Int. J. Metrol. Qual. Eng. 15, 13 (2024)
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https://doi.org/10.1051/ijmqe/2024014

International Journal of Metrology and Quality Engineering

Available online at:
www.metrology-journal.org

RESEARCH ARTICLE — OPEN ACCESS

Remote water meter calibration based on weighted least squares algorithm

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Received: 18 July 2023 / Accepted: 4 July 2024

Abstract. In response to issues such as poor-fitting accuracy in the remote water meter measurement curve, unsatisfactory fitting effects, and challenges in depicting real data characteristics, a weighted least squares algorithm is proposed based on the remote water meter measurement error curves. Firstly, we have combined the remote water meter measurement error formula with the traditional least squares algorithm to generate an integrated algorithm. Subsequently, the weighting theory is introduced into the integrated mathematical model. The polynomial fitting curve parameters are then calculated by assigning different weights to the data under various flow rates. Simulation experiments are also conducted, demonstrating that the proposed algorithm exhibits higher curve fitting accuracy compared to the conventional least square method. It can accurately analyze the metering performance of remote water under different working conditions and precisely measure its metering error.

Keywords: Remote water meter / metrological verification / error of indication / weighted least squares algorithm

1 Introduction

Serving as a crucial element in modernized urban automated metering and charging systems, the remote water meter boasts advantages such as simplicity, speed, accuracy, and timeliness. It finds widespread application in the daily lives of residents. As a prerequisite before leaving the factory, the accuracy of the remote water meter measurement's error curve has become a crucial criterion for staff to analyze water meter performance and statistical flow data [1–3]. Remote water meter measurement errors are generated during the measurement process and are used to discuss the reliability, accuracy and calibration of water meters. Due to the non-linear nature of the remote water measurement's metering error curve, which conventional mathematical formulas can't express, staff can only conduct water meter calibration against the traditional metering error fitting curve during remote water measurement's metering error statistics. This leads to lower calibration accuracy and challenges in meeting the statistical requirements of daily water meter metering projects [4].

Presently, scholars have conducted extensive research on polynomial curve fitting methods. Zhou et al. [5] have proposed an empirical fitting formula for the water meter error curve, which is an effective solution to the problem of accurately estimating the water meter error when there are fewer flow points for verification. The result confirms that the formula can better restore the change of water meter error. Li et al. [6] propose a calibration scheme for chassis monitoring system based on polynomial curve fitting, and the results show that the proposed calibration scheme can effectively improve the accuracy of various monitoring circuits inside the chassis. Yao [7] uses the calibration method based on fitting linear equations, divides the flat part of the curve into a number of calibration segments, and fits them with the corresponding linear equations. This ensures that the water meter error curve is controlled within a small error range and that calibration efficiency is significantly improved. However, the above documented methods are not suitable and accurate for the calibration of remote water measurement. Literature [8–10] proposes an adaptive segmented curve fitting localization algorithm based on the influence of environmental factors to enhance curve fitting accuracy. Nevertheless, this algorithm tends to overlook data points with less impact on the fitted curves, resulting in a somewhat one-sided consideration.

In literature [11–13], a polynomial algorithm based on weighted least squares is suggested by analyzing the characteristics of the target data to reduce error in the curve fitting process through assigning different weight ratios to the data. However, the precise size of the weights assigned to the data points is not explicitly defined in the

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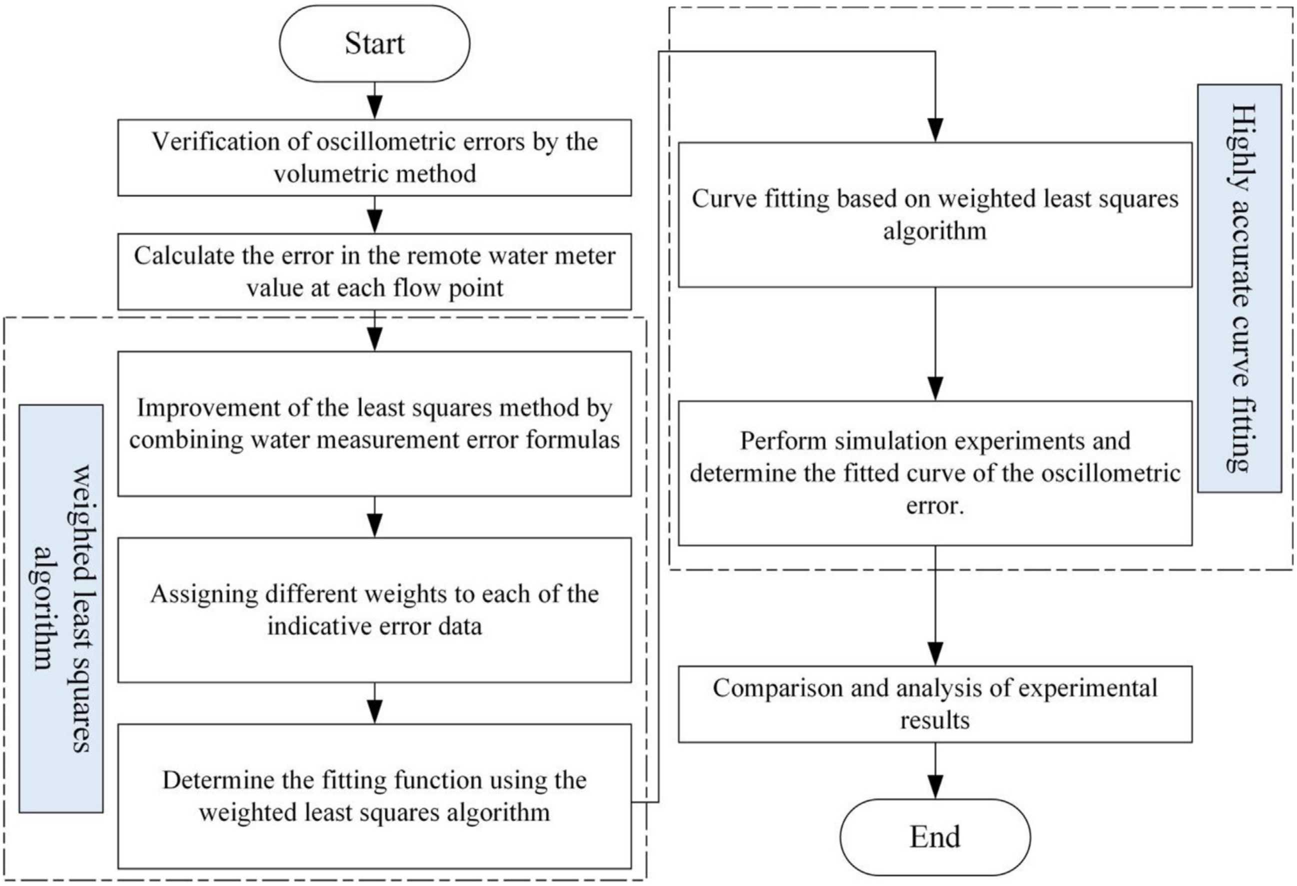

Fig. 1. Flowchart of curve fitting algorithm for remote water measurement error.

modeling process, which makes the concept of weights somewhat ambiguous. Yin et al. [14] propose a binary amplitude calibration method based on least square method. The experimental results show that this method can accurately calculate the calibration coefficient and realize the calibration of the amplitude. Tao et al. [15] has achieved further calibration of the calibration system based on least-squares fitting for environmental and component parameter deviations, enabling high-precision measurements in the voltage (0–10 V) and current (0–150 A) ranges. In order to solve the calibration problem of ultra-short baseline installation deviation, Zhao et al. [16] propose the constrained least square method. Wang et al. [17] use cubic curve-fitting compensation curves to compensate the built-in real-time clock (RTC) module of the meter SoC chip to meet the required accuracy. Accurately characterizing the remote water measurement error curve using the conventional least squares method is challenging due to the influence of actual water meter calibration factors. Efficiently recovering remote water meter characterization error curves from limited calibration data is an urgent problem to be solved [18,19].

In this research, a novel weighted least squares algorithm based on the error curve of the remote water meter measurement is proposed. In the initial stage, the remote water used for the experiment is calibrated, and the error data at several experimental flow rates are calculated. Subsequently, the error data of these points is sorted, and the mathematical model is obtained by combining the water meter calibration formula with the conventional least square's method. Then, the weighting theory is introduced to fit the error curve of the remote water meter measurement, resulting in the weighted least squares algorithm. Finally, several water meters are calibrated, and curve fitting of error data is carried out to simulate the experiments.

2 Curve fitting algorithms for remote water measurement errors

Despite the numerous studies on the characteristics of polynomial fitting curve changes, no effective curve fitting algorithm has been proposed to address the lack of accuracy in fitting the error curve of remote water measurement table values. This research proposes a novel weighted least squares algorithm based on the error curve. The curve fitting algorithm for the remote water measurement error is illustrated in Figure 1.

2.1 Least-squares model combined with the equation for the error of the indication

Assuming that the error data for remote water meter measurements is $(x_i,\ y_i)(i{=}0,1,2...,m)$, the least squares method is to consider the approximation function $S(x_i)$ and the error between the indication of the value and the error (x_i,y_i). The relationship is expressed in equation (1):

$$R_i = S(x_i) - y_i(i = 0, 1, ...m). \tag{1}$$

In equation (1), R_i represents the residuals in the least square's framework, i.e., the fitting function $S(x_i)$ for the actual observations y_i of the fitting error; $S(\cdot)$ represents the approximation function;x_i (i=0,1,2,...,m) represents the experimental flow point; y_i represents the actual water volume corresponding to the experimental flow point, and y_i is a numerical value, which can be either positive, negative or zero; the values of i range from i=0,1,2,...,m, where m is the total number of experimental flow points.

In order to fit the experimental data using the polynomial P_n (Q) and solve the polynomial coefficients through the least-squares method, aiming to establish an appropriate mathematical model for the error data in remote water meter measurement, the data (x_i,y_i) is transformed into (Q_i,D_i)(i=0,1,...m), with Q_i denoting the experimental flow point x_i and D_i denoting the actual water volume corresponding to the experimental flow point. By solving P_n $(Q)\in\varphi$, where φ represents the set of functions consisting of all polynomials with degree not greater than n. The sum of squares of the errors $P(Q_i)$-D_i (i=0,1,...m), is minimized, namely:

$$P_n(Q) = \sum_{k=0}^{n} a_k Q^k. \tag{2}$$

In equation (2), P_n $(\cdot)$ represents the fitting polynomial used for the experiment; a_k represents the correlation coefficient of the fitting polynomial; k represents the order of each term in the polynomial; Q^k represents the term to the k-th power of Q in the fitted polynomial P_n (Q).

Integration of equation (2) under the pre-existing conditions yields:

$$I = min\sum_{i=0}^{m}\left(\sum_{k=0}^{n} a_k Q_i^k - D_i\right)^2. \tag{3}$$

In equation (3), I represents the multivariate function of (a_0, a_1, ..., a_n), n represents the highest number of times we chose to fit the polynomial.

The above problem can be transformed into a problem of solving the extremum of I(a_0, a_1, ..., a_n) via taking a partial derivation of I:

$$\frac{\partial I}{\partial a_j} = 2\sum_{i=0}^{m}\left(\sum_{k=0}^{n} a_k Q_i^k - D_i\right)$$
$$Q_{ij} = 0 \quad (j = 0, 1, ...n). \tag{4}$$

In equation (4), j is an indicator that denotes the partial derivative of the objective function I with respect to the polynomial coefficients a_j; Q_{ij} represents the j-th power of Q at the experimental flow point i.

Expressing equation (4):

$$\sum_{k=0}^{n}\left(\sum_{i=0}^{m} Q_i^{j+k}\right) a_k = \sum_{i=0}^{m} Q_{ij} D_i. \tag{5}$$

Combining equation (5) with the flow points of the remote water meter, the corresponding improved system of linear equations, expressed as a matrix:

$$\begin{bmatrix} \sum_{i=0}^{m} Q_i \\ \sum_{i=0}^{m} Q_i D_i \\ \cdots \\ \sum_{i=0}^{m} Q_i^n D_{i-1} \end{bmatrix} \times \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} n+1 & \sum_{i=0}^{m} Q_i & \cdots & \sum_{i=0}^{m} Q_i^{n-1} \\ \sum_{i=0}^{m} Q_i & \sum_{i=0}^{m} Q_i^2 & \cdots & \sum_{i=0}^{m} Q_i^n \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{i=0}^{m} Q_{i-1}^n & \sum_{i=0}^{m} Q_i^{n+1} & \cdots & \sum_{i=0}^{m} Q_i^{2n-1} \end{bmatrix} \tag{6}$$

The matrix of equation (6) is changed to the form of equation with the expression is given below:

$$XA = Z. \tag{7}$$

2.2 Improved weighted least squares algorithm modelling

After completing the calculation of the conventional least square's method and the remote water meter measurement data along with the metering error, and through the analysis of the characteristics of the detected flow points, a higher weight is assigned based on higher measurement accuracy, and a lower weight is assigned to those with low measurement accuracy. A weighting operation is carried out on the measured value of each water meter.

To better assess the accuracy of the selection of weighting indicators, the mean value of the remote water metering error data corresponding to a number of experimental flow points obtained in the test process were calculated. The specific calculation formula is as follows:

$$\overline{E} = \frac{1}{n}\sum_{i=1}^{n} E_i. \tag{8}$$

In Equation (8), E_i (i=0,1,2...,n) represents the mean value of the remote water measurement error data corresponding to the experimental flow point.

After determining the mean value of the sample, the next step is calculating the variance of the metering error for each experimental flow point. The variance of the sub-sample of the remote hydrometer indication error is:

$$s_i^2 = \frac{1}{n-1}(E_i - \overline{E})^2. \tag{9}$$

The coefficient of variation method is an objective assignment that uses the variability of the data points to determine the weights. The inverse of the coefficient of variation as a weight not only effectively reduces the impact of noise and outliers on the model (noise and outliers with large coefficients of variation will have correspondingly lower weights, and this weighting makes the model focus more on data points with high reliability, which enhances the robustness of the model), but also reduces the negative impact of heteroskedasticity on the fitted results by assigning higher weights to data points with low variability , thus reflecting the importance of more stable and reliable data points. The inverse of the coefficient of variation $C_{V_i} = \frac{S_i}{E_i}$ was selected to estimate the weights of the individual water measurement values, i.e.:

$$\omega_i = \frac{1}{C_{V_i}}. \tag{10}$$

In equation (10), V_i represents the volume of increase (or decrease) recorded on the indicating device during the calibration time; C_{V_i} is the coefficient of variation of the sub-sample of remote water meter value errors at the corresponding experimental flow point i; ω_i represents the weight assigned to the water meter measurements at the experimental flow point i, which is estimated by the reciprocal of the coefficient of variation C_{V_i}.

After assigning different weights to the remote water meter measurement error data, the matrix of equation (6) is multiplied by the corresponding weights in order to obtain the following polynomial relationship matrix equation for the remote water measurement error:

$$\begin{bmatrix} \omega_i \sum_{i=0}^{m} Q_1 \\ \omega_2 \sum_{i=0}^{m} Q_2 D_1 \\ \dots \\ \omega_n \sum_{i=0}^{m} Q_i^n D_{n-1} \end{bmatrix} \times \begin{bmatrix} a_0 \\ a_1 \\ \dots \\ a_n \end{bmatrix} = \begin{bmatrix} \omega_1 (n+1) & \omega_1 \sum_{i=0}^{m} Q_1 & \dots & \omega_1 \sum_{i=0}^{m} Q_i^{n-1} \\ \omega_2 \sum_{i=0}^{n} Q_1 & \omega_2 \sum_{i=0}^{m} Q_2^2 & \dots & \omega_2 \sum_{i=0}^{m} Q_i^n \\ \dots & \dots & \dots & \dots \\ \omega_n \sum_{i=0}^{m} Q_{i-1}^n & \omega_n \sum_{i=0}^{m} Q_i^{n+1} & \dots & \omega_n \sum_{i=0}^{m} Q_i^{2n-1} \end{bmatrix}. \tag{11}$$

Similarly, the matrix in equation (11) is transformed into the following representation:

$$\boldsymbol{WXA} = \boldsymbol{WZ}. \tag{12}$$

In equation (12), the matrix $\boldsymbol{W}$ represents a diagonal array of $i \times i$, and i represents each experimental flow point for the water meter.

The matrix $\boldsymbol{W}$ of equation (13) is shown below:

$$\boldsymbol{W} = \begin{bmatrix} \omega_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \omega_i \end{bmatrix}. \tag{13}$$

In equation (13), $\boldsymbol{W}$=diag(ω_1,ω_2,...,ω_i).

Combined with the least square's solution formula, the formula for the weighted least squares solution for equation (12) is determined as follows:

$$\boldsymbol{A} = (\boldsymbol{X}^T \mathbf{CX})^{-1} \boldsymbol{X}^T \boldsymbol{CZ}. \tag{14}$$

In equation (15), $\boldsymbol{C}$= $\boldsymbol{W}^T \boldsymbol{W}$, which is the weight matrix.

By solving the matrix of computational equation (15), a_k is obtained to finalize the curve fitting and polynomial parameterization of the error in the value of the remote water meter measurement.

3 Experimental validation

3.1 Data acquisition

This experiment utilizes a sampling survey to analyze and screen the data from a water meter factory's qualified remote water meter value, ensuring that the distribution of the randomly selected indication error data shows uniformity [20–22]. The remote water meter measurement verification site is shown in Figure 2.

According to the JJG 162-2019 calibration specification, four groups of flow parameters are generally selected to characterize the data characteristics of the remote water meter measurement error, including: minimum flow rate Q_1, divided flow rate Q_2, Common flow Q_3, and overloaded flow Q_4. In this study, considering the larger data span between Q_2 and Q_3 in the actual water indication value verification, two additional flow points, $0.35(Q_2 + Q_3)$ and $0.7(Q_2 + Q_3)$, are added to the original four flow points, recorded as Q_5 and Q_6 [23–25]. The range and meaning of each experimental flow point are shown in Table 1.

3.2 Experimental design

The verification of remote water meter measurement and the calculation process of indication error were carried out under the experimental conditions of 2 5°C and 0.3 MPa

Fig. 2. Remote water meter verification site.

Table 1. Range and meaning of each experimental flow point.

Experimental flow points	Abridge	Realm	Hidden meaning
Minimum flow	Q_1	Q_1~$1.1Q_1$	The minimum flow rate, Q_1, is the lowest flow rate for which the meter is required to comply with the maximum allowable error.
Divided flow	$Q_{22}Q_2$~$1.1Q_2$		The divided flow rate Q_2 between the common flow rate Q_3 and the minimum flow rate Q_1, is the water meter flow rate range delineation of the high zone and the low zone of the flow rate. Where the high and low zones have their own corresponding maximum allowable error.
Common flow	Q_3	$0.9Q_3$~Q_3	The common flow rate Q_3 is the maximum flow rate under rated operating conditions. Under this flow rate, the normal operation of the water meter is within the maximum allowable error.
Overload flow	Q_4	–	The overload flow rate Q_4 is the maximum flow rate allowed to exceed the rated flow range for a short period. At this flow rate, the water meter measurement error is within the maximum and allowable error range, and the meter metering characteristics remain unchanged when the rated operating conditions are restored.
First attachment point flow	Q_5	$0.35\ Q_2+Q_3$	The first additional point of flow, Q_5, is an experimental flow point added to account for the large span of data between Q_2 and Q_3.
Second attachment point flow	Q_6	$0.7\ Q_2 + Q_3$	The second additional point of flow, Q_6, is the second experimental flow point added after Q_5 to account for the large span of data between Q_2 and Q_3.

pressure, and the starting flow rate was set to –50% [26–28]. A number of remote water meters with a nominal diameter of DN15 of different service life were randomly selected as the verification water meters, and the volume method was used to check the remote water measurements. Firstly, install the remote water meter measurement on the water indication value verification device, and pass in the water flow for verification. In the process of eliminating the existence of air in the piping system of the test instrument, the impact of air on the water indicated value of the test is eliminated; then, let the remote water meter measurement operate smoothly at the specified test flow rate for a period of time, and then adjust the flow control valve to test the flow rate of the test point, so that the water flows through the remote water meter measurement for testing and then into the device's containers; and finally, determine the

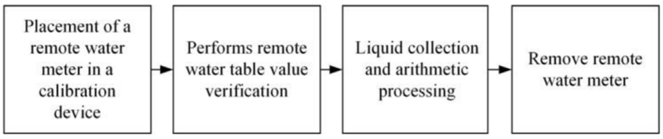

Fig. 3. Remote water measurement verification process.

corresponding water volume, read and record the remote water meter measurement indication value and the volume of water flowing into the container. The remote water meter measurement verification process is shown in Figure 3.

According to the formula for calculating the value error of the water meter and the data from each experimental flow point, compute the metering error data at each experimental flow point for the remote water meter. The remote water measurement metering error calculation formula is:

$$E = \frac{V_i - V_a}{V_a} \times 100\%. \tag{15}$$

In equation (15), E represents the relative display error of the test remote water meter measurement; V_i represents the volume of increase (or decrease) recorded on the indicating device during the test time in m^3 or L; and V_a represents the volume of the actual water volume of the workload apparatus (or standard meter) during the test time in m^3 or L.

3.3 Simulation experiment and result analysis

Based on the six experimental flow points Q_1, Q_2, Q_3, Q_4, Q_5 and Q_6 specified in subsection 3.1, the remote water meter indication values at the flow points of 0.025, 0.04, 0.9, 1.8, 2.5, and 3.125 $(L)/(h)$ are verified. In accordance with JJG 162-2019 calibration specification, three tests are carried out on the three flow points Q_1, Q_2, and Q_3 with repeatability requirements, and two tests are carried out on the three additional flow points (repeatability is not required in the calibration specification) to derive the corresponding metrological errors, and the average value is calculated to ensure the accuracy and reliability of the experiment. Key parameters such as flow rate, number of tests, metrological error and average error is recorded in detail. The data obtained from the remote water meter calibration are shown in Table 2.

In the process of model order selection, if the order of fit is too low (e.g., 1st order, 2nd order), it will not capture the complexity of the data, resulting in underfitting. If the order is increased to 7, the flexibility of the model increases, but it leads to overfitting. An overfitted model performs well on training data but performs poorly on new data because it captures noise in the data rather than the true pattern of the data. During the simulation process of fitting the remote water meter measurement error curve, the fitted curve is smoother as the number of polynomial curve fitting increases. By utilizing the appropriateness degree to select the order of the fitting polynomial, the final weighted least squares algorithm for far-transmission water meter measurement error curve fitting under the sixth-order curve fitting condition is found to have a better effect on the smoothness and accuracy of the fitted curve. In this study, the sixth-order weighted curve fitting and the conventional least squares method are chosen to simulate the curve fitting of the experimentally obtained value error data. The comparison results of the simulated curve fitting between the proposed method and the conventional least squares method are shown in Figure 4.

Table 2. Verification and error calculation data of remote water **measurement** value.

Experimental site (L/h)	Experimental flow points (L/h)	Number of tests	Display value error/%	Average error/%
Q_1	0.025	1	0.100	0.130
		2	0.138	
		3	0.152	
Q_2	0.040	1	0.150	0.220
		2	0.250	
		3	0.260	
$0.35(Q_2+Q_3)$	0.900	1	0.366	0.370
		2	0.374	
$0.7(Q_2+Q_3)$	1.800	1	0.783	0.833
		2	0.882	
Q_3	2.500	1	1.079	1.020
		2	1.089	
		3	0.893	
Q_4	3.125	1	1.608	1.480
		2	1.352	

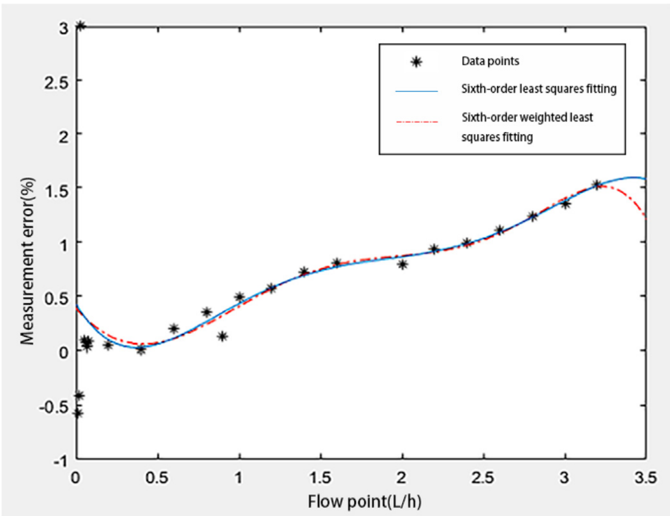

Fig. 4. Error curves for control fitting of remote water measurement error.

Table 3. Comparison of fitting curve errors between sixth-order weighted least squares fit and sixth-order least squares fit.

Experimental flow points (L/h)	Sixth-order least squares fitting/%	Sixth-order weighted least squares fitting/%	Display value error/%	Deviations from the sixth-order least squares fitting/%	Deviations from the sixth-order weighted least squares fitting/%
0.025	0.367	0.344	0.133	+0.234	+0.211
0.400	0.333	0.321	0.217	+0.116	+0.104
0.900	0.345	0.347	0.370	–0.025	–0.023
1.800	0.820	0.840	0.833	–0.013	+0.007
2.500	1.030	1.015	1.020	0.010	–0.005
3.125	1.471	1.482	1.480	–0.009	+0.002

According to the simulation experiment results in Figure 4, the sixth-order fitting curve results of the improved weighted least squares algorithm and those of the conventional least squares algorithm are analyzed. The two types of curve-fitting error data are recorded at each flow point and compared with the correct error to derive the corresponding deviation value, so as to validate the curve-fitting accuracy effect of the two methods. The comparison results are shown in Table 3.

The improved weighted least squares algorithm in Table 3 shows smaller deviation values across multiple experimental flow points, indicating more accurate fitting of the measurement error curve. Compared to the conventional least squares method, the proposed method demonstrates higher fitting accuracy for remote water measurement, effectively avoiding data offset problems during curve fitting and accurately reflecting the trend of the value error curve. This verifies the effectiveness and accuracy of the proposed method for evaluating remote water measurements.

4 Conclusion

Aiming at the problems of low accuracy and long manual time-consumption in the fitting curve of remote water meter measurement error, a weighted least squares algorithm based on the remote water meter measurement error curve is proposed. The water measurement error calculation formula and experimental flow points are combined with the least squares method to realize the enhancement of the conventional least squares method; then different weights are assigned to different experimental flow points, and the weighting operation is carried out on each experimental flow point, which results in the improved weighted least squares algorithm. After completing the construction of the model, the MATLAB simulation software is used to curve-fit the improved weighted least squares algorithm and the conventional least squares algorithm respectively, and the deviation values of the fitting results of the two are compared with those of the actual metering error to verify that the proposed method has a higher curve-fitting accuracy.

Funding

This work was supported by research on automatic straightening technology and equipment development for high-precision slender shafts (GG18E050045).

Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

The data that have been used are confidential.

Author contributions statement

Data curation: Juan Zhou, Shengwei Zhou and Zhibo Cen; Methodology: Juan Zhou, Shengwei Zhou and Shun Zhang; Supervision: Juan Zhou; Writing-original draft: Juan Zhou and Shengwei Zhou; Writing-revised draft: Juan Zhou and Shengwei Zhou.

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Cite this article as: Juan Zhou, Shengwei Zhou, Shun Zhang, Zhibo Cen, Remote water meter calibration based on weighted least squares algorithm, Int. J. Metrol. Qual. Eng. **15**, 13 (2024)