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An On-line Automatic Flow Measurement Method for an Open Channel under Complex Flow Conditions

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Abstract

Buildings flow measurement method using the pre-established upstream and downstream water levels and flow to estimate the flow is the common method for open channel flow measurement. However, due to the changes of import and export, flow pattern, and hydraulic boundary conditions, traditional mechanism modeling-based flow measurement methods which establish the relation between the upstream-downstream water levels and flow by historical records and empirical equation models are usually not able to meet the demands of precision and adaptability. The improvement is based no the neural network (data-driving). However, the neural network based method is commonly offline and the model parameters are constant in the application.If the degree of opening of the weir sluice gate changes frequently, it is hard to construct a neural network model of high precision for on-line and real-time measurement. This research designs a real-time on-line automatic measurement system, for the Pi River canal weir gate, that collects upstream and downstream water levels and the degree of opening of the gate. Moreover, it establishes a three layer BP neural network model based on on-line real-time data correction. This model comprised of a Kalman filter with forgetting factor and a three layer BP neural network data fusion center. In contrast to the standard hydrometric propeller based method, the average relative error is lower than 5%, meeting the "River Discharge Measurement Criterion" proposed by Ministry of Water Resources of the People's Republic of China. Both the precision and the repeatability can cater for the engineering applications.

Keywords: *complex flow pattern; open channel flow-measurement; hydraulic structure method; error correction*

1. Introduction

Measurements of free surface flow in a river or artificial water channel are collectively called Open-Channel Flow-Measurement in the international standard[1]. With the increase of water consumption for industrial and agricultural production and living, the balance between supply and demand of water resources is becoming more and more threatened. On-line real-time measurement of open channel flow offers quantitative reference for an entire canal system for water distribution and planning, can be used as an important technical foundation for water rights transactions, and can aid in the implementation of water saving irrigation and the construction of a digital irrigation area. Long-term observation data not only can be used on an experimental basis in the Yellow River irrigation area, but also can be used as design criteria for billing; thus, promoting water conservation and rational use of water. So, fast and accurate implementation, along with stable measurement of open channel flows is essential.

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The current method for open channel flow measurement can be divided into two types: the velocity-area method and the hydraulic structures method.

(1) The velocity-area method divides the cross section into several sub-sections by measuring verticals. Then, it computes the area, averaging velocity, and discharge of sub-sections according to the measured velocities and depths. Finally, it sums each area of sub-sections to obtain the total discharge. However, there are many imprecisions and uncertainties because of the complexity in field conditions and the limitations for automated monitoring via current measurement methods, measurement accuracy, and measurement cost [3-4].

(2) Buildings flow measurement method uses the measuring weir, flumes surveying, or weir gates, holes, culverts, and other hydraulic structures, whereby pre-established upstream and downstream water levels and flow are used to estimate the flow[5-6]. This water-flow relationship can be established according to the basic laws of physics, and can also be determined based on the experimental measurements of its simple empirical formula. Open channel is the most economical and widely used method for measuring water because special head loss facilities are not required. Analysis of a hydraulic fluid state model is based on establishing an expert system model [7-8] , The short message transmission mechanism trunk (front gate) and branch canals (back gate) level and start gate height measurements, experts library selection formula, and the amount of water on the gate flow calibration factor are used to implement soft measurement. The Juwan hydrological station was applied using broad crested weir flow freely out of the measured data when the weir formula reverse thrust coefficient, thus greatly improving the efficiency of data compilation. In actual open channel flow measurement engineering applications, floating debris can clog the gate and impact the opening and closing of the water gate, which results in dramatic morphological changes. Because of the lack of robustness for water level measurement data acquisition methods,, there is a need to develop automated real-time measurement of flow, with greater measurement accuracy, measurement of the cost and scope of defects [10-12].

This paper designs a real-time on-line automatic measurement system to measure discharge when the opening of the weir sluice gate frequently changes by collecting upstream and downstream water levels and the degree of opening of the gate. A Kalman filter with forgetting factor algorithm is used as a real-time signal level recorder that is calibrated to effectively filter the water fluctuations caused by random errors and floating debris intrusion or interference caused by mechanical means gross error. A three- LM-BP neural network model was established for measuring flow, and the learning algorithm iteration speed was improved. Automatic measuring devices and systems suitable for typical gate weir flow measurement conditions for open channel flow measurement technology were developed to build the ideal software and hardware platforms.

2. Open Channel Flow Online Automatic Measurement System Mode

2.1. System Construction

In this study, we provide the background for the Anhui Pishihang Irrigation, build a Pi River main canal flow line automatic measuring system model, and propose a LM-BP neural network measuring flow model based on online real-time correction of the measurement data. System testing weir gates and hydrological stations are located at 9 km lower than the Pi River main stream Lianghekou. The stage-discharge relations of weir gate are affected mainly by gate opening and closing factors and upper and lower water levels, the main flow pattern is a submerged orifice flow, with a hydrological station catchment area of 4370km^2, 72% of the total basin. There are a total of 59 years (1953–2012) of runoff data, of which the data series is representative and reliable. Since the establishment of the station, the station flow meter has measured high, medium and low water, whereas manual operation may take a long time and be susceptible to measurement error influence. The test area reach is straight for about 800m, left Bank is a sandy loam, riverbed is a sand pebble structure, right bank is shale stretch, riverbed is broad and shallow, and erosion changes little. The basic parameters of channels and hydraulic structures are shown in Table l.

In the water conservancy project, the most widely used outflow form includes outflow over weirs [13] and flow under sluice gates [14], which are common for irrigation and flood discharge of hydraulic structures. In this paper, construction of open channel flow line automatic measuring system shown in Figure 2 is combined with the practical situation of Pi River main stream of a weir gate flow under sluice gate. The key to the system is to determine the secondary variables for open channel flow and to establish a stable and reliable flow calculation model. A BP measured flow model based on the corrected data was used to analyze the hydraulics mechanism model of system implementation area.

2.2. Mechanism Model of Flow under Sluice Gate

The mechanism model has a certain outflow and inflow relationship and water works environmental conditions, based on the empirical formula or measuring water formula under various flow states. The simplified model of the five typical flow patterns in Pi River flat channel are analyzed under the conditions of a plate gate, then the main two variables of different hydraulic balance relationship are examined.

(1) Free overflow. When $e/H > 0.65$ and $h_H/H < 0.7$, the shutter is not in contact with the surface, regarded as the shutter is fully open, the measuring water formula is:

$$Q = mbH\sqrt{2gH} \tag{1}$$

where Q is the flow to be measured, g is acceleration of gravity, m is aggregate discharge coefficient, and b is the rectangular culvert width. Thus, the set of flow pattern criterion is $\{e/H,\ h_H/H\}$, the set of secondary variable is $\{H\}$.

(2) Submerged overflow. When $e/H > 0.65$ and $h_H/H \ge 0.7$, the downstream water level is considered to be higher than the gate threshold, even the lower edge of the gate above water. The measuring water formula is:

$$Q = \varphi b h_H \sqrt{2g(H - h_H)} \tag{2}$$

where φ is the aggregate discharge coefficient of submerged overflow, $\{e/H,\ h_H/H\}$ is the set of flow pattern criterion and $\{h_H, H\}$ is the set of secondary variable.

(3) Free orifice flow. When $e/H \le 0.65$ and $h/e < 1$, for holes with brake hydraulic structures, water flow discharged from the gate resistance, play a controlling role, the measuring water formula is:

$$Q = \mu be\sqrt{2g(H - 0.65e)} \tag{3}$$

where μ is the aggregate discharge coefficient of free orifice flow, $\{e/H,\ h/e\}$ is the set of flow pattern criterion, and $\{e, H\}$ is the set of secondary variable.

(4) Submerged orifice flow. When $e/H \le 0.65$ and $h/e > 1$, judged bottom of the gate has been flooded water, produce submerged hydraulic jump, the measuring water formula is:

$$Q = (1 + 0.6e/H)\mu' be\sqrt{2g(H - h_H)} \tag{4}$$

where μ' is the aggregate discharge coefficient of submerged hole flow, $\{e/H,\ h/e\}$ is the set of flow pattern criterion, and $\{e, H, h_H\}$ is the set of secondary variable.

(5) Pressure undercurrent. When h_H exceeds the set height of culvert gate a ($h_H/a > 1$), the culvert gate is determined to be no free water, completely submerged exit gate, the measuring water formula is:

$$Q = f(m, e, a) be\sqrt{2g(H - h_H)} \tag{5}$$

where $f(m,e,a)$ is the aggregate discharge coefficient experience formula of Pressure undercurrent, $\{h_H/a\}$ is the set of flow pattern criterion, and $\{e,H,h_H\}$ .is the set of secondary variable.

2.3. Data Correction and BP Nerual Network Based Flow Measurement Model

This paper presents a weir gate traffic integration model that consists of data correction and data integration layers, as shown by the model structure in Figure 2. Data after the correction layer, in front of the wireless sensor data collection and extraction, uses a Kalman filter with forgetting factor algorithm for error correction. The data integration layer receives the correction data first to be normalized, and then are passed into a good training neural network unit derived flow calculations. Meanwhile, the calculation result and the received calibration measurements are stored to the database, to conduct data layer correction of wireless sensor nodes and data integration layer for station necessary feedback adjustment. The model uses the Levenberg-Marquardt (LM) algorithm [18] for training and learning rules of neural networks in a timely manner, and the structures of the model parameters are estimated and updated to ensure accuracy. The following introduces error correction and model training using two main algorithms.

Because of the open channel flow water levels and flow rates and other physical changes to the next time state with the "distance size" properties, generally, the closer the state value the greater the impact, the longer the time interval the greater error exists and the smaller the degree of influence. Therefore, a forgetting factor $\lambda_i = (1-\lambda)/(1-\lambda_i)$ is introduced, where $0<\lambda<1$is a custom experience, and i is the time. Define the memory window, compute the approaching moment measurement state, and gives different effects on strength such as the influence of the most recently measured value that is higher than the value of the forward, forward impact value becomes gradually smaller until the eject memory window while achieving memory length of the filter control. Using the sensor as a coordinate system reference point, the water level of self-recording wells rises and falls by an approximated state of uniform motion, the motion model can be described by the equation of state and measurement equation:

$$\boldsymbol{X}_{k+1} = \boldsymbol{\Phi}_k \boldsymbol{X}_k + \boldsymbol{W}_k \tag{6}$$

$$\boldsymbol{Y}_k = \boldsymbol{H}\boldsymbol{X}_k + \boldsymbol{V}_k \tag{7}$$

where $\boldsymbol{X}_k = [h_k\ v_k]^{\mathrm{T}}$, $\boldsymbol{Y}_k = [y_k]$, $\boldsymbol{\Phi}_k = \begin{bmatrix} 1 & T_k \\ 0 & 1 \end{bmatrix}$, $\boldsymbol{H} = [1\ 0\ 0]$, $\boldsymbol{W}_k$ and $\boldsymbol{V}_k$ are independent zero mean white noise, h_k and v_k are the actual water level and water temperature rise and fall of the rate of change, respectively, T_k is measurement period, and y_k are water level observations. Also introduced in a 2×2 order symmetric positive definite noise covariance matrix $\boldsymbol{Q}(t)$ and measurement noise variance $\boldsymbol{R}(t)$, is the online measurement noise estimate. Initial value is X (0) and its state error covariance matrix P (0), σ and ξ are forecast confidence parameters. Kalman filtering error correction algorithm with forgetting factor is as follows:

Input: λ, $\boldsymbol{Y}(k+1)$, $\boldsymbol{X}(0)$, $\boldsymbol{R}(0)$, $\boldsymbol{P}(0)$, σ, ξ

Output: $\hat{\boldsymbol{Y}}(k+1)$ //Predicted output

1) $\lambda_{k+1} \leftarrow (1-\lambda)/(1-\lambda^k)$ //Forgetting factor weighting factor

2) $\hat{\boldsymbol{X}}(k+1|k) \leftarrow \boldsymbol{\Phi}(k+1|k)\hat{\boldsymbol{X}}(k)$ //State prediction

3) $\boldsymbol{P}(k+1|k) \leftarrow \boldsymbol{\Phi}(k+1|k)\boldsymbol{P}(k)\boldsymbol{\Phi}^{\mathrm{T}}(k+1|k) + \boldsymbol{Q}(k+1)$ //Prediction error covariance

4) $\boldsymbol{V}(k+1) \leftarrow \boldsymbol{Y}(k) - \boldsymbol{H}\hat{\boldsymbol{X}}(k+1|k)$ //New measurement noise

5) $\boldsymbol{R}(k+1) \leftarrow (1-\lambda_{\mathrm{k}}) - \boldsymbol{R}(k) + \lambda_{\mathrm{t}}[\boldsymbol{V}(k+1)\boldsymbol{V}(k+1)^{\mathrm{T}} - \boldsymbol{H}^{\mathrm{T}}\boldsymbol{P}(k+1|k)\boldsymbol{H}^{\mathrm{T}}]$ //Measurement noise variance update

6) $\boldsymbol{K}(k+1) \leftarrow \boldsymbol{P}(k+1|k)\boldsymbol{H}^{\mathrm{T}}[\boldsymbol{HP}(k+1|k)\boldsymbol{H}^{\mathrm{T}} + \boldsymbol{R}(k+1)]^{-1}$ //Filter gain

7) $\hat{\boldsymbol{X}}(k+1) \leftarrow \hat{\boldsymbol{X}}(k+1|k) + \boldsymbol{K}(k+1)\boldsymbol{v}(k+1)$

8) $\hat{\boldsymbol{Y}}(k+1) \leftarrow \boldsymbol{H}(k+1)\hat{\boldsymbol{X}}(k+1|k)$ //Data predictive value)

9) if probability $\left\{|\boldsymbol{Y}(k+1) - \hat{\boldsymbol{Y}}(k+1)| > \sigma\right\} \geq \xi$

10) then output $\hat{\boldsymbol{Y}}(k+1)$

11) endif, Go to step 1

This method does not need to store a large amount of historical data, suitable for applications such as water level, velocity, and other data measurement sensor nodes. Figure 3 shows the water level measurement node FPGA structure, an internal algorithm using VHDL hardware description language to design, according to the top-down design, the system is divided into a buffer unit, an arithmetic unit, control unit, forgetting factor vector memory unit, Kalman filtering correction and other basic unit, and is connected with the external ultrasonic transducer device through the serial interface, and connected via an enhanced Zigbee [15-17] wireless data transmission unit USB bus. The apparatus has a solar power supply, with a non-occluded communication radius of 3km.

After the system is put into operation, the data integration layer uses an LM algorithm to replace the original BP neural network gradient descent learning algorithm, timely re-learning to ensure flow estimation accuracy, with training and learning steps as follows:

Input: ε //Training error allowed values

μ_0 //The initial value of the threshold vector

Output: R //Computing network output

$\mathrm{E}\left(w^k\right)$ //Error index function

1) Initialization weights and thresholds vector, make k=0, $\mu = \mu_0$

2) Calculate Jacobian matrix $\mathbf{J}\left(w^k\right)$

3) Calculate Δw)

4) if $\mathrm{E}\left(w^k\right) < \varepsilon$, Go to Step 6

5) $w^{k+1} \leftarrow w^k + \Delta w$ as weights and thresholds vector calculation error indicator function $\mathrm{E}\left(w^{k+1}\right)$

6) if $\mathrm{E}\left(w^{k+1}\right) < \mathrm{E}\left(w^k\right)$,then $k \leftarrow k+1$, $\mu \leftarrow \mu\beta$, output R , $E\left(w^k\right)$

7) else $\mu \leftarrow \mu / \beta$ // $0 < \beta < 1$

8) endif, Go to Step 3

Among: $\mathrm{E}(\mathbf{w}) = \frac{1}{2}\sum_{i=1}^{p}\|\mathbf{Y}_i - \mathbf{Y}_i'\|^2 = \frac{1}{2}\sum_{i=1}^{p}e_i^2(\mathbf{w})$ (8)

In the formula, $\mathbf{Y}_i$ is the vector of the desired output of the network, $\mathbf{Y}_i'$ is the actual network output vector, P is the number of samples, $\mathbf{w}$ is the vector consisted by network weights and thresholds, $e_i(\mathbf{w})$ is the error.

Let $\mathbf{w}^k$ represents the vector k-th iteration weights and thresholds composed, the new weights and thresholds consisting of vectors $\mathbf{w}^{k+1} = \mathbf{w}^k + \Delta\mathbf{w}$. Weight increment $\Delta\mathbf{w}$ is calculated as:

$$\Delta\mathbf{w} = \left[\mathbf{J}^T(\mathbf{w})\mathbf{J}(\mathbf{w}) + \mu\mathbf{I}\right]^{-1}\mathbf{J}^T(\mathbf{w})e(\mathbf{w}) \qquad (9)$$

In the formula, $\mathbf{I}$ is the identity matrix, μ is the custom learning rate, and $\mathbf{J}(\mathbf{w})$ is the Jacobian matrix.

Since the LM algorithm improves the convergence speed iteration, the model can significantly improve the efficiency of training and learning when calibrating the model parameters, in particular the case of high accuracy requirements, can significantly improve the overall performance of the model.

3. Model Test

3.1. Data Correction Layer Test

Although the current channel is mostly built for special water logging, the measurement errors caused by various factors are unavoidable because:

a) They are well within the error induced by waves, and if the water inlet pipe length is not long enough or has bad sealing design, the well water waves will make the borehole water small wave, cause the float with wave upper and lower jitter or interference ultrasonic transducer echo, thereby, causing random errors of the water level.

b) Floating debris, foreign invasion physical and mechanical errors caused by friction resistance itself. Floating debris intrusion or grinding resistance between interference machinery and water level mechanical transmission parts will cause coarse level measurement errors.

According to ultrasonic level sensor measured data, a construct containing only random error and two sample sequence contains both random error and gross error, the sampling period is set to 1s, using the proposed data correction method to conduct the correction of detected 60s value, and the recording calibration results. The results of measurement data correction containing both random error and gross error are shown in Figure 4.

Accuracy of calibration results are analyzed by calculating results using the arithmetic method of variance analysis and comparison:

$$\text{Relative deviation} = \frac{|\,\text{the i - th sampling filter value} - \text{the i - th sampling ideal value}\,|}{\text{the i - th sampling ideal value}} \times 100\% \tag{10}$$

The relative deviation contains only random errors and simultaneously uses two ultrasonic level sensor measurements with random error and gross error data for testing, whereby equation (10) can be used to calculate the average relative deviation. Results indicate that 120 contained only random error of measurement data of 4.3%, 120 also contained both random error and gross error of measurement data with a mean relative deviation of 6.1%. For comparison, the calculation of the same average two data sets under the relative deviation were 14% and 37%, respectively, using the average value method, and the Kalman filtering error correction method with forgetting factor.

3.2. Training and Testing Data Integration Layer

The flow estimation effect of model data fusion layer was tested using the Pi River near 2 year runoff data represented by $\Delta Z - e - Q$ data for training and testing models, with Table 2 showing the sample data for training and testing. Algorithm testing was completed on a hardware platform that consisted of a 1.5GHz dual core processor with 2Gb memory and used MATLAB 7 software with the initial parameters：BP neural network algorithm numbers of hidden layer nodes is 17, the center width is 0.55, the target error square sum of the relative error is 10^{-5}, the output node bias is 1.2210, the optimal weight matrix is the center width is 0.55, the target error square sum of the relative error, the output node bias is 1.2210, and the optimal weight matrix is W =[39.8396, -34.2473, 67.0501, 57.2020, 0.7696, 6.9675, 321.8037, 30.299 0, -76.5744, -339. 2439, 13.2168, -0.8173, -17.2026].

Figure 5 shows a comparison of relative deviation of water formula and LM-BP flow measurement model. The suspension type current meter at the 425m downstream (section $268m^2$) gate obtained the average velocity profile, and based on the velocity area method was used to measure value as the standard flow of traffic. Experimental results show that in contrast to the standard hydrometric propeller based method, the average relative error is lower than 5%. The fusion model forecast flow and standard method of data consistency are good, with an accurate reaction section $\Delta Z - e - Q$ relationship. The standard method of measurement of mean time was 150min, using the fusion calculation model can realize the real-time on-line measurement.

4. System Integration and Application

Based on system tests and weir gates, the hydrologic response is characteristics of runoff data and small changes in erosion. System integration and application of the hydrologic system is very conducive to the establishment and implementation of the system data -driven model.

Program flow level measurements and the wireless node for Station program flow are shown in Figure 5 for the monitoring terminal. Water level measurement sensors enable real-time acquisition gate height signal (e) and water level signal (H、 h_H 、 h) and other secondary variables, the correction was sent after filtering through enhanced Zigbee data transmission unit to monitor the side as a signal for Station fusion model inputs. Monitoring client program runs in station control room, secondary variables can be set according to the needs of the measurement cycle, timed or answer mode is set to the receiving secondary variables measured data; provide water level in the monitoring area measurement nodes, gate opening device and a flow meter such as monitoring, recording, and alarm function of the sensor device status; view the range of ultrasonic level sensors and blind to make timely adjustments; by comparison with standard methods and model training the model parameters calibrated ; may search each measuring point level, the instantaneous flow, gate opening through real-time data and video surveillance equipment operating status; may be minutes, hours or days per view traffic distribution within a specified period of time, and can choose from the perspective of data in an intuitive way using comparison graphs. We compare our method with the standard hydrometric propeller based method.

A large part of the discharge measurements conducted in open-channels are performed using the velocity–area method, which consists of sampling flow velocity and depth throughout the crosssection for discrete integration of discharge. Velocities and water depths are sampled at given positions on verticals distributed throughout the section. At a given vertical j ($1 \le j \le m$), the following parameters are measured: distance from the start edge y_j, water depth d_j, and point velocities perpendicular to the cross-section $v_{j,k}$ measured at depths $d_{j,k}$. While distances are measured using conventional calibrated devices, point velocities are measured with either mechanical (propellers), electro-magnetic (Hall effect based), or acoustic (Doppler effect based) current-meters, which are typically mounted on a wading-rod, or deployed from a cableway or from a bridge. The total discharge, Q, is the sum of partial discharges Q_i over the N subsections i of the cross-section:

$$Q = \sum_{i=1}^{N} Q_i = \sum_{i=1}^{N} B_i D_i V_i \tag{11}$$

with B_i, D_i, and V_i, the width, mean depth, and mean normal velocity of each subsection i, respectively.

In contrast to the standard hydrometric propeller based method and field measurement results, the average relative error is lower than 5%, meeting the “River Discharge Measurement Criterion” proposed by Ministry of Water Resources of the People's Republic of China.

Station monitoring client software interface and flow calculation results of integration are shown in Figure 6, the system records from 8:00 on January 18, 2013 to 9:59 on the 20th to process $268m^2$ waterway traffic statistics sectional area of the test process three self-recording water level produced a total of 29 significant deviations are corrected; gate opening to maintain 1.6m, level difference between the average 2.42m; statistical test period average daily flow of $158.3m^3/s$, the maximum instantaneous flow rate of $173.m^3/s$, appeared on the first day 11:23, 2 days of accumulated water reaching $2640 \times 10^4 m^3$.

5. Conclusions

This study takes Pi River of Pishihang Irrigation District in Anhui Pishihang Irrigation Area of Pi River canal of a weir gate for test application environment, construction of the on-line automatic measure system of Pi River Channel Flow. First, through the hydraulic mechanism analysis, determined the secondary variable of Open-channel flow measurement. To be aimed at the main reason for random errors in measured variable quantity and gross error, apply a forgetting factor Kalman filtering error correction algorithm to wireless devices of water level measurement, achieved monitoring data online real-time correction. Data were normalized by a data aggregation layer after calibration, and entered into the trained LM-BP fusion unit that obtains the flow calculation results. The comparative analysis with the measured data and the application of test system indicate that the proposed method of measuring accuracy and repeatability meet the requirements of the project. On this basis, the development of automatic measuring devices and systems suitable for typical gate weir flow measurement conditions for open channel flow measurement technology to build the ideal software and hardware platforms.

Unpredictable problem solving process variables based on a data-driven model (which is calculated by secondary variables, estimated with some additional measured variables that are directly measured to improve confidence in unmeasured variables) is an attractive application research of water conservancy, civil engineering, and other engineering fields. In future work, we will deepen and promote the flow measurement model and its application, try to combine water, point velocity and surface velocity field and other measurements to achieve projected artificial open channels or mountain river runoff.

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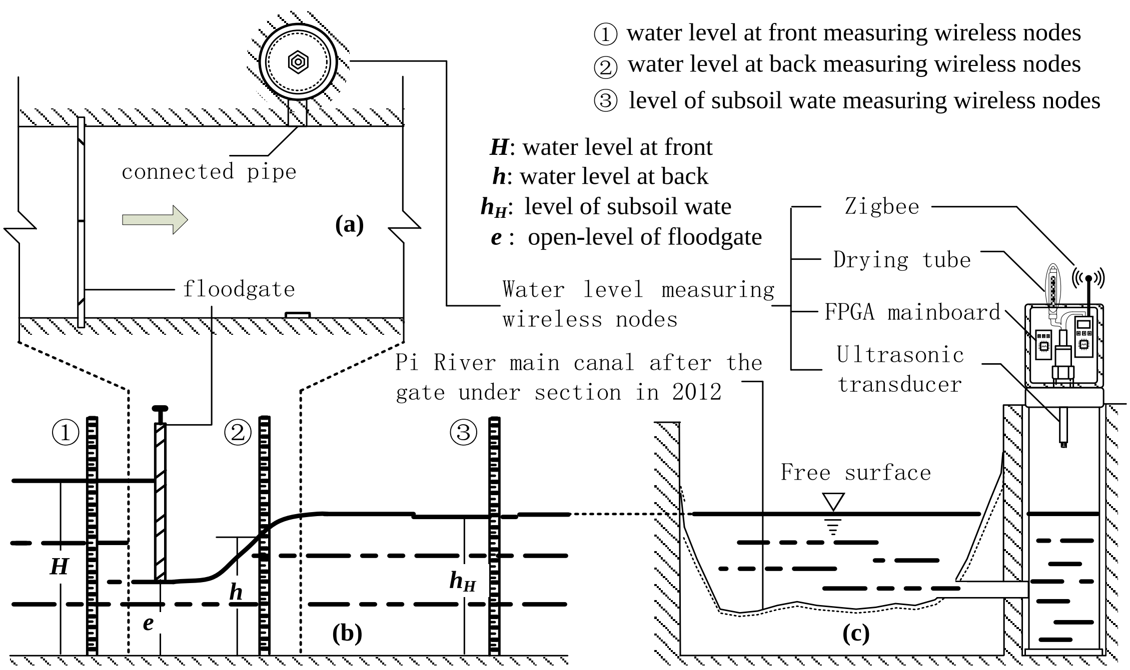

Figure 1. On-line Automatic System for Open-Channel Flow Measuring

(a)Top view of downstream gate static drains
(b) Principle side view of building flow measurement
(c) Front view of section downstream from gate

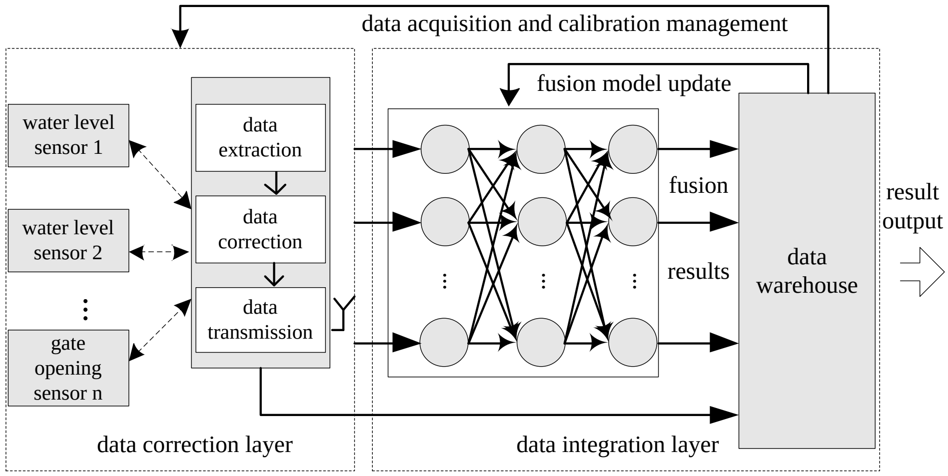

Figure 2. LM-BP Flow Measurement Model Structure Based on Data Correction

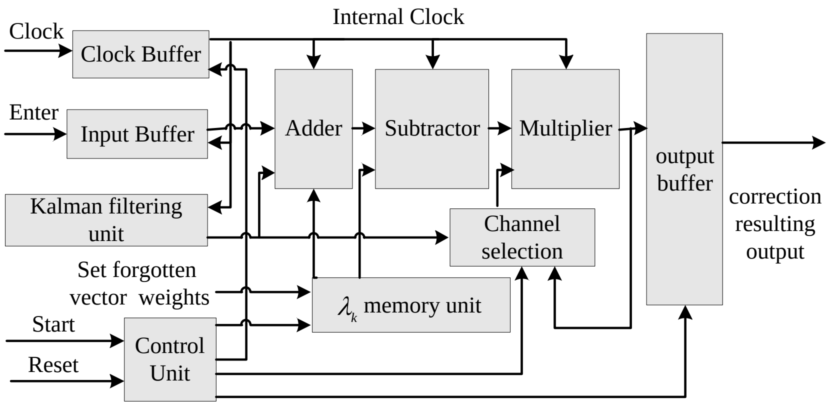

Figure 3. Front-End FPGA Structure Diagram of Measured Data

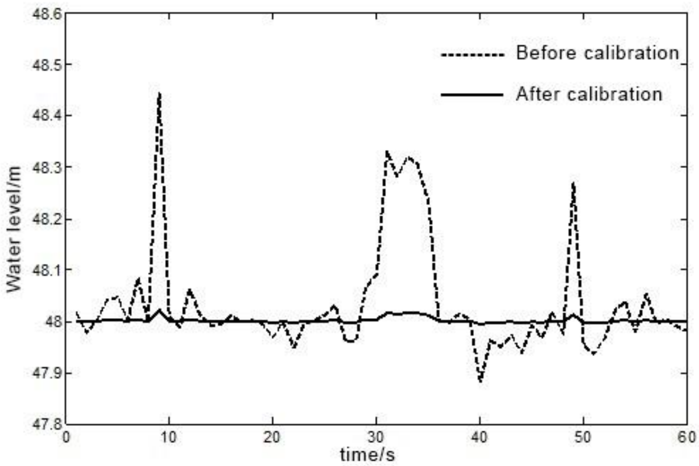

Figure 4. Measurement of Ultrasonic Exchanger for the Water Level Real-Time Correction

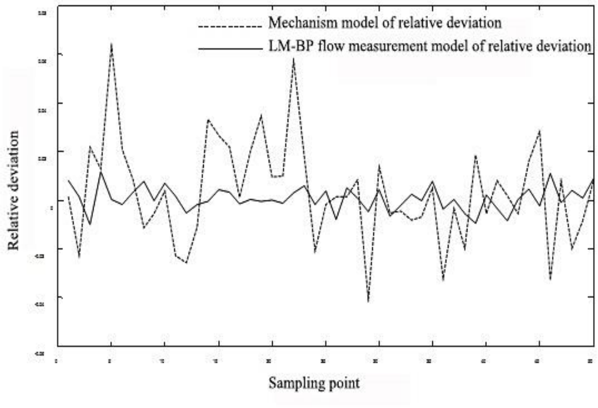

Figure 5. The Error Comparison of the Formula and BP Water Flow Measurement Model

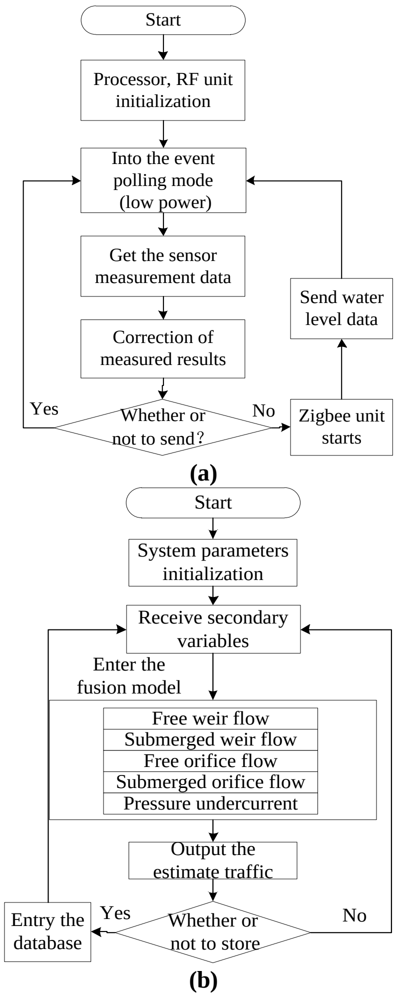

Figure 6. Open-Channel Flow Automatic Online Measurement System

(a) Level measurement wireless node program flow
(b) Monitoring client program flow for Station

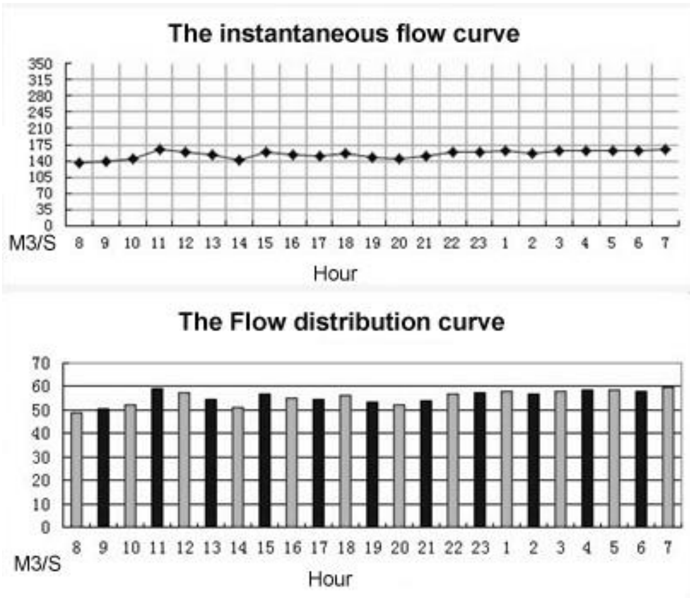

Figure 7. Software Interface and Flow Calculation Results

