Journal of Computers Vol. 31 No. 6, 2020, pp. 169-181
doi:10.3966/199115992020123106014

Optimization Method Based on Weighted Filtering and Genetic Algorithm for Stage-Discharge Relation

Meng Wang[1*], Dunyao Zhu[2], Hongsheng Li[3]

[1] School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, Wuhan, China
wangmwuhan@aliyun.com

[2] Wuhan KOTEI Informatics Co., Ltd., Wuhan, China
woaipapamamajiejie@126.com

[3] School of Mechanic and Electronic Engineering, Wuhan University of Technology, Wuhan, China
651601954@qq.com

Received 6 October2019; Revised 7 March 2020; Accepted 13 April 2020

Abstract. Discharge measurement of irrigation canal is important for planning and managing water resource. Stage-discharge relation model is used for discharge measurement, which is regarded as a traditional soft measurement method. In order to fit out an accurate stage-discharge curve, enough sample data of water stage and discharge are required. Usually, the process of extracting sample data is labor-intensive and time-consuming. Aiming at improving the accuracy and efficiency, this paper puts forward an optimization measurement method for stage-discharge relation model. Firstly, repeated measurement is implemented separately at several steady flow status. For each steady flow status, filtered sample data of water stage and discharge are calculated through filtering method. Then, the filtered sample data are used for searching the solutions for stage-discharge relation model through genetic algorithm. Lastly, Kalman filter is used to calculate the optimal solution for the stage-discharge relation model. By this way, the demand quantity of sample data decreases significantly. Some experiments are conducted, and the results indicate that the performance of optimization measurement method is superior in accuracy and efficiency to that of traditional method. The stage-discharge relation model built by the proposed method can serves for engineering implementation in discharge measurement.

Keywords: genetic algorithm, irrigation canal, Kalman filter, stage-discharge curve, weighted filtering algorithm

1 Introduction

Irrigation canals are important agricultural infrastructures. They undertake the tasks of water delivery, flood control and power generation. Flow discharge of irrigation canal is an essential element in hydrology study fields, since it defines the inflow and outflow quantity of water resource. Forecasting the flow discharge plays an important role in short or long-term planning and management in the irrigation area, e.g. optimized reservoir and hydroelectric operation or agricultural irrigation [1]. Precisely forecasting discharge is significant to reduce economic losses and is always pursued by reservoir operators. Therefore, government is committed to promoting online monitoring projects of water resource, and researchers are encouraged to pay tremendous attention on measurement method.

Commonly, water discharge is estimated from cross-sectional area and flow velocity at a gauging station of irrigation canal. Because measurement of flow velocity is expensive, time-consuming and encounters risk of life, alternative methods of discharge forecasting are more suitable [2]. Soft

* Corresponding Author

measurement method provides one approach to estimating discharge of irrigation canal. There exists a unique relation model between water level and discharge at the given cross-section of canal. The relation model is represented by stage-discharge curve. Given enough sample records of measured water stage and the corresponding discharge, the fitting curve can be generated. Then, the stage-discharge curve provides an estimation of canal discharge based on measured stage. Usually, water stage can be conveniently measured. With the measured stage and the stage-discharge curve, discharge can be calculated on line. Typical fitting methods, such as least square method (LSM) [3], polynomial fitting method [4] and Bayesian method [5], are adopted to build the stage-discharge curve. Other intelligent algorithm, such as genetic algorithm (GA) [6] and artificial neural network (ANN) [7], are also used for more complex nonlinear stage-discharge model.

The key of soft measurement is to collect enough sample records to build an accurate stage-discharge curve. Enough sample data can significantly promote the precision of the fitting curve. However, it is usually time and effort consuming. In practice, many irrigation canals have no historical records data, and it needs days' workload to collect the sample data of water stage and discharge.

In order to decrease the workload of collecting sample data and increase the accuracy of fitting curve, this paper puts forward an optimization method for stage-discharge relation model. At several steady flow statuses, water stage and discharge are repeatedly measured, so as to obtain the filtered sample data. Then GA is used to search the solutions for stage-discharge relation model. At last, the optimal solution is obtained through Kalman filter. Based on the optimization method, some research and comparison are done through experiment to explain the better performance than traditional method. The proposed method not only guarantees the precision of fitting cure, but also reduces the demand of sample data significantly.

The rest of the paper is organized as follows: Section 2 summarizes the related work. Section 3 demonstrates the proposed optimization method for stage-discharge relation model. In section 4, the experiments of the optimization method and traditional method are carried out. At last, section 5 provides the conclusion.

2 Related Work

For irrigation canals, discharge measurement methods are classified into two kinds: direct measurement method and soft measurement method. Direct measurement utilizes velocity-area method, which means the discharge is equal to flow velocity times area of section as shown in Fig. 1. Soft measurement is call indirect method, which needs to build the relation model between water stage and discharge as shown in Fig. 2.

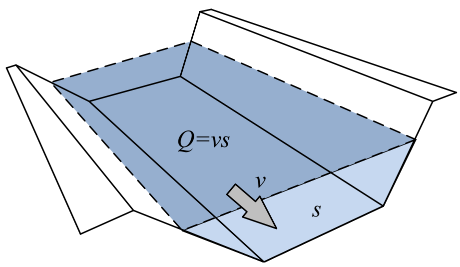

Fig. 1. Schematic of velocity-area method

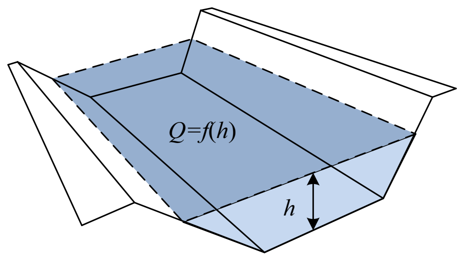

Fig. 2. Schematic of soft measurement method

Lee et al. [8] adopted direct measurement method that has high precision. Acoustic Doppler Current Profiler (ADCP) is the favorite measuring device for flow velocity. By measuring both water velocity and section area, water discharge across the section can be directly calculated according to the discharge formula $Q=vs$. However, direct measurement method does not support long-term online operating because of the high cost of ADCP device.

Soft measurement method is suitable for online measuring in most irrigation area. Comparing with directly measuring flow velocity, measuring water stage is more convenient. By generating the relation model between stage and discharge, the discharge can be calculated indirectly.

One kind of soft measurement method is to build the relation model between stage and discharge according to hydraulic model. Ghobadian et al. [9] and Vatankhah et al. [10] proposed the relation models for circular sharp-crested weir and Parshall flume respectively. As special hydraulic structures, weir and Parshall flume have specific hydraulic models. The hydraulic models indicates the relation between discharge and parameters that contains water stage, canal width, and so on. These parameters are preplanned or readily available. Water discharge can be calculated indirectly according to the parameters. Obviously, this kind of soft measurement method depends on the structure of canal. For most rural areas in China, trapezoidal canal is the main form, and it does not support for the specific hydraulic models.

Another kind of soft measurement method is to generate the stage-discharge relation based on sample data of stage and discharge. Zhang [1] collected years' historical data of Iffezheim reservoir in Germany, and applied ANN to generating the stage-discharge relation model. With this ANN model, discharge can be forecasted when inputting the real-time water stage. Aim at discharge measurement for irrigation canal, Mou [11] tried to extract sample data of stage and discharge, and train the ANN model that is used for forecasting discharge. Kashani [2] took the formula $Q=ah^b$ as the relation model between water stage and discharge. Given enough sample data, the parameters (a, b), were solved through GA. Ibeje [12] adopted polynomial function model to describe the relation between stage and discharge. Years' historical data were also provided in order to fit out the stage-discharge curve. Generally, this kind of soft measurement method focuses on generating the single value function for stage and discharge. Once the function is generated, the discharge can be online calculated with the measured water stage. These soft measurement methods are easy to be realized in engineering practices. However, the stage-discharge relation model is based on enough sample data. The quantity of sample data determines the precision of relation model. Usually, collecting the sample data costs too much labor, and it needs days' labor to collect enough samples data.

Table 1 reports the summary of the above review. The direct measurement method is not suitable for long-term online operation, and labor costs of soft measurement method is high. So, new approaches of discharge measurement need to satisfy both accuracy and economy.

Table 1. Summary of discharge measurement methods

Author, Year	Method	Application	Limitation
Ghobadian, et al 2012	Soft measurement method circular sharp-crested weir	Long-term Online measuring	Special hydraulic structure. It needs to rebuild the canal.
Lee, et al 2014	Direct measurement $Q=vs$, ADCP	Offline measuring	High cost of ADCP device. It is not suitable for online measuring.
Vatankhah, et al 2015	Soft measurement method Parshall flume	Long-term Online measuring	Special hydraulic structure. It needs to retrofit the canal.
Kashani, et al 2015	Soft measurement method $Q=ah^b$, GA	Long-term Online measuring	The accuracy depends on quantity of sample data. High labor cost.
Zhang, et al 2017	Soft measurement method ANN model	Long-term Online measuring	The accuracy depends on quantity of sample data. High labor cost.
Mou, et al 2017	Soft measurement method BPNN model	Long-term Online measuring	The accuracy depends on quantity of sample data. High labor cost.
Ibeje 2018	Soft measurement method Polynomial, curve fitting	Long-term Online measuring	The accuracy depends on quantity of sample data. High labor cost.

3 Optimization Method for Stage-Discharge Relation

The sample data of stage and discharge are used to fit out the stage-discharge curve. By traditional methods, the accuracy of fitting curve is determined by the quantity of sample data. The proposed optimization method tries to reduce the demand of sample data, while the precision is guaranteed.

3.1 Overview of Optimization Method

The proposed optimization method is mainly divided into three steps: sample data processing, model resolving and model optimizing.

3.1.1 Sample Data Processing

In traditional method, the sample data are equally distributed as shown in Fig. 3. Each sample data represents the real-time water stage *h* with the corresponding discharge *q*. When extracting one set of sample data, it is necessary to keep steady water flow, which means water stage and flow velocity are both constant. However, water flow varies as time, and the transition from one steady flow to another costs long time. So, extracting enough sample data is difficult and time-costly.

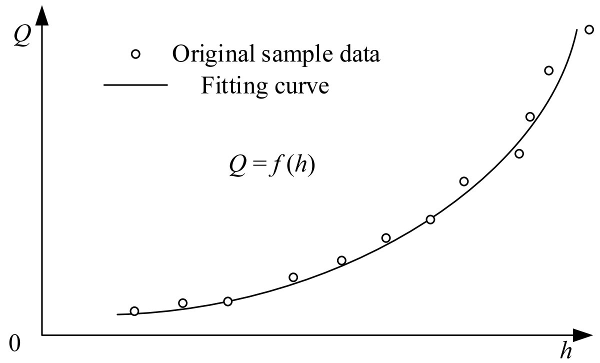

Fig. 3. Sample data distribution of traditional method

Instead of equal distribution, sample data of optimization method are just distributed at several steady water flow, as shown in Fig. 4. In each steady flow, measurement of stage and discharge is repeated. Obviously, the aggregation distribution pattern makes it much easier to implement the process of extracting sample data. Designers just need to keep several steady flow, such as low level of water flow, middle level of water flow and high level of water flow. By this way, it is no longer for designers to wait for the water flow from one steady flow to another steady flow. So, the efficiency of extracting sample data can be improved significantly.

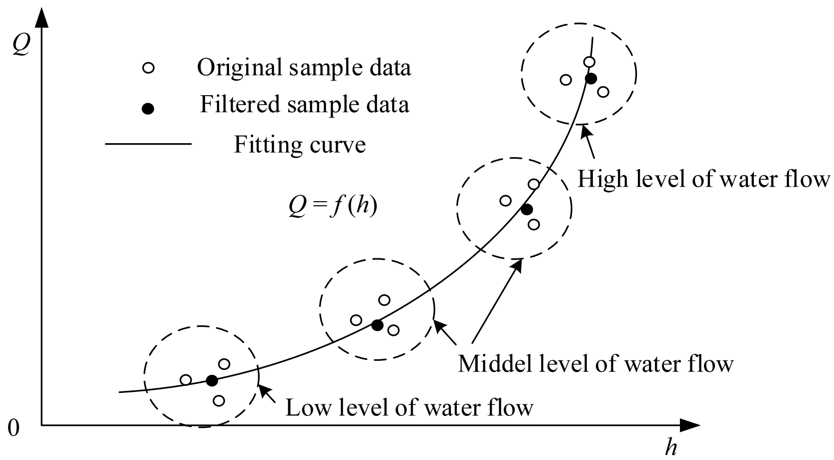

Fig. 4. Sample data distribution of optimization method

Original sample data are extracted firstly. With these original sample data, filtered sample data of water stage and discharge at each steady flow are calculated through weighted filtering algorithm.

3.1.2 Model Resolving

Discharge monitoring station is usually selected in the place where the segment of canal is regular structure, and the surface of canal is smooth and clean. Under this environment condition, trapezoidal canal has a unique relation model between water stage and discharge. A stage-discharge relation model is normally expressed by [4]

$$Q = a(h - c)^b, \tag{1}$$

where Q is the discharge, h is the water level, a, b and c are parameters to be solved. According to filtered sample data of stage and discharge, a stage-discharge relation curve can be obtained. Considering that the relation model is nonlinear, genetic algorithm is presented to solve the nonlinear optimization problem based on principle of encoding, selection, crossover and mutation operations.

GA has good performance on optimization and overall search, and it can search the global optimum by iterating.

3.1.3 Model Optimizing

For the randomness of classical GA which appears in calculation process, the optimization carried out by GA produces a set of solutions, not just only one. In order to choose the optimal solution for stage-discharge relation model, the Kalman filter is adopted.

Supposing that the solving process of GA is repeated M times, and M solutions of stage-discharge relation model can be obtained accordingly. The M solutions are expressed as

$$(a_i, b_i, c_i),\ i = 1, 2, \cdots, M. \tag{2}$$

All solutions searched by GA is different, which causes the fitting curve is not the only one. So, Kalman filter algorithm is used to obtain the optimal solution. In model optimizing step, M solutions are regarded as the sample data of Kalman filter. After performing Kalman filter, the corresponding filtered solutions are

$$(\overline{a}_i, \overline{b}_i, \overline{c}_i),\ i = 1, 2, \cdots, M. \tag{3}$$

Then, the optimal estimation solution can be obtained through mean processing as following:

$$\tilde{a} = \sum_{i=1}^{M} \overline{a}_i, \tilde{b} = \sum_{i=1}^{M} \overline{b}_i, \tilde{c} = \sum_{i=1}^{M} \overline{c}_i. \tag{4}$$

The whole flow chart of the optimization measurement method is given as Fig. 5.

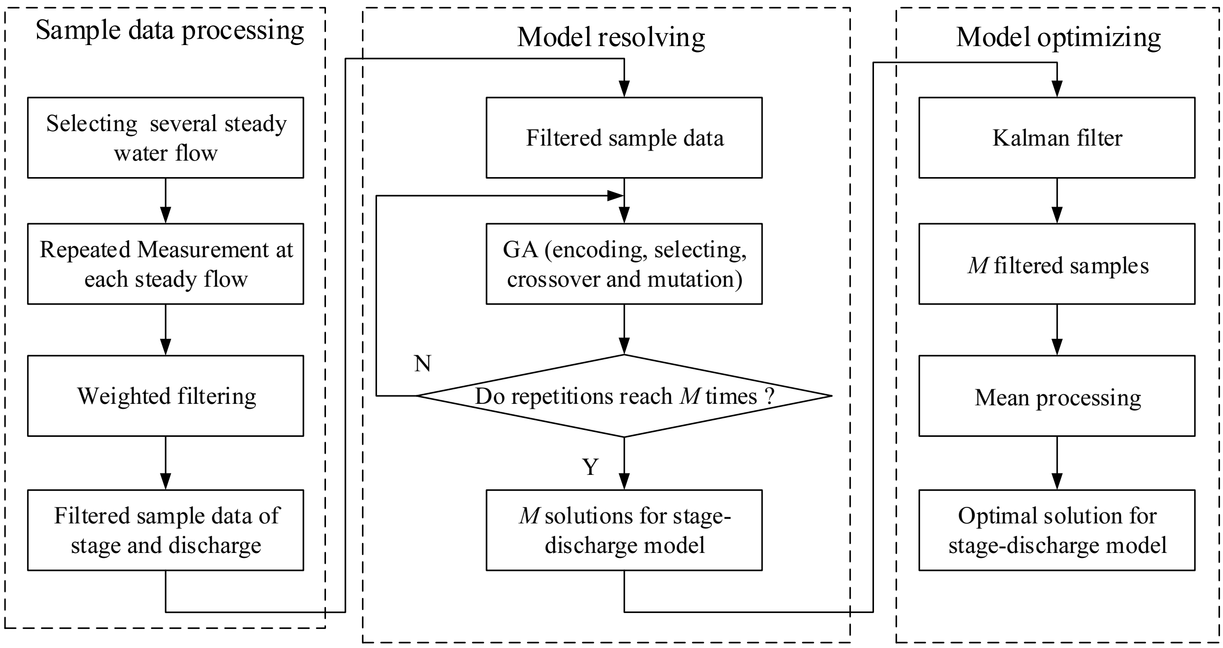

Fig. 5. Flow chart of the optimization measurement method

3.2 Sample Data Processing

Considering the measuring errors mixed in sample data, weighted filtering algorithm is adopted. According to median filtering method, sample data are sorted according to their numeric value, and the median observation is regarded as filter output. Supposing that there are k sets of sample data at one steady flow:

$$(h_1,q_1),(h_2,q_2),\cdots,(h_i,q_i)\cdots,(h_k,q_k), \tag{5}$$

where h_i represents the water level, and q_i is the corresponding discharge. The median value of k sets of sample data is expressed as

$$h_p = Median(h_1,h_2,\cdots,h_k)\,,\; q_p = Median(q_1,q_2,\cdots,q_k). \tag{6}$$

Then, adaptive weights are calculated according to the variance between median value and each sample data. The weighted values are expressed as

$$\omega_i = 1-\frac{(h_p-h_i)^2}{\sum_{j=1}^{k}(h_p-h_j)^2}\,,\; \psi_i = 1-\frac{(q_p-q_i)^2}{\sum_{j=1}^{k}(q_p-q_j)^2}. \tag{7}$$

So, the outputs of weighted filtering algorithm are

$$\overline{h} = \sum_{i=1}^{k} h_i\omega_i \Big/ \sum_{i=1}^{k}\omega_i\,,\; \overline{q} = \sum_{i=1}^{k} q_i\psi_i \Big/ \sum_{i=1}^{k}\psi_i. \tag{8}$$

Supposing N is the number of steady flow, filtered sample data of stage and discharge can be expressed as

$$(\overline{h}_1,\overline{q}_1),(\overline{h}_1,\overline{q}_1),\cdots,(\overline{h}_N,\overline{q}_N). \tag{9}$$

3.3 Model Resolving

Given the filtered sample data, model solution is introduced using GA. Genetic algorithm is a nonlinear search and optimization method inspired by biological processes of natural selection and the survival of the fittest [13]. On the basis of fitness function, GA realizes the individual's search through initial encoding, selecting and eliminating, crossover and mutation. In this paper, we use GA to obtain the solution for stage-discharge relation model.

Supposing the stage-discharge relation model is

$$Q = a(h-c)^b. \tag{10}$$

The process of solving the model is divided into four steps: encoding, selecting, cross-over and mutation.

Encoding. In encoding step, parameters (a, b, c) are separately encoded as 10 bits' binary substrings v_i, i=1, 2, 3. The substrings generate 30 bits' binary code V that represents an individual. The binary code is randomly generated 10 times, which forms the initial population V_j, j=1, 2, ⋯, 10.

Selection. Each individual is evaluated and selected according to the fitness function. Some individuals will be selected, while some will be eliminated. This process simulates the principle of survival of the fittest in biological evolution. For each individual, the average fitting error is

$$E_j = \frac{\sum_{i=1}^{N}[a_j(\overline{h}_i-c_j)^{b_j}-\overline{q}_i]}{N}. \tag{11}$$

where E_j is the fitting error of individual V_j, and parameters (a_i,b_i,c_i) are the corresponding solution determined by individual V_j. According to the fitting error, fitness function is designed as:

$$fitnsss(j) = 1-\frac{E_j}{\sum_{j=1}^{10}E_j}. \tag{12}$$

Fitness function determines the chances to be selected of one individual. It also means that the ones with better fitness have more chances to be selected.

Crossover and mutation. Crossover reflects the phenomenon of information exchange in nature. Two individuals, V_m= (v_{m1}, v_{m2}, v_{m3}) and V_n= (v_{n1}, v_{n2}, v_{n3}) are randomly selected, as well as the crossover position. Then, new individuals, V_m'= (v_{m1}', v_{m2}', v_{m3}') and V_n'= (v_{n1}', v_{n2}', v_{n3}') are generated through gene exchange from the crossover position.

Mutation simulates the genetic mutation caused by accidental factors in the genetic environment of nature. Mutation position is selected randomly. Then, the binary code at mutation position is changed, which generates the corresponding new individual. The probability of mutation is small, but it adds excellent performance of global optimization.

Iteration. Given the initial population, the operation of selection, crossover and mutation is repeated. By cyclic iteration, one solution for stage-discharge relation model is searched.

3.4 Model Optimizing

The solutions of GA are not unique. Kalman filter algorithm is used to get optimal solution. Supposing that the solving process of GA is conducted 50 times, and the corresponding solution samples are

$$(a_i, b_i, c_i),\ i = 1, 2, \cdots, 50. \quad \textbf{(13)}$$

Kalman filter defines the state equation and measurement equation of discrete systems. In order to use Kalman filter, it is need to establish the discrete systems. Considering that the parameters of the state-discharge model is constant, the state equation is established as

$$X(k) = X(k-1) + w(k). \quad \textbf{(14)}$$

The corresponding measurement equation is

$$Y(k) = X(k) + v(k), \quad \textbf{(15)}$$

where $X(k)$ is process state vector, $w(k)$ and $v(k)$ are noise vectors that are assumed to be white noise with covariance Q and R, and $Y(k)$ is vector of measurements. Under the given initial conditions and solution samples, the best estimate of the current state $X(k)$ is obtained through state equation and measurement equation. One step prediction algorithm is

$$X(k \mid k-1) = X(k-1 \mid k-1), \quad \textbf{(16)}$$

$$H(k) = p(k \mid k-1)\left[p(k \mid k-1) + R(k)\right]^{-1}, \quad \textbf{(17)}$$

$$p(k \mid k-1) = p(k-1), \quad \textbf{(18)}$$

$$p(k) = \left[I - H(k)\right]p(k \mid k-1), \quad \textbf{(19)}$$

$$X(k \mid k) = X(k \mid k-1) + H(k)\left[Y(k) - X(k \mid k-1)\right]. \quad \textbf{(20)}$$

The flow of Kalman filter algorithm is shown in Fig. 6.

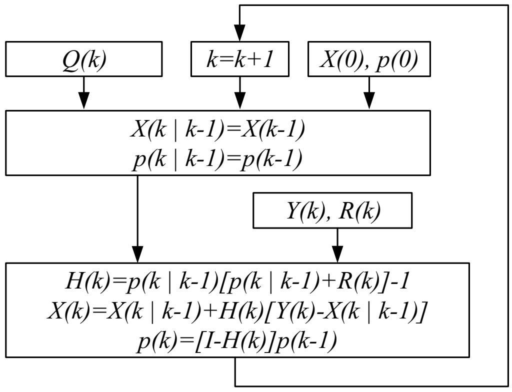

Fig. 6. Flow chart of Kalman filter

Supposing the filtered solution samples are (a_i', b_i', c_i'), i=1, 2, ⋯,50 after performing Kalman filter. Then the optimal solution for stage-discharge model can be obtained through mean processing as following:

$$(\bar{a},\bar{b},\bar{c}) = (\sum_{i=1}^{50} a_i', \sum_{i=1}^{50} b_i', \sum_{i=1}^{50} c_i') . \quad \textbf{(21)}$$

4 Experimental Study

In order examine the performance of proposed method, experiments are conducted. The experiments are based on a practical irrigation canal in Guangdong Province, and the canal model is supposed to be known. The canal is a typical trapezoidal canal. A smooth and clean segment is selected as the observation point. The normal operation level of the canal is between 0.3 meters and 1.2 meters, while the normal operation discharge is between 0 m^3/s and 2 m^3/s. When extracting sample data, the steady water flow should satisfy the condition of stage and discharge.

Sample data of stage and discharge can be extracted according to the theoretical model. The sample data are mixed with measuring error, which simulates the measurement process. By using different method, fitting curves are obtained. The fitting curves are compared with the theoretical model in order to evaluate the performance of different methods. Supposing the theoretical model of stage-discharge relation is

$$\begin{cases} Q = a(h-c)^b \\ a = 1.8336 \\ b = 1.2112 \\ c = 0.2742 \end{cases} . \quad \textbf{(22)}$$

According to the theoretical model, the stage-discharge curve is shown in Fig. 7.

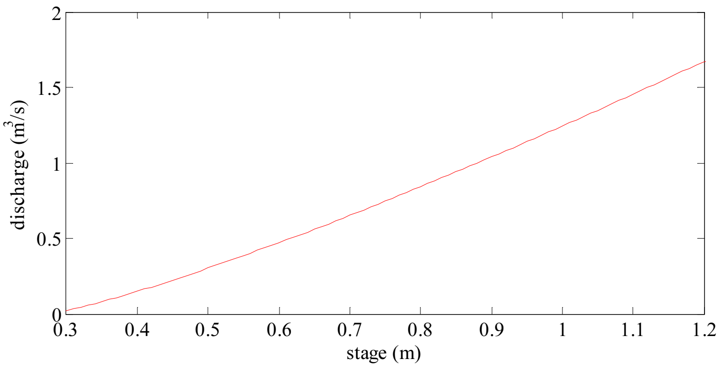

Fig. 7. Theoretical stage-discharge curve

The rest of this section is about two parts of experiments. One part is to use the traditional methods, LSM and GA. Another part is to use the proposed optimization method. Fitting curves of these methods are compared with theoretical curve, and the fitting errors are calculated respectively.

4.1 Traditional Methods for Stage-Discharge Curve

LSM and GA are typical traditional fitting methods, and they are adopted to fit out the stage-discharge curve. Simulating the measuring process, twenty sets of sample data are extracted as shown in Table 2. The sample data are evenly distributed.

Table 2. Sample data for traditional methods

Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)
0.292	0.0231	0.540	0.3469	0.760	0.7612	1.023	1.2104
0.361	0.0733	0.584	0.4510	0.838	0.8890	1.055	1.4316
0.388	0.1376	0.630	0.5205	0.884	0.9654	1.097	1.5029
0.461	0.2218	0.664	0.6088	0.901	1.1188	1.151	1.6313
0.490	0.2793	0.723	0.6665	0.948	1.1632	1.201	1.6427

By using LSM and GA, the fitting curves are obtained and shown in Fig. 8 to Fig. 9. According to Fig. 8 to Fig. 9, the fitting curves of LSM and GA both basically reflect the relation between water stage and discharge, and they have a certain coincidence with theoretical curve. The fitting errors are correspondingly calculated. The average fitting error of LSM is 0.0096 m/s^3, while the average fitting error of GA is 0.0445 m/s^3.

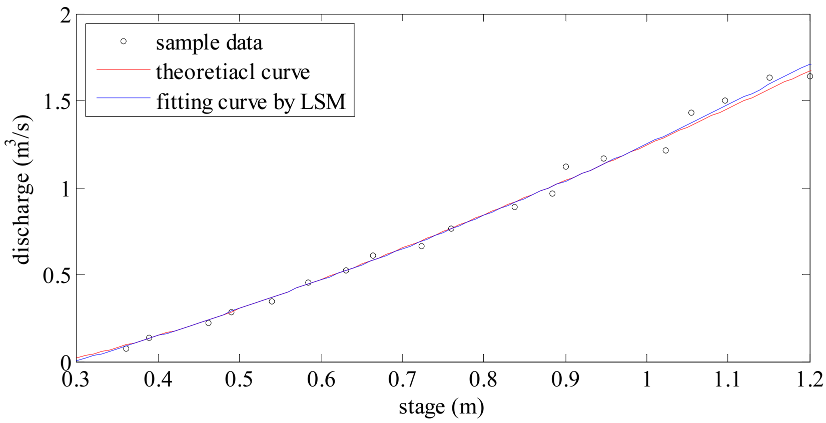

Fig. 8. Fitting curve by LSM (Q=0.5633h^2+1.0491h-0.3621, E=0.0096)

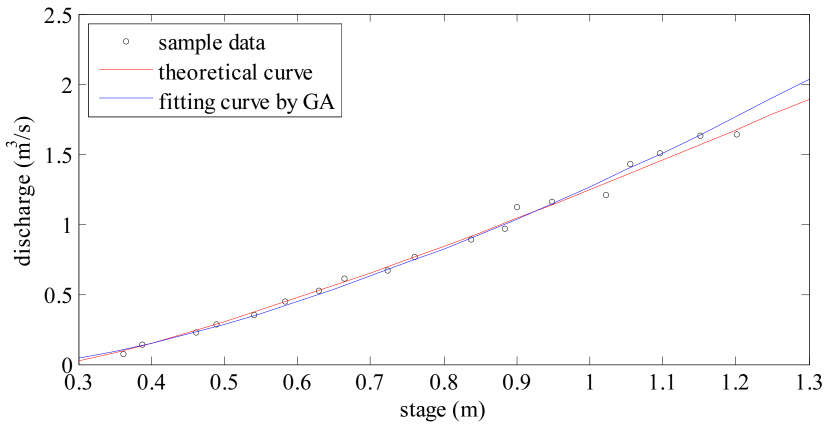

Fig. 9. Fitting curve by GA (Q=1.8117(h-0.2184)$^{1.4542}$, E=0.0445)

4.2 Proposed Methods for Stage-Discharge Relation

Different with the traditional fitting methods, the sample data of proposed method are not necessary to be distributed evenly. According to the proposed method, sample data are just distributed at several steady flow. So, three steady flow, four steady flow and five steady flow are correspondingly considered.

Firstly, we take three steady flow into consideration. Simulating the measuring process, nine sets of sample data are extracted as shown in Table 3. Through the proposed method, the fitting curve is obtained as shown in Fig. 10. The corresponding average fitting error is 0.0144 m/s^3.

Table 3. Sample data for proposed method using three steady flow

Stage (m)	Discharge (m3/s)	Stage (m)	Discharge (m3/s)	Stage (m)	Discharge (m3/s)
0.313	0.023	0.767	0.770	1.210	1.690
0.303	0.020	0.741	0.783	1.195	1.669
0.302	0.023	0.760	0.742	1.203	1.655

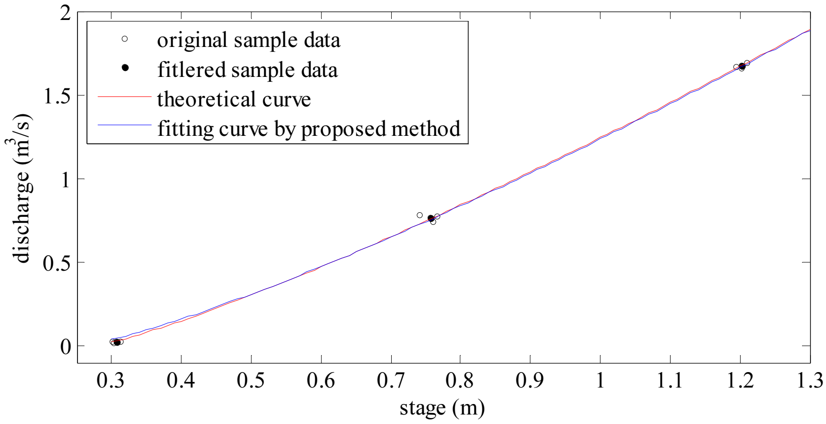

Fig. 10. Fitting curve by proposed method using three steady flow (Q=1.7805 (h-0.2529)$^{1.2520}$, E=0.0144)

Then, four steady flow is taken into consideration. Simulating the measuring process, twelve sets of sample data are given as shown in Table 4. Through the proposed method, the fitting curve is obtained as shown in Fig. 11. The average fitting error is 0.0118 m/s^3.

Table 4. Sample data for proposed method using four steady flow

Stage (m)	Discharge (m3/s)	Stage (m)	Discharge (m3/s)	Stage (m)	Discharge (m3/s)	Stage (m)	Discharge (m3/s)
0.283	0.022	0.587	0.460	0.902	1.002	1.196	1.600
0.290	0.023	0.586	0.454	0.914	1.052	1.190	1.607
0.297	0.023	0.615	0.475	0.894	1.041	1.187	1.627

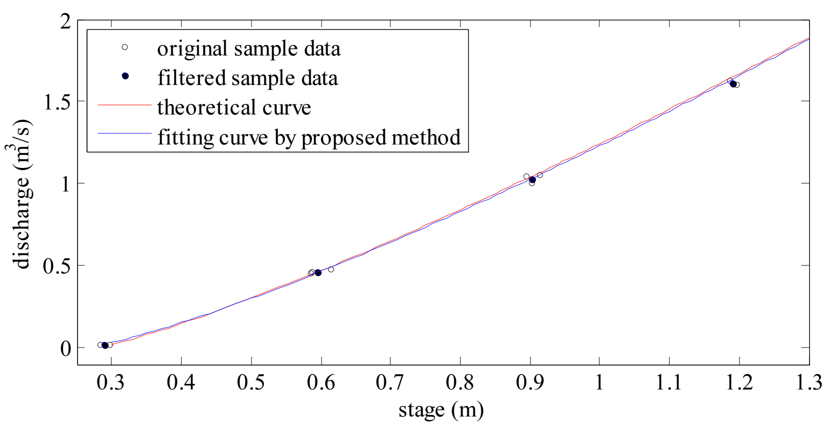

Fig. 11. Fitting curve by proposed method using four steady flow (Q=1.7913 (h-0.2601)$^{1.2460}$, E=0.0118)

Lastly, five steady flow is taken into consideration, and fifteen sets of sample data are given as shown in Table 5. Through the proposed method, the fitting curve is obtained as shown in Fig. 12. The average fitting error is 0.0046 m/s^3.

Table 5. Sample data for proposed method using five steady flow

Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)	Stage (m)	Discharge (m^3/s)
0.297	0.020	0.516	0.357	0.740	0.739	0.978	1.140	1.182	1.615
0.316	0.024	0.520	0.330	0.734	0.718	0.964	1.175	1.206	1.709
0.300	0.022	0.536	0.340	0.768	0.780	0.988	1.134	1.206	1.662

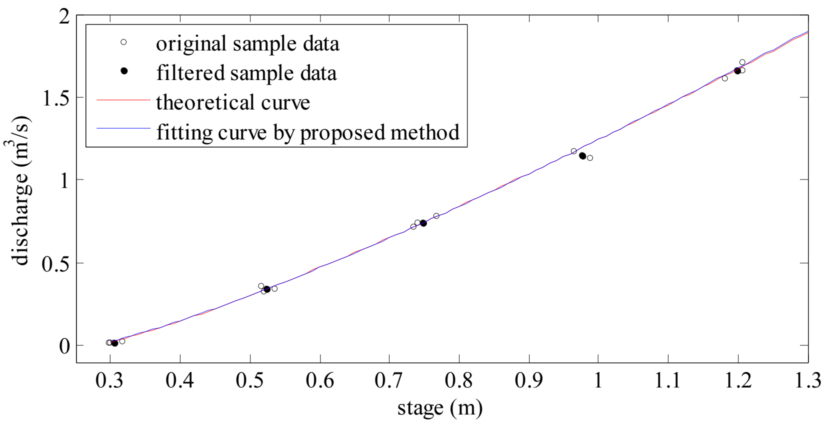

Fig. 12. Fitting curve by proposed method using five steady flow (Q=1.8248 (h-0.2667)$^{1.2343}$, E=0.0118)

According to Fig. 10 to Fig. 12, the fitting curves by proposed method are almost coincided with the theoretical curve. Especially, the fitting error decreases significantly by using five steady flow.

4.3 Results and Discussion

The results of above experiments are summarized in Table 6. Traditional methods and the proposed method have different fitting precision. For traditional methods, both the number of steady water flow and the number of sample data are twenty. Nevertheless, the numbers of the proposed method are much smaller.

Table 6. Performance statistics

Method		Model adopted	Average error (m^3/s)	Number of steady flow	Number of sample data
Traditional method	LSM	$Q=a_0+a_1h+a_2h^2$	0.0096	20	20
	GA	$Q=a(h-c)^b$	0.0450	20	20
Proposed method	Three steady flow	$Q=a(h-c)^b$	0.0145	3	9
	Four steady flow	$Q=a(h-c)^b$	0.0114	4	12
	Five steady flow	$Q=a(h-c)^b$	0.0041	5	15

From the results, we can know that the optimization method proposed in this paper achieves approximately equal or better performance of fitting precision. Especially, when using five steady flow method, the fitting error is further reduced comparing with traditional methods. Moreover, only several steady flow are required by using proposed method, and the number of sample data needed is much small than traditional methods. It means that it is no longer for designer to extract enough sample data as much as possible. As a consequence, the proposed method can simplify the sampling process and reduce labor costs greatly.

When applying the proposed method to engineering practices, five steady flow method is recommended. The designers need to select five steady water flow, and repeatedly extract sample data at each steady water flow. With the sample data, stage-discharge curve is fitted out through the proposed method. Then, the stage-discharge curve can be used for long-term online measurement of water discharge.

5 Conclusions

Soft measurement method of water discharge is widely used in irrigation canals. Traditionally, enough sample data of stage and discharge is required in order to fit out an accurate stage-discharge curve. However, the process of extracting sample data is time-consuming and labor-intensive. In order to simplify the process of extracting sample data and guaranteeing the fitting accuracy, an optimization measurement method is put forward in this paper. The experiments verifies the performance of proposed optimization method. Comparing with the traditional methods, the proposed method not only increases accuracy of stage-discharge model, but also significantly simplifies the process of extracting sample data. So, the proposed method and results of this research can be served as the guidance when implementing engineering practices for discharge measurement.

This paper mainly focuses on the discharge measurement method for trapezoidal canal. Trapezoidal canal is the simplest and most common form in irrigation areas in China. The proposed measurement method is verified, and it is suitable for trapezoidal canal. Whether the proposed method can be applied to some other typical kinds of canals, such as rectangular canal, U-shape canal and irregular shape canal, needs more analysis and experiments, and that will undoubtedly be out future work.

Acknowledgements

The authors would like to appreciate anonymous reviewers and the editor for their constructive comments.

References

[1] Q. Zhang, B. Aljoumani, G. Hillebrand, T.O. Hoffmann, Forecasting monthly inflow discharge of the Iffezheim reservoir using data-driven models, in: Proc. Egu General Assembly Conference, 2017.

[2] M.H. Kashani, R. Daneshfaraz, M.A. Ghorbani, M.R. Najafi, O. Kisi, Evaluation of capabilities of different methods for development of a stage-discharge curve of the Kizilirmak River, Journal of Flood Risk Management 8(2015) 71-86.

[3] F.C. Ros, H. Tosaka, L.M. Sidek, M.N. Desa, K. Arifin, Stage discharge curve for Guillemard Bridge streamflow sation based on rating curve method using historical flood event data, in: Proc. IOP Conference Series: Earth and Environmental Science, 2013.

[4] S.J. Li, X.P. Ma, H. Yu, Analysis of hydrological data based on BP neural network approximation and polynomial fitting, Advanced Materials Research 518(523)(2012) 4115-4118.

[5] T. Reitan, O.A. Petersen, Bayesian methods for estimating multi-segment discharge rating curves, Stochastic Environmental Research and Risk Assessment 23(5)(2009) 627-642.

[6] E.A. Meselhe, E.H. Habib, Stage-discharge relations for low-gradient tidal streams using data-driven models, Journal of Hydraulic Engineering 132(5)(2006) 482-492.

[7] C. Sivapragasam, M. Muttil, Discharge rating curve extension – a new approach, Water Resources Management 19(5)(2005) 505-520.

[8] K. Lee, H-C. Ho, M. Marian, C-H. Wu, Uncertainty in open channel discharge measurements acquired with StreamPro ADCP, Journal of Hydrology 509(2014) 101-114.

[9] R. Ghobadian, E. Meratifashi, Modified theoretical stage-discharge relation for circular sharp-crested weirs, Water Science and Engineering 1(2012) 30-37.

[10] A.R. Vatankhah, Discussion of “Supercritical Flow Measurement Using a Large Parshall Flume”, Journal of irrigation and drainage engineering 141(3)(2015) 07014041.1-07014041.3.

[11] Y. Mou, H. Li, M. Wang, Q. Zhang, Research on multi cross-section stage-discharge relationship based on BP neural network, in: Proc. 2017 32nd Youth Academic Annual Conference of Chinese Association of Automation (YAC), 2017.

[12] A.O. Ibeje, Use of lower-order and higher-order streams in modelling the rating curve, Water Resources Management 33(2019) 819-830.

[13] G. Zucco, G. Tayfur, T. Moramarco, Reverse flood routing in natural channels using genetic algorithm, Water Resources Management 29(12)(2015) 4241-4267.