



Water Irrigation Decision Support System for Practical Weir Adjustment Using Artificial Intelligence and Machine Learning Techniques

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Abstract: This research proposes a decision support system for weir sluice gate level adjusting. The proposed system, named AWARD (Appropriate Weir Adjustment with Water Requirement Deliberation), is composed of three modules, which are (1) water level prediction, (2) sluice gates setting period estimation, and (3) sluice gates level adjusting calculation. The AWARD system applies an artificial neural network technique for water level prediction, a fuzzy logic control algorithm for sluice gate setting period estimation, and hydraulics equations for sluice gate level adjusting. The water requirements and supplies are deducted from the field-survey and telemetry stations in Chiang Rai Province, Thailand. The results show that the proposed system can accurately estimate the water volume. Water level prediction shows high accuracy. The standard error of prediction (SEP) is 2.58 cm and the mean absolute percentage error (MAPE) is 7.38%. The sluice gate setting period is practically adjusted. The sluice gate level is adjusted according to the water requirement.

Keywords: artificial intelligence; machine learning; ANN; fuzzy logic control; weir; sluice gate; water resource management; irrigation system; croplands

1. Introduction

Water resources are one of the most important issues of our time [1]. To manage water resources in an efficient manner, an innovative tool must be used to support a decision maker. In an area with water scarcity, to manage the resource without sacrificing the water ecosystem and community relationship, an un-biased predictive tool should be used. To promote equity and reduce conflict upon water supply during water scarcity in the dry season, integrated water resource management (IWRM) is considered. This is mentioned in the United Nations' Sustainable Development Goal (SDG) Goal 6 with the targets of 6.4 and 6.5 synergized to SDG Goal 10 as well. Agriculture plays a major role in Thailand's economy, making up about 8.1% of the country's GDP (World Bank, 2018). Almost 90% of fresh water is used for agriculture and related activities. While water resources are managed by the Royal Irrigation Department, Ministry of Agriculture and Cooperatives, there are reoccurring problems of flooding in the rainy season and water shortage in the dry season every year. To overcome these problems, several groups of local people were founded for water usage management. They work along with local farmers and local office agencies. However, the management is done manually, which often



causes community conflicts. An unbiased decision support tool for local people is introduced based on optimization and predictive techniques.

In the rural areas of Thailand, the weir system is applied widely for water resource management. The weirs and irrigation canals are managed by an elected weir controller person. A weir controller is elected from the farmers in the agricultural area. The weir controllers negotiate with each other to request the water for their croplands. This elected weir controller organization for water resource management has been established since B.E. 1100 and is called the Meng Rai Irrigation system [2]. Traditionally, the sluice gates are managed by the consideration of weir controllers. In order to achieve that, the weir controllers consider the recent river water level and their cropland water requirement, then they estimate the sluice gate level to let the water flow out to their irrigation canals. After the sluice gates are adjusted, the sluice gate levels remain in that level position for about a month. The weir controllers estimate the sluice gate level from their experiences and negotiation results. The flowing water in the river changes continuously. Thus, the greater frequency of the sluice gates adjustment, the more accuracy of water flow management. However, the sluice gate level cannot be adjusted on a daily or weekly basis because the weir controllers cannot arrange their meetings for negotiation [3,4]. Thus, the weir controller must predict the water level in the near future to estimate their sluice gate level setting. However, with the global climate change problems, the weir controller prediction for water volume may err. Thus, the water flow through the sluice gates may not meet the requirement of agricultural activities [5].

The proposed AWARD system (Appropriate Weir Adjustment with Water Requirement Deliberation) is the decision support system for weir's sluice gate operation adjustment. The AWARD system is composed of three modules: (1) Water level prediction, (2) sluice gate setting period estimation, and (3) sluice gate level adjustment calculation. In the water level prediction module, the future water levels are predicted using the artificial neuron network (ANN) technique. The sluice gate setting period estimation module takes the predicted water level as one of its inputs to estimate the frequency of sluice gate adjustment. In this module, the fuzzy logic control is applied to result in the practical sluice gate adjustment frequency. The weir controller is able to make a good effort to adjust the sluice gate level in a timely manner. Moreover, the predicted water levels from the ANN module can be used in the sluice gate level calculation. The weir sluice gate is operated to control the water volume distributed to the croplands. The proposed hydraulics equations in the sluice gate level adjustment calculation module takes the predicted water level, setting period, and the cropland water requirements. Thus, the results of the sluice gate levels and the sluice gate level setting period, and the water according to the farming activities.

This paper is organized as follows: Section 2 explains the principles applied in the proposed system, which includes hydraulics and hydrological principles and machine learning techniques (i.e., the artificial neural network and fuzzy logic control system). Section 3 describes the proposed system, named AWARD. Section 4 discusses the evaluation of AWARD system simulation results. Section 5 compares the AWARD system to the related works. Finally, Section 6 presents the conclusion.

2. Principles and Technique

This section describes the principles and techniques applied in this research. The basic background of the weir systems for water irrigation is described in Section 2.1. In Section 2.2, the details of the telemetry station for water level monitoring are explained. In Section 2.3, the flow principles composed of the hydraulic equations and stage–discharge relation techniques are presented. Then, the artificial neural network (ANN) and the fuzzy logic control mechanism are explained. in Section 2.4.

2.1. Weir Systems

The water resource management in the northern region of Thailand is operated using the weir systems. A weir is a construction that blocks the river and divides water to the agricultural areas as

shown in Figure 1. The sluice gates of the weir are used to control the amount of water distributed to the irrigation canal. The sluice gate operation is controlled by a weir controller who is elected from local farmers. The weir controllers have adjusted the sluice gate level according to the water situation using their experience for years. During the drought season, the farmers scramble for their cropland watering. The weir controllers are faced with the difficulties in sluice gate operations because of the water scarcity. The accuracy of water irrigation to meet the cropland water requirement becomes the key issue of weir controllers. In this research, the weir network is represented using flow principles. The amount of water is calculated as water discharge, which takes water level as an input. The flow principles are used to explain the water flow characteristic that flows out of the weir. The stage–discharge relation describes the relation between the water level and the water flow rate.



Figure 1. Typical weir system in Northern Thailand consists of weirs and canals.

2.2. The Telemetry Station

The water level data has been measured by a telemetry station installed at a bridge on the Mae Chan River, Mae Chan district, Chiang Rai, Thailand. The location of the telemetry station is shown in Figure 2. The distance between the telemetry station installation location and the case study weir is 5 km. The water level data are measured in centimeter units using an ultrasonic sensor to avoid the damage from flash flooding, and then the sensing data package is sent to the base server through a mobile network [6,7]. The interval time of sensing and sending the water level data is 5 min. When the data packages arrive at the base server, the water level data are preprocessed to reduce hardware and transmission errors. The preprocessed water level data are collected in the database. The water level data are also displayed on the website (www.crflood.com). Table 1 shows the telemetry station specification.

Table 1. Telemetry station specification.

Specifications	Values	
Weight	20 kg	
Dimensions	$30 \text{ cm} \times 20 \text{ cm} \times 55 \text{ cm}$	
Solar cell panel	40 W	
Battery	20 Amp 12 V	
Sensing Types	Ultrasonic, Temperature and Humidity	



(a) Mae Chan district location. (b) The location of the telemetry station.

Figure 2. The location of the telemetry station and the case study weir.

From Table 1, the dimensions of the telemetry station are $30 \text{ cm} \times 20 \text{ cm} \times 55 \text{ cm}$. The weight is about 20 kg. Since the telemetry station is installed in an area with no electricity, a 20 Amp, 12 V battery is used to store the electrical power generated by a 40 W solar cell panel. The measure data (i.e., water level, temperature, and humidity) are transmitted via a cellular network.

Figure 3 shows how the ultrasonic sensor measures the water level. The ultrasonics work by beaming out a sound wave at frequencies above the scope of human hearing and wait for the sound to be reflected back. The distance is calculated based on reflection time using Equation (1). In Equation (1), T is a turn around time period of the sound wave in the second unit. *C* is the speed of the sound wave (343 m/s) at 20 °C. In Equation (2), the water level is calculated as the clearance of *H* and the measured distance. *H* is the distance between the river bottom and the installed ultrasonic position as shown in Figure 3.

$$Distance = 0.5 * T * C \tag{1}$$

$$WaterLevel = H - Distance \tag{2}$$

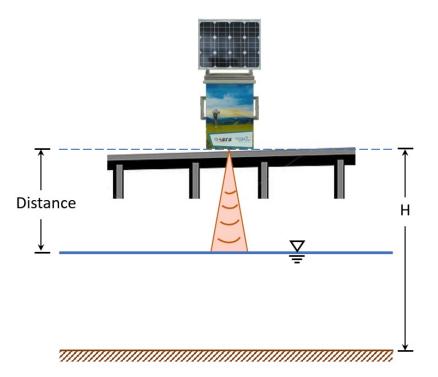


Figure 3. Water level measurement by an ultrasonic sensor.

2.3. Flow Principles

2.3.1. Hydraulics Equations

The flow velocity and the river's cross-section area are the main parameters of the water flow calculation. By using the hydraulics principles which describe the mechanic properties of fluids, the water discharge (flow rate) is calculated as shown in Equation (3).

$$Q = AV \tag{3}$$

In Equation (3), Q represents water discharge (in m³/s) which is calculated from a river cross-section area, (A) in m², multiplied by the velocity of the water flow, (V) in m/s.

$$Q_1 = Q_2 + Q_3$$
 (4)

$$A_1 V_1 = A_2 V_2 + A_3 V_3 \tag{5}$$

Generally, the main river is divided into river branches as shown in Figure 4. Equation (4) is the continuity equation used for describing this flow characteristic. The total water discharge of the main river (Q_1) is equal to the sum of the river branches' water discharges (Q_2+Q_3). Equation (5) represents the equation in terms of the river's cross-section area and water velocity by applying the hydraulics equation.

$$\frac{P_1}{\gamma} + \frac{v_1^2}{2g} + y_1 = \frac{P_2}{\gamma} + \frac{v_2^2}{2g} + y_2 + h_L \tag{6}$$

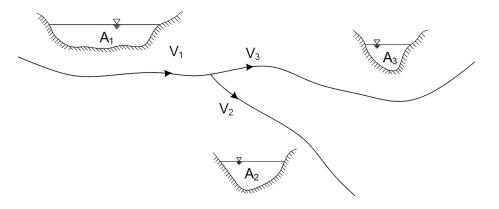


Figure 4. The main river can be divided into river branches.

As mentioned earlier, the water flow is controlled by the sluice gate of the weir. Bernoulli's equation, shown in Equation (6), is applied to calculate the water discharge that flows out of the weir through the sluice gate which opens *a* meter. In Figure 5, the referenced position number 1 locates before the sluice gate. The referenced position number 2 locates after the sluice gate. P_1 and P_2 represent the water pressures, V_1 and V_2 represent the water velocities, y_1 and y_2 are the water levels at position numbers 1 and 2, respectively. h_L is the total energy loss between position number 1 and 2. γ represents the specific weight of water (9.807 kN/m³) and *g* is the gravitational acceleration (9.806 m/s²).

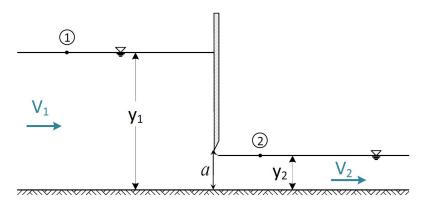


Figure 5. Water flow through a sluice gate.

2.3.2. Stage–Discharge Relation

In this research, the water level data is measured by the telemetry station. By using the stage–discharge relation method, the water discharge can be derived from the water level. Figure 6 shows the relation between the water discharge and the water level. This hydrograph is concluded from the field surveying.

$$Q = \alpha (h - h_0)^{\beta} \tag{7}$$

Equation (7) is the equation that represents the stage–discharge relation characteristic. Q represents the water discharge (i.e., flow rate). h_0 is the zero gauge level at the telemetry station location and h is the water level measured by the telemetry station. α and β coefficients are the constant values applied to calibrate for the river's cross-section.

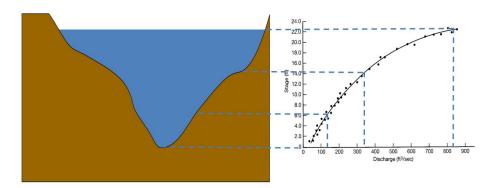


Figure 6. Stage-discharge relation.

2.4. Artificial Intelligent

Since the sluice gate setting period may last for months, the sluice gate level should be adjusted using the water level in the future. Thus, the accuracy of water level prediction becomes an important factor for water resource management. Then, the frequency to adjust the sluice gate should be practical for the weir controllers to operate the weir in a timely manner. If the sluice gate setting period is too long, the amount of water distributed to the croplands cannot meet the farming requirements. If the sluice gate setting period is too short, the weir controllers cannot follow the weir operation instruction in such a high frequency.

Thus, machine learning techniques have been applied in the AWARD system. The artificial neural network (ANN) used for the water level prediction is described in Section 2.4.1. Then, in Section 2.4.2, the fuzzy logic control technique used for determining the frequency of the sluice gate adjustment is explained.

2.4.1. Artificial Neural Networks (ANN)

Artificial neural network (ANN) is the mathematics model for information processing. The concept of the model is imitated from the neural system of the human brain which consists of neurons and synapses. The connections between neurons and synapses work as a network. The ANN is widely applied in flow prediction. The results of ANN provide a high accuracy in flow prediction compared with several machine learning techniques and traditional conceptual models [2,3]. Moreover, the parameter requirement for configuring the ANN is not complicated compared with other techniques.

The artificial neural network is the group of parallel processing units. The model consists of a set of nodes which are the input nodes, the output nodes, and the hidden nodes. Each node is connected to other nodes as the network. The connection lines between nodes have weight values. The model starts by assigning the value of input nodes. The values of the input node are assigned by the specialist or get from the variety of sensors or come from other systems. The values of input nodes will be forwarded to the hidden nodes in the next layer and processed with the weight values. The output values are forwarded as input values to the next layer until the last as shown in Figure 7.

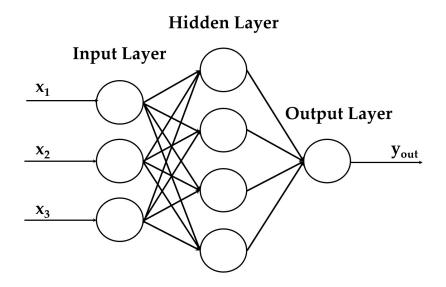


Figure 7. Standard artificial neural network structure.

In this research, the ANN is applied to predict the next day water level. The inputs are water level data the last three days. The initiated weights are random values. The output is the next day water level. The predicted water level is compared with the measured water level to calculate an error. The error is used to adjust the weight values for the next round. The method for adjusting the weight valued is called back-propagation.

$$Y_{out} = A(w_{ij}^k + \sum_{i=1}^{M_{k-1}} w_{ij}^k * X_i^{k-1})$$
(8)

In Equation (8), Y_{out} , which is the predicted water level, is the result of the ANN. The predicted water level is calculated by using the sum of the product between the weight of the connection between neuron node *i* and *j* (w_{ij}) and the water level data (X_i) at the previous time *i*. *A* is an activity function that the sigmoid function is applied to in this research.

The input data, which is the water level data, is divided into a training set and a test set in ANN. The training set is used to train the ANN model for letting the model learn and tune up its weight values. During the learning process, the learning rate is defined to adjust the errors in each round. These affect the training time and the accuracy level. After the learning process, the test dataset is applied to test how well the model works.

2.4.2. Fuzzy Logic Control

Water resource management using the weir system is controlled by the weir controller persons who are the senior villagers with great experience. The weir controllers negotiate and discuss with each other to adjust the sluice gate level and sluice gate setting period based on the present situation. However, nowadays, the climate change problem affects the river flow characteristics. The water management needs more accuracy of information to support the decision making. Moreover, the weir controller's work is hard and dedicated. Therefore, some river basins may lack weir controllers in the future. The fuzzy logic control technique is applied to support water resource management, which is not up to people. Besides, the expert consideration is applied in the fuzzy logic control technique. The accuracy of the sluice gate adjusting can be increased with less human interventions.

Fuzzy logic control is a heuristic approach that works like the decision making process of a human. It supports the problem which responds as linguistic values [8–10]. Fuzzy logic control is composed of four processes, (1) fuzzification, (2) fuzzy rule base, (3) fuzzy inferencing, and (4) defuzzification, as shown in Figure 8. Fuzzification is a process that transfers the crisp input into a fuzzy input which is called a membership function. The membership function is the graph that defines how the crisp value, i.e., the input value, is mapped to the degree of membership, i.e., DOM. The fuzzy rule-based conditions are IF–THEN constructions; each of them is in the general form of if A then B. The rule-based conditions are defined by experts. Fuzzy inference is a process to analyze the conditions using fuzzy rule-based conditions. Defuzzification is a process of converting the fuzzy outputs into the crisp outputs (i.e., the numerical values).

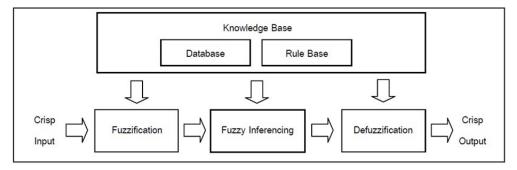


Figure 8. Fuzzy logic control structure.

3. The AWARD System

The Appropriate Weir Adjustment with water Requirement Deliberation (AWARD) system is a decision support system for weirs with sluice gates operation management. The AWARD system consists of three modules: (1) Water level prediction, (2) sluice gate setting period estimation, and (3) sluice gates level adjusting calculation as shown in Figure 9.

3.1. Water Level Prediction

The water level prediction module is the process to estimate the next day water level. The input of this module is the last three days' water level dataset which is measured by the telemetry station. The input dataset is divided into two ranges, (1) the low-flow rate of water level data which represent the flow rate in the dry season in Thailand (i.e., January to July 2015 and November 2015 to February 2016), and (2) the high-flow rate of water level data which represents the water flow rate in the rainy season in Thailand (i.e., August to October 2015) [11,12]. The two ranges of the flow rate impact on the frequency of the sluice gate adjustment's estimation.

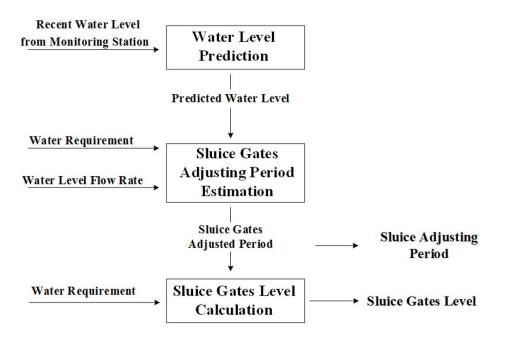


Figure 9. The structure of Appropriate Weir Adjustment with water Requirement Deliberation (AWARD) system.

The input data is processed with the weight values which are initially random. The output is produced as the predicted water level (or the next day water level). The predicted water level is compared with the water level which is measured by the telemetry station. The ANN technique is applied to find the predicted water level. The input nodes are connected to the nodes in hidden layers. There is a weight value assigned at each connection. Then, the weighted sum is calculated as the outputs. The weight values are adjusted at each iteration. The error of the predicted water level to the observed water level is applied to tune up the weight for the next round; this process is called the backpropagation process. In this research, the sigmoid function is applied in the backpropagation process. These operations are repeatedly invoked to adjust the weight value; this is the process to train the machine. The 432 data points are applied to train the ANN. Then, the trained ANN model can be used for water level prediction. Table 2 shows the ANN parameter setting used in this module. The 90 percent of water level at sent through the next module as one of the inputs of the sluice gates setting period estimation module.

Table 2.	The ANN	configuration.
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ANN Parameters				
Input Layer	3			
Hidden Layers	4			
Learning Rate	0.00005			
Iteration	1000			
Data Parameters				
Training Data	90% (432)			
Testing Data	10% (48)			

3.2. Sluice Gates Setting Period Estimation

Generally, the sluice gates are adjusted by the weir controllers who are elected by villagers. The weir controllers adjust sluice gates using their experience. The sluice gates are adjusted periodically up to water level situation. In the rainy season, the water level is high and changes often. The sluice gates should be frequently adjusted. While in the dry season, the water level is very low, so there is no need to adjust the sluice gates or it is rare to adjust the sluice gates.

As mentioned above, the weir controllers adjust the sluice gate using their experience. Surely, each weir controller does not have the same experience. Some do not have adequate data to make the decision about when and how often to adjust the sluice gates. These cause inefficient water resource management, especially in the rainy season.

The fuzzy logic control is applied in the AWARD system to determine the frequency of the sluice gate adjustment. There are three parameters considered for determining the frequency of the sluice gate adjustment: (1) The water levels, (2) the degree of water requirement, and (3) the water level rate. Figure 10. shows the graphs of the membership function used in this module. For each graph, the y-axis represents the degree of membership (DOM), while the x-axis represents the value of the water level, the degree of water requirement, the water level rate, and the frequency of the sluice gate adjustment, respectively. In Figure 10a, the fuzzy set of the water level is divided into low, medium, and high water level (cm) in the normalized form of the DOM. In Figure 10b, the fuzzy set of water requirement is divided into low and high level of water requirement ($10^3 \text{ m}^3/\text{month}$). In Figure 10c, the fuzzy set of water level rate is divided into negative (–) which represents the water level is decreasing, zero (0) which represents the water level is stable, and positive (+) which represents the water level is increasing. These membership function graphs are gathered by a survey and by interviewing the weir controllers and the heads of villages.

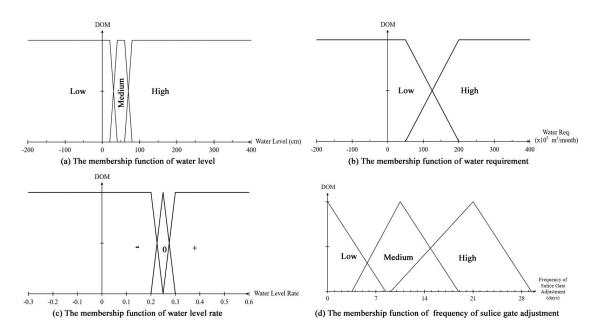


Figure 10. Membership functions.

The fuzzy rule base was determined by the experts, two water resource engineers, using three considered parameters, as shown in Table 3. The rule base has been discussed and rechecked. For example, when the water level is high, the water requirement is also high, and the water flow rate is "+" (positive), which means the water level rate is increasing. Thus the frequency to adjust the sluice gate should be high to respond to the changes. In Figure 10d, the fuzzy set of the sluice gate adjusting frequency is divided into low, medium, and high. This graph is used for the defuzzification process to transform the fuzzy values to the number of the sluice gate adjustment.

Water Level	Water Requirement	Water Flow Rate	Adjusted Frequency
Low	Low	-	Low
Medium	Low	-	Low
High	Low	-	Low
Low	High	-	Low
Medium	High	-	Medium
High	High	-	Medium
Low	Low	0	Low
Medium	Low	0	Low
High	Low	0	Low
Low	High	0	Low
Medium	High	0	Medium
High	High	0	High
Low	Low	+	Low
Medium	Low	+	Medium
High	Low	+	High
Low	High	+	Medium
Medium	High	+	Medium
High	High	+	High

Table 3. Fuzzy rule base.

3.3. Sluice Gates Level Adjusting Calculation

Traditionally, the sluice gate is used to control the water flow that flows out of the weir. To irrigate sufficient water and avoid floods in the agriculture area, the weir controllers have to adjust the sluice gate level by considering the recent water level and the water requirement which is collected for the cropland areas of each farmer in the historical record.

The water requirements are calculated using cropland areas multiplied by water requirement for each crop.

$$Q_3 = \frac{CBa\sqrt{2gy_1}}{\sqrt{\frac{a}{y_1} + 1}}$$
(9)

Bernoulli's equation, Equation (6), is applied for calculating the sluice gate level. Equation (9) has been rearranged from Equation (6). It represents the discharge flowing through a sluice gate using a recent water level as input. In this equation, *C* and *B* are the coefficients of the sluice gate and sluice gate width, respectively. *a* represents the sluice gate level, y_1 is the water level in front of the sluice gate, and *g* is gravity acceleration. The actual water flow through the sluice gate is the result of Equation (9). This result (i.e., water discharge) is compared with the water requirement of farmers. Finally, the sluice gate level is adjusted for balancing the predicted water level and the water requirement.

4. Evaluation

4.1. Location and Data (Simulation Setup)

A practical testbed for the water resource management model used the weir and upstream telemetry station located along Mae Chan River in Chiang Rai Province, Thailand as displayed in Figure 11. The watershed area covered 1197 square kilometers of farmland in Pa Tueng District, Mae Chan City, Chiang Rai Province.



Figure 11. Location of the case study weir.

The water level data was automatically measured and sent from the telemetry station to the research lab's computer server. The data was used for the prediction of the following day water level. The historical fourteen-month data was used in this study displaying low-flow level and high-flow level during January–July 2015 and November 2015–February 2016, respectively, as displayed in Figure 12.

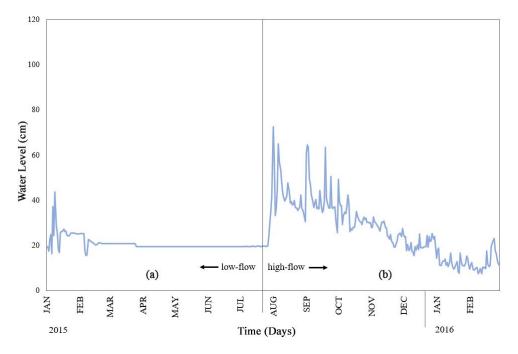


Figure 12. The observed water level: (a) Low flow season and (b) high flow season

The agricultural land data were collected by in-depth interviews of farmers in the areas. Then, the agricultural data was digitized to the GIS system for calculation of water requirements based on crop types and their area. Table 4 displays the agricultural areas in Pa Tung District. The product of the crop area and the water requirement coefficient of each crop per square meter is the water requirement for the interested farming area.

	Area of Rice Farm (m ²)	Water Requirement (m ³ /m ² /month)	Water Requirement (m ³ /month)
			-
January	3250	507	1,646,280
February	3250	404	1,313,037
March	3250	456	1,482,892
April	3250	470	1,527,572
May	3250	93	301,932
June	12,210	8	93,223
July	12,210	178	2,176,618
August	12,210	32	391,114
September	12,210	2	22,296
Ôctober	12,210	179	2,188,327
November	12,210	168	2,045,426
December	12,210	1	6995

Table 4. Farming area of Pa Tung District, Chiang Rai Provence.

Three datasets were gathered in this study: (1) Water level, (2) water requirement for the farming activity, and (3) water level rate in the river. Daily water level data was gathered from telemetry for 14 months. The observed water level data is shown in Figure 12.

The water level rate is calculated from the water level. This parameter shows that the water level rate is increasing or decreasing. The water level rate also shows how the water increases, gradually or rapidly.

4.2. Evaluation Results

4.2.1. Water Level Prediction

The predicted water level data (the results of the ANN Model) were compared with the observed water levels as shown in Figure 13. The x-axis represents time period (months) and the y-axis represents the water level (m). As can be seen in the graph, the predicted water level that is represented by the solid blue line has a similar pattern as the observed water level that is represented by the solid orange line.

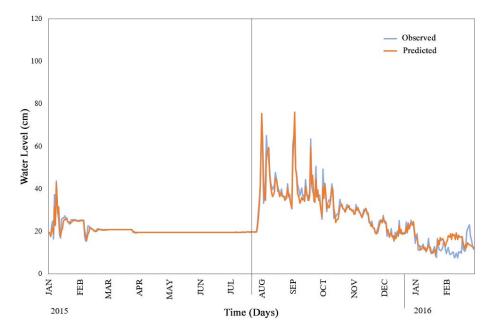


Figure 13. The predicted water levels and the observed water levels.

The standard error of prediction (SEP) is a measurement metric of the accuracy of prediction and is calculated using Equation (10). d_i is the difference between the predicted water level (P_i) and the

$$SEP = \sqrt{\frac{\sum d_i^2}{n}} \tag{10}$$

$$d_i = P_i - O_i \tag{11}$$

The mean absolute percentage error (MAPE) is used to measure the percentage of prediction error. Equation (12) shows how to calculate the MAPE. The MAPE is 1.56% in low-flow season and 13.16% in high-flow season. The MAPE of overall water level data is 7.38%.

These results (SEP and MAPE) show that the predicted water level data correspond to the observed water level data.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{O_i - P_i}{O_i} \right| * 100$$
(12)

4.2.2. Sluice Gate Adjustment

The sluice gates level is calculated using the hydraulics formula by taking the monthly amount of water requirement of the local croplands, the predicted water level, and the sluice gate adjustment period as the parameters. The monthly amount of water requirement of the local croplands is calculated from the area of each crop type times with the amount of estimated water requirement for the crop at the period. The predicted water level is the result of the ANN described in the previous section. The sluice gate adjustment period is the result of the fuzzy logic control algorithm which takes the predicted water level, the water requirements, and the water level rate as its inputs.

Figure 14 shows the frequency (times/month) for adjusting the sluice gate level which is the result of the fuzzy logic control system. The result shows that in the high-flow season, August 2015 to October 2015, the sluice gate should be adjusted more often to handle the dramatic water level changes. The water discharge from the sluice gate should be sufficient for the cropland's water requirements and avoid cropland flooding. In the low-flow season, January 2015 to July 2015 and January 2016–February 2016, the river water level is statically low. The intake of water discharge from the river is very low. The sluice gate should open widely to irrigate the water to the croplands. Since in the low-flow season the water level remains statically low, the frequency to adjust the sluice gate can be low in order to comfort the weir controllers.

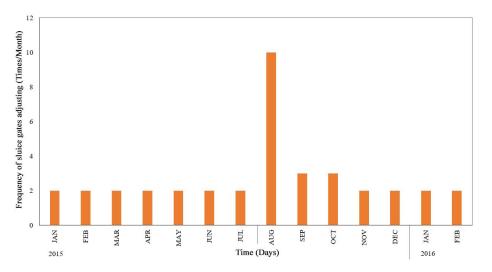


Figure 14. The frequency of sluice gates adjusting.

4.2.3. Scenario Comparisons

In Figure 15, four scenarios are compared, (1) sluice gates adjusted using weir controller's experience (noPre+NoEq), (2) daily adjusted using calculation results with recent water level as input (NoPre+Eq), (3) daily adjusted using calculation results with predicted water level as input (Pre+Eq), and (4) the proposed system: The sluice gate level setting period is adjusted using fuzzy logic control and calculation results with predicted water level as input (Pre+Eq+Fuzzy). Figure 15 shows the accumulative water discharge errors from the four scenarios in 14 months. The water discharge error is calculated as the difference of the water discharge from the sluice gate to the cropland's water volume requirements.

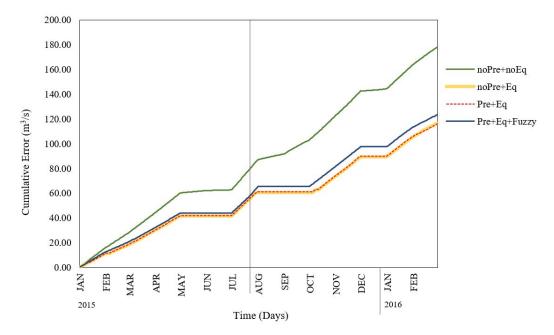


Figure 15. The comparison of cumulative errors.

Figure 15 shows that the highest accuracy of water irrigation to meet the croplands' water requirements comes from the scenario daily adjusted using predicted data as an input parameter (Pre+Eq). This happens because the sluice gate level is adjusted every day to the predicted water level. However, it is not practical since the weir controller persons cannot manually adjust the sluice gate level every day. Then, the result from the daily adjusted using the observed water level as input data (NoPre+Eq) comes to the second rank of accuracy. The errors of this scenario (NoPre+Eq) come from the water level changes. The sluice gate is adjusted with the water level in the past. Then, the lowest accuracy comes from the traditional weir operation of the weir controller persons. This happens because of the low frequency of the sluice gate level adjustment and the incorrect water level estimation. The proposed AWARD system (scenario Pre+Eq+Fuzzy) can maintain high accuracy while keeping the low frequency of sluice gate level adjustment; the weir controllers are able to adjust the sluice gate level weekly. The AWARD system contributes the practical sluice operations for the weir controller persons.

5. Related Works

Weirs and sluice gates were studied in several fields such as economics, robustness, policy, sustainable, historical, hydrology, etc. [2,13,14]. Ounvichit, T [4] has studied self-reliant farmers in small- and large-scale weir systems. The structural equilibrium and water sharing transparent and accountable to members were discussed. However, the water distribution accuracy, the sluice gate setting period were not focused on in the research. In contrast, the AWARD system applies

ANN and fuzzy logic control techniques to improve the water distribution accuracy and sluice gate adjusting period.

The studies of sluice gates adjusting level calculations mostly focus on the mechanical equations [15,16]. Ghidsian, M [17] studied side sluice gates which are the same sluice gate type as in this research. The suitable discharge equations and coefficients were proposed. The equations provide the water discharge from the sluice gate level setting with high accuracy. However, the water distribution to meet the water requirements from the croplands was not considered. The sluice gate level setting period is not the result from the paper. In the AWARD system, the sluice gate level adjustment is calculated from the mechanical equations and fuzzy logic control techniques. The sluice gate level and the setting period can be provided from the AWARD system.

Moreover, the integration of machine learning techniques (e.g., ANN: Artificial neural network and SVM: Support vector machine) and artificial intelligence techniques (e.g., fuzzy logic control, evolutionary computation, and decision tree) in water irrigation systems has not been widely discussed and evaluated. Fuzzy logic was applied for several purposes in water resource management, such as flow estimation [18], water table of ground water [19], flow and ecological simulation in rivers [20,21]. In [20], the fuzzy logic control technique was applied for fish habitat simulation. CASiMiR [22,23], a fuzzy logic-based ecohydraulic modeling system, was integrated with the HEC-RAS model [24,25]. The effect of weirs on a fish habitat was considered, not weir and sluice gate management. Mostly, the fuzzy logic control in hydrological field focuses on the reservoir operations. Goyal, M.K. and others [26] studied reservoir operation by using ANN with a backpropagation algorithm similar to this proposed system. However, the proposed AWARD system integrates the artificial neural network, fuzzy logic control, and the hydraulics equations to result in the appropriate sluice gates level and practical setting period to maintain the balance of the water discharge to the cropland's water demand. The weir controllers are able to apply the results of the proposed decision support system to manually operate their sluice gates practically.

6. Conclusions

Weir controllers are the key persons to manually operate the weirs and distribute the water along the irrigation canals to the croplands. With the effects of climate change, the weir controller experiences become not adequate to handle the croplands' high-water demand and reduce the flooding risk. This research paper proposes a water irrigation decision support system for practical weir adjustment named AWARD (Appropriate Weir Adjustment with Water Requirement Deliberation). The AWARD system is composed of three modules, (1) water level prediction, (2) sluice gates setting period estimation, and (3) sluice gates level adjusting calculation. Machine learning and artificial intelligence techniques are integrated in the proposed AWARD system. The artificial neural network algorithm is applied to predict the near future water level. Then the fuzzy logic control is applied to estimate the sluice gate setting period module by taking the predicted water level as its input. The sluice gate setting period, the water predicted water level and predicted intake water volume are applied in the hydraulics equations to calculate the sluice gate adjusting level. The key design concept of the AWARD system is the sustainability in irrigating the water to meet the cropland water requirements with practical hand-operated sluice gate level adjustment by a weir controller person.

The AWARD system has been evaluated with the actual observed water level data from the telemetry station and the surveyed cropland water requirements for 14 months. The predicted water level resulting from the ANN is in high accuracy with SEP 2.58 cm, and MAPE is 7.38%. Then, using the predicted water level as an input in the fuzzy logic control module and hydraulic equations results in the practical frequency hand-operated sluice gate level adjustment. The AWARD system recommends that the sluice gate level adjusting frequency in high-flow season be higher than that in low-flow season to sustain the water balance of cropland water requirement and the intake water volume along the river. By average, the weir controller persons should manually adjust the sluice gate level two

times per month in the low-flow season to meet the local cropland water requirements and four times per month in the high-flow season to reduce the chance of cropland flooding situations.

The AWARD system provides the practical sluice gate adjustment recommendation for the weir controller persons. The weir controllers can adjust the weir sluice gate level at a low frequency while maintaining the balance of the water discharge to the cropland's water demand. The system can be adopted into any application for decision making support systems initially, in which the final goal is to be fully automated into any integrated water resource management (IWRM). However, the limitation of the system is based on the water flow in a rural area which is slightly different from those in an urban area. In the future, the research challenge is to design an algorithm for the series of weirs. The parameter values in the degree of membership in the fuzzy process have to be adjusted for the other weirs. To avoid the parameter setting error from the experts, the AWARD systems should adjust all of the parameter values using the machine learning process. In the long term goal, the possibility to apply the AWARD system in the large water basin should be studied.

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