IOT TECHNOLOGY BASED SMART WATER LEVEL PREDICTION SYSTEM IN TAIWAN TAO-YUAN MAIN CANAL

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ABSTRACT

Taiwan is located in the subtropical zone and the Ring of Fire. It suffers from natural disasters such as typhoons, heavy rains, droughts and earthquakes every year. In order to solve the impact of extreme rainfall, the Irrigation Associations in Taiwan developed a hydrological automatic forecasting system in 2005, and then adopted the IoT (Internet of Things) technology to construct hydrological monitoring system for irrigation water management in 2018.

The spread all over of ponds for regional irrigation in the terrace-based terrain is the unique characteristic of Tao-Yuan Irrigation Association (TIA). 284 ponds with a total storage of 45 million m3 of water is used in response to insufficient water supply in Taoyuan main canal. Under the influence from climate change, the control of storage capacity in ponds need to be improved and effectively utilized. Therefore, the study uses the Internet of Things (IoT) technology to construct the dynamic management system that enhances the utilization efficiency of the ponds management for effectively allocating the water resources.

The study was carried out in 2018 through field investigation, monitoring station architecture planning, on-site contracting and construction, supplemented by hydraulic model and Back-Propagation Networks (BPN) to construct a canal water level prediction model and develop pond dynamic analysis management platform to present and predict the water level for allocation decision support to the manager. The system effectively achieves the goal of modernization of irrigation water allocation and pond management. In view of the impact of climate change and the more difficult agricultural water environment, this study can be used as a reference for countries that are also facing similar water management challenges.

Keywords : Internet of Things; Irrigation Pond management; Tao-Yuan main canal, Taiwan.

1. INTRODUCTION

Taiwan Tao-Yuan Irrigation Association (TIA) is located in the northwest of Taiwan, the irrigation system is Tao-Yuan Main Canal and Guang-fu Canal. The terrain in the area is tilted from the main canal to the coast with the slope between 1/100 and 1/120, formed the natural water supply system and hundreds of ponds. The irrigation water source provided by Shimen Reservoir accounted for 56%, the rest by river intake and effective rainfall accounted for 44%. Although Shimen Reservoir exerts great function in mediation and storage, but the source from river and rainfall are not included. Farm ponds distributed in the jurisdiction of TIA contributed effectively in water allocation in combination with the water available from the above mentioned

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two Canals and rainfall. The 284 existing farm ponds not only become a natural feature of TIA, with the total water storage capacity of 4,520,000 m^3 (quarter capacity from Shimen Reservoir) also play an important role in water conservation in Tao-Yuan irrigation area.

Taiwan is under the influence of climate change and, although it has 2500 mm annual rainfall but due to climate change the rainy and dry season ratio in Northern Taiwan has already become 6:4. This dramatic distribution difference makes it extremely difficult to store and utilize water resources effectively. In order to grasp the real time water volume of the ponds, TIA paid lots of resources to build monitoring stations in the past, but yielded little contribution to water management, because of the poor efficiency and high cost of equipment and their maintenance. Nowadays, through the advancement of equipment technology and communication technology in Internet of Things (IoT), the hydrological monitoring system of farm ponds were setup and equipped with dynamic analysis management model.

2. SYSTEM PLANNING AND CONSTRUCTION

2.1 Field Survey and System Design

The construction of the IoT architecture has many projects and involves professional technology and system integration. First of all, in the local system part, the field survey and investigation work is indispensable for selecting the best setting location to monitoring stations in the future. The investigation focuses on confirming the physical range and accuracy level requirements of the sensor and confirming the sensor construction and measuring the surrounding dimensions of the installation site, evaluating the life of the sensor, thinking about the sensing and installation of the sensor to the current water supply channel and ponds. Impact of maintenance, investigation and analysis of networks, communications and telecommunications, and final review of monitoring stations are also required.

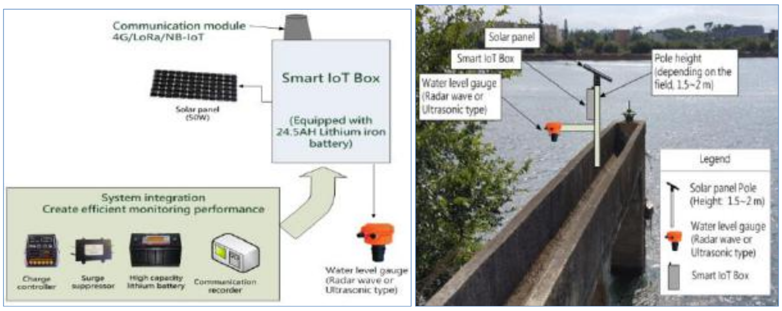

Figure 1. Scheme of integrated smart IoT box and pond field station.

In this study, the planning of field station changes of the traditional monitoring and measurement methods, combined with the integrated system under the development of the new technology of the material network to achieve miniaturization, wireless, modularization and weather resistance of the monitoring and transmission components (with waterproof, impact, etc.) was implemented as shown in Figure 1. In order to achieve relevant monitoring and management, instant transmission and cloudization the study also established integrated database, analysis module, decision system and interactive information platform for further analysis of the data collected from the 61 field stations established in 2018, (shown as Figure 2.)

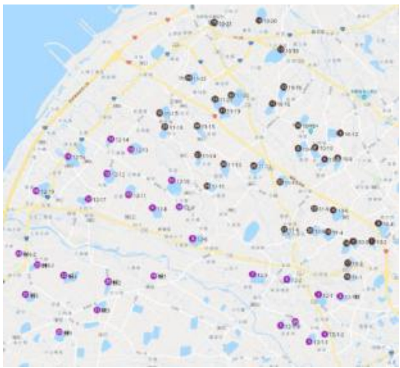

Figure 2. Scheme of field stations established in 2018

2.2 System Construction

In order to safeguard farmers' water rights and enhance the sustainable use efficiency of water resources, under the pressure of water resources development and the need of agricultural water demand, this study aims at mastering the management and operation of the current irrigation ponds. In order to improve the effective use of water resources, grasp instant water quantity and quickly make water resources counter measures. This study uses the mature and developed network communication and IoT technology, to construct this system, the relevant work items were as follows:(1) Pond water level sensing system construction;(2) Using interface of the Water Resources IoT System establishment;(3) Construction of the main canal water level prediction model;(4) Suggestion model construction for water storage allocation in the pond;(5) Monitoring of abnormality of water level in pond;(6) The establishment of the dashboard and workstation display system

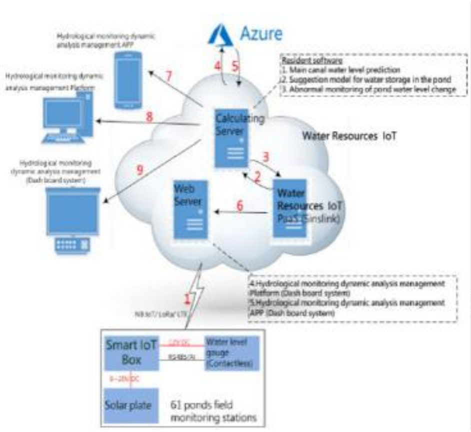

Figure 3. System communication flow chart

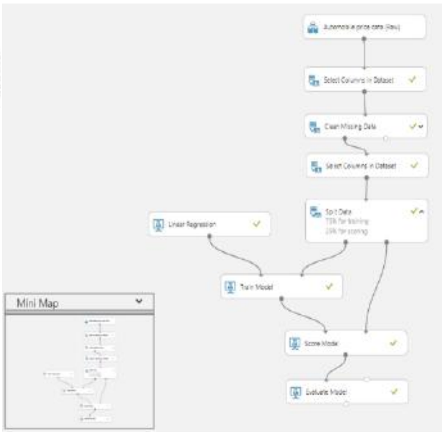

Figure 4. Schematic diagram of chart Azure Platform interface

The communication flow chart as shown in Figure 3, through the IoT communication technology, collecting the water level data and transmit it to the Water Resources management. By combining Azure computing resources (Figure 4), the relevant hydrological simulation calculations were carried out immediately to overcome the operation of the pond strategy, disaster prevention response, pond management recommendations, etc., and to build relevant web pages, so that managers can view relevant outputs on mobile devices, desktop computers, and display systems and workstations.

3. METHODOLOGY

3.1 Study Area and Data Inputs

The study aims at the water level forecast for the No.10 and No.12 sub canal of Tao-Yuan Main Canal, predicting the water level within 1,2, and 3 hours as t+6, t+12 and t+18 in the future (time interval as 10 minutes). According to the eight rainfall stations, the average rainfall is calculated by the Xu-Sheng method as the input factor of the prediction model. The range of the catchment area is shown in Figure 5. The Xu-Sheng weights calculated according to the eight rainfall stations are shown in Table 1.

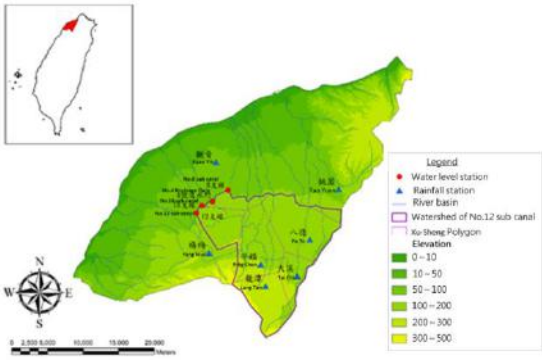

Figure 4. Tao-Yuan Main Canal Watershed

Table. 1 Rainfall Station and Xu-Sheng Weight

Station No	Site name	Data recorded From	Xu-Sheng weight
C0C650	Ping Chen	2007/12/1	0.232
C0C490	Pa Te	2011/12/1	0.277
C0C590	Kuan Yin	2007/10/1	0.059
C0C660	Yang Mei	2013/08/1	0.131
C0C630	Tai Chi	2007/12/1	0.094
C0C480	Tao Yuan	2008/01/1	0.022
C0C670	Lung Tan	2014/04/1	0.185

3.1.1 Independent Rainfall Events Filtration

The study selects training data that meet the start-up criteria, that the rainfall is greater than 0 at Pa Te, Ping Chen, Tai Chi and Long Tan rainfall stations. And then the minimum interval is selected by Minimum Inter-event Time (MIET) method as Figure 6. The MIET means if no independent rainfall occurs at the beginning of an independent rainfall event within 24 hours, and the independent rainfall event is determined. The minimum rainfall interval is determined according to the Poisson distribution method. When the average ratio of the rainfall event interval to the standard deviation is equal to 1, the minimum rainfall interval can be determined, and the average rainfall is cut out from the independent rainfall event according to the minimum rainfall interval. The independent rainfall events supply data required for prediction model training and testing.

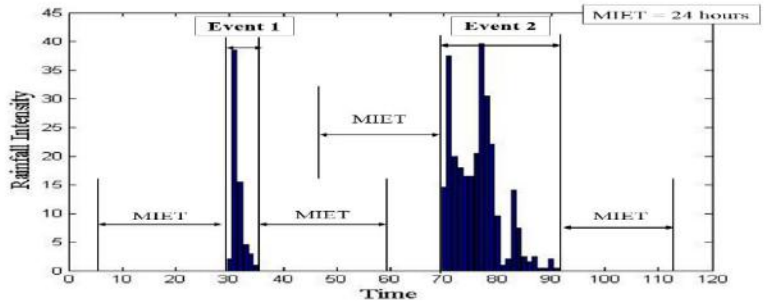

Figure 5. Schematic diagram of independent rainfall events (MIET is 24 hours))

3.1.2 Factor Screening

The Pearson product correlation coefficient analysis method was used to screen the factors related to the high water level of the main canal. The analysis results of No.10 and No.12 sub canal are shown in Table 2 and Table 3.

In Table 2, it shows that the highest correlation falls between the future 60 minute predicted value of No.10 sub canal (S10t+6) and the average rainfall delay time of 210 to 260 minutes, indicating that the rainfall hydrological history in this catchment area started in the order from surface flow, groundwater flow and open channel flow. And the flow reached to the intake of No.10 sub canal after 270 minutes (210 + 60). The water level autocorrelation coefficient of the No.10 sub canal is the most relevant within 100 minutes (40+60), which can provide effective prediction information. Similarly, the average rainfall of the No.12 sub canal predicted value (S12t+6) for the next 60 minutes and the related factor inputs from No.10 and No.12 sub canal water level Rt-26, Rt-25, Rt-24, Rt-23, are shown as Table 3 respectively.

Table 2. The related factor inputs from No.10 sub canal

R_{t-i}	CC	$S10_{t-j}$	CC
i = 18	0.11	j = 0	**0.87**
i = 19	0.12	j = 1	**0.85**
i = 20	0.12	j = 2	**0.82**
i = 21	**0.12**	j = 3	**0.80**
i = 22	**0.13**	j = 4	**0.77**
i = 23	**0.12**	j = 5	0.75
i = 24	**0.13**	j = 6	0.72
i = 25	0.13	j = 7	0.69
i = 26	0.13	j = 8	0.67

Table 3. The related factor inputs from No.10 and No.12 sub canal

R_{t-i}	CC	$S10_{t-j}$	CC	$S12_{t-k}$	CC
i = 20	0.08	j = 0	0.58	k = 0	0.74
i = 21	0.09	j = 1	0.56	k = 1	0.71
i = 22	0.10	j = 2	0.55	k = 2	0.69
i = 23	0.10	j = 3	0.54	k = 3	0.67
i = 24	0.09	j = 4	0.52	k = 4	0.65
i = 25	0.10	j = 5	0.51	k = 5	0.63
i = 26	0.10	j = 6	0.49	k = 6	0.61
i = 27	0.10	j = 7	0.47	k = 7	0.59
i = 28	0.10	j = 8	0.45	k = 8	0.56

Table 4. Predicted water level inputs for No.10 and No.12 sub canal

Interval	Input factor
No.10 sub canal	
t+6	R(t-24), R(t-23), R(t-22), R(t-21), S10(t-4), S10(t-3), S10(t-2), S10(t-1), S10(t)
t+12	R(t-18), R(t-17), R(t-16), R(t-15), S10(t-4), S10(t-3), S10(t-2), S10(t-1), S10(t)
t+18	R(t-12), R(t-11), R(t-10), R(t-9), S10(t-4), S10(t-3), S10(t-2), S10(t-1), S10(t)
No.12 sub canal	
t+6	R(t-26), R(t-25), R(t-24), R(t-23), S10(t-3), S10(t-2), S10(t-1), S10(t), S12(t-4), S12(t-3), S12(t-2), S12(t-1), S12(t)
t+12	R(t-20), R(t-19), R(t-18), R(t-17), S10(t-3), S10(t-2), S10(t-1), S10(t), S12(t-4), S12(t-3), S12(t-2), S12(t-1), S12(t)
t+18	R(t-14), R(t-13), R(t-12), R(t-11), S10(t-3), S10(t-2), S10(t-1), S10(t), S12(t-4), S12(t-3), S12(t-2), S12(t-1), S12(t)

4. OVERVIEW OF MODE CONSTRUCTION

In order to maintain farmer's water rights and improve water use efficiency, accurate water resource allocation is necessary, and an efficient and accurate canal water level prediction model is established to allocate water storage more immediately which increases the water storage capacity in ponds for dry seasons. This water level prediction model of Tao-Yuan Main Canal can provide effective information for decision makers and allocate water storage to ponds. The project plans to build a canal-based water level prediction model based on the neural network, and collect data such as the rainfall and the water level history of the rainwater station near the Taoyuan irrigation area in Taoyuan city. Use the Pearson product correlation coefficient analysis method to screen the effective factors related to the high water level of the main line, and put the effective factors of the screening into the Neural Network Regression (NNR) in the Azure platform. The Back-Propagation Networks (BPN) constructs a canal water level prediction model to predict the water level at the access points of the 10 and 12 branch lines of the Tao-Yuan Main Canal. Finally, the most common evaluation indicators such as Root Mean Square Error (RMSE), Mean Average Error (MAE), Correlation Coefficient (CC), and Coefficient of Efficiency (CE) are selected to evaluate canal water level prediction model and its prediction results. The established canal water level prediction model and its prediction results are written back to the Water Resources IoT, and the data can be read through the platform's Sensor Thing Application Programming Interface to facilitate other programming languages such as R and Python, or other cloud data analysis platforms such as Azure and Tensor Flow are interlinked. Therefore, based on the existing neural network of the Azure platform (Figure 4), the project establishes a canal water level prediction model to predict the water level for the next 1, 2, and 3 hours in every 10 minutes

4.1 Main Canal Water 1level Prediction Model Construction

The study developed a predictive water level model through the Machine Learning Studio of the Microsoft Azure Cloud Computing Platform service. Azure provides different methods for classification, regression and cluster analysis, for regression methods such as regression-like neural networks (Neural). Network Regression, NNR), Bayesian Linear Regression, Decision Forest, and Linear Regression can be used. This study applied NNR to construct the water level prediction model. The flow chart for constructing the canal water level prediction model for this project is shown in Figure 7. The process of constructing the model is divided into model construction and model prediction. The model construction is based on historical observation of rainfall and water level through data pre-processing, independent rainfall event identification, factor screening and parameter determination.

After the model is developed, from the instantaneous rainfall, it is judged whether the starting standard is reached, and the built-in Web NNR model is introduced together with the instantaneous monitoring water level to predict the future t+6 to t+18. Water level.

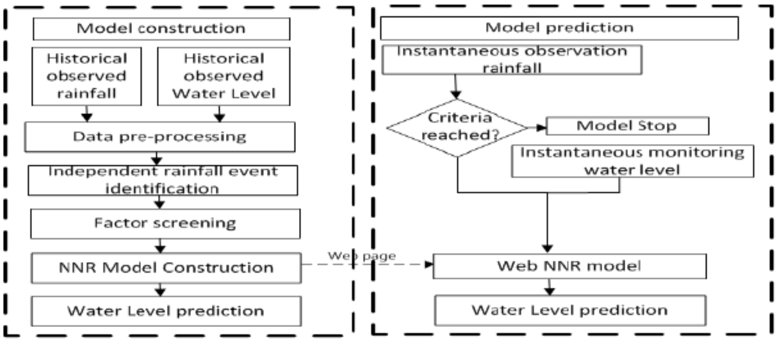

Figure 6. Schematic diagram of main canal water level prediction model

The NNR constructs a prediction model with a three-layer network structure of an input layer, a hidden layer, and an output layer. The parameters that the NNR has to set are the number of neurons (Number of hidden nodes, learning rate, number of iterations, initial learning weights, momentum and normaliser, the No.10 and 12 sub canal water level parameters were set by the grid search method to search for the best parameters. The search range is from 1 to 10 neurons, the learning rate is between 0.1 and 0.000001, and the number of iterations is from 100 to 1000, the initial weight is between 0.01 and 2. The inertia term is between 0 and 1. The normalization is selected from the standardization of dispersion, Gaussian standardization and maximum and minimum normalization. In the parameter calibration process, the No.12 sub canal learning rate sensitivity is the largest, that is, fine-tuning, as shown in Figure 8. It can be seen that as the learning rate is smaller, the evaluation index RMSE and MAE are better, and the learning rate is 0.000066, the best results. The No.10 sub canal parameter training process is determined by using the automatic parameter rate. The result is the same as the t+6 to t+18 automation rate setting result. The No.12 sub canal uses the manual method to determine the t+6 parameter, and the t+12 and t+18 settings are the same

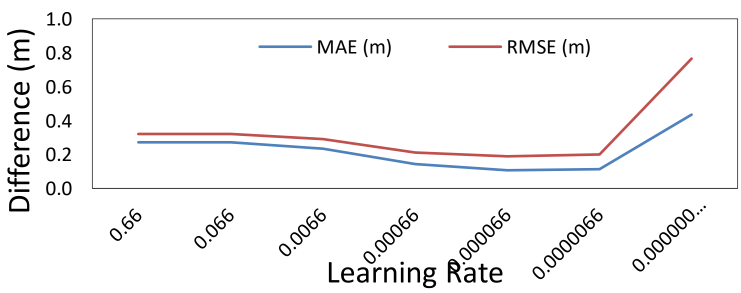

Figure 7. Learning rate of No.12 sub canal calibration

5. RESULTS AND DISCUSSION

5.1 Results of No.10 Sub Canal

The calculation of the 10-line water level prediction evaluation index for this project is shown in Table 3.12. The RMSE, MAE, CE and CC values of the t+6 model in the training phase are 0.069 m, 0.034 m, 0.963 and 0.982, respectively. CC and CE More than 0.9, indicating that the NNR prediction water level model training results are very good, and the CC value of the test period t+6 forecast time prediction result is also greater than 0.9, representing the NNR prediction water level model has a good prediction of water level capacity, can be practically applied In the future games. The t+6 training and test RMSE and MAE have very similar values and the calculation results of each statistical value are small, and the error value between the model prediction and the observation value is very small. The CE values of t+6 and t+12 training and test are both greater than 0.9, t+18 is greater than 0.8, and the values of CC and t+6 to t+12 training and test results are greater than 0.9, indicating that the NNR model can accurately predict the water level. Overall, the RMSE error range for the t+6, t+12, and t+18 models is 0.079 to 0.140 m; MAE is 0.034 to 0.077 m; CE is 0.962 to 0.877 to CC of 0.981 to 0.936, demonstrating that the SVM model has Stable and accurate predictive performance.

Figure 9 shows the t+6, t+12 and t+18 water level historical data. As the forecast time increases, the time-lag is more obvious, that is, the time difference between the peak of the forecast and the observed water level is more obvious. And the peak underestimation gradually increases, and the forecast and observation water levels are very close where the water level is small and the fluctuation is not obvious. In order to highlight the single event forecasting ability, the plan uses the water level historical data between 2018/1/6 and 2018/1/10 as an example (Figure 9) to explore time delay and peak underestimation, and its t+6 forecast and observation. There is a 60-minute time delay between the water levels, and as the prediction time increases, the time delay increases. The t+6 prediction and observation peak error is about 0.07 m, and the error is very small, indicating that the model has good prediction performance.

Table 5. Evaluation indicators of model construction in No. 10 and No.12 sub canal

Model	Training					Testing			
	RMSE (m)	MAE (m)	CE	CC		RMSE (m)	MAE (m)	CE	CC
No.10sub canal									
t+6	0.07	0.03	0.96	0.98		0.08	0.03	0.96	0.98
t+12	0.11	0.05	0.92	0.96		0.11	0.06	0.92	0.96
t+18	0.13	0.07	0.86	0.93		0.14	0.08	0.88	0.94
No.12sub canal									
t+6	0.14	0.07	0.89	0.93		0.14	0.08	0.90	0.95
t+12	0.18	0.10	0.84	0.89		0.18	0.11	0.86	0.93
t+18	0.22	0.14	0.75	0.84		0.21	0.14	0.80	0.90

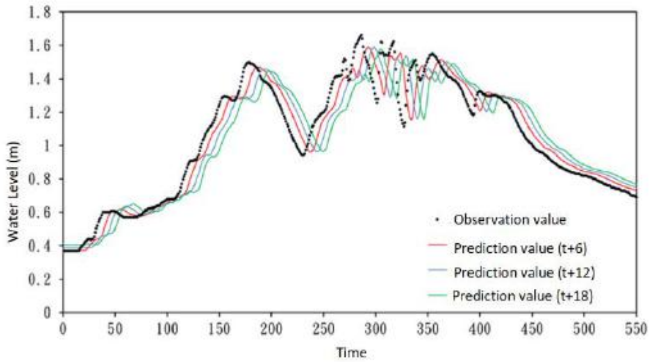

Figure 8. Model testing result of No.10 sub canal (2018/1/6 13:10to2018/1/10 9:50)

5.2 Results of No.12 Sub Canal

The performance of the No.12 sub canal model t+6, t+12, and t+18 water level prediction evaluation indicators is shown in Table 5. The RMSE, MAE, CE, and CC values of the t+6 model in the training stage are 0.141 m, 0.074 m, 0.894, and 0.934, respectively. Its CC value is greater than 0.9, which is equivalent to the No.10 sub canal t+6 model evaluation index, which means that the NNR predicted water level model has the ability to predict the water level, and the CC value of the test stage t+6 model is also greater than 0.90. For the evaluation index of t+6 training and test, the calculation results of RMSE and MAE are small, and the error value between model prediction and observation is small. The longer the prediction time is, the CE value decreases. The overall result of NNR prediction water level model shows a match trend of the observed water level.

The training results of the No.12 sub canal model are worse than those of the No.10 sub canal model. The main reason is that the observation of the water level of the No.12 sub canal event is large, and there are often sudden turning points, resulting in inaccurate model prediction. See Figure 10 at time 467, when the water level of the No.12 sub canal is 1.98 m, the current predicted input factor Rt-26 is 0, Rt-25 is 0.0283, Rt-24 is 0, and Rt-23 is 0. And the water level factors of S10 and S12 are all decreasing, but the current prediction of S12 t+6 is 1.98 m, which is the sudden increase of water level. Since the pre-term sub-factor is a downward trend, it is difficult to predict the water level and reflect the water level prediction at the sudden turning point. If the pre-term factor can reflect the predicted water level trend, the prediction will be more accurate. As shown in Figure 11, the water level performance of the pre-position is rising at the 71th time point. The current peak value is 1.71 m and the predicted peak value is 1.62 m. The peak difference is 0.08 m; the observations are very close to the predicted values. The overall result appears that the water level prediction model can show the actual water level trend.

6. SUMMARY

Using the correlation coefficient of Pearson's product difference, the results show that the correlation coefficient between the average rainfall of Rt-21 to Rt-26 and the observed water level S10t+6 is the largest, and the correlation coefficient is about 0.12 to 0.13, indicating that if rainfall occurs, after 270 minutes to 320 minutes, and the flow is transferred to the intake of No.10 sub canal; while the average rainfall of Rt-23 to Rt-26 of the No.12 sub canal is the largest correlation coefficient with the observed water level S12t+6, the result shows that it takes about 290 minutes to 320 minutes. At the time, the rainfall was collected to the downstream and reached the intake of No.12 sub canal. Therefore, the time required is longer than the time from No.10 sub canal, so the factor screening is reasonable.

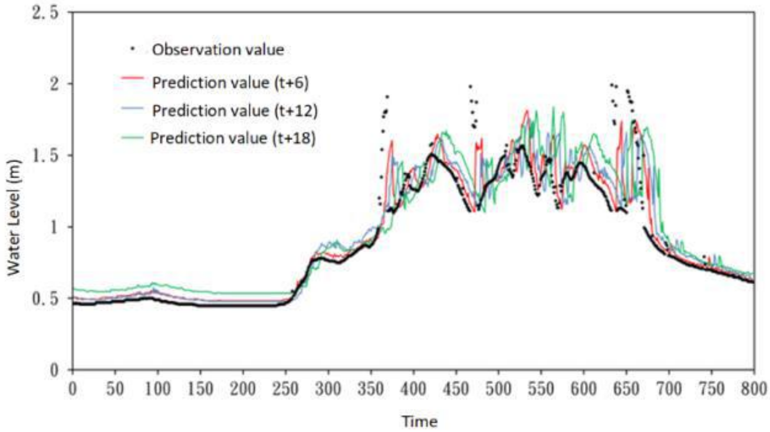

Figure 9. Model testing result of No.12 sub canal (2018/1/4 21:00 to 2018/1/10 9:50)

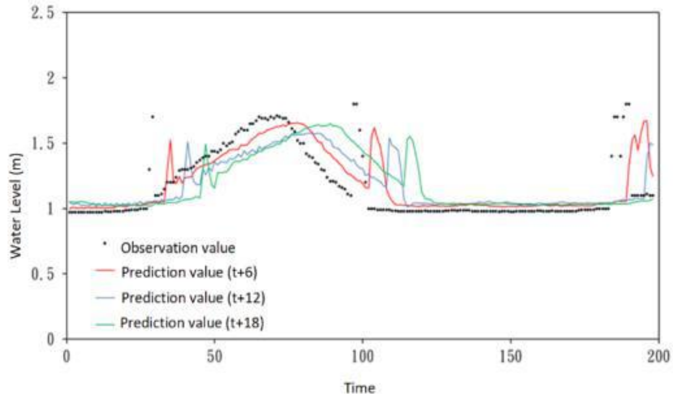

Figure 10. Model testing result of No.12 sub canal (2018/2/7 19:30to2018/2/9 4:20)

The No.10 sub canal water level prediction model is constructed by NNR. In the predictions of t+6, t+12 and t+18, the RMSE error does not exceed 0.140 m, the MAE error is less than 0.077 m, CE is greater than 0.877, and CC is greater than 0.936. The NNR predicted water level model can accurately predict the water level. For the model, the predicted water level trend CC and CE values are very high, indicating that the predicted water level result of the model can accurately match the trend between the observed water level and the peak error is very small.

No.12 sub canal water level prediction model, the evaluation index test results show t+6 to t+18, RMSE and MAE are lower than 0.206 m and 0.143 m, CC and CE values are greater than 0.800 and 0.904, indicating that the predicted water level model can accurately predicting the water level and the trend between the predicted and the observed water level, in the case of the test phase, the peak error of the predicted and observed water level is very close, indicating that the predicted water level model has the ability to predict the peak.

The Azure platform constructs a No.10 and No.12 sub canal NNR predicted water level model. After evaluating the indicators and predicting the water level and observing the water level, the results show that the No.10 and No.12 sub canal water levels at t+6, t+12, and t+18 are constructed by NNR. Predictive model with the ability to predict water levels.

In the future, by monitoring the rainfall and water level transferring to IoT, the model can receive and be started after the start-up standard is reached, to predict the future water level. The prediction result can provide effective information for decision makers and allocate water storage capacity in the ponds.

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