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RNN-Driven Smart Water Quality Management for Vannamei Shrimp Aquaculture

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ABSTRACT

The food crisis that may occur is due to the increasing population and the dwindling number of food sources. So the Indonesian government in a structured manner carries out a program to increase vannamei shrimp (Litopenaeus vannamei) cultivation intensively, to ensure its survival in the future. Intensive vannamei shrimp cultivation requires intensive management of water quality control, which of course requires high-tech equipment. This study proposes modeling of control parameters, namely shrimp feed, CaCO3 to maintain acidity levels, extra aerators to maintain dissolved oxygen conditions, and alarm flags to provide notification of abnormal conditions in shrimp ponds. These control parameters are set based on the results of multimodal sensor readings, namely pH sensors, delta pH, dissolved oxygen sensors, and water surface temperature. Since shrimp pond conditions are dynamic and non-linear, Recurrent Neural Network-based modeling was implemented. Because of the machine learning base applied, we named this system smart water quality management (SWQM). The results show that RNN-based modeling has an accurate RMSE value and can be applied in real time according to expert rules obtained from shrimp farmers. Levenberg Marquardt-based RNN can produce optimal RMSE for feed scheduling modeling with RMSE of 0.0007 and 0.0057 for CaCO3 scheduling.

1. Introduction

Indonesia, as an archipelagic country, has strong potential in fisheries, with shrimp farming as one of its main export commodities. Vannamei shrimp (*Litopenaeus vannamei*) is a leading commercial white shrimp product [1], contributing an average of 36.27% to Indonesia's fisheries export value during 2012–2018 [2]. In 2019, shrimp production reached 517,397 tons and is targeted to increase 2.5 times to 1,290,000 tons by 2024, with production value expected to rise from 36.22 trillion to 90.30 trillion [3]. Achieving this target requires technological support, especially in water quality management, since limited technology adoption has led to suboptimal production. Important water parameters such as temperature, pH, turbidity, salinity, and dissolved oxygen directly affect shrimp growth and survival, making monitoring and control systems essential. To modernize shrimp farming under the Industry 4.0 concept, the government introduced the Millennial Shrimp Farming (MSF) program, which promotes practical, flexible, and land-efficient circular pond systems suitable for intensive cultivation [4], [5]. Previous studies show that in intensive systems, dissolved oxygen levels of 3.9–7.8 mg/L, pH 6.47–7.65, temperature 24–29°C, and salinity 15–19 ppt resulted in an average shrimp growth rate of 0.24 gram/day and a survival rate of 84% [6]. Various technologies have been applied to manage water quality, including Programmable Logic Controllers (PLC) [7], which achieved high detection accuracy for pH, salinity, dissolved oxygen, and temperature [8], as well as fuzzy logic systems using temperature, salinity, and pH as inputs to produce a 0–100 water quality index based on 27 rules [9]-[11]. Neural network approaches have also been implemented, such as in the study by Zhen Ma, which involved data collection [12]-[28], preprocessing [29]-[62], model structure determination [63], and training using the Levenberg–Marquardt algorithm to predict water quality in intensive ponds, although the focus was mainly on monitoring rather than control [63]. Therefore, this research focuses on a control scheme for pond conditioning, where the controlled parameters are the feeding schedule [64], water acidity level and dissolved oxygen level as well as the addition of alarm flags for abnormal conditions. Multimodal sensors are used as control reference indicators provided for the pond, with references provided by shrimp farmers. With internet of things technology, this research offers not only a control scheme but also real-time monitoring based on MQTT which makes it reliable and responsive in terms of supervision and system control input. The novelty of this research is the use of recurrent neural networks as a solution for non-linear modelling of our standing auto feeder control system.

2. Method

The overall design process of smart water quality management (SWQM) by using a Recurrent Neural Network (RNN) can be explained as a flowchart in Fig. 1.

2.1. Experiment Data

Data used in this experiment consist of 8 parameters. The four parameters are multimodal sensors: a pH sensor, a delta pH sensor, a dissolved oxygen meter, and a temperature sensor. These four parameters serve as RNN reference indicators to determine the appropriate CaCO3 levels, as well as when the extra aerator should be activated to supply oxygen, as well as when the system should issue an alarm for abnormal conditions, and as a basis for shrimp feeding scheduling.

Shrimp Farm used in this experiment is circular a circular pond with a diameter of 20 m. The figure of the pond can be seen in Fig. 2 the pond's constituent materials consist of a concrete foundation, with an iron support frame, and water-retaining material made of tarpaulin. The pond is also equipped with a piping system that is used for water circulation, to enter or remove water from the pond. The pool water level is in the range of 1.5 meters so the volume of water in the pond is estimated at 480 m^3. The Standing Auto Feeder (SAF) used in this experiment was placed on the edge of the shrimp pond, which is equipped with various components as shown in Fig. 3.

From Fig. 3 it can be seen that SAF has four main components. The components are: solar panels as an energy source, input channels to enter feed and treatment materials, panel box controller that is equipped with RNN-based program, which also contains a hazard alarm, for certain conditions and the ejection system is the actuator of the SAF which uses a motor as its propulsion device. In the SAF input chimney, there are three channels containing different materials used according to their respective functions. The first channel is used for feed. The second channel is used for $CaCO_3$, which is used to raise the PH and maintaining PH stability because high changes in PH even in the normal range affect the vannamei shrimp's appetite.

2.2. Proposed Method

The SAF developed in this study is programmed using an artificial intelligence algorithm. For the artificial intelligence programming process to be easy the stages are as follows:

1. Hardware Installation consisting of Sensors, Processors, and Actuators as shown in Fig. 3.
2. RNN Model (Structure) Determination.
3. Retrieval of input-output pair data for the training process.
4. NN training process using the Matlab toolbox.
5. The weight generated from the training process is implanted into the SAF Microprocessor with C++ Software.
6. Sensor and Actuator Calibration in preparation for SAF implementation.

The NN model for SAF has 3 (Three) inputs and 7 (Seven) Outputs. With inputs are:

1. pH sensor data.
2. Temperature sensor data.
3. Oxygen Sensor Data.

And the outputs are.

1. Amount of feed in Kg.
2. Amount of CaMg in Kg.
3. Amount of CaCo3 in Kg.
4. Water drain valve.
5. Water Inlet Valve.
6. Aerator (Backup).
7. Alarm.

In general, the objectives and control algorithms for Smart Water Quality Management (SWQM) can be:

1. Keeping the PH in the range of 7 – 8.5.
2. Maintaining PH changes in the range (1), within 12 hours, should not be more than 0.2 (calculations are made at 06.00 in the morning and 18.00 in the afternoon).
3. Maintain Dissolve Oxygen at 1500 -9750 mg/l or 1.5 ppm to 9.75 ppm.
4. Keeping the temperature in the range $of\ 28 - 31$. This range is the best temperature range for growth, although shrimp can live at temperatures of 28 - 31.
5. Planning for the circulation of water in and out of the pond.

The RNN model for Water Quality Management (SWQM) can be described in Fig. 4. In general, the SWQM operating procedure can be explained as follows:

1. Feeding: Under normal conditions, shrimp feed is given four (4) times a day, namely at 06:00, 12:00; 17:00; at 22:00, with feed capacity for each feeding determined by water quality.
2. PH control: If the PH is below 7, $CaMg(CO_3)_2$ is added according to a size that is decided based on water quality.
3. Delta PH Control: If the pH change in the normal range (7-8.5) from 06.00 am to 6.00 pm is more than 0.2, then CaCo3 is added according to a size that is decided based on water quality.
4. Alarm: If the PH exceeds 8.5, an alarm will sound, and bacteria will be added manually according to size.
5. DO Control: If DO is below 1.5, the water output valve will work to remove water at the bottom of the pond, for a certain duration of time. And the Aerator is turned on/plus its speed.

6. Temperature Control: If the temperature exceeds 31°, then the input water valve from the reservoir to the pond will work, to cool the pool temperature, (to maintain the temperature of the reservoir water, try to place the reservoir in a shady place - room temperature).
7. Temperature Control: If the temperature is below 27° then the Water Output Valve will work to drain the water out of the pool, so the water level in the pond will be made slightly lower to increase the pool temperature.

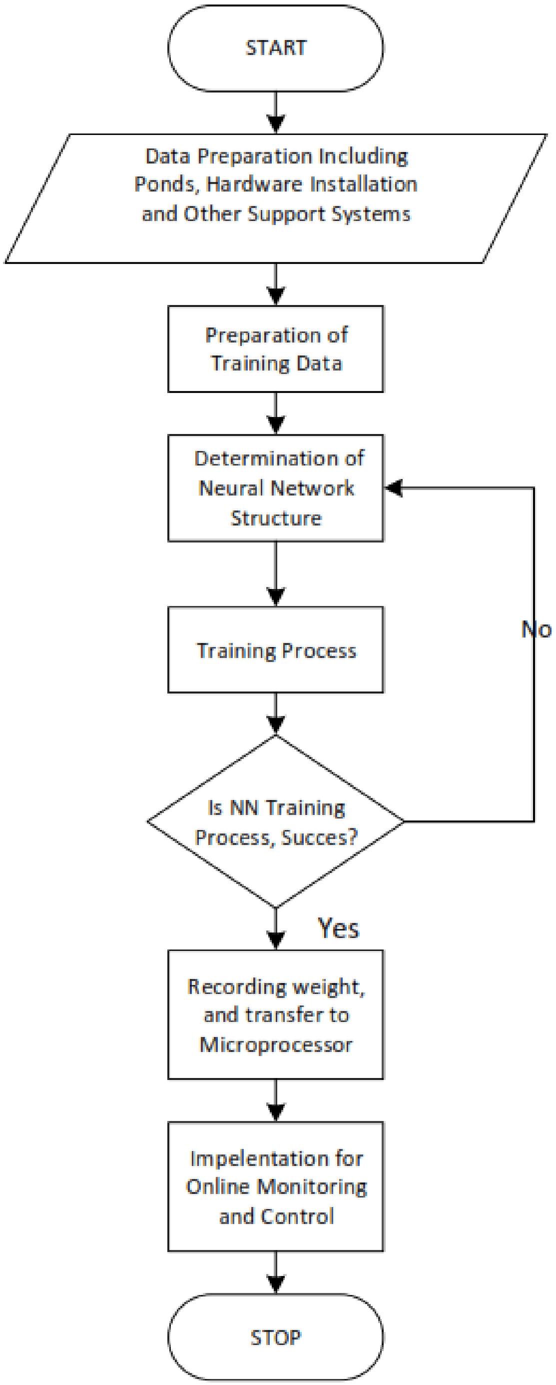

Fig. 1. Flowchart of design water management system

2.3. Neural Network (NN) Training Stage

A standard Feedforward Neural Network (FNN) processes data in one direction without memory, so each input is independent. Its hidden representation is:

$$h = f(Wx + b)$$

Where x is the input vector, W the weight matrix, b the bias, and f the activation function. The weight update is:

$$W = W - \eta \frac{\partial L}{\partial W}$$

where η is the learning rate and L the loss. In contrast, an RNN includes recurrence:

$$h_t = f(W_{xh}x_t + W_{hh}h_{t-1} + b)$$

Where h_t is the hidden state at time t, and shared weights enable efficient sequential training. For reasons of efficiency, RNN was chosen in this study. Some of the data used for RNN training can be seen in Table 1, due to space limitations, not all data is shown in this paper.

Fig. 2. Shrimp farm system

Table 1. Input-output data

Input					Output					
PH	**ΔPH**	**DO (ppm)**	**ºC**	**Feed (Kg)**	**CaMg (Kg)**	**CaCO3 (Kg)**	**Vout (m^3)**	**Vin (m^3)**	**Extra Aerator**	**Alarm**
8.1	0	7.0	28	3.8	0	0	0	0	0	0
8.0	0.5	7.5	30	4	0	0.5	0	0	0	1
8.7	0.7	6.9	28	3.8	0	0.7	0	0	0	1
8.5	0.2	7.1	30	4	0	0	0	0	0	0
8.3	0.2	7.3	28	3.8	0	0	0	0	0	0
8.0	0.2	7.2	30	4	0	0	0	0	0	0
7.8	0.2	7.3	28	3.8	0	0	0	0	0	0
6.9	0.9	1.4	28	3.8	0.9	0.9	5	5	1	1

The data was obtained based on daily logs of CaCO3 administration, routine feeding, and aerator conditions from shrimp farmers. The recorded data represents the optimal formulation for shrimp pond management, so the total data used is limited to 27 data, with 80% for RNN training purposes (22 data) and 20% for testing purposes (5 data). For TNN training purposes, this study used a structure with 4 inputs, 2 hidden layers (each with 9 hidden neurons and 7 hidden neurons), and 4 output neurons. The activation function used is a combination of logsig, since the input and output parameter data used have positive values. The method used in the training process for determining the weight is backpropagation. The training process is carried out using the MATLAB toolbox, with convergent results as shown in Fig. 5.

Fig. 3. Standing auto feeder

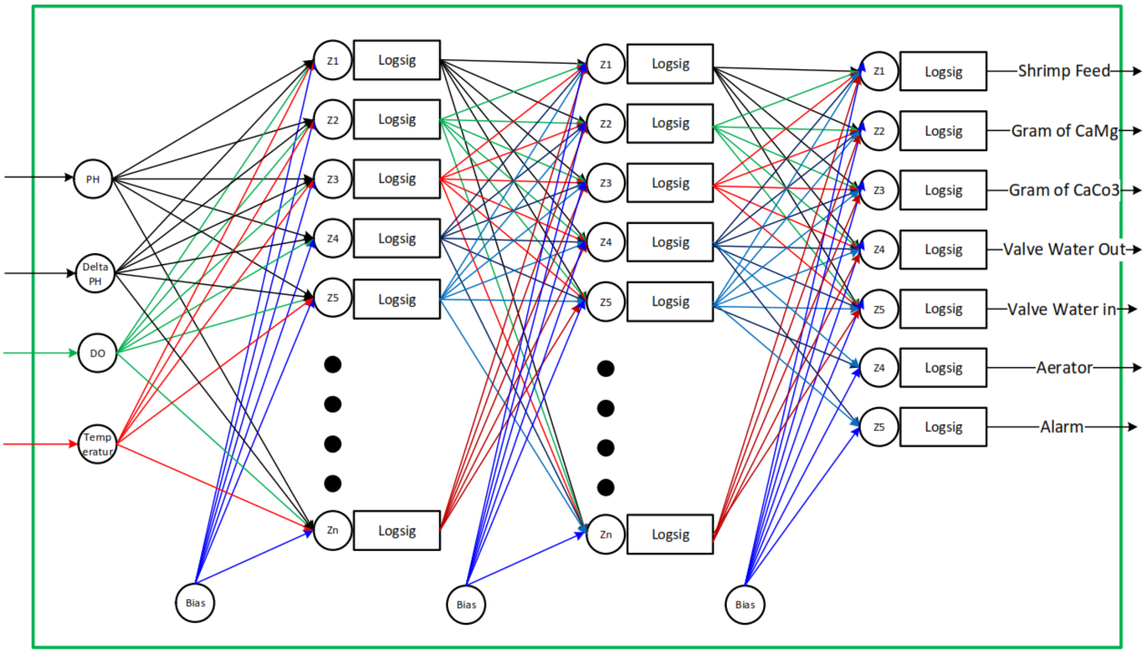

Fig. 4. Structure of recurrent neural network

The training process, training results converge on epoch 16 with MSE 2.63e^{-9}. RMSE comparison between training functions is shown in Table 2.

Table 2. Training functions comparison

Id	training function	RMSE			
		Feed (Kg)	CaCO3 (Kg)	Extra Aerator	Alarm
1	trainlm	0.0007	0.0057	0.0073	0.0073
2	trainbr	0.0009	0.0081	0.0047	0.0047
3	traingd	0.0426	0.2328	0.1186	0.1186
4	traingda	0.0256	0.1434	0.1022	0.1022

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Fig. 5. Training process data with the RNN toolbox

Based on Table 2, it shows that the Lavenberg-Marquardt-based training function has a more optimal RMSE value when compared to Bayesian regression, gradient descent, and gradient ascent in modeling feed scheduling and CaCO3. While Bayesian regression is superior in terms of modeling extra aerators and alarm flags since both output parameters have only 2 conditions, namely on and off, so it will be easier for regression-based methods to approach these 2 values. RNN training result and testing result shown in Fig. 6.

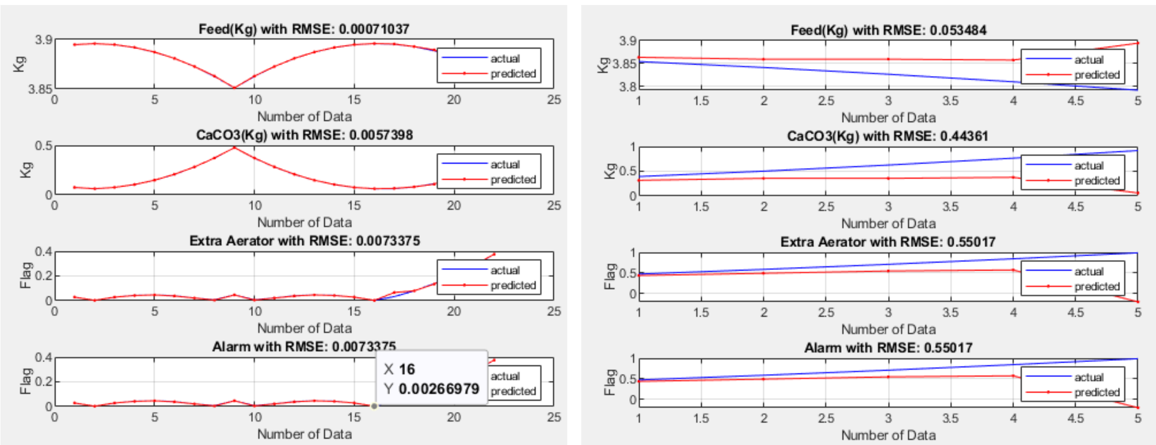

Fig. 6. RNN training result (left) and testing result (right)

3. Results and Discussion

3.1. Experimental Case Study

This paper, to test the performance of SWQM, was carried out in 4 shrimp ponds, as shown in Fig. 7 with four case studies described as follows:

Fig. 7. Shrimp farm with 4 ponds for experimental case study

The data in Fig. 7 is real Shrimp farm data, taken using Google.

- **Case-1:** Monitoring PH in real-time with SWQM for one month, and compared with manual measurements.
- **Case-2:** Monitoring DO in real-time with SWQM for one month, and compared with manual measurements.
- **Case-3:** Monitoring Temperature in real-time with SWQM for one month, and comparing with manual measurements.
- **Case-4:** Implementation of SWQM in real-time at Shrimp Farm for water quality control.

3.2. Experimental Data and Validation

- **Case-1 PH Validation**

PH Monitoring pH levels in shrimp ponds is crucial for successful shrimp farming, as it directly impacts shrimp health, growth, and survival. Maintaining pH within the optimal range helps prevent issues like ammonia toxicity, which can be lethal to shrimp. Regular monitoring allows for timely adjustments to water quality, ensuring a healthy environment for the shrimp and maximizing production. H monitoring in real-time with SWQM for one month was carried out by taking manual measurement data sampling in one day two PH measurement data were taken, PH measurements were carried out in the morning and evening. So the data presented is 60 data, the data was taken in November 2022. The results of the comparison between SWQM data and manual measurements can be seen in Fig. 8.

From the data in Fig. 8, it can be seen that the data between SWQM and manual measurements shows good consistency. The slight difference is only due to the difference in reading the number behind the comma, for manual measuring instruments it only detects 1 digit after the comma, while for SWQM it can detect 2 digits after the comma. From Fig. 8 it is known that the highest pH is 8.8 occurring in Pond-2, while the lowest pH is 7.98 occurring in all Ponds. The pH range indicates a safe value.

- **Case-2 DO Validation**

Monitoring dissolved oxygen (DO) levels is crucial for successful shrimp farming as it directly impacts shrimp health, growth, and survival. Maintaining adequate DO levels prevents stress, disease susceptibility, and mortality, leading to increased yields and improved feed conversion ratio. The monitoring results of Dissolved Oxygen (DO) can be seen in Fig. 9.

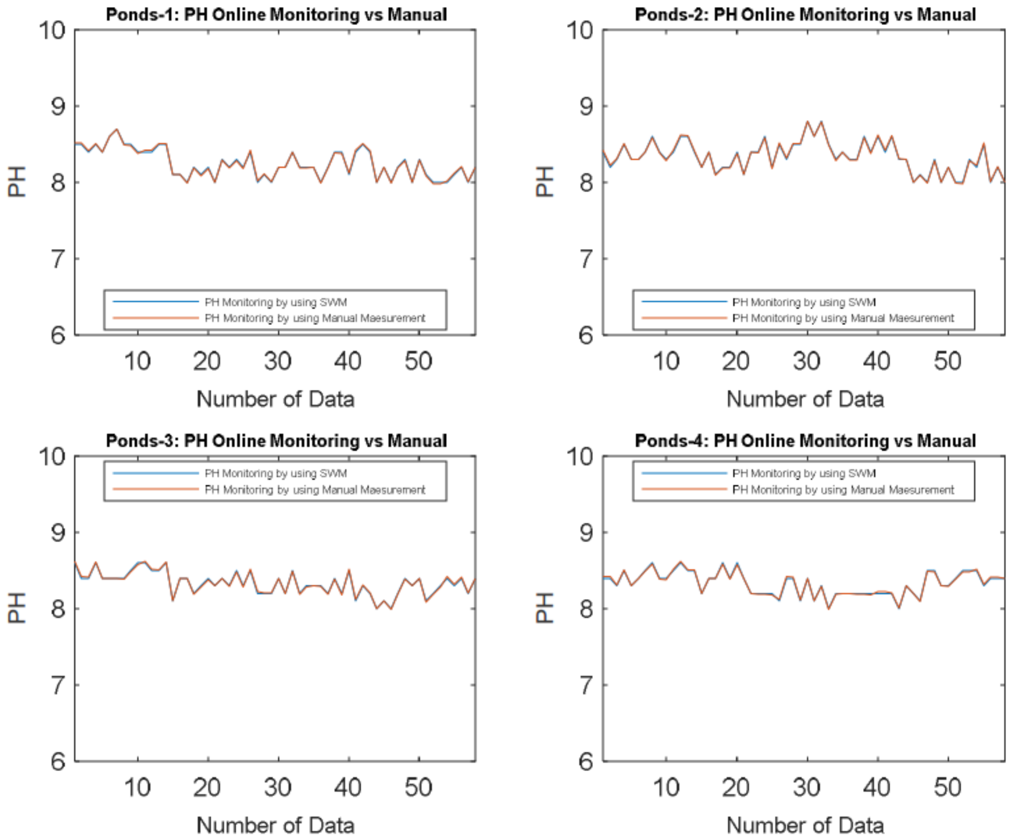

Fig. 8. Comparison PH data resulted from SWQM and manual measurement

From the data in Fig. 9, it can be seen that the DO measurement data between SWQM and manual measurements shows good consistency. The highest DO was 8.5200 which occurred at Pond-2, while the lowest DO was 5.9940 which occurred at Pond-4. Pond-4 has a vulnerability to decreased DO compare to other Ponds because the size of Pond-4 is 6 m in diameter. However, the measurement results still show safe results.

- **Case-3 Temperature Validation**

The monitoring results of Temperature can be seen in Fig. 10. From the data in Fig. 10, it can be seen that the temperature data between SWQM and manual measurements shows good consistency. The highest temperature that occurred during November at the Shrimp Farm was 31^{o} and occurred at Pond-2 and Pond-3, while the lowest temperature was 26^{o} and it happened at Pond-4. Pond-4 has a higher risk because it has the smallest size compared to other ponds. So that for this temperature the SAF will work, opening the out valve, to reduce the volume of water. Which will be explained in Case 4.

- **Case-4 SWQM Action Control**

Testing in case 4 uses sensor reading input data pH = 8.4, Delta pH = 0, DO = 6.9 and Temperature is 26. In this case, the temperature needs to be increased. In the Shrimp Farm area which has a relatively high temperature because it is at the equator, it is enough to increase the temperature by reducing the volume of water. This means that the action that must be taken is to open the Valve Out. The action of SAF can be seen in Fig. 11.

Fig. 9. Comparison DO data resulted from SWQM and manual measurement

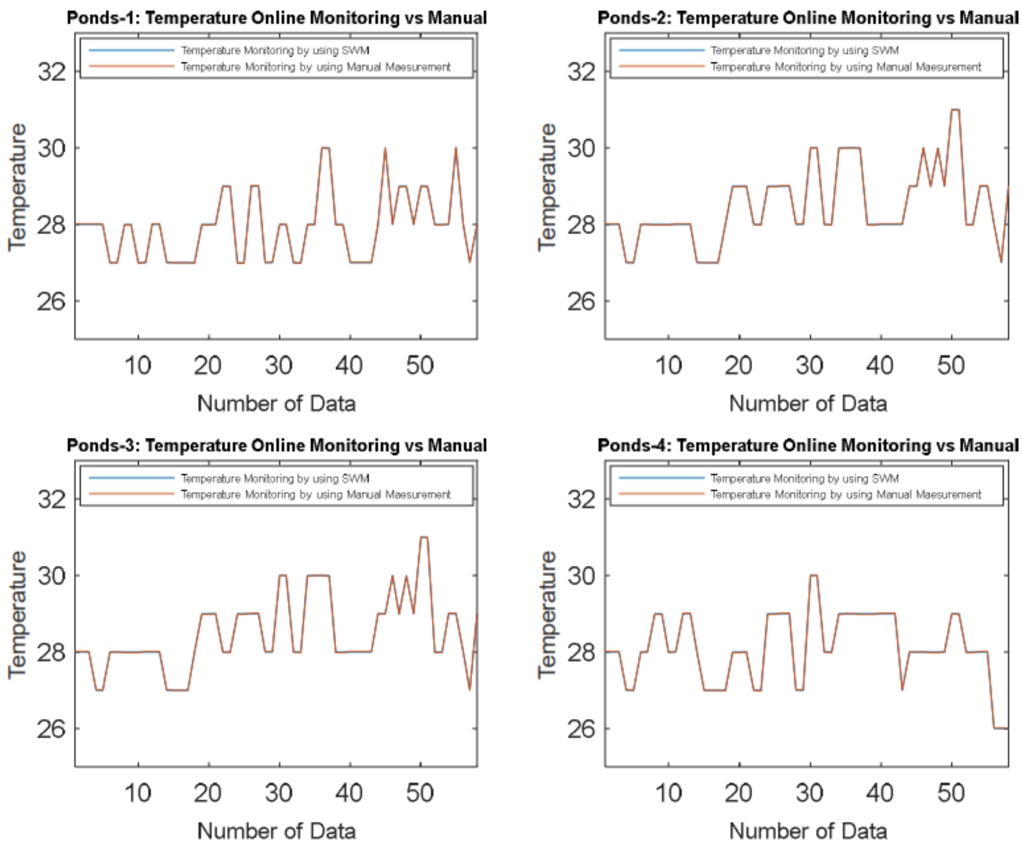

Fig. 10. Comparison temperature data resulted from SWQM and manual measurement

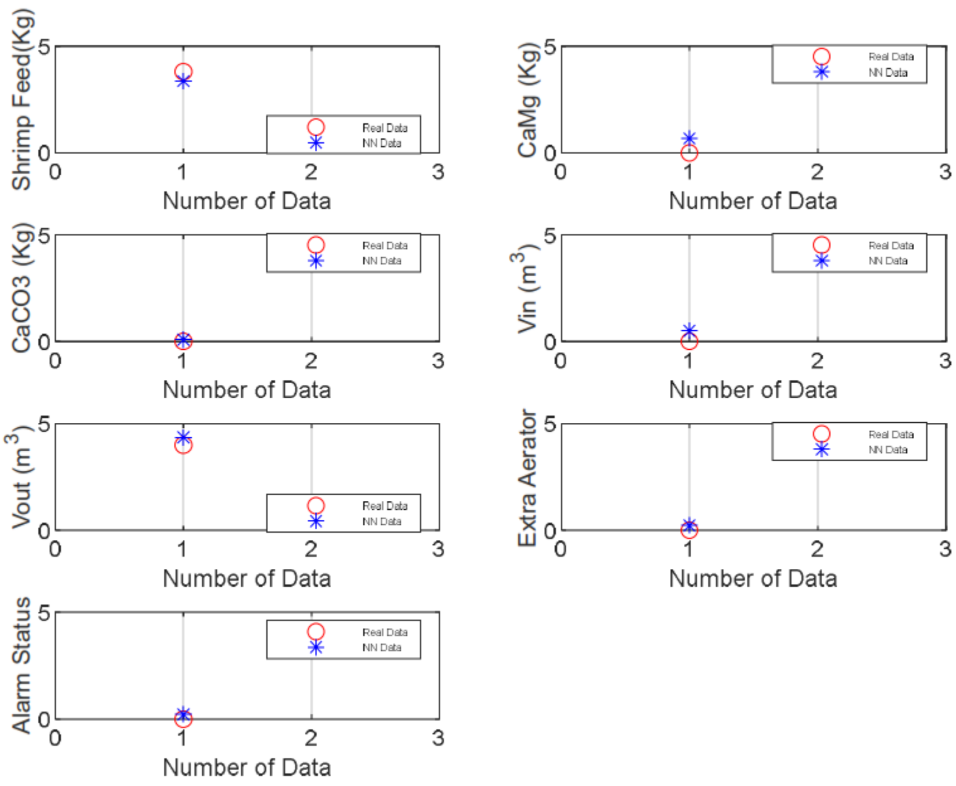

Fig. 11. SAF action

Fig. 11 shows that the water that must be removed is 4 cubic meters, and the results show consistent results between manual operation and SAF operation in SWQM.

4. Conclusion

From the experimental results, it is known that SWQM shows good results in water quality management for vannamei shrimp farming with an optimal RMSE for feed scheduling modeling with RMSE of 0.0007 and 0.0057 for CaCO3 scheduling. The experimental results show that the smaller pond size will have a higher risk compared to ponds that have a larger size. This is because a smaller amount of water tends to be less stable than a larger amount. The SWQM test also shows that the Recurrent Neural Network planted on the SAF microprocessor provides good performance, in acting, both in providing regular feed and controlling water quality. As a further mitigation step, a self-calibration system can be developed to maintain accuracy and precision on the standing auto feeder unit.

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