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A new method for on-line demand calibration of WDS hydraulic model

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ABSTRACT

The current approaches to the demand calibration of hydraulic models in water distribution system (WDS) are typically slow and not sufficiently reliable. This study introduces "deep fuzzy mapping" (DFM) as the fast and reliable tool for an on-line demand calibration of WDS hydraulic models based on supervisory control and data acquisition. Also, an on-line WDS hydraulic simulation platform is built which consists of a data resource layer, a model processing layer, and an access display layer. The on-line simulation platform is applied to the demo network, and it is verified that a DFM learning algorithm serves as an effective method for the on-line demand calibration of WDS hydraulic model in WDS.

Keywords: Water distribution system; Fuzzy mapping; Deep learning; Demand calibration

1. Introduction

The on-line hydraulic simulation of water distribution system (WDS) is the important basis for making scientific decision of daily operation, making plan for expansion, reconstruction of pipe network, and the handling of emergencies such as burst detection and localization [1,2] as well as contamination sources identification [3]. The error of WDS hydraulic model mainly is attributed to two aspects: one is the pipe network's calibration, including devices' parameters and pipes' topology; the other is whether the node demand of the pipe network is correct or not. Among them, the accuracy of node demand has the greatest impact on the model results. The efficiency and reliability of node demand calibration are the keys to realize on-line simulation of WDS hydraulic model. Here, the reliability of the calibration results is not only reflected in the low error between the monitoring value and the calculated value of the pressure meters and flow meters, but also reflected in the corrected node demand which should be consistent with the actual pipe network.

In order to solve the problem of slow calibration speed and difficulty to realize on-line calibration of hydraulic model in WDS, we proposed an on-line calibration of WDS hydraulic model by means of recently introduced "deep fuzzy mapping" (DFM) models. The learning algorithm of DFM, at every time point, utilizes supervisory control and data acquisition (SCADA) to calibrate the node demand via identifying the mathematical mapping between pressure/flow sensor data and nodes demand. First, the method simulates a training dataset consisting of at least 300 inputs-outputs data pairs for the learning of DFM at every time point. The model calibration performance can be used for real time as it takes less than 1 min to calibrate the nodes demand at every time point. Further, the method is robust against the inaccuracy in

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base demand. Finally, the calibration algorithm could help us to find the problems related to basic data of water network such as the network structure, sensor data, and valves' state. The calibration of basic data of water network would further improve the accuracy of the model. Therefore, the node demand calibration algorithm is well suitable for a real practical situation.

In this paper, we synchronized the revenue data of the demo network to its geographic information system data and established the on-line hydraulic calibration model using DFM learning algorithm based on SCADA, and analysed the accuracy of the modelling approach on the on-line WDS hydraulic simulation platform. Finally, we analysed the superiority of the proposed method in comparison with the traditional optimization method and discussed the direction of further improvements.

2. The current status of WDS hydraulic model calibration methods

Hydraulic model is the basis for the analysis, design, operation, and maintenance of water supply network. Before the hydraulic model can be used for daily work, the model needs to be calibrated first. Hardy Cross proposed the basic equations of pipe network hydraulics, which combined the node demand, pipe friction, pipe flow, and nodal head together. It is generally believed that the friction of pipe changes little, and the node demand is changed in real time. Therefore, the on-line calibration of node demand is the key to realize the on-line simulation of hydraulic model. So how to improve the calculation efficiency and the reliability of node demand calibration method is still a hot and difficult problem in the field of pipe network research.

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At present, the methods of hydraulic model calibration can be divided into three categories. The first is iterative (repeated trial) process calibration model [4]. Second is the explicit calibration (hydraulic simulation) [5]. Third is implicit calibration model (optimization model). Among them, the optimization method is the main method to achieve the pseudo-steady state hydraulic model calibration. The core idea of the method includes two aspects: first, the objective function and the constraint condition; second, the optimization algorithm to calibrate the model parameters. At present the main objective functions to solve the problem are as follows: least absolute value [6] function, weighted least absolute value [7], least squares (LS) [8] function, weighted least squares [9] function. And the optimization algorithm mainly has genetic algorithm [10,11], Levenberg–Marquardt algorithm [12], Gauss–Newton optimization method [13], simulated annealing method [14], first-order second-moment method [15], particle swarm optimization [16], and singular value decomposition [17]. Recently, Bayesian inference has been broadly adopted for quantifying uncertainties in varieties of WDS problems [18–20].

There are four limitations in the optimization method. First, the method has huge amount of calculations and needs long time to find the optimal solution, so this method is mainly applicable to steady or quasi-steady state pipe network model calibration, but it is difficult to achieve on-line calibration for large urban water supply network. The second is that the initial flow distribution has a great influence on the result, which leads to the low accuracy. The third is that the method requires higher accuracy of monitored data but has poor noise immunity. So if an individual sensor got the wrong records at a certain time due to instrument failure, an erroneous calibration result will be obtained. Fourth, this method defaults the equipment status in the pipe network, the topology of the pipe network and the parameters of the pipes are accurate. In fact, due to the lack of equipment parameters, state inaccuracy, the man-made errors in the pipe network, the modeling pipe network, and the actual pipe network are difficult to achieve. Therefore, the nodes demand calibration by this method cannot truly reflect the node demand of the actual network.

3. On-line calibration of hydraulic model for water supply network

3.1. Hydraulic equation of water supply network

Pipe network operation condition refers to the hydraulic characteristics of pipe network under certain water supply and water use conditions, mainly contains the nodal head H (or pipe head loss h) and pipe flow rate q. The operation condition of the pipe network depends on two parameters, that is, pipe section friction S and node demand Q, which reflect the discharge capacity and water consumption of the pipe network respectively. S and Q are called independent variables, and H (or h) and q are called state variables. The independent variable determines the state variable, and the state variable is the reflection of the independent variable. Follow equations describing the hydraulic steady state of flows and pressure in a water distribution network, which includes mass continuity and energy conservation equations:

$$Q_i + \sum q_{ij} = 0 \qquad (i = 1, 2, \cdots, N) \tag{1}$$

$$\sum h_{ij} = 0 \tag{2}$$

where N represents the number of nodes in the pipe network, q_{ij} represents the flow rate from the node i to the node j, Q_i represents the node demand of i, and h_{ij} represents the head loss of the pipe from the node i to the node j.

3.2. On-line calibration of hydraulic model based on DFM learning algorithm

A recent work [21] has suggested a mathematical way to study the propagation of the uncertainty through an uncertain nonlinear function. The concept of "fuzzy mapping" was introduced [21] to represent the uncertainty of any nonlinear function. A fuzzy mapping uses an infinite-dimensional fuzzy membership function to represent the uncertainties regarding a functional relationship and is thus the fuzzy equivalent of Gaussian process. The main idea is of introducing a finite pairs of input-output points (referred to as the auxiliary inducing points) to be interpolated for defining a fuzzy membership function on functional output values. The designed fuzzy membership function–based data model can be applied for solving filtering, prediction, and classification problems. It is suggested [21] to maximize the over uncertainties averaged log-membership values of the observed data as the design criterion for determining fuzzy membership function on the variables. This maximization problem can analytically only partially be solved. Another significant feature of the approach [21] is that the intractability problem is circumvented by carefully and sensibly constraining the solution space to develop a practical algorithmic solution which is not only competitive in the modeling performance but also computationally remarkably faster than its probabilistic counterpart.

A DFM is formed via a nested composition of a finite number of fuzzy mappings. The composition of fuzzy mappings would further enhances the capabilities in learning complex data structures. Our research group has introduced a fuzzy theoretic approach to the learning of DFM. The most significance feature of the learning approach is that all of the unobserved variables and parameters associated to the deep model are averaged out where the averages are computed taking into account the uncertainties (on variables and parameters) being represented by the fuzzy membership functions optimally learned from the observed data. Several issues are addressed to design fast, competent, and robust modeling algorithms. A mathematical theory is provided to facilitate the application of fuzzy theoretic data models in prediction, filtering, and classification problems. As the uncertainties have been handled in a principled mathematical manner, the built DFM models are robust against noise.

The DFM learning algorithm, every time a new sensor data (i.e., pressure, flow, and total input demand) is received, is applied for node demand calibration as follows:

(1) N = 300 number of independent EPANET (Application for Modeling Drinking Water Distribution Systems of United States Environmental Protection Agency) simulations are performed on a given water distribution network via randomly generating demand values from a uniform distribution on an interval around an initial guess. The simulations could be performed using parallel computing to reduce computational time.
(2) The simulation data are meant to identify the inverse mapping from pressure/flow values to node demand values.
(3) The inverse modeling problem is generally ill-posed, and therefore DFM is used to calibrate node demand values from sensor data.

Fig. 1 shows the process of on-line hydraulic simulation of WDS. After the completion of the initial node demand distribution, the program can run automatically without manual operation.

4. Application of hydraulic simulation in demo network

4.1. Identification of pump characteristic curves in demo network

The demo network contains 3 water sources, 2,534 nodes, 223 valves, and 2,504 pipes after simplification. Because some pumps have been running for many years, the pump characteristic curves are no longer in accordance with the factory characteristic curves and need to be recalibrated. We established the identification model of the pump characteristic curve by using the nonlinear LS method according to the clear-water reservoir (suction well) level, the pump status, the pump frequency, and the total flow of the water source provided by the SCADA system:

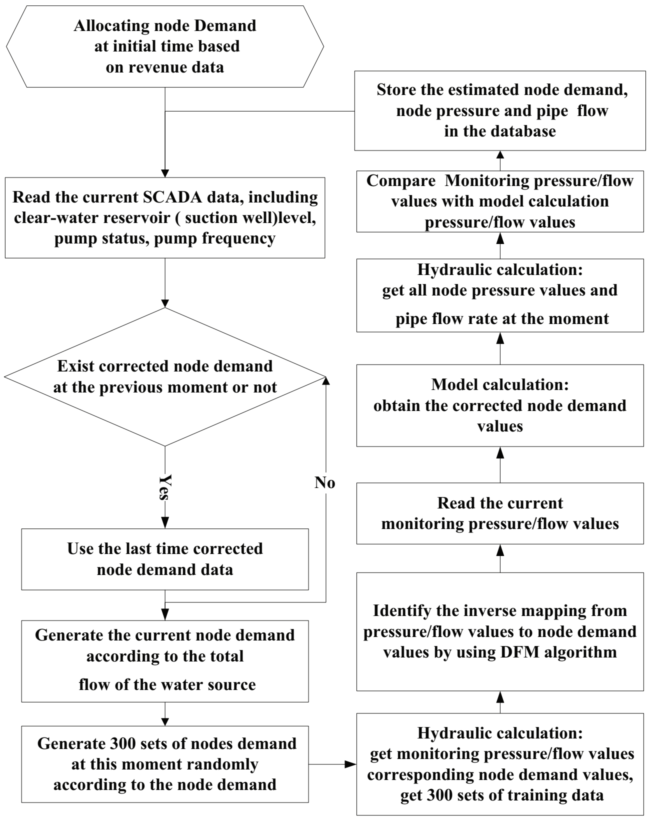

Fig. 1. Flow chart of on-line WDS hydraulic simulation.

$$\left\{\hat{A}_i,\hat{B}_i,\hat{C}_i\right\}_{i=1}^{N} = \arg\min_{\{A_i,B_i,C_i\}_{i=1}^{N}} \sum_{t=1}^{T}\left(Q(\mathrm{t})-\sum_{i=1}^{N}\pi_i(t)q_i(t)\right)^2 \tag{3}$$

$$\frac{h_i(t)}{s_i(t)^2} = A\left(\frac{q_i(t)}{s_i(t)}\right)^B + C \tag{4}$$

where A, B, and C are the calibrate parameters, $Q(t)$ represents the total flow at time number t, $\pi_i(t)$ represents the running status of the pump number i at time point t, $\pi_i(t) = 1$ stands for pump opened, $\pi_i(t) = 0$ stands for pump closed, $q_i(t)$ is the pump flow of pump number i at time point t, $h_i(t)$ is the delivery lift of pump number i at time point t, and $s_i(t)$ is the speed ratio of pump number i at time number t. The characteristic curve of each pump can be obtained by solving the optimization Eq. (3) using the trust-region-reflective algorithm.

Figs. 2–4 are the comparison of the measured and calculated values of the pumps' flow of the S-1 water source, S-2 water source, and S-3 water source, respectively.

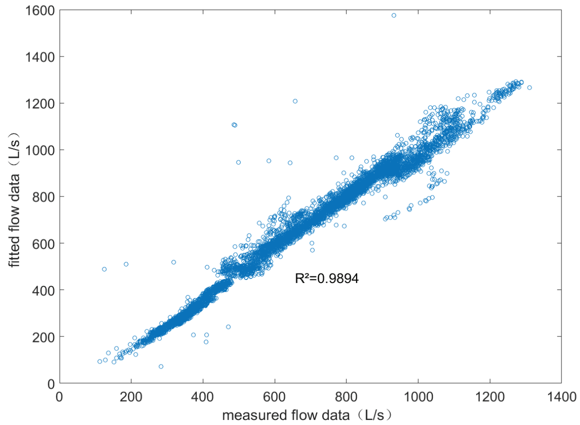

Fig. 2. Measured and calculated pumps' flow of S-1 source.

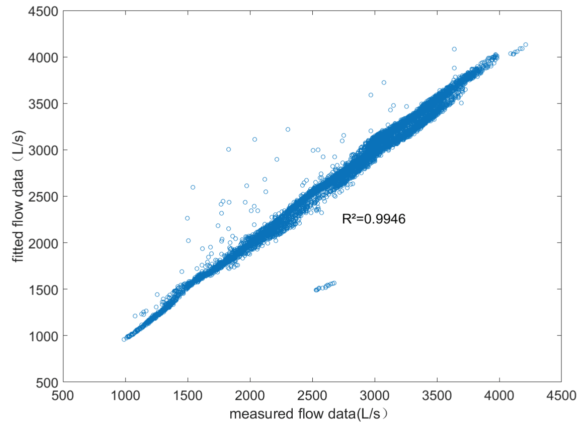

Fig. 3. Measured and calculated pumps' flow of S-2 source.

4.2. *On-line hydraulic simulation platform of the demo network*

Using the established calibration model of node demand, we developed an on-line hydraulic simulation platform for WDS. Fig. 5 is the frame. The data resource layer realizes the structured storage, update and format conversion of the partial static data, dynamic real-time data, model input and output data, and front-showing data. The model processing layer performs on-line node demand calibration and hydraulic calculation by reading database data. The access display layer implements the visualization of the final results.

4.3. *On-line hydraulic simulation results and accuracy evaluation*

The platform adjusts the node demand every 15 min, and 23 pressure meters and 42 flow meters of SCADA were applied in the on-line hydraulic simulation. Hydraulic model accuracy evaluation should include the evaluation of nodal head and pipe flow between estimated value and measured value. Fig. 6 is the comparison between the calculated and monitored values of three pressure meters. It can be seen from the P-12 pressure meter that the abnormal pressure value at individual time has little influence on the estimated pressure value. Fig. 7 is the error distribution of all pressure meters, the number of pressure meters with pressure error less than

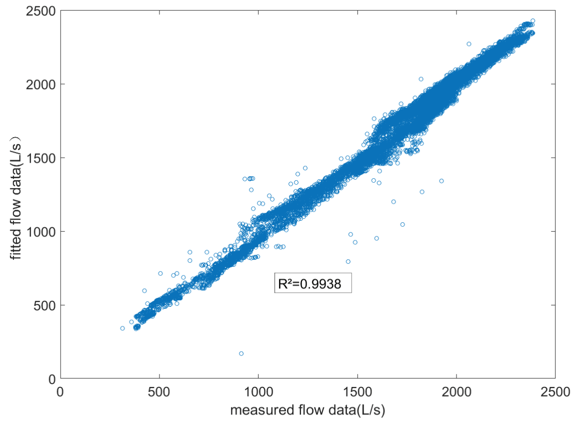

Fig. 4. Measured and calculated pumps' flow of S-3 source.

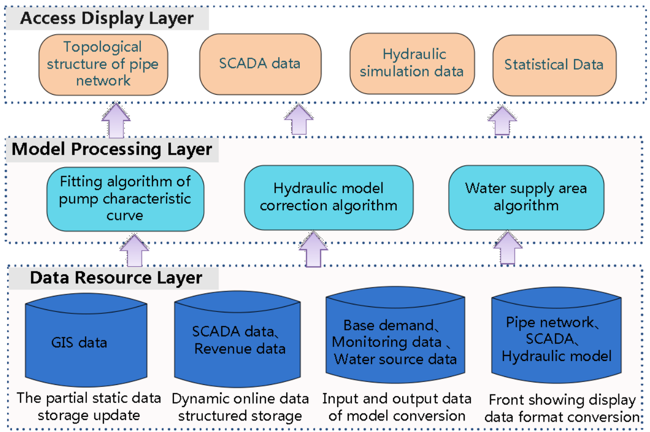

Fig. 5. On-line hydraulic simulation platform for water distribution system.

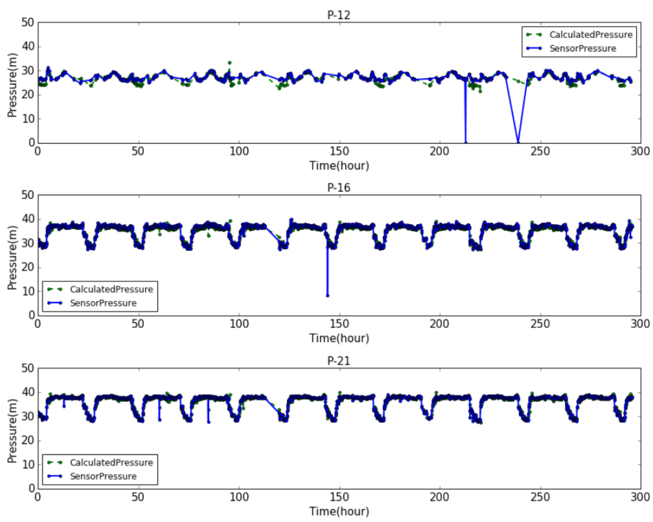

Fig. 6. Calculated pressure and sensor pressure.

1 m account for 68.3%, and with pressure error less than 2 m account for 86.4%, reaching the standard of British water research centre (WRC) quasi-steady state water quality modeling which requires that the error of 70% is within ±2.1 m.

Fig. 8 is the comparison of three flow meters (F-25, F-28, and F-30) between sensor value and calculated value, which shows the good stability and high accuracy in the on-line WDS calibration process.

Because the manager of water plants decided the water supply plan mainly according to the water source flow rate, the requirement for accuracy of the water source flow rate was higher in the hydraulic model. Fig. 9 is a comparison between the measured and estimated values of six water sources, the average relative error of water sources flow is 8.01%, and the average relative error of monitoring point flow is 9.62%, which basically meets the requirements of British Water Association for flow accuracy (relative error of water source flow is less than 10% and relative error of monitoring point flow is less than 20%).

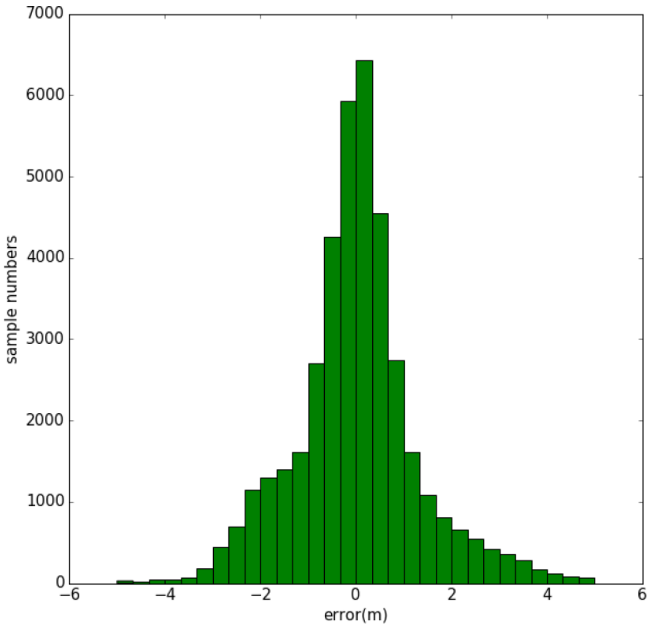

Fig. 7. Error distribution of pressure meters.

4.4. Water supply subarea of each water source in the demo network

Identifying water supply subarea of each water source and water distribution demarcation line can provide the basis for optimizing the operation and scheduling of the pipe network. The topological relationship between nodes and pipes of the demo network can be described by the associated matrix $A_{m \times n}$ (m is the number of nodes, and n is the number of pipes), and each element in the associated matrix is defined

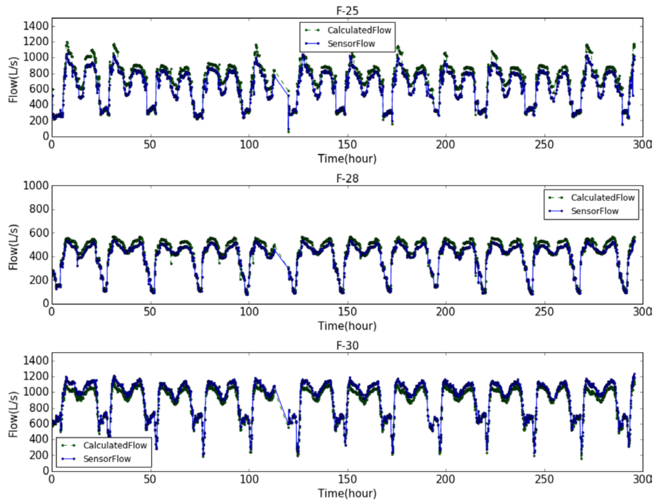

Fig. 8. Calculated and sensor flow rate.

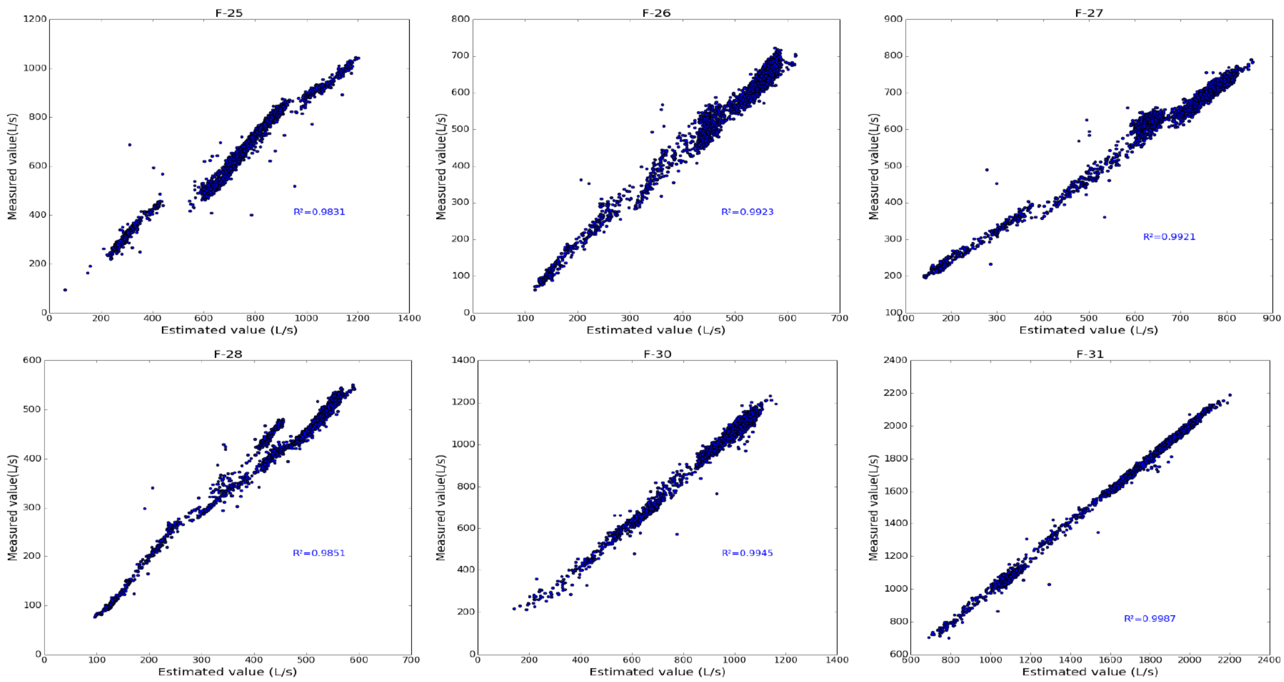

Fig. 9. Estimated and measured values of six outlet flow rates in three water source.

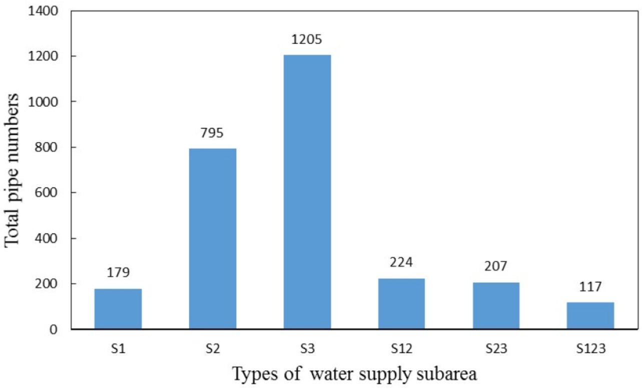

Fig. 10. Numbers of each type of water supply subarea.

as Eq. (5), which we can calculate by using the result of the on-line hydraulic corrected model.

$$a_{ij}\begin{cases}1 & \text{Pipe } j \text{ is connected with Node } i\text{, and the flow direction is from } i \text{ to } j \\ -1 & \text{Pipe } j \text{ is connected with Node } i\text{, and the flow direction is from } j \text{ to } i \\ 0 & \text{Pipe } j \text{ is not connected with Node } i\end{cases} \quad (5)$$

According to the associated matrix, first we find the node vector corresponding to the first source node number, and then search out all the pipes numbers where the value in the node vectors value is “1”, and then get the corresponding pipe vectors, then search out all the node numbers where the value in the pipe vectors obtained from the upper level where the pipe vectors value is “–1”. Save each pipes numbers and node numbers obtained from the each time searching. The search process is finished until the number of nodes is zero. The saved set of pipe numbers and the node numbers are the water distribution area of the water source. Search method for other water sources is the same. Fig. 10 is the result of numbers of each type of water supply subarea in the demo network, in which S1 represents the single water supply area of S-1water source, S2 represents the single water supply area of S-2 water source, S3 represents the single water supply area of S-3 water source, S12 represents the common water supply areas of S-1 and S-2 water sources, S23 represents the common water supply areas of S-2 and S-3 water sources, and S123 represents the common water supply areas of S-1, S-2, and S-3 water sources.

5. Conclusion

We realized the on-line calibration of the node demand by using the DFM learning algorithm, which has a fast calibration performance, high precision, and strong noise immunity for developing an on-line hydraulic model calibration platform. The work has verified the feasibility and broad application prospects of the algorithm by studying the water supply demo network.

The traditional optimization algorithm is to continuously adjust the node demand to minimize the difference between model simulated pressure/flow values and the measured pressure/flow values, which could get good calibration accuracy even in the case of wrong topology. The DFM learning algorithm identifies the functional relationship between pressure/flow values and the node demand at every time point. Therefore, the influence of initial flow distribution is very small, and it can achieve high accuracy at the initial stage of on-line hydraulic simulation. In addition, the accuracy of the model simulations would depend on the goodness of the approximation between the constructed pipe network and the actual pipe network; a good simulation accuracy would confirm a reliability of the pipe network as well.

At present, the on-line hydraulic model calibration algorithm estimates only the node demand. The future work is concerned with the simultaneous calibration of node demand and the pipe friction coefficient.

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References

[1] J. Meseguer, J.M. Mirats-Tur, G. Cembrano, V. Puig, J. Quevedo, R. Perez, G. Sanz, D. Ibarra, A decision support system for on-line leakage localization, Environ. Modell. Software, 60 (2014) 331–345.
[2] G. Sanz, R. Perez, Z. Kapelan, D. Savic, Leak detection and localization through demand components calibration, J. Water Resour. Plann. Manage., 142 (2016) 04015057.
[3] C.D. Laird, L.T. Biegler, B.G.V. Waanders, R.A. Bartlett, Contamination source determination for water networks, J. Water Resour. Plann. Manage., 131 (2005) 125–134.
[4] T.M. Walski, Case-study-pipe network model calibration issues, J. Water Resour. Plann. Manage., 112 (1986) 238–249.
[5] P.F. Boulos, D.J. Wood, Explicit calculation of pipe-network parameters, J. Hydraul. Eng., 116 (1990) 1329–1344.
[6] L.E. Ormsbee, Implicit network calibration, J. Water Resour. Plann. Manage., 115 (1989) 243–257.
[7] M.J.H. Sterling, A. Bargiela, Minimum norm state estimation for computer control of water distribution-systems, IEE Control Theory Appl., 131 (1984) 57–63.
[8] C.T.C. Arsene, B. Gabrys, Mixed simulation-state estimation of water distribution systems based on a least squares loop flows state estimator, Appl. Math. Modell., 38 (2014) 599–619.
[9] W.P. Cheng, T.C. Yu, G. Xu, Real-time model of a large-scale water distribution system, Procedia Eng., 89 (2014) 457–466.
[10] N. Do, A. Simpson, J. Deuerlein, O. Piller, Demand estimation in water distribution systems: solving underdetermined problems using genetic algorithms, Procedia Eng., 186 (2017) 193–201.
[11] N.C. Do, A.R. Simpson, J.W. Deuerlein, O. Piller, Calibration of water demand multipliers in water distribution systems using genetic algorithms, J. Water Resour. Plann. Manage., 142 (2016) 04016044.
[12] A. Vassiljev, T. Koppel, Estimation of real-time demands on the basis of pressure measurements by different optimization methods, Adv. Eng. Software, 80 (2015) 67–71.
[13] P.V.N. Reddy, K. Sridharan, P.V. Rao, WLS method for parameter estimation in water distribution networks, J. Water Resour. Plann. Manage., 122 (1996) 157–164.
[14] T. Tucciarelli, A. Criminisi, D. Termini, Leak analysis in pipeline systems by means of optimal valve regulation, J. Hydraul. Eng., 125 (1999) 277–285.
[15] S. Diaz, J. Gonzalez, R. Minguez, Uncertainty evaluation for constrained state estimation in water distribution systems, J. Water Resour. Plann. Manage., 142 (2016) 06016004.
[16] L.K. Letting, Y. Hamam, A.M. Abu-Mahfouz, Estimation of water demand in water distribution systems using particle swarm optimization, Water, 9 (2017) 593.

[17] G. Sanz, R. Perez, Sensitivity analysis for sampling design and demand calibration in water distribution networks using the singular value decomposition, J. Water Resour. Plann. Manage., 141 (2015) 04015020.
[18] C.J. Hutton, Z. Kapelan, L. Vamvakeridou-Lyroudia, D.A. Savic, Dealing with uncertainty in water distribution system models: a framework for real-time modeling and data assimilation, J. Water Resour. Plann. Manage., 140 (2014) 169–183.
[19] C. Bragalli, M. Fortini, E. Todini, Enhancing knowledge in water distribution networks via data assimilation, Water Resour. Manage., 30 (2016) 3689–3706.
[20] X. Xie, H.J. Zhang, D.B. Hou, Bayesian approach for joint estimation of demand and roughness in water distribution systems, J. Water Resour. Plann. Manage., 143 (2017) 04017034.
[21] M. Kumar, Y.H. Mao, Y.H. Wang, T.R. Qiu, C. Yang, W.P. Zhang, Fuzzy theoretic approach to signals and systems: static systems, Inf. Sci., 418 (2017) 668–702.