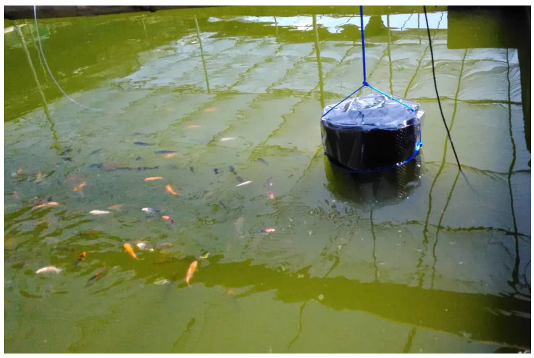
Fig. 3. Buoy deployed in a concrete pond at BFAR – ITSO (Ambulong, Batangas)

The researchers allowed the buoy to gather data for a total of three weeks. From this period, the buoy has logged a total of 1,190,189 data from the pond. This data was then filtered to eliminate the erroneous measurements, such as the period before the device settles down.

C. Utilization of Python for Parameter Analysis

After the data has been filtered and processed, the researchers then allowed the Python program that they have developed to construct the necessary graphs, illustrating the needed parameter relationships for further analysis.

III. DESIGN CONSIDERATIONS

The students have developed a buoy-like device that obtains different water parameters (temperature, pH, conductivity, salinity and total dissolved solids) and uses the data to define the value of dissolved oxygen through machine learning. In the prototype of the device, the dissolved oxygen sensor was included to facilitate supervised machine learning. The prototype also included the Arduino circuit; the purpose of which was primarily to collect data for the machine learning process. However, the final device only consists of the temperature, pH, conductivity sensors, and the Raspberry Pi circuit, in lieu of the Arduino circuit. The following are the technical specifications and data sheets of the circuits, drivers, and other components that were used in the construction of the device[7-10]:

TABLE I
Specifications of the Sensors

Specifications	EZO-DO™ Embedded Dissolved Oxygen Circuit	EZO-EC™ Embedded Conductivity Circuit	Industrial pH electrode (SKU: FIT0348)	Digital Temperature Sensor (SKU: DFR0198)
Range	0.01 − 100+ mg/L 0.1 − 400+ % saturation	0.07 − 500,000+ µS/cm	0-14pH	-55 to 125°C (-67°F to +257°F)
Accuracy	+/− 0.05 mg/L	+/− 2%	≦0.02pH	±0.5°C from -10°C to +85°C
Response time	1 reading/sec	1 reading/sec	10sec	750 ms
Operating voltage	3.3V − 5V	3.3V − 5V	3.0V to 5.5V	3.0V to 5.5V

IV. EXPERIMENTS AND RESULTS

A. Parameter Trend Visualization

In order to obtain an optimal result, the data gathered during the three-week-deployment of the device were filtered to make a concise and good quality training set for machine learning. To better understand the matter, it is helpful to visualize how these pond water parameters vary over time.

Fig. 4 shows the daily trend of dissolved oxygen as observed during the weeks that have passed. As seen on the graph, the readings have a pattern as the day goes on. The level of dissolved oxygen reaches it peak in the middle of the day and eventually decreases as the day comes to an end, and then goes back up again as the day starts.

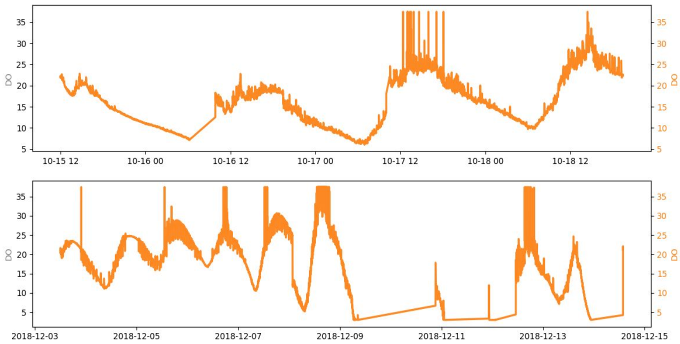

Fig. 4. Daily Trend of Dissolved Oxygen

The following graphs illustrates the nature of how other parameters vary over time with reference to the daily trend of dissolved oxygen present in the background. The graph depicted in Fig. 5 shows the relationship of dissolved oxygen and temperature. It can be inferred that the two parameters are directly proportional to each other.

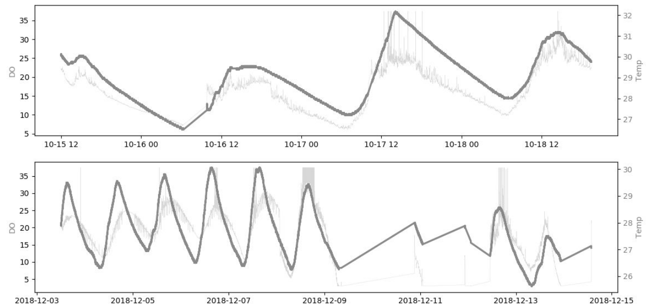

Fig. 5. Daily Trend of Temperature

Fig. 6 below shows the daily trend of dissolved oxygen and the pH level. The first week of the figure displays a direct relationship among the two parameters. However on the second week, the data were a bit ambiguous but still appears that when one parameter decreases, so does the other parameter. The trend of pH with time can be explained through the presence of sunlight. The presence of sunlight increases the number of algae performing photosynthesis, increasing the alkalinity of water by absorbing the Carbon Dioxide present in the said body of water.

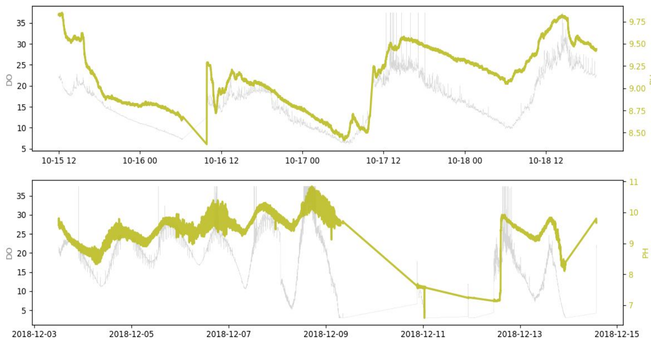

Fig. 6. Daily Trend of pH

As shown in the figures, Fig. 5 and Fig. 6, temperature and pH levels vary in time in trends not dissimilar to that of DO. It is explained through time, as temperature increases with the presence of sunlight, the water heats up.

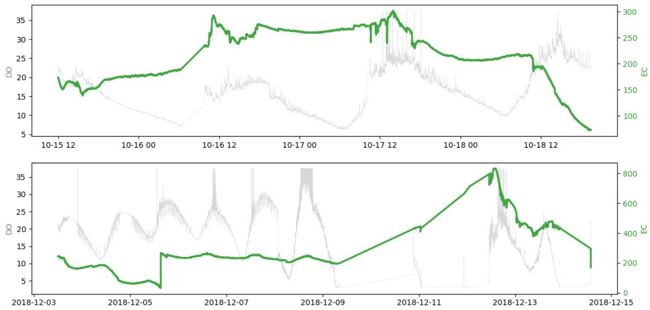

Fig. 7. Daily trend of Electric Conductivity

Meanwhile, Fig. 7 and Fig. 8, EC and TDS have very similar trends, yet different scales or values. This shows that the number of dissolved solids present in the water greatly influence the conductivity of it.

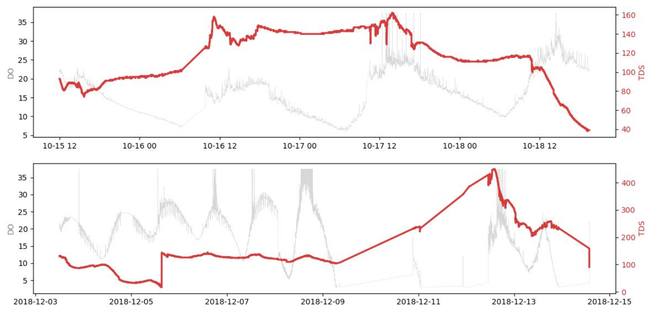

Fig. 8. Daily trend of Total Dissolved Solids

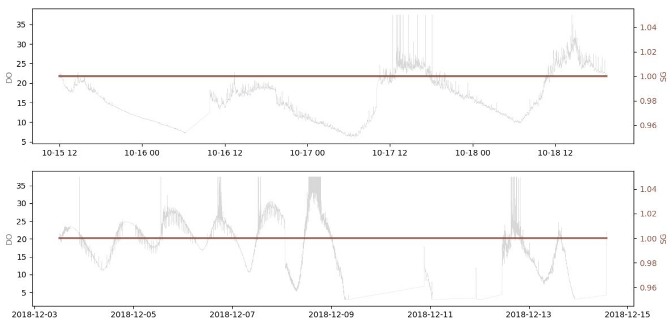

Fig. 9. Daily trend of Specific Gravity

In Fig. 9, Specific Gravity does not change, as it is the ratio of the density of a substance with reference to water. As the data was gathered in water, it is effectively 1.

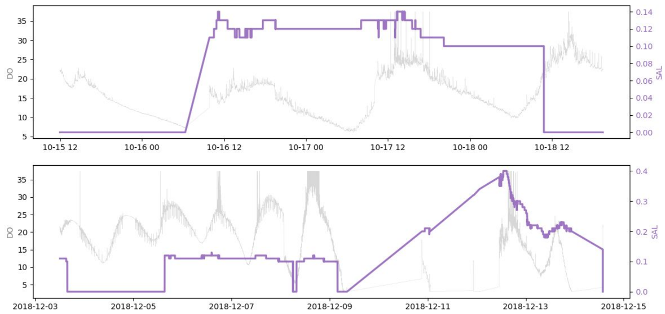

Fig. 10. Daily trend of Salinity

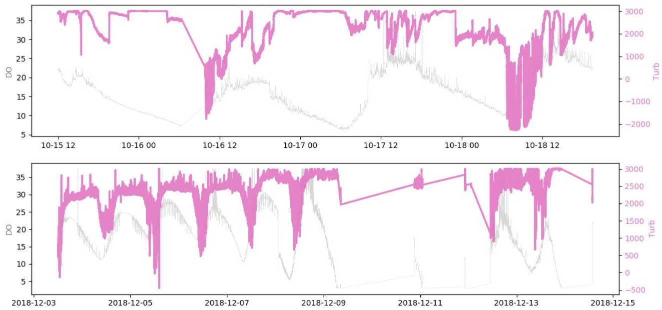

Fig. 11. Daily trend of Turbidity

The trend of Turbidity, as shown in Fig. 11, shows errant values. This is signified by the weekly change in water by the fish pond handlers, the decrease or increase in the number of algae present in the water and various other factors.

The figures shown helps in visualizing which parameters may be correlated to the DO level.

B. Parameter Evaluation

Table 2 shows how relevant each parameter is to the level of DO, from 1-minute and 5-minute intervals.

TABLE II
PARAMETER RELEVANCE – EVERY MINUTE AND EVERY 5 MINUTES

Parameter	**Every Minute**		**Every 5 Minutes**	
	RFR	**DTR**	**RFR**	**DTR**
TIME	0.341	0.347	0.331	0.252
PH	0.325	0.314	0.330	0.338
TEMP	0.131	0.001	0.144	0.110
EC	0.118	0.123	0.120	0.196
TDS	0.051	0.041	0.034	0.038
SAL	0.024	0.028	0.009	0.015
TURB	0.009	0.025	0.033	0.0446
DAY	0.001	0.002	0.0001	0.007
SG	0	0	0	0

It can be seen from Table 2, time and pH are most relevant parameters for both algorithms. On the other hand, day, and specific gravity are least relevant. Table 3 shows parameter importance from 10-minute and 30-minutes interval.

TABLE III
PARAMETER RELEVANCE – EVERY 10 MINUTES AND EVERY 30 MINUTES

Parameter	Every Minute		Every 5 Minutes	
	RFR	DTR	RFR	DTR
TIME	0.330	0.258	0.027	0.169
PH	0.332	0.353	0.427	0.376
TEMP	0.145	0.126	0.102	0.114
EC	0.126	0.195	0.381	0.226
TDS	0.012	0.027	0.011	0.034
SAL	0.028	0.012	0.010	0.012
TURB	0.020	0.025	0.029	0.065
DAY	0.007	0.005	0.014	0.004
SG	0	0	0	0

Evidently, relevant parameters are time, pH and temperature for 10-minute time interval. For 30-minute time intervals, pH and electrical conductivity are most relevant parameters for both algorithms. Table 4 shows parameter relevance from the hourly time interval.

TABLE IV
PARAMETER RELEVANCE – Hourly

Parameter	Every Hour	
	RFR	DTR
TIME	0.022	0.057
PH	0.328	0.354
TEMP	0.137	0.131
EC	0.429	0.374
TDS	0.021	0.044
SAL	0.012	0.020
TURB	0.036	0.015
Day	0.014	0.006
SG	0	0

As can be seen in Table 4, pH and electrical conductivity yield greater coefficients suggesting that these two are relevant to the DO level for both algorithms. Among the least significant parameters are day, salinity and specific gravity.

V. CONCLUSION

With all these finding, the researched arrived at the following conclusions.

The pond water's physical properties vary in accordance to one another. Electrical conductivity and dissolved oxygen are directly proportional to one another, with respect to time.

Dissolved oxygen level, being the focus of this study, is affected by key properties namely, the time of the day, pH level, temperature and electrical conductivity.

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