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VALVE LOSS CURVE ESTIMATION USING REAL-TIME SCADA DATA

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Abstract

Real-time operation of drinking water networks (DWN) through supervisory control and data acquisition (SCADA) systems can potentially reduce energy consumption. This can be achieved by controlling pumps and valves to reduce pumping costs and energy dissipated at valves. Moreover, other objectives can be improved, such as pressure levels and water quality throughout the DWN. With the integration of hydraulic models and real-time data sources, optimization of the real-time operation of DWNs has become more feasible in recent years. An accurate hydraulic model of a DWN is necessary to realize the benefits of real-time modelling and control, as the model is required for estimating the state of the network for different operating conditions. Pumps and valves curves estimation is a key step toward achieving an accurate model. Valves, which act as energy sinks, are vital elements in DWNs and stabilize pressures in certain parts of the network. Therefore, accurate flow-head loss relationships of the valves thorough a range of valve openings are essential for real-time modeling. For example, to estimate pressures downstream of the valves and optimize the operation of pumps and valves for forecasted demands to reduce the overall energy spent for DWN operation. Head loss across valves is conventionally modeled as proportional to the velocity head across the valve, with the proportionality factor called the minor-loss coefficient. The minor-loss coefficient, in turn, is a non-linear function of the valve opening degree, and valve manufacturers generally provide relationships between the minor-loss coefficient and the valve percent opening. Our experience is that using these original manufacturer curves can lead to significant prediction errors compared to operational data and should be tested and estimated. We show how to use measurements of valve opening, pressure differential, and flow through an individual valve or a valve facility for the estimation of valve curves. The approach can be used as a batch process as part of network calibration or may also be used in real-time to maintain accurate valve characteristics over time. A method is presented to estimate valve loss curves represented by a simple function (e.g., power-law or polynomial), using measured flow and pressure differential and measurement of valve opening degree. The method uses a gradient-based optimizer to solve a least-squares estimation (LSE) problem, where the residual error is the difference between predicted and measured flow through the valves. This method is applicable for valve facilities that contain more than one valve in parallel, where flow measurements are available for the valve facility or individual valves. The method developed was applied to estimate 77 valve curves for a large water transmission network in the USA as part of the development of a digital twin for the DWN. Results will summarize the statistical prediction errors for this set of control valves, before and after estimation, and will show the impact on network hydraulic predictions from using estimated valve headloss curves.

Keywords
Valve curve estimation, SCADA, real-time modelling, digital twin.

1 INTRODUCTION

Drinking water networks (DWN) consume about 4% of the total energy produced in the United States of America [1,2]. A large fraction of the consumed energy is used for pump operation. Pumps and valves are key control elements that are used by the network operators to drive the operation of a WDN to maintain adequate water quality and pressure throughout the system. While pumps are sources of energy (head) into the drinking water system, valves act as sinks of energy as they locally lose some of the energy. The use of valves has varied purposes, such as reducing pressure and maintaining water quality (e.g., enhancing chlorine residuals by altering hydraulic paths [3]). In most utilities across the USA, the pumps and valves are operated by experienced operators to achieve objectives such as maintaining minimum pressure at certain locations and tank recycling. Such manual operation objectives rarely consider energy consumption, and hence opportunities exist for energy consumption reduction by optimizing DWN operations.

Increasingly SCADA systems are being used by DWNs to collect a considerable amount of data (e.g., tank levels, pressures, water quality, and pump station flow measurements), which describes the real-time state of DWNs. Digital twins, which are real-time representations of DWNs, can predict the state of the network in space and time by coupling the collected SCADA data with hydraulic models and enable better operational decision-making [4,5]. The accuracy of digital twins is dependent on the accuracy of the underlying hydraulic model. For that, water demand is predictied using history of past states of the network from SCADA [6,7]. With the availability of accurate demand predictions and accurate hydraulic models, real-time operation optimization becomes feasible [8–11]. Therefore, an accurate hydraulic model is essential for generating a digital twin configuration. A calibrated hydraulic model can accurately predict the pressures and flows throughout the network. Two of the most important parameters that need to be predicted by the hydraulic models are the head gains across pumps and headloss through the valves. Hydraulic models, such as the EPANET [12], often use curves to predict the flow through pumps and headloss through valves. Therefore, the calibration of these pumps' and valves' curves using measured data is an important first step toward developing an accurate hydraulic model. Traditionally, these curves are estimated in field tests. However, field tests are expensive and can not be done often. Thus, using SCADA data for curve estimation is advantageous [13].

Headloss through valves is conventionally modeled as the product of the velocity head and a minor loss coefficient expressed as a function of valve opening. The valve curve relates the valve opening degree to a minor loss coefficient. While these curves are provided by the manufacturers of the valves, experience shows that the use of the manufacturer-provided curves most often leads to significant model prediction errors when compared to operational data [14]. Therefore, pump and valve curves need to be tested and calibrated before use for successful developments of digital twins and real-time operation optimization capabilities. The manufacturer valve curves can be use as base curves for the calibration process using real-time operational data to ensure the valve characteristics are accurately reflected by the curves.

Despite the importance of well-calibrated pumps and valves curves for many applications, only a few studies have addressed this issue. Araujo et al. [15] used a genetic algorithm to calibrate valves curves to minimize leakage pressure control technique. Campisano et al. [16] suggested real-time pressure control for the same goal of leakage reduction, they presented a calibration method based on a comprehensive dimensionless analysis of simplified hydraulic systems under real-time scenarios. The battle of the water calibration network [17] presents the challenge of overall network calibration. Within this challenge, calibration of pump curves and opening percentage of valves had to be addressed.

The objective of this paper is to present a novel method to calibrate valve curves using real-time SCADA measurements of pressures and flows along with valve opening data stream. The method can be used for real-time calibration of valve characteristics. The method is applicable for a single valve and for a group of valves in a valve facility that are arranged in parallel with individual or totalized flow measurements. The method can be used as a batch process as part of network calibration or may also be used in real-time to maintain accurate valve characteristics over time.

2 METHOD

2.1 Curve parameter estimation

The valve loss curve relating valve opening x with its minor loss coefficient k is conventionally modeled with a power-law curve of the form $k = ax^b$, with the parameters a and b to be estimated. To model a positive and monotonically decreasing minor loss coefficient with increasing valve opening, the parameter a needs to be positive, while the parameter b needs to be negative. For a given minor loss coefficient, headloss h_L across a valve is estimated as a multiple of the velocity head as

$$h_L = k\frac{V^2}{2g} \tag{1}$$

where $V = q/A$ is velocity, q is flow, A is cross-sectional area of the valve, and g is the acceleration due to gravity. Rearranging Eq. 1 in terms of valve flow and replacing k with the power law equation, the estimated flow q_e through a valve facility with N valves in parallel is given by Eq. 2.

$$q_e = \sum_{i}^{N} \left(2gh_L\left(a_i x_i^{b_i}\right)^{-1} A_i^2\right)^{\frac{1}{2}}. \tag{2}$$

Measured flow q_m through the valve facility can be used to develop a least-square estimation problem to estimate the parameters of the power-law curves for the N valves such that the mean of squared flow errors (MSE), given in Eq 3, for T discrete time steps is minimized.

$$\begin{gathered}\min_{\theta}\frac{1}{T}\sum_{t=1}^{T}\left(q_{e,t} - q_{m,t}\right)^2, \theta = \{a_1, b_1, \dots, a_N, b_N\} \\ a_i > 0, i = 1, \dots N \\ b_i \leq 0, i = 1, \dots, N\end{gathered} \tag{3}$$

Although a power-law curve was used in this research, any other suitable form can be used, and their parameter can be estimated similarly using Eq. 2. A parameter estimation program was written in the Python programming language, which can connect with SCADA through a digital twin of any network for which valve curves need to be estimated. The estimator program utilizes the Scipy library [18] to perform the least square optimization using the L-BFGS-B algorithm.

2.2 Data connections

The required data for valve curve calibration include the cross-sectional area of the valve, valve position data, the pressure upstream and downstream of the valve facility, accurate elevations of the pressure measurement locations, and flow measurements through the valve station. Except for the static information (i.e., valve diameter and elevations), the rest of the data are acquired from SCADA.

A facility description file describes the structure of the valve facilities in a network, i.e., the groupings of valves that forms a valve facility and the pressure and flow measurement locations for the facility in the network model. An in-house digital-twin system powered by EPANET-RTX

[19] contains information about the different available SCADA data streams and their mapping to the network model elements within a configuration file. The configuration file also contains different timeseries transformation instructions, e.g., resampling, outlier removal, moving average filters, etc., that is required to transform the raw SCADA data to data suitable for parameter estimation.

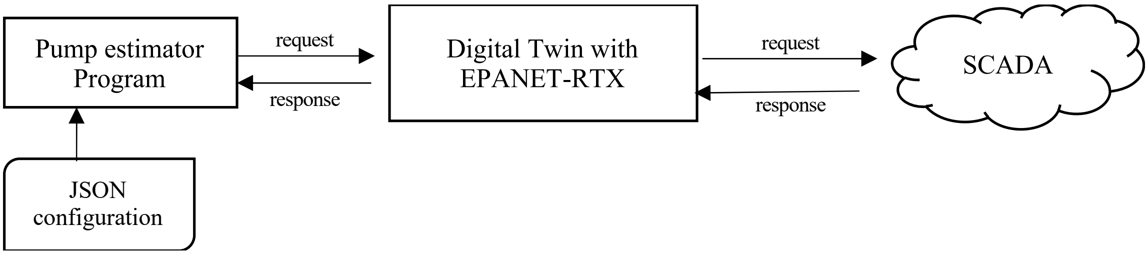

Figure 1. Data request and response structure from the estimator code to SCADA

Figure 1 shows how the data requests by the parameter estimator code are handled by the different parts of the digital twin and SCADA system. The curve estimator program uses the facility description file to request relevant data from a server that the digital twin program listens to using a representational state transfer (REST) protocol. After receiving the request, the digital twin connects to the SCADA and fetches the required data. The data is then processed by the digital twin and returned to the parameter estimator program (residing on a local machine or on a server). The parameter estimator uses the processed data for the optimization to estimate the parameters of the valve characteristics curves.

2.3 Case Study

The parameter estimation method was applied to estimate valve curves for 77 flow control valves for a large metropolitan water utility (peak production of around 800 MGD). The water utility operates a transmission network and supplies water to smaller regional distribution networks through these flow control valves. Figure 2 shows one such valve facility through which the transmission network supplies a distribution network tank. A digital twin for the transmission network for the utility was developed, which enable real-time network information monitoring and operation optimization for energy consumption reduction and water quality objectives. The utility collects high-density pressure measurements upstream and downstream of the valves, flow measurements across individual valves, and valve opening degree measurements. No manufacturer curves for the valves were available, and hence a power-law curve with the parameters $a = 35, b = -1.25$ was assumed to be the base (an initial guess) curve for all valves. The curves were estimated using measured operational data ranging from 2021-07-05 through 2021-11-15.

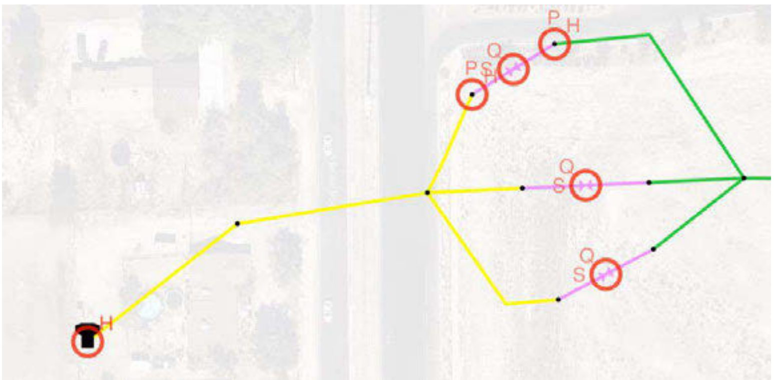

Figure 2. A valve facility with three valves supplying water to a tank in a regional distribution network. The red circles indicate the availability of measurement data at those model elements, with letters H, P, Q, and S indicating the availability of head, pressure, flow, and valve settings data streams, respectively.

Results for four valve facilities, VF1 through VF4, are presented to demonstrate the application of the estimator program. Flow measurements for all individual valves were available for this network, and therefore it was possible to estimate valve curves by considering each individual valve as one valve facility (i.e., $N = 1$ in Eq. 3). VF1 has three valves in parallel, and Figure 3 shows its valve percent opening timeseries for the three valves obtained from SCADA.

Figure 3. Valve opening degree in percentage for the three valves at VF1.

Since individual flow measurements were available for each of the valves in VF1, two scenarios were considered: Scenario 1, the valve curves were estimated by considering the sum of the individual flow measurement as the facility flow ($N = 3$ in Eq. 3). Scenario 2, each of the three valves curves were calibrated with their respective flow by considering each valve to be a valve facility ($N = 1$ in Eq. 3) for calibration purposes.

3 RESULTS

Starting from the initial guess for the parameters, the least square estimation method successfully converged to optimal parameter sets for the valve facilities. These parameter sets minimized the MSE between the estimated and measured flow timeseries of the facilities. For comparison of flow prediction error before and after calibration, the metric normalized root mean squared error NRMSE $= \sqrt{MSE}/q_{avg}$ is used. Where q_{avg} is the averaged measured flow for T timesteps for the facility. Figure 4 shows the empirical cumulative frequency distribution function (CDF) of NRMSE for the initial and the calibrated curves for the 77 valve facilities (i.e., each valve is treated as a facility). The median value for the NRMSE for the base curve and the calibrated curve is 0.66 and 0.07, respectively, and about 80% of the valves have NRMSE less than 0.25 after calibration (Figure 4). Valves with post calibration NRMSE greater than 0.25 have all been found to have data issues such as bad valve status information or inconsistency of measured flow with valve opening.

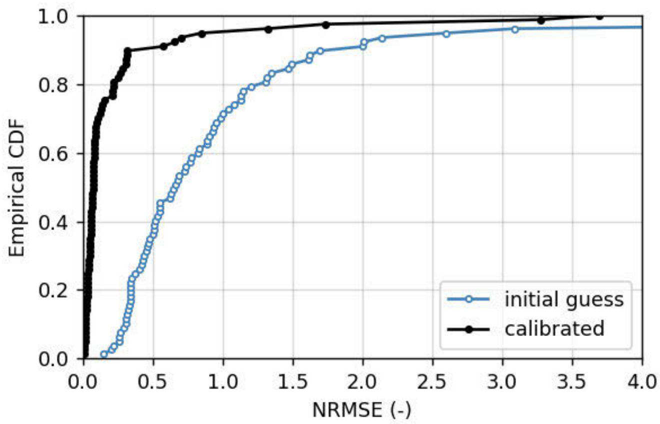

Figure 4. Empirical CDF of NRMSE for the base curve and the calibrated curve

Figure 5 shows the estimated vs. measured flow scatter plot for the initial guess and calibrated valve curves for VF1 for Scenario 1, and most of the estimated flow after calibration lies close to the 45-degree line of perfect correlation. The NRMSE for the initial guess and calibrated valve curves for Scenario 1 are 0.99 and 0.01, respectively. Figure 6 shows the calibration results for Scenario 2. Figures 6a through c show scatter plots similar to Figure 5 for the individual valves. Figure 6d through f shows scatter plots of calculated minor loss coefficients (rearranging Eq. 1 for k) with valve opening degree along with the initial and calibrated valve curves (a similar figure is not possible for Scenario 1). The estimated parameters for the two scenarios are shown in Table 1. The NRMSEs for Scenario 2 for the three valves for the base curve were 2.14, 0.27, and 1.00, and for the calibrated curve were 0.02, 0.02, and 0.01. Estimated flows for both scenarios matched well with measured flows and had low NRMSE (≤ 0.02). The difference in estimated parameters for each valve shown in Table 1 translates to very little difference in the estimated flows for VF1, and the minor loss curves for each valve for the two scenarios are essentially indistinguishable.

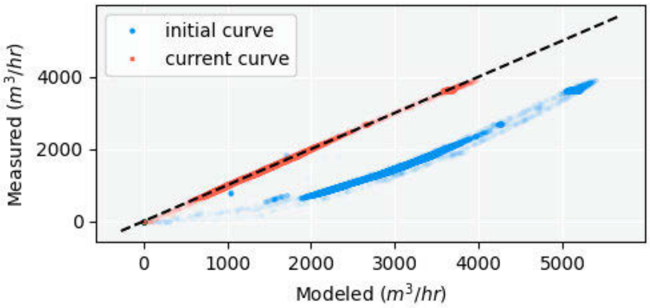

Figure 5. Scatter plot for measured vs. modeled totalized flow for the valve facility VF1. The initial curve refers to the initial guess of the parameters, and the current curve refers to the calibrated parameters of the power-law curve. The black dashed line represents the line of perfect correlation.

Figure 7 shows the calibration results for facility VF2 and VF3, both of which had NRMSE greater than 0.25, and demonstrates some of the issues in the measured data. The facility VF2 (Figure 7a) had a post-calibration NRMSE of 0.31 and is suspected to have inconsistent measurements as a significant part of the measured flow stays constant while the estimated flow varies (e.g., with varying valve opening or pressure). The facility VF3 (Figure 7b) had a post calibration NRMSE of 0.84, and the vertical scatter of measured flow data at zero modeled flow indicates that the valve opening degree timeseries is out of sync with the flow timeseries and therefore the estimated flow is zero when the measured flow is not. Additionally, VF3 flow data is relatively more noisy than flow data at other locations. The resolution of such data issues (e.g., fixing the misalignment of valve opening degree and measured flow) should improve the calibration results at valve facilities with poor NRMSE. Although the calibration process did not achieve the purpose of high accuracy prediction for these valves, it is still beneficial for exposing data streams issues that need to be resolved for the accuracy of the digital twins model and in general.

Table 1. Calibrated parameters for the three valves at VF1

	Scenario 1		Scenario 2	
	a	b	a	b
Valve 1	173.03	-2.221	167.65	-2.162
Valve 2	26.78	-2.113	26.34	-2.120
Valve 3	73.49	-2.031	76.53	-2.049

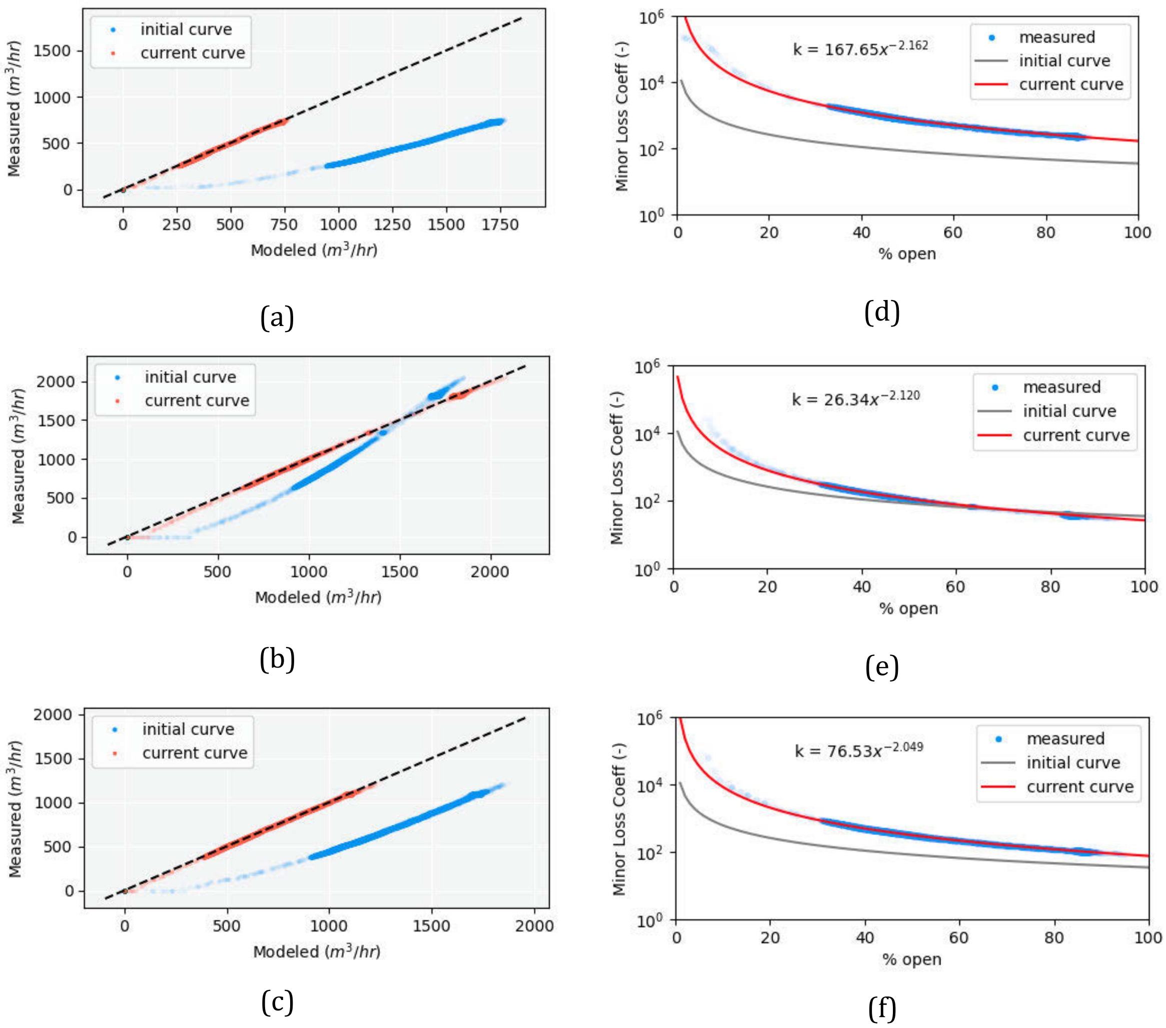

Figure 6 (a) through (c) scatter plot for measured vs. modelled flow measurement through the three valves at VF1. The black dashed 45-degree line represents the line of perfect correlation. (d) through (f) calculated minor loss coefficients, initial and calibrated minor loss curves. The initial and current curve refers to the initial guess and the calibrated parameters of the power-law curve, respectively.

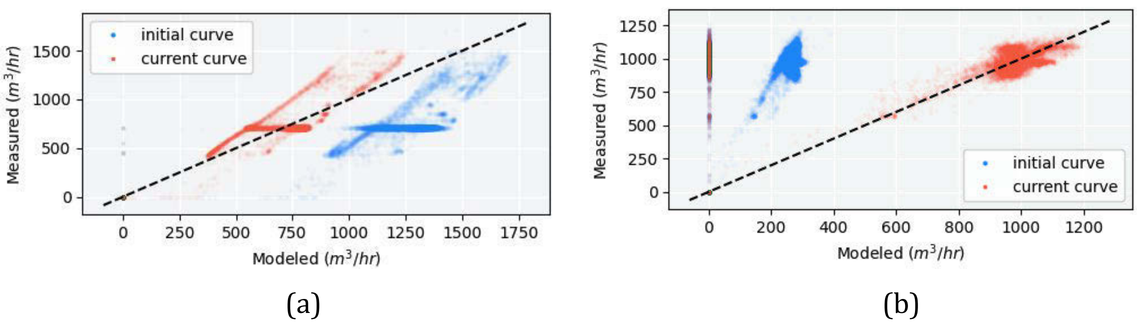

Figure 7. scatter plot for measured vs. modeled flow measurement through the (a) VF2 and (b) VF3 facilities. The initial and current curve refers to the initial guess and the calibrated parameters of the power-law curve, respectively. The black dashed line represents the line of perfect correlation.

4 CONCLUSION

A framework for valve curve calibration using SCADA data was presented which was used to calibrate the valve curves of flow control valves in a transmission network of a large water utility in the USA. Valve curves were successfully calibrated and resulted in flow prediction with high accuracy obtained by low NRMSE. A power-law model was used to model the valve curves relating valve minor loss coefficients with valve opening measurements obtained from daily operations. While the power-law model worked well, other models can be easily incorporated into this optimization framework. Poor calibration for some of the valves helped uncover data issues, and the calibration can be improved by resolving those underlying data issues.

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