Solar-powered IoT based smart hydroponic nutrition management system using FARM

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Abstract. Good nutrition and water conditions are significant in a hydroponic system. Nutrients in hydroponic systems are periodically re-mixed to target the right amount of TDS. The TDS amount needs to be regularly measured after the weather changes, namely temperature, humidity, light intensity, and rainfall. The research proposes developing a solar-powered Internet of Things (IoT) based Smart Hydroponic Nutrition Management System using Fuzzy Association Rule Mining (FARM). The system consists of an IoT connected to a TDS (Total Dissolved Solids) sensor, a relay module connected to two 5v mini pumps that supply AB Mix nutrients, and a solenoid valve to supply water. The IoT system is also connected to sensors for temperature and humidity, light intensity, and rainfall to record the causes of weather changes that cause changes in TDS in hydroponic water. FARM is used to extract fuzzy association rules (FAR) from IoT sensors. The system targets a TDS of 1200 for leafy plants such as lettuce. The system prototype was developed in a small 5×7cm single layer PCB using the wire-wrapping technique. The test results produce a standard deviation of 2.345 for the TDS average of 1196.17 and threshold 50. In one week of evaluation, three times of rain and four times of hot weather were considered to change the TDS, and seven actions of the relay module were carried out. FARM has extracted fuzzy rules with average support of 0.401 and confidence of 0.826.

1. Introduction
Good nutrition and water conditions are significant in a hydroponic system [1]. Nutrients in hydroponic systems are periodically re-mixed to target the right amount of total dissolved solids (TDS) [2]. The TDS amount needs to be periodically measured after the weather changes, namely temperature, humidity, light intensity, and rainfall [3].

The research proposes developing a solar-powered Internet of Things (IoT) based Smart Hydroponic Nutrition Management System using Fuzzy Association Rule Mining (FARM). The system consists of an IoT connected to a TDS sensor, a relay module connected to two 5v mini pumps that supply AB Mix nutrients [4], and a solenoid valve to supply water.

The IoT system is also connected to sensors for temperature and humidity, light intensity, and rainfall to record the causes of weather changes that cause changes in TDS in hydroponic water. The IoT is also connected to two 6WP solar panels and a 1.2Ah battery that supplies the IoT system and pumps and solenoid valves. The system was tested on a previously developed solar-based DFT hydroponic system.
FARM is used to extract fuzzy association rules (FAR) from IoT sensors. The system targets a TDS of 1200 mg/L for leafy plants such as lettuce.

2. Related research
Research related to the Arduino-based nutrition feeding automation system of a prototype scaled nutrient film technique (NFT) hydroponics using total dissolved solids (TDS) sensor have been proposed [7, 8]. Measurement and controlling of pH and TDS in Automated Hydroponics System also have been presented [9]. Both types of research focused on the automation of nutrition feeding based on pH and TDS by adjusting the precision of the water pumps. The proposed research also considers the effects of environmental variables, including light intensity, ambient temperature and humidity, and rain intensity, to the change of the TDS in the nutrition system.

Implementation of algorithms for nutrient control systems have been presented using K-nearest neighborhood [10], forward and backward chaining inference technique [11], and fuzzy mamdani [12]. Each research focused on developing its own rules manually to automate the control system. The proposed system extracts regulations based on environmental conditions and uses FARM fuzzy rules extractor to adjust the nutrition supplies. The proposed method is capable of describing the ecological situation based on FAR.

3. Review of the system
Figure 1 shows the general view of the system. The IoT system uses ambient temperature and humidity (DHT11), light intensity (BH1750), and rain intensity as environmental data input for the microcontroller, which is the precedence. The TDS sensor functions as dependent data input (effect). The increased TDS value will turn on the solenoid valve to drain the water, and the reduced TDS value will turn on the pumps for the nutrition AB mix. Both of these decisions aim to stabilize the TDS value.

The system is equipped with two solar panels and batteries for each microcontroller and nutrition pump. The solenoid valve is connected to a water tap and uses an AC power source via a 12v adapter. Three power supply units are used to stabilize the electrical system.

Figure 2 shows a flowchart of the system. The preparation includes IoT, hydroponic, and FARM algorithms. Precedent data collection contains ambient temperature and humidity, light intensity, and rain intensity data in one array. Meanwhile, dependent data collection only contains TDS data and relates it to precedent to detect cause and effect. If TDS increases, the relay module will turn on the solenoid valve. Conversely, if it is reduced, 5v mini water pumps nutrition AB Mix. FARM rule extraction will arrange precedent, dependent, and decision into the rule pool. Furthermore, the FARM evaluates support and confidence in the extracted rule. Rule extraction continues to produce satisfied support and confidence.
4. **Results and evaluation**

The results include an explanation of the results of the developed IoT system. The evaluation compares the threshold of TDS changes to the stability of TDS levels and the extracted rule, a comparison of the fuzzy membership of each variable in the cluster, and evaluation of support and confidence in the extracted rule.

4.1. **Developed IoT system**

Figure 3 shows the circuit developed IoT system. The circuit uses two microcontrollers containing Arduino nano and wemos d1 mini. Both microcontrollers are connected through software serial. Arduino nano connects analogue based sensors, including light intensity, rain intensity, and TDS. Arduino nano also combines digital sensors which monitor ambient temperature and humidity (DHT11). Wemos D1 mini connects a relay module that controls two 5v water pumps and a 12v solenoid valve. Two pairs of solar cells and batteries supply a 5v to microcontrollers and two 5v water pumps. Meanwhile, a 12v adaptor provides a 12v to a solenoid valve.

![Figure 2. The Flowchart.](image)

![Figure 3. Circuit of the system.](image)
Figure 4 shows the actual view of the system. Part (a) shows the fundamental components of the system, which includes two 5v water pumps with an 8mm pipe and solenoid valve. Part (b) shows the PCB layout that connects every part using pin headers and 30 AWG cables. Each cable connects through a wire wrapping technique [13] to the male pin headers. We use the wire wrapping technique to maximize the connection layer to the small size (5×7 cm) single layer PCB.

![Whole Component of The System](image1.png) ![PCB with Wire Wrapping Technique](image2.png)

**Figure 4.** Actual View of The System.

### 4.2. The comparison of TDS threshold

Table 1 shows the comparison between different TDS thresholds that trigger the relay module to supply AB Mix to increase or water to decrease TDS. The best result reached by threshold 50 with a standard deviation of 2.345 and an average of 1196.17 mg/L. A lower TDS threshold triggered more action to the relay module and resulted in a lower average, shown by threshold 10 with 1023.52 mg/L and 30 with 1092.93 mg/L. An oversupply of water by a solenoid valve with more capacity than a mini water pump could affect this condition. The highest threshold, 100, had a closed standard deviation and average to threshold 30 and better than threshold 10. The higher point would decrease the system's energy usage due to less action on the relay module.

| Threshold | Std Dev | Average (mg/L) | Extracted Rules |
|-----------|---------|----------------|-----------------|
| 100       | 7.827   | 1091.27        | 12              |
| 50        | 2.345   | 1196.17        | 5               |
| 30        | 6.781   | 1092.93        | 4               |
| 10        | 79.290  | 1023.52        | 2               |

Table 1 also shows the number extracted by the threshold value. A higher threshold extracted more rules than a lower threshold. The effect of weather changes on the TDS value could be more apparent when it was not frequently interrupted by the action of the relay module. The results also showed that uncontrolled excessive action reduced the stability of the TDS value. So in the current research results, a higher threshold value is considered more profitable. This threshold comparison was made daily, so more extended tests and different weather conditions might have different effects.

### 4.3. The extracted fuzzy membership

Tables 2 and 3 show the extracted fuzzy membership of environment variable based on evolutionary rule-based clustering that had been proposed in previous research [14]. The fuzzy object-oriented database (FOOD) was separated into two clusters based on effect to the TDS decrement and increment.
Table 2. Cluster of TDS Decrement

| Feature         | σ1   | μ    | σ2   |
|-----------------|------|------|------|
| Rain Intensity (%) | 23.25 | 59.12 | 60.62 |
| Light Intensity (Lux) | 93   | 8903 | 20319 |
| Temperature (°C) | 28.23 | 32.14 | 32.74 |
| Humidity (%)    | 38   | 45   | 47   |
| TDS (mg/L)      | 1023.78 | 1092.42 | 1192.86 |

Table 2 shows the conditions that caused a decrease in TDS, namely a high rain intensity, humidity, low light intensity, and ambient temperature. Rainwater, humid air, and low evaporation may be the cause of the reduced TDS. Excessive water supply can also be a cause outside of natural conditions.

Table 3. The cluster of TDS increment

| Feature         | σ1   | μ    | σ2   |
|-----------------|------|------|------|
| Rain intensity (%) | 0    | 0    | 1    |
| Light intensity (Lux) | 20014 | 48378 | 61243 |
| Temperature (°C) | 31.13 | 31.12 | 32.32 |
| Humidity (%)    | 30   | 40   | 42   |
| TDS (mg/L)      | 1109.16 | 1128.17 | 1201.01 |

Table 3 shows the conditions that caused TDS increase, namely nearly zero rain intensity and ambient humidity and high light intensity and ambient temperature. This condition increased the evaporation of water and caused cloudiness of the water. The AB Mix supply with a mini pump is easier to calibrate. In the future, the water supply will also be calibrated using a water flow sensor or a pump to produce a stable water flow.

4.4. **Extracted rules and evaluation**

Table 4 shows the extracted rules and the evaluation using support and confidence [15]. The precedent consists of rain intensity (R), light intensity (L), ambient temperature (T) and humidity (H). Dependent consists only of TDS (Tds).

Table 4. Extracted rules and evaluation

| Index | Precedent | Dependent | Support | Confidence |
|-------|-----------|-----------|---------|------------|
| 1     | {R₁}      | {Tds₁}    | 0.384   | 0.982      |
| 2     | {R₁, L₁}  | {Tds₁}    | 0.312   | 0.820      |
| 3     | {R₁, L₁,T₁} | {Tds₁} | 0.302   | 0.927      |
| 4     | {R₁, L₁,T₁,H₁} | {Tds₁} | 0.236   | 0.892      |
| 5     | {R₁,L₂}   | {Tds₁}    | 0.121   | 0.679      |
| 6     | {R₂}      | {Tds₂}    | 0.728   | 0.991      |
| 7     | {R₂, L₂}  | {Tds₂}    | 0.678   | 0.829      |
| 8     | {R₂, L₂,T₂} | {Tds₂} | 0.692   | 0.892      |
| 9     | {R₂, L₂,T₂,H₂} | {Tds₂} | 0.621   | 0.891      |
| 10    | {R₂,L₁}   | {Tds₂}    | 0.293   | 0.657      |
| 11    | {R₂, L₁,T₂} | {Tds₂} | 0.226   | 0.652      |
| 12    | {R₂, L₁,T₂,H₂} | {Tds₂} | 0.219   | 0.690      |

Average 0.401 0.825

Rules 1 to 4 show fuzzy membership for all conditions in table 2, and it appears that rain intensity has the highest effect, followed by light intensity. Rules 6 to 9 show all conditions in table 3, and it seems that rain intensity is more dominant. Rule 5 shows sunny conditions during infrequent rains. Rules
10 to 12 show combined conditions which also rarely occur, indicated by low support and confidence. The results show average support of 0.401 and confidence of 0.825.

5. Conclusion

The prototype of the system was developed in a small 5×7cm single layer PCB using wire-wrapping technique. The test results produce a standard deviation of 2.345 for the TDS average of 1196.17 mg/L and threshold 50. In one week of evaluation, three times of rain and four times of hot weather were considered to change the TDS, and seven actions of the relay module were carried out. FARM has extracted fuzzy rules with average support of 0.401 and confidence of 0.826. Data retrieval is considered insufficient to perform regression because it requires sequential data that is more than the same case for changes in TDS, which becomes a task for future research. In addition, the development of the IoT system also needs to be improved so that it is more resistant to water and humid temperatures.

References

[1] F. Ahmadi, A. Samadi, E. Sepehr, A. Rahimi, and S. Shabala, “Improving Essential Oil Compositions of Purple Coneflower (Echinacea Purpurea L.) Medicinal Plant Using Novel Growing Media and Nutrition Pattern in Hydroponics,” 2021.
[2] I.-H. Ho, S. Li, and S. Abudureyimu, “Alternative hydronic pavement heating system using deep direct use of geothermal hot water,” Cold Reg. Sci. Technol., vol. 160, pp. 194–208, 2019.
[3] R. Prybysh, M. Al-Hussein, B. Fleck, M. Sadrzadeh, and J. Osolu, “Experimental Study on the Palatability Impacts of Potable Water as a Hydronic Medium,” Water, vol. 10, no. 2, p. 218, 2018.
[4] H. Prabowo, E. Yuniastuti, A. Yunus, and others, “Effects of media combination with concentration of AB-Mix nutrient on growth of banana shoots on in vitro.,” Bulg. J. Agric. Sci., vol. 24, no. 3, pp. 404–410, 2018.
[5] W. Wedashwara, A. H. Jatmika, I. W. A. Arimbawa, and others, “Smart solar powered hydroponics system using internet of things and fuzzy association rule mining,” in IOP Conference Series: Earth and Environmental Science, 2021, vol. 712, no. 1, p. 12007.
[6] W. El-Ssawy et al., “The Impact of Advanced Static Magnetic Units on Water Properties and the Performance of Aeroponic and NFT Systems for Lettuce.,” Polish J. Environ. Stud., vol. 29, no. 4, 2020.
[7] D. Eridani, O. Wardhani, and E. D. Widianoto, “Designing and implementing the arduino-based nutrition feeding automation system of a prototype scaled nutrient film technique (NFT) hydroponics using total dissolved solids (TDS) sensor,” in 2017 4th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), 2017, pp. 170–175.
[8] L. Ardhiansyah and D. A. Prasetya, “Design And Implementation Of An Automation System For A Nutrition Pump In Hydroponics Using Arduino Uno,” Universitas Muhammadiyah Surakarta, 2021.
[9] R. Ratan and others, “Measurement and Controlling of pH and TDS in Automated Hydroponics System,” in Applications of Computing, Automation and Wireless Systems in Electrical Engineering, Springer, 2019, pp. 295–304.
[10] D. Adidrana and N. Surantha, “Hydroponic Nutrient Control System based on Internet of Things and K-Nearest Neighbors,” in 2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA), 2019, pp. 166–171.
[11] H. T. Sakti and A. Thoriq, “Expert System for Hydroponic Vegetable Cultivation Using Forward and Backward Chaining Inference Technique,” Inform, vol. 6, no. 2, 2021.
[12] I. M. Sudana, O. Purnawirawan, and U. M. Arief, “Prediction system of hydroponic plant growth and development using algorithm Fuzzy Mamdani method,” in AIP Conference Proceedings, 2017, vol. 1818, no. 1, p. 20052.
[13] M. Hossain and others, “Rapid prototyping for an edukit using 3D printer and CNC machine,” 2019.
[14] W. Wedashwara, S. Mabu, M. Obayashi, and T. Kuremoto, “Evolutionary Rule Based Clustering for Making Fuzzy Object Oriented Database Models,” in *Advanced Applied Informatics (IIAI-AAI), 2015 IIAI 4th International Congress on*, 2015, pp. 517–522.

[15] A. Telikani, A. H. Gandomi, and A. Shahbarami, “A survey of evolutionary computation for association rule mining,” *Inf. Sci. (Ny)*., vol. 524, pp. 318–352, 2020.