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Article

Integration of Sensing Framework with a Decision Support System for Monitoring Water Quality in Agriculture

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Abstract: Water is an essential element for every plant to survive, absorb nutrients, and perform photosynthesis and respiration. If water is polluted, plant growth can be truncated. The aim of this research is to develop a water quality monitoring system for agriculture purposes based on integration of sensing framework with a smart decision support method. This research consists of three stages: (1) the first stage: developing sensing framework which has four different water quality parameter sensors such as potential hydrogen (pH), electrical conductivity (EC), temperature, and oxidation-reduction potential (ORP), (2) the second stage: developing a hardware platform that uses an Arduino for sensor array of data processing and acquisition, and finally (3) the third stage: developing soft computing framework for decision support which uses python applications and fuzzy logic. The system was tested using water from many sources such as rivers, lakes, tap water, and filtered machine. Filtered water shows the highest value of pH as the filtered machine produces alkaline water, whereas tap water shows the highest value of temperature because the water is trapped in a polyvinyl chloride (PVC) pipe. Lake water depicts the highest value of EC due to the highest amount of total suspended solids (TSS) in the water, whereas river water shows the highest value of ORP due to the highest amount of dissolved oxygen. The system can display three ranges of water quality: not acceptable (NA), adequate (ADE) and highly acceptable (HACC) ranges from 0 to 9. Filtered water is in HACC condition (ranges 7–9) because all water quality parameters are in highly acceptable ranges. Tap water shows ADE condition (ranges 4–7) because one of the water quality parameters is in adequate ranges. River and lake water depict NA conditions (ranges 0–4) as one of the water quality parameters is in not acceptable ranges. The research outcome shows that filtered water is the most reliable water source for plants due to the absence of dissolved solids and contaminants in the water. Filtered water can improve pH and reduce the risk of plant disease. This research can help farmers to monitor the quality of irrigated water which eventually prevents crop disease, enhances crop growth, and increases crop yield.

Keywords: water pollution; sensors; fuzzy logic; Arduino; membership function

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1. Introduction

Water is an important element in many daily activities such as drinking, cooking, agricultural, recreational and business sectors. Agriculture is a highly water dependent sector globally and accounts for 70% of total water consumption worldwide [1]. Agriculture is frequently linked to non-urban pollutants. Organic materials, fertilizers, sediments, and pesticides are all examples of agricultural pollutants [1].

In Malaysia, water pollution occurs due to urban land use (87%), agricultural land use (82%), forest land use (77%), and other land uses (44%) [2]. The use of possibly polluted water, especially wastewater in agriculture, can lead to the accumulation of chemical and biological pollutants in crops, livestock products, land, and water resources, which eventually affects consumers.

Crops need water for several metabolic processes such as photosynthesis and respiration. Water is used to transport amino acids, dissolved nutrients, and other active substances from the soil to each part of the crop [3]. Thus, water quality is an important element to assist the growth of crops. Many methods have been adopted such as using spectroscopy [4,5], optics, and laser sensing [6,7], Arduino [8], Internet of Things (IoT) and real time monitoring [9–11], multi-sensor array [12], and cyber physical systems [13–15]. Reviews on water quality monitoring methods have been done recently involving electronics and optical sensing [16,17]. Real-time monitoring of water quality parameters is needed to assist authority and farmers [9,18]. The surface water quality index method for irrigation is an important tool to determine the overall impact of various parameters that are used as a single variable [19]. The irrigation water quality index (IWQI) model was developed by combining eight water quality parameters; sodium adsorption rate (SAR), residual sodium carbonate (RSC), electrical conductivity (EC), pH, total dissolved solids (TDS), sodium (Na), and chloride (Cl) [19,20]. In addition, El Osta et al. [21] studied the suitability of groundwater for drinking and irrigation using water quality indices and multivariate modeling.

In comparison to the previous methods, Hong et al. [9] applied IoT and Arduino ATMega328 to interface with multiple sensors such as pH, temperature, turbidity, and total dissolved solids (TDS) to monitor water quality of rivers or streams. Decision-making for water quality was not included, and the data was more complex. Meanwhile, Khatri et al. [22] used Raspberry Pi as the main microcontroller whereas the system in Mahajan et al. [23] used an Arduino as the microcontroller. The system in Mahajan et al. [23] also used graphical user interface (GUI) for human–machine interface (HMI) and fuzzy modeling in Python to display results from five different types of water sensors to monitor water quality, but analysis for each type of water was not shown in the study. Additionally, Taru et al. [8] used an Arduino, interfaced with the LabVIEW to control water quality parameters such as pH, turbidity, and temperature.

Here, we developed a water quality monitoring system by integrating a sensing framework with a smart decision-making method for testing water sources used in irrigation such as a river, lake, tap, and a filtered device. The water quality parameters were detected using four sensors; pH, temperature, electrical conductivity (EC), and oxidation-reduction potential (ORP). These four parameters are commonly used to measure water quality [24]. The sensors were controlled by an Arduino, and Python programming language was used to display the data. Fuzzy logic was applied for the decision-making method based on a range of water quality parameters in terms of membership functions. Our developed system improves the method in Taru et al. [8] by adding sensors such as electrical conductivity (EC) and oxidation-reduction potential (ORP). The previous method, He et al. [25] was more complex to be applied by consumers due to many mathematical derivations involved. The system used water quality index method to conduct scientific analysis at the end of the process to decide on water quality. Our developed system applies fuzzy logic which is useful because the approach is less mathematically intensive than neural networks and genetic algorithms [22]. Thus, the proposed system can provide simplicity and flexibility to produce reliable results.

2. Materials and Methods

The developed system was basically divided into three stages; (1) Developing a sensing framework; (2) Developing a hardware platform, and (3) Developing a soft computing framework. The flow chart of the system is shown in Figure 1. Four sensors to monitor water quality parameters; pH, temperature, electrical conductivity (EC), and oxidation-reduction potential (ORP) were applied, and data from the sensors were displayed. The water quality parameters were chosen because the parameters were commonly sampled or monitored for water quality [26]. Fuzzy logic was used for decision making and parameter ranges of membership functions (MF) were selected.

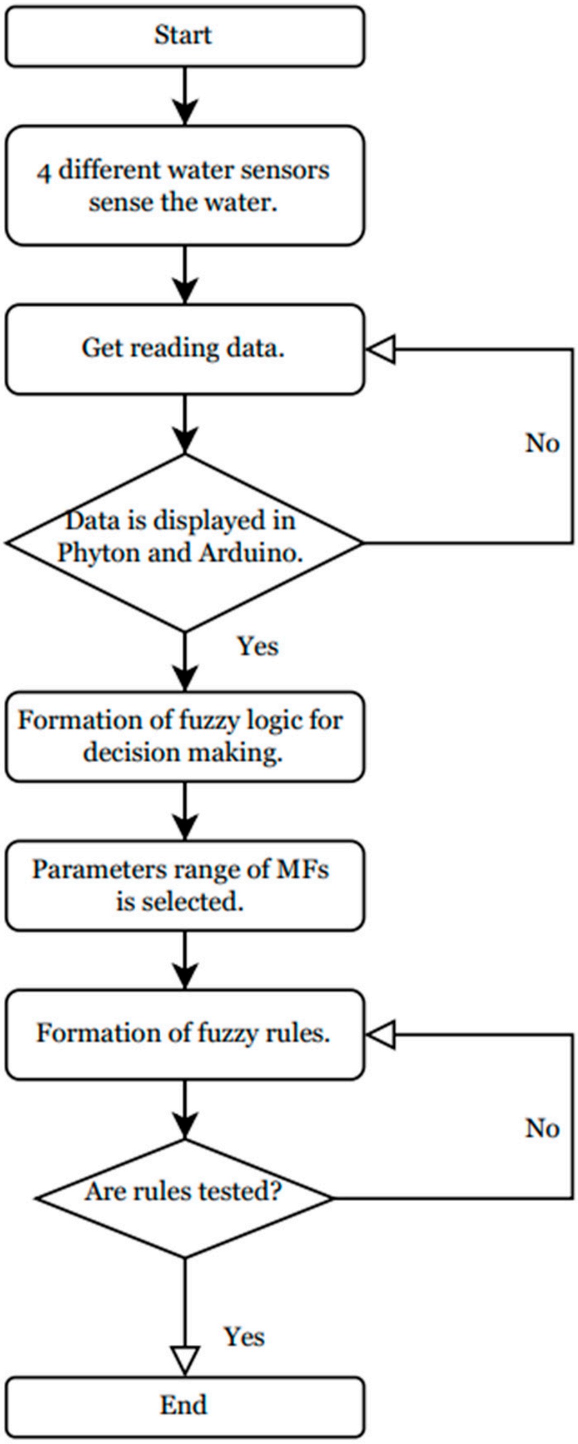

Figure 1. Flow chart of the system.

Testing and collecting data were performed from August to December 2021 during the movement control order (MCO) using water sources such as Limau River (Kulim, Kedah), Azure Lake (Kulim, Kedah), tap, and filter device (Cuckoo, Yangsan, South Korea). Limau River and Azure Lake water were quite turbid compared to tap and filtered water.

2.1. First Stage: Developing Sensing Framework

At the first stage, four different water quality parameter sensors were selected: pH, electrical conductivity (EC), temperature, and oxidation-reduction potential (ORP). The water sample is neutral if the pH value is ~7 [27–29]. pH is an important parameter to measure the acidity and alkalinity of the water [30,31]. Alkalinity and pH are among important factors to determine suitable irrigation water [32]. A good pH range is important for crop growth and to increase the quality and quantity of production.

EC sensor is also important to determine the quality of water and to detect the presence of chemicals [33]. EC needs to be paired with the temperature sensors to determine the accuracy of the reading. Dissolved minerals can appear in water which also can be referred to total dissolved solids (TDS) or total dissolved salts. If these minerals exist at high concentrations, they can be toxic to the water. EC sensor can detect the TDS and can be used as an indicator of salt concentration. Higher concentration of dissolved minerals in water results in higher conductivity and EC value in water [33]. Meanwhile, the purer the water, the lower the conductivity of electricity which also refers to a good insulator. Thus, the EC value of safe water that can be used cannot exceed 400 µS/cm [34].

ORP sensors can measure the oxidization of water where it can detect the cleanliness of the water. Lower ORP values indicate a higher possibility of pollution [35]. ORP measures the capability of water to break down waste products. The process of oxidizing occurs when the substance lacks some electrons. The increase in oxidizing agents gives a higher ORP value, whereas the increase in reducing agents indicates a lower ORP value [35]. The ORP of water is an important key indicator of contamination levels. The acceptable range of ORP value for water should be high, between 300 and 500 millivolts. A low ORP reading indicates less dissolved oxygen, an increase in toxicity of certain metals and pollutants, and many dead and decaying materials in the water [35,36]. According to the United States Environmental Protection Agency (EPA), the acceptable range of ORP value in water is around 250 mV [37]. Filtered water can have a range of reading between 357 mV to –25 mV depending on the brand and type of filters [38]. Lozano et al. [14] stated that nicotine, arsenic trioxide, and *Escherichia coli* are very sensitive to water quality parameters such as pH, electrical conductivity, and dissolved oxygen. Thus, it is beneficial and useful to monitor these parameters.

The individual sensor nodes are able to support open-source architectures that could reduce the total device cost significantly [13,39]. In addition, the sensors were easily connected to an Arduino. In this study, the sensors consisted of a pH sensor (SEN0161, Analog, 0 pH to 14 pH, Gravity Series, DFRobot, Shanghai, China), used to measure the acidity and alkalinity of the irrigated water; electrical conductivity (EC) sensor (DFR0300-H, Output voltage: 0 V to 3.2 V with gravity connector, DFRobot, Shanghai, China), used to measure the ability of irrigated water to conduct electrical current; temperature sensor (DFR0198, Digital Temperature Sensor, Waterproof, DS18B20, −55 °C to 125 °C, DFRobot, Shanghai, China), used to measure the suitability of irrigated water for plant; and oxidation-reduction potential (ORP) sensor (SEN0165, measuring range from −2000 mV to 2000 mV, suitable temperature from 5 to 70 °C, DFRobot, Shanghai, China), used to measure the oxidation of irrigated water.

Calibrations of the sensors were done to determine the accuracy of the reading from all sensors where the reading (actual) was compared with the reference standard and the percentage relative error was measured. The percentage relative error, P was calculated based on Equation (1) [22]. In the developed system, the percentage relative errors of sensors ranged from 0 to 1%.

$$Percentage\ relative\ error,\ P = \frac{Actual - reference}{Actual} \times 100 \tag{1}$$

2.2. Second Stage: Development of Hardware Platform

The second stage consisted of the development of a hardware platform that used an Arduino for sensor array of data processing and acquisition. Implementation of a hardware system is an important part of data display and acquisition because complex data matrices are generated through a sensor array [13]. To connect with the sensor array, Arduino Mega 2560 and Arduino Uno were used where the Arduino board operated with an external supply range between 6 and 20 volts, whereas the system used voltage between 5 and 15 V [8]. Arduino was used in the system because it was easy to implement and inexpensive compared to other microcontroller platforms [31]. A low-power platform device was adequate to sustain overall operations and batteries simultaneously. The data points were generated from a multi-sensor array unit and were displayed in the Arduino serial monitor.

2.3. Third Stage: Developing Soft Computing Framework

The third stage consisted of a soft computing framework that utilized the features of Python programming languages and fuzzy logic for effective decision support.

2.3.1. Python Framework

Python is an open-source, high-level programming language that supports data processing and computing frameworks [22]. Python has an extensive library such as NumPy, Panda, SciPy, and Scikit-Learn for powerful toolsets such as Mathematics, Statistics, and Computational Science and other scientific domains [22]. In this system, the data from the Arduino were supplied to Python through a serial port. The system used the functionalities of scientific NumPy and Matplotlib libraries simultaneously. With the wide use of Python in many ranges of tools, the NumPy library is basically the core library for scientific and numeric computing, whereas the output segment of Python is produced by Matplotlib [13].

To generate and collect the data points that were produced from multiple sensors, the system interfaced Python with Arduino software, an integrated development environment (IDE). The coding simulation used C/C++ programming languages at the serial monitor. Pycharm module text editor was used to interface Python with the Arduino. Pyserial and Numpy libraries were installed and imported to Python. To read data from the sensors, the Pycharm module editor was used to compute the codes.

2.3.2. Fuzzy Logic Approach

For the decision support process, the system assisted the user to decide whether the quality of water in the distribution network was not acceptable (NA), adequate (ADE), or highly acceptable (HACC). Multiple sensor nodes generated a huge data set of information. Fuzzy logic is one of the effective techniques that can support the decision support system. Fuzzy logic can translate natural language expression into a mathematical universe [13]. In a fuzzy inference system (FIS), the linguistic rule is presented. Vagueness in decision-making and reasoning can be included in FIS results in a less mathematically intensive way than neural networks, and it supports approximate reasoning. There are three important steps to design fuzzy logic: (1) Each variable is given a membership function, (2) fuzzy inference is implemented based on the inference method, and (3) the defuzzification method is selected to determine water quality [22]. There are basically two processes in FIS which are fuzzification and defuzzification. Fuzzification is a process where the inputs are converted from a crisp value to a linguistic variable, which is then fed into the system of inference, whereas defuzzification is the process backward from fuzzification where a new set of linguistic variables is converted to a crisp value [22]. Generally, a few steps were used to develop the decision support system. In the first step, the range of parameters of water quality was selected. Then, suitable membership functions (MFs) were picked based on the complexity of the system that was considered for decision-making [22]. In our system, the triangular membership function was chosen to fuzzify the crisp variable into a linguistic variable because it was simple, linear, and gave the best response [22].

Three parameters are important in the triangular membership function, l, m, and n, given by Equation (2) [22].

$$f(x;l,m,n) = \begin{cases} 0 \; for \; x < l \\ \frac{x-l}{m-l} \; for \; l \leq x \leq m \\ \frac{n-x}{n-m} \; for \; m \leq x \leq n \\ 0 \; for \; x > n \end{cases} \tag{2}$$

meanwhile, Equations (3)–(5) show the logic operations in the fuzzy logic. A and B are two subsets [22].

$$\mu_{A\cup B(x)} = \max\left[\mu_{A(x)}, \mu_{B(x)}\right] \tag{3}$$

$$\mu_{A\cap B(x)} = \min\left[\mu_{A(x)}, \mu_{B(x)}\right] \tag{4}$$

$$\mu_{\overline{A}(x)} = 1 - \mu_{A(x)} \tag{5}$$

After that, the *"if–then"* rule was applied with three principles by using four fuzzy inputs (temperature, pH, EC and ORP), and single defuzzified output (water quality) based on Mamdani FIS method. The method utilizes the centroid defuzzification method to generate a more accurate response and is spontaneous rather than the Takagi-Sugeno model system [22].

Three MFs (membership functions) were assigned; not acceptable (NA), adequate (ADE), and highly acceptable (HACC). Finally, the MFs were arranged based on different ranges of water quality parameters. Table 1 shows the MFs arrangement for various water quality parameters. The pH of water is in the NA range if the value is more than 8.5 (high alkaline) and less than 5.7 (high acid), whereas the temperature is in the NA range if the value is more than 35 °C and less than 2 °C. EC and ORP are in the NA range if the value of EC is more than 1000 S/m and 600 mV, respectively. The chosen parameter ranges are based on international water quality standards for safe water to be used by humans. We believe that if water is safe for humans, it is safe for plants and animals. The parameter range can be adjusted accordingly depending on types of crops and plants to solve issues in irrigated agriculture such as salinity, water infiltration rate, ion toxicity, and excessive nutrients. Higher salts in water can affect yield, and chloride in water can cause crop damage and reduce yield [40,41]. Our system is limited to sensing four water quality parameters but can be upgraded by adding more water quality parameters such as chloride, sodium, nitrate, and heavy metals.

Table 1. The parameter ranges for safe water based on three different membership functions (MFs) of fuzzy logic [13,40,41]. NA, ADE and HACC refer to Not Acceptable, Adequate, and Highly Acceptable respectively.

Parameter	**'NA' (Not Acceptable)**	**'ADE' (Adequate)**	**'HACC' (Highly Acceptable)**	**'NA' (Not Acceptable)**
pH	<5.7	6.0–6.5	6.5–8.5	>8.5
Electrical Conductivity (mS/cm)	-	350–1000	100–400	>1000
Oxidation-Reduction Potential (mV)	-	300–600	100–250	>600
Temperature (°C)	<2	1.9–10	9–35	>35

Formation of rules with the selected MFs was basically done by using Python programming language with the help of Skfuzzy module (fuzzy logic toolbox). Python frameworks can operate with fuzzy sets and develop them based on designated rules to define water quality. The principles of the rules are given as follows:

1. If any of the water quality parameters are NA, overall water quality will be NA;
2. If all water quality parameters are HACC, then overall water quality will be HACC, otherwise it will be ADE;
3. Based on two assumptions; (1) water quality of the individual parameters will fluctuate between HACC and ADE provided that no single water quality parameters are NA, and (2) if a single water quality parameter is ADE, the overall water quality will be ADE.

3. Results and Discussion

Four types of water sources were tested in the system; filtered, tap, river, and lake water. In the first stage, four types of sensors (pH, temperature, EC, and ORP sensors) were used to determine the quality of water: In the final stage, the sensor's reading was inserted into the fuzzy logic system by using Jupyter software that is available online. Table 2 shows the results of each sensor for four types of water. The values were averaged from 30 measurements every day. Taking many measurements is important to observe if any fluctuation occurs in sensor's reading.

Table 2. The average reading of sensors for four types of water in terms of potential hydrogen (pH), temperature, Electrical Conductivity (EC) and Oxidation-Reduction Potential (ORP).

Types of Water Sources	Sensors			
	pH	Temperature	EC (mS/cm)	ORP (mV)
Filtered Water	8.13	28.51	0.31	243.6
Tap Water	8.11	29.68	0.12	422
River	5.86	27.73	0.27	259
Lake	7.28	27.74	0.88	417

To decide on the water quality of each sample, the fuzzy logic approach was applied to the data. Four rules were applied in the system. The rules were generated based on the reading of each sensor which referred to the range of parameters that were acceptable for irrigation purposes. Three membership functions (MFs) such as not acceptable (NA), adequate (ADE), and highly acceptable (HACC) were assigned to the specific parameter ranges. First, the membership functions should be synchronized to the reading of the pH, EC, ORP, and temperature based on the assigned ranges. For example, if pH is 8.2, it is in HACC condition, whereas if the EC reading is 530 mS/cm, it is in adequate condition. Then, the rules can be computed, and the output can be generated. Figure 2a–e show the graphical representation of data outputs based on rules that were formulated. It shows that the water quality range for NA ranges from 0 to 4, ADE ranges from 4 to 7, and HACC ranges from 7 to 10. The vertical coordinate shows the degree of membership function (MF) where the water quality ranges are assigned by MF. MF can provide decision to validate water quality.

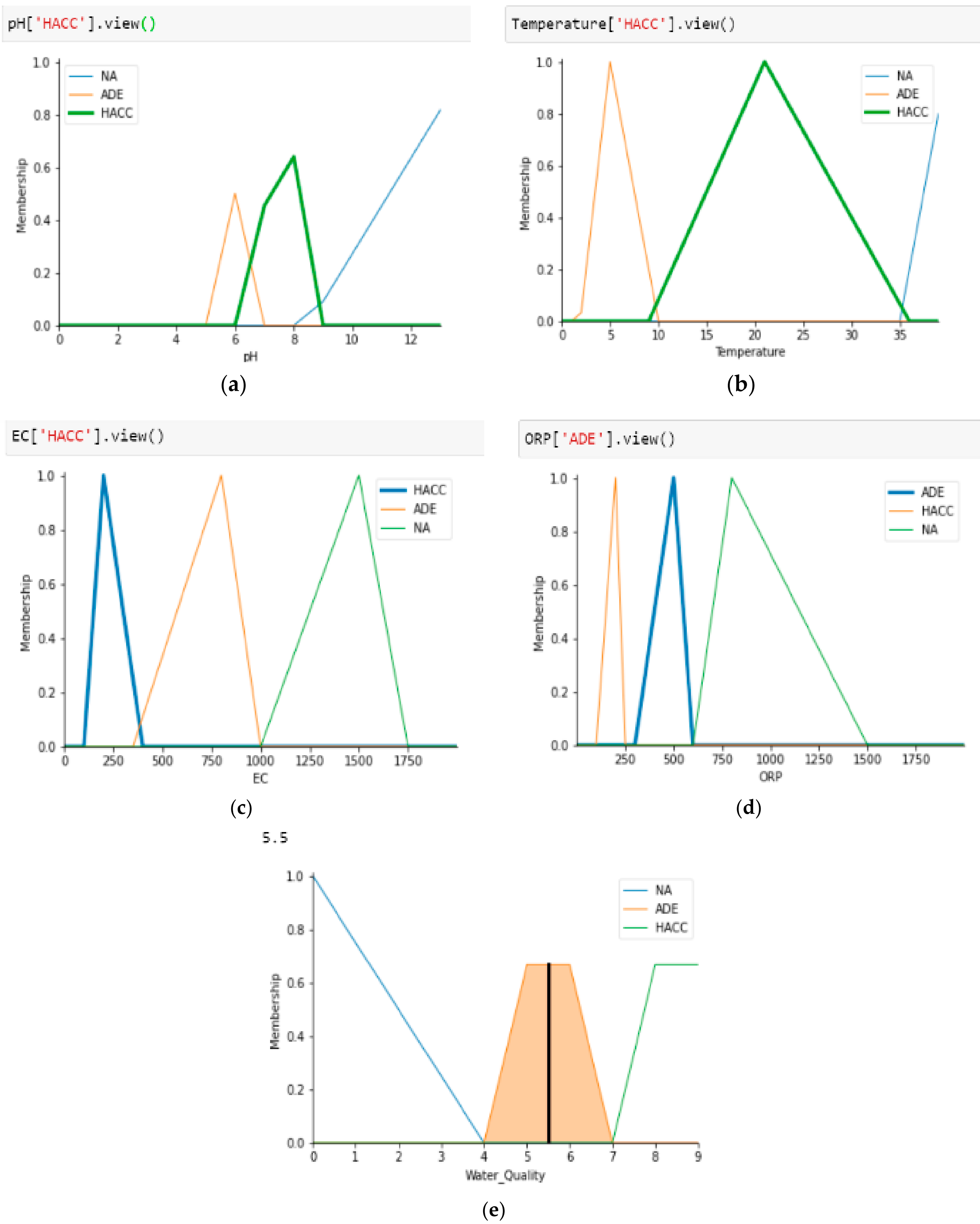

Figure 2. Graphical representation based on the fuzzy rule for (**a**) pH, (**b**) temperature, (**c**) electrical conductivity (EC), and (**d**) oxidation reduction potential (ORP) for tap water. (**e**) The water quality graph shows that the sample is in adequate condition. NA, ADE and HACC refer to Not Acceptable, Adequate, and Highly Acceptable respectively.

The output of four water samples is depicted from Figures 3–6 which consists of filtered water, tap water, river water, and lake water. Figure 3 shows that filtered water is in the HACC ranges where the overall water quality is 8.19. The decision is made because the readings of pH, EC, ORP, and temperature sensors are in HACC ranges.

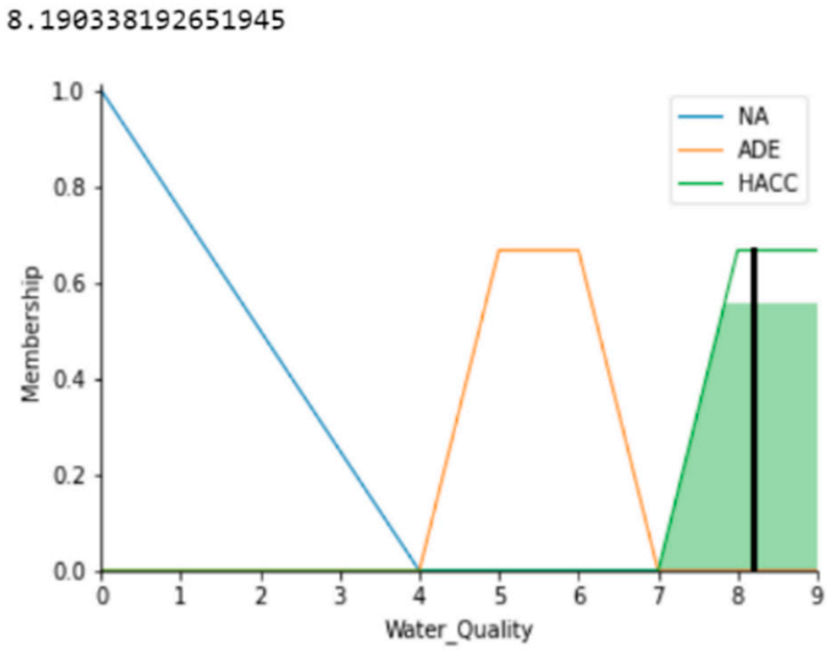

Figure 3. Decision support for water quality of filtered water. NA, ADE and HACC refer to Not Acceptable, Adequate, and Highly Acceptable respectively.

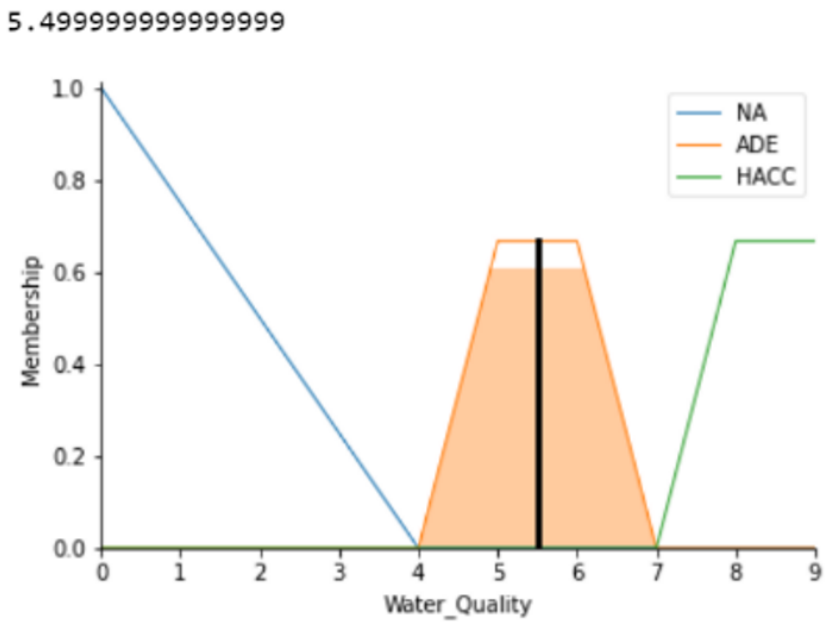

Figure 4. Decision support for water quality of tap water. NA, ADE and HACC refer to Not Acceptable, Adequate, and Highly Acceptable respectively.

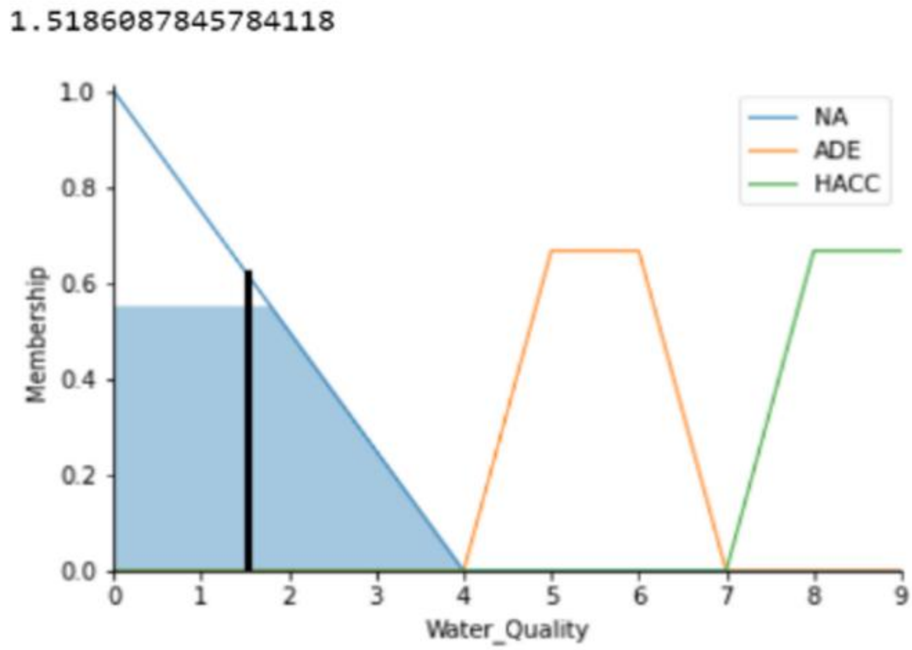

Figure 5. Decision support for water quality of river water. NA, ADE and HACC refer to Not Acceptable, Adequate, and Highly Acceptable respectively.

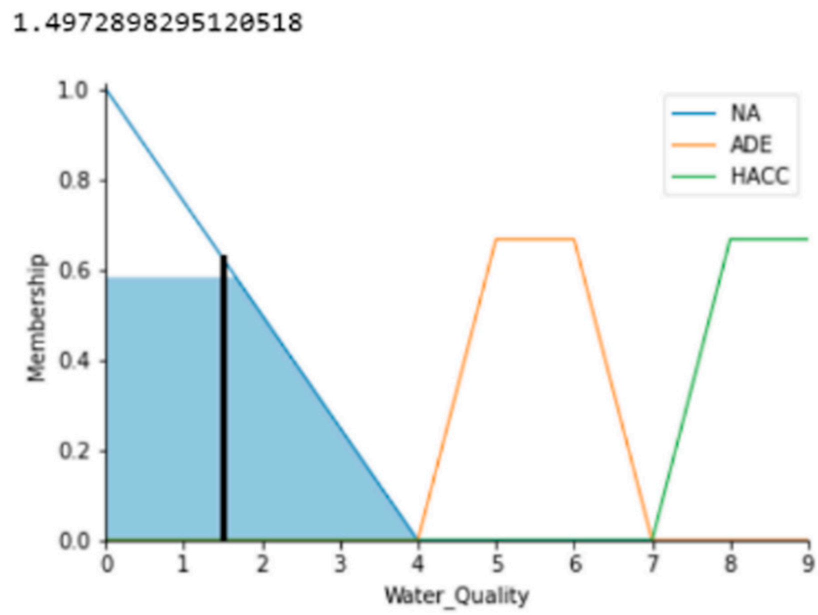

Figure 6. Decision support for water quality of lake water. NA, ADE and HACC refer to Not Acceptable, Adequate, and Highly Acceptable respectively.

Figure 4 shows that tap water is in the ADE ranges where the overall water quality is 5.5. Tap water shows that pH is 8.11, which is in HACC ranges; EC is 120 µS/cm, which is in HACC ranges; ORP is 422 mV, which is in ADE ranges; and temperature is 29.68, which is in HACC ranges. Based on the rules in Section 2.3.2, if any of water quality sensors are in ADE ranges, the overall water quality is ADE.

Figure 5 shows that river water is in the NA ranges where the overall water quality is 1.52. The rule applied to the river water is based on the readings of pH in NA ranges, EC in HACC ranges, ORP in HACC ranges, and temperature in HACC ranges. If one of the water quality sensors is in NA ranges, the overall water quality is NA.

Figure 6 shows that lake water is in the NA ranges where the overall water quality is 1.497. Overall quality of lake water is NA as the water quality parameter, EC lies at NA regions, similar to river water. The rule applied to the lake water is based on the readings of pH in HACC ranges, EC in NA ranges, ORP in ADE ranges, and the temperature in HACC ranges.

Table 3 summarizes the decision-making on water quality for filtered water, tap water, river water, and lake water in terms of pH, temperature, ORP, and EC. The water quality decision made is based on fuzzy logic rules as explained in Section 2.3.2. Meanwhile, Table 4 shows that only filtered water produces HACC results. The rest of the samples show that tap water is ADE for irrigation, whereas river and lake water are NA for irrigation.

Table 3. Decision support on water quality for each sample based on pH, temperature, ORP, and EC. Three membership functions (MFs) such as Not Acceptable (NA), Adequate (ADE), and Highly Acceptable (HACC) are applied.

Water Samples	Decision on Water Quality			
	pH	Temperature	ORP	EC
Filtered water	HACC	HACC	HACC	HACC
Tap water	HACC	HACC	ADE	HACC
River water	NA	HACC	HACC	HACC
Lake water	HACC	HACC	ADE	NA

Table 4. Decision support in terms of Not Acceptable (NA), Adequate (ADE), and Highly Acceptable (HACC) on overall water quality for each sample.

Water Samples	Overall Decision on Water Quality
Filtered water	HACC
Tap water	ADE
River water	NA
Lake water	NA

Among four types of water samples, filtered water shows the highest pH value. It indicates that filtered water is good for irrigation. River water is found to be acidic. The toxicity can be caused by acid rain or industrial pollution with the presence of metals such as aluminum, copper, and zinc, as well as acidifying chemicals such as calcium oxide and sodium carbonates [27]. High sodium or low calcium in water can decrease the amount of irrigation water entering the soil to such an extent that insufficient water infiltrated to supply the crop [40].

Tap water depicts the lowest EC value, 0.12 mS/cm showing that tap water has less TDS. Lake water has the highest EC value showing a good electricity conductor suggesting a high amount of TDS. Chemicals such as chloride, phosphate, and nitrate ions in water can increase the electrical conductivity which shows the possibility of water pollution [42]. Besides that, the ions may accumulate in a sensitive crop to the high concentration that can cause crop damage and reduce yields [40].

Based on the observations, the ORP value of filtered water is 243.6 mV which is in the acceptable range for safe water to be used. Meanwhile, the ORP values of tap water, lake water, and river water are 422 mV, 417 mV, and 259 mV, respectively. The ORP values for tap and lake water are in healthy ranges.

Fuzzy logic was implemented to determine the acceptable range for safe water to be used. The result categorized the filtered water as HACC, tap water as ADE, and both river and lake water as NA. These findings support previous studies which reported that domestic filters improved water quality [28], and Malaysian tap water quality was safe to be used [29,43]. Both river and lake water are untreated water, therefore it is expected that the water quality from these two sources is not acceptable. Thus, we believe that the proposed system, which consists of a sensing and decision support method, is efficient to monitor water quality. In comparison with the previous methods, the developed system introduces soft computing for water quality status. It has high autonomy and fast quality detection due to quick process of decision-making, and it is efficient and flexible. It is also communicative where the data can be shared and connected throughout the system.

4. Conclusions

In conclusion, we have developed a water quality monitoring system by integrating a sensing framework with a decision support method that can be applied in agriculture. Four sensors; pH, temperature, ORP, and EC, controlled by an Arduino were used in the system where it can support the decision making of water quality using fuzzy logic. The membership functions were selected for decision-making methods such as Not Acceptable (NA), Adequate (ADE), and Highly Acceptable (HACC). Results show that filtered water is HACC and tap water is ADE, whereas both river and lake water show NA conditions for irrigation purposes. The system is user-friendly, applies an open-source platform, and reduces the complexity of data obtained from multiple sensors. The system can assist farmers in identifying polluted water and make decisions on reliable irrigation water based on the generated data. Then, they can opt for the best water resources.

In future, the system can be applied to test polluted rivers in Malaysia such as the Kim Kim River in Johor, the Klang River in Selangor, and the Melaka River in Melaka. The system can be further improved by adding chemical and biological sensors to detect any bacteria or virus in the water and integrating with IoT for easy monitoring using mobile phones.

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