Redundant flow estimation methods for robust hydraulic control in water supply networks
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ABSTRACT
The implementation of robust hydraulic control in water supply networks relies upon the utilisation of redundant flow estimation methods. In this paper, we propose a novel model-based flow estimation method for diaphragm-actuated globe valves based on three pressure signals, namely the valve inlet pressure, valve outlet pressure and control chamber pressure (the 3P flow estimation method). The proposed flow estimation method relies upon the accurate determination of a valve stem position based on a force-balance analysis for the diaphragm of a valve, the measured pressure differential across a valve and the flow coefficients of a valve ($C_v$, $K_v$). A novel stem position estimation model for diaphragm-actuated globe valves has been formulated and experimentally validated. The non-linear parameterised valve stem position estimation model results in multiple solutions. We combine advances in signal processing with support vector machine classification to find a correct solution. We compare the proposed 3P flow estimation method with a method that uses stem position sensor measurements of a valve and two pressure signals. A unique set of experimental data have been acquired for performance validation. We derive uncertainty bounds for the proposed flow estimation method and demonstrate its application for robust pressure control in water supply networks.

Key words | automatic control valve, flow estimation, water supply networks

INTRODUCTION
Advanced hydraulic control for the management of water supply networks (WSNs) provides multiple benefits, which include the reduction in leakage, pressure-driven demand and pipe failures (Giustolisi et al. 2008; Lambert & Thornton 2012; Mutikanga et al. 2015; Wright et al. 2015; Vicente et al. 2016). Various electronic pilot controllers exist (i2O 2016; Cla-Val 2017; HWM 2017; Technolog 2017) and are retrofit to control valves to incorporate control methods such as simplistic time-based fixed-outlet pressure, closed-loop control from a critical point and flow modulation (FM) for pressure-managed areas (PMAs) (Wright et al. 2015). The implementation of FM schemes has been steadily increasing both in the UK (EPSRC 2017) and across Europe (Vicente et al. 2016).

The performance of the FM method for pressure management in WSNs relies on continuous and accurate flow measurements at the location of a control valve. The FM method has the advantages of a closed-loop (feedback) control as it utilises measurements of the head loss between the inlet of a single-feed PMA and its critical point, and the flow rate at the location of a valve in order to define the flow versus outlet pressure control profile (Ulanicki et al. 2000; Prescott et al. 2003; Wright et al. 2014). Flow modulating electronic pilot controllers would then adjust the outlet pressure setting of a diaphragm-actuated globe valve according to the locally measured flow.

If a flow meter, which provides a signal to a control valve, fails (and/or its output signal), the valve pilot controller commonly enters a fail-safe mode of much higher fixed-outlet pressure or attempts to revert to control settings of the outlet pressure from previous days. The first approach might result in pipe failures, while the second approach...
might not deliver the regulatory pressure if demand increases (e.g. water demand for fire fighting).

A redundant flow estimation method is therefore required in order for an FM control mode to be maintained upon the loss of a flow meter signal within operationally acceptable error bounds of the FM curve. Consequently, a redundant flow estimation method, which utilises pressure measurements from the inlet, outlet and control chamber of a control valve, improves the robustness of the FM control and provides additional benefits in terms of continuous valve condition monitoring and the detection of process (hydraulic) instabilities (Changklom & Stoianov 2017).

The work presented in this paper investigates and experimentally validates a robust flow estimation method using diaphragm-actuated globe valves and for the application of flow modulating pressure control in WSNs. The flow estimation method is based on three pressure signals, namely the valve inlet pressure, valve outlet pressure and valve control chamber pressure. The problem formulation and control valve model development are described in the ‘Problem formulation: estimating the stem position of a control valve’ section. The model includes a force-balance analysis for the diaphragm of a control valve and its Cv characteristic equation. The proposed flow estimation method solves a force-balance equation, which utilises three pressure signals, for estimating the valve stem position, and it then applies the Cv to quantify the flow. The force-balance equation for estimating the valve stem position has multiple solutions. In ‘The 3P flow estimation method and multiple solutions’ section, we describe the application of a support vector machine (SVM) classification method that utilises advances in signal processing to identify the correct valve stem position. In the ‘Validation and implementation of the flow estimation methods’ section, the accuracy of the novel flow estimation method is investigated in a laboratory pipe rig and an operational WSN. Its performance is compared with a method that applies two pressure signals and a valve stem position signal (2P&Pos), and also flow data acquired from electromagnetic flow meters. The discussion of results, conclusions and the relevance for robust pressure control are also presented in the ‘Validation and implementation of the flow estimation methods’ section.

**PROBLEM FORMULATION: ESTIMATING THE STEM POSITION OF A CONTROL VALVE**

**Problem formulation**

The measurement of flow is the quantification of bulk fluid movement. Flow in pipes can be measured using a variety of methods and technologies. Examples include electromagnetic, mechanical, optical, vortex and pressure-based flow meters. The flow estimation across a diaphragm-actuated globe valve is comparable to a differential pressure flow meter; however, a diaphragm-actuated globe valve has a continuously varying area of the constricted section, which is defined by the position of the diaphragm and, therefore, by the valve stem position.

A differential pressure flow meter uses

\[ q = K \sqrt{h_{\text{in}} - h_{\text{out}}} \]  

(1)

to estimate the flow rate; where \( q \) is the flow rate through the flow meter (m³/h), or (l/s), \( K \) is the flow coefficient (\( C_v \) or \( K_v \)) of the constriction and \( (h_{\text{in}} - h_{\text{out}}) \) is the differential pressure head across the constriction, (m).

A differential pressure flow meter introduces a constriction in the pipe that creates a pressure drop across the flow meter. When the flow increases, the pressure drop also increases. The flow is estimated from the measured pressure differential across the constriction (or in this case, the opening of a valve) and the flow coefficient of the constriction. It should be noted that for differential pressure flow meters, 10% of the full-scale flow produces only 1% of the full-scale differential pressure. Different geometries are used in differential pressure flow meters that include either fixed-area constrictions (e.g. the orifice plate, flow nozzle, laminar flow element, low-loss flow tube, segmental wedge, V-cone and Venturi tube) or variable-area constrictions (e.g. a rotameter, a variable aperture flow meter) (Hardy 1999).

Previous work by Atmanand & Konnur (1999), Leephakpreeda (2005) and Choi (2012) investigated methods of using a control valve for the measurement of flow. These published methods rely on sensor data for monitoring the opening of the flow constriction, e.g. the valve stem position for a globe valve or the angle for a butterfly valve. For diaphragm-actuated globe valves, which require sensing and
control electronics that operate at ultra low-power, direct measurements (sensors) of the valve stem position could significantly increase the power consumption. Furthermore, the retrofit of such stem position sensor is complex and it requires bypassing the main valve. Operators are reluctant to do this as it might significantly change the hydraulic conditions within a WSN and cause discoloration and pipe failures. Pressure sensors, on the other hand, consume low power and their installation does not introduce operational disruptions. Therefore, it is desirable to use three pressure signals to estimate the valve stem position, the valve discharge coefficient and, consequently, the flow rate that defines the outlet pressure settings for flow modulating control.

A diaphragm-actuated globe valve is shown in Figure 1(a), with an annotation of the relevant variables. \( h_{in} \) is the control valve inlet pressure, \( h_c \) is the control chamber pressure and \( h_{out} \) is the control valve outlet pressure. \( q \) is the flow through the main valve. \( x_m \) is the valve stem position. Figure 1(a) also indicates that the pressure acquired at the valve-mounted measurement locations for the inlet and outlet of the valve (measured pressure) differs from the pressure acting upon the disc retainer and the diaphragm (actuating pressure for setting the valve stem position; and labelled actuating pressure). The pressure difference results from the energy loss due to the valve geometry. This difference is a non-linear function of the flow velocity. A force-balance mathematical model, which takes into account all forces acting on the diaphragm of a control valve (Figure 1(b)), is applied to estimate the valve stem position and consequently the flow rate across the valve. The force-balance mathematical model is applied to the main (Hytrol) valve. The hydraulic performance of the control loop is implicitly taken into account as it affects the acquired pressure signals.

The control valve model can be formulated using empirical methods, mechanistic methods or a combination of both. Dynamic models of diaphragm-actuated globe valves have been described by Prescott & Ulanicki (2001, 2003). We select two phenomenological models for further investigation: (i) the full phenomenological model, which includes differential equations of motion and (ii) the simplified phenomenological model (SPM), which includes a force-balance equation. The force-balance equation suffices for quasi-unsteady-state and steady-state flow estimations. Continuous measurements of pressure at high sampling rates provide a continuous validation of the steady-state and quasi-unsteady-state hydraulic conditions and facilitate the derivation of uncertainty bounds of the unsteady-state approximation due to flow dynamics and pressure transients. We have designed and conducted a unique set of experiments to acquire data for the derivation and validation of the model equations using both a laboratory pipe rig and an operational WSN (the ‘Validation and implementation of the flow estimation methods’ section).

**Experimental programme**

The experimental programme has been designed and conducted to acquire data for the model development and
validation from a wide range of hydraulic conditions. A schematic of the laboratory pipe rig is shown in Figure 2, which complies with the ANSI/ISA75.02.012008 standard, entitled Control Valve Capacity Test Procedures. In addition, the experimental programme included the acquisition of pressure, flow and stem position data for three control valves: Cla-Val 90GE-01 DN100 (or also labelled as Cla-Val DN100 GE), Cla-Val 90GE-01 DN150 (or Cla-Val DN150 GE) and Cla-Val NGE90-01 DN80 (or Cla-Val DN80 NGE). The experimental programme has also included continuous pressure measurements from control valves, which were specifically installed in an operational WSN (the ‘Validation and implementation of the flow estimation methods’ section).

In compliance with ANSI/ISA75.02.012008, the pressure sensors for measuring the differential pressure across a valve should be placed two (2x) times the nominal valve diameter upstream of the tested valve and six (6x) times the nominal valve diameter downstream of the tested valve. We refer to such pressure measurements as ‘standard-defined’. However, the proposed flow estimation method utilises pressure signals acquired within the main body of a valve (valve-mounted pressure sensors) due to space constraints in manholes and the retrofit installation in operational networks. As pressure data acquired within a body of a valve are used to derive and fine-tune the energy loss relationships for estimating the valve stem position, the impact of the sensor measurement locations is incorporated into the empirically derived relationships.

The data acquisition system for gathering the experimental data continuously records valve inlet pressure, valve cover chamber pressure and valve outlet pressure using the three valve-mounted pressure sensors, flow from an electromagnetic flow meter, valve stem position (valve opening), ‘standard-defined’ inlet pressure and ‘standard-defined’ outlet pressure. The sampling rate for the data acquisition system was 1200 S/s, which had been selected to exceed the dynamic response of the pressure transducers (1 ms). This sampling rate allowed for various signal processing and decimating (downsampling) methods to be applied and investigated (e.g. 100 S/s, 10 S/s and 1 S/s).

The flow was measured using ABB ProcessMaster FEP500 (DN150) with an accuracy of 0.2% of a reading and a response time of 1 s. The data acquisition system (including the pressure transducers) had an accuracy of 0.1% full scale for the pressure transducers (20 bar, gauge). The magnetostrictive linear position sensor (BTL6-E500-M0050-PF-S115), which was used for measuring the valve stem position, had an accuracy of 0.002% full scale (1 μm for a 50 mm sensor range).

The experimental programme was carried out in three stages. Stage 1 acquired steady-state hydraulic data under controlled laboratory conditions and within the operational range of each control valve. Stage 2 acquired quasi-unsteady-state and unsteady-state hydraulic data (rapidly changing hydraulic conditions) under controlled laboratory conditions and within the operational range of the tested control valves. Stage 3 acquired hydraulic data from an

Figure 2 | An experimental set-up for the laboratory pipe rig.
operational WSN using the same type control valves as tested under laboratory conditions in order to investigate the applicability and performance of the developed flow estimation method for robust pressure control (the ‘Validation and implementation of the flow estimation methods’ section). Consequently, the data from Stage 1 contain various steady-state hydraulic conditions, which represent valve stem positions within the full range of a control valve, and the data from Stages 2 and 3 represent steady-state and quasi-unsteady-state hydraulic states. An example of the acquired experimental data is shown in Figure 3.

Flow coefficient of a control valve

The flow coefficient of a control valve is a relative measure of its efficiency for allowing fluid flow. The flow coefficient notations are labelled with respect to their associated units; for example, $C_v$ is generally defined for a flow in gal/min and pressure drop in psi and $K_v$ is defined for a flow in m$^3$/h and pressure drop in bar. Here, we use $C_v$ as a notation although it can have a different unit. For clarity, the $C_v$ is always shown with the associated units. It relates the pressure head drop across the valve with the flow rate across the valve (see Equation (1)). In this case, $C_v(x_m)$ is a function of the valve stem position (valve opening), $x_m$.

We apply the ordinary least squares (OLS) regression method to find a sixth-degree polynomial for the $C_v$ curve. The $C_v$ curves of three control valve sizes are shown in Figure 4. The experimental data for Cla-Val DN80 NGE and Cla-Val DN100 GE valves were acquired within their full stem position range (100%), whereas the experimental data for Cla-Val DN150 GE were acquired for up to 60% opening of the valve. The experimental data differed from those of the $C_v$ curves provided by the valve manufacturer and the impact of that difference in the accuracy of the flow estimation method precluded their use for the purpose of flow estimation. In addition, the onsite calibrated $C_v$ curves on the flow estimation are discussed in the ‘Validation and implementation of the flow estimation methods’ section. In addition, the pressure data acquired from ‘standard-defined’ pressure signals differed from the pressure data acquired from the body of a valve (valve inlet and outlet) as the flow velocity increased.

Parametric force-balance equation

The valve stem position ($x_m$) is determined by the balance of forces acting on the diaphragm and the disc retainer and moving the valve stem downwards or upwards (Figure 1(b)). The downward force, which acts on top of the diaphragm, is defined by the control chamber pressure ($h_c$), the spring force and the combined weight of the stem, the disc retainer and the diaphragm. The upward force is defined by the pressure beneath the valve diaphragm and the flow momentum change. The force from the flow momentum change is negligible compared to the force from the pressure acting...
beneath the disc retainer and the diaphragm. Furthermore, the pressure, which defines the upward force, is different from the pressure acquired at the inlet and outlet of the valve body (see Figure 1(a)). This pressure difference has a non-linear relationship. We introduce an ‘actuating’ pressure beneath the valve diaphragm, \( h_b \), to represent the pressure acting on the disc retainer and the valve diaphragm. An effective pressure acting above the valve diaphragm, \( h_a \), includes the pressure measured in the control chamber, the weight of the disc retainer and the spring force. An animation, which illustrates the operation of the investigated diaphragm-actuated globe valve, is presented in Cla-Val (2016).

Due to minor losses between the pressure measured by the valve-mounted sensors and the pressure acting on the diaphragm (Figure 1), the force-balance equation in the SPM is not sufficiently accurate for the application of flow estimation. Two approaches can be applied to re-formulate an accurate force-balance relation for the globe diaphragm valve using data that are acquired by the valve-mounted pressure sensors. These include a computational fluid dynamics (CFD) analysis as outlined in Davis & Stewart (2002) and an empirical (data-driven) approach. The flow across a control valve is expected to be highly turbulent and hence it requires a number of parameters in the CFD analysis, whereas the empirical (data-driven) approach parameterises turbulent and non-linear relationships between measured pressure and pressure acting on the diaphragm from experimental data. As a result, a data-driven approach has been applied in this work to formulate the force-balance equation.

We refer to \( h_{\text{in}} \) and \( h_{\text{out}} \) as pressure head data that are acquired at the inlet and outlet of a valve, respectively, using the valve-mounted pressure sensors. Equations (2a) and (2b) represent minor losses for the inlet and outlet sections of a diaphragm-operated globe valve, respectively (Figure 1(a)):

\[
\begin{align*}
    h_{\text{in}} - h_b &= K_1 \frac{V_1^2}{2g} \quad (2a) \\
    h_b - h_{\text{out}} &= K_2 \frac{V_2^2}{2g} \quad (2b)
\end{align*}
\]

where \( K_1, K_2 \) are minor loss coefficients and \( V_1, V_2 \) are the flow velocities. From the mass conservation, \( q_{\text{in}} = q_{\text{out}} \), and the valve geometry of its inlet and outlet, the flow velocities are assumed to be equal, \( V_1 \approx V_2 \) (see Figure 1). Consequently, Equations (2a) and (2b) are rearranged into

\[
h_b = \frac{1}{1 + \frac{K_1}{K_2}} h_{\text{in}} + \frac{K_1}{K_2 \left(1 + \frac{K_1}{K_2}\right)} h_{\text{out}} \quad (3)
\]
Since the loss coefficients are functions of the valve geometry, Equation (3) holds at a particular valve opening. An additional constant is introduced to account for uncertainties due to the hydraulic conditions, the non-uniform pressure distribution beneath the diaphragm and the assumption that $V_1 \approx V_2$. As a result, and further to Equation (3), $h_b$ for a valve opening is formulated as follows:

$$h_b | x_m = \text{const} = c_1 h_{in} + c_2 h_{out} + c_3$$

(4)

where $c_1$, $c_2$ and $c_3$ are constants for a specific valve opening. As the loss coefficients depend on the geometry of a valve, the coefficients $c_1$, $c_2$ and $c_3$ change at different valve openings. $h_b$ is expressed as a function of the main valve stem position, $x_m$. We formulate the $c_i$ coefficients as $c_i(x_m)$ polynomials: $c_1(x_m)$, $c_2(x_m)$ and $c_3(x_m)$. The pressure heads acting above ($h_a$) and beneath ($h_b$) the valve diaphragm are described by the following equations:

$$h_a = h_a(x_m, h_c) = h_c + \frac{k_{spr}(x_0 + x_m) + m_m g}{\rho g a_{top}}$$

(5)

$$h_b = h_b(x_m, h_{in}, h_{out}) = c_1(x_m)h_{in} + c_2(x_m)h_{out} + c_3$$

(6)

where $k_{spr}$ is the main valve spring constant, $x_0$ is the initial displacement of the spring, $m_m$ is the mass of the main valve plug, $\rho$ is the water density and $a_{top}$ is the area of the valve diaphragm. As different pressures are applied from above and below the same surface area of the valve diaphragm, the resulting balance of forces is analogous to the balance of pressure heads. From a quasi steady-state approximation, the force-balance principle strongly holds. Therefore, the forces acting above and beneath the diaphragm are equal for a valve opening (this assumption excludes the fully closed and fully opened valve states):

$$h_c + \frac{k_{spr}(x_0 + x_m) + m_m g}{\rho g a_{top}} = c_1(x_m)h_{in} + c_2(x_m)h_{out} + c_3$$

(7)

The balance of forces acting on the diaphragm of a control valve is shown in Figure 1(b). The $x_m$ dependent term and the constant term on the left-hand side (LHS) of Equation (7) can be included into the $c_3$ polynomial. As a result, the equation that describes the balance of forces acting on the diaphragm of a control valve (the force-balance equation) is written as follows:

$$h_c = c_1(x_m)h_{in} + c_2(x_m)h_{out} + c_3$$

(8)

The $c_i$ polynomials are obtained by least squares linear regression and hence, Equation (8) is a polynomial algebraic equation of $x_m$. Equation (8) is then rearranged into a valve stem position estimation function defined by the following equation:

$$f_c(x_m; h_{in}, h_{out}) = c_1(x_m)h_{in} + c_2(x_m)h_{out} + c_3(x_m) - h_c = 0$$

(9)

The coefficients $c_1(x_m)$, $c_2(x_m)$ and $c_3(x_m)$ are fitted through an OLS method to a fourth-degree polynomial. The estimation functions of three valve sizes are fitted using data from Stage 1 of the experimental programme.

### 3P and 2P&Pos flow estimation methods

The considered flow estimation methods for a diaphragm-actuated globe valve are based on the following equations:

$$f_c(x_m; h_{in}, h_{out}) = c_1(x_m)h_{in} + c_2(x_m)h_{out} + c_3(x_m) - h_c = 0$$

(10)

$$q = C_{rm}(x_m) \sqrt{h_{in} - h_{out}}$$

(11)

All polynomial coefficients, $C_{rm}(x_m)$, $c_1(x_m)$, $c_2(x_m)$ and $c_3(x_m)$, are derived from experimental data, and these coefficients vary for different size valves. The polynomial coefficients can also be derived for valves in operational networks without prior knowledge. The 3P flow estimation method is applied by initially solving Equation (10) for the valve stem position estimate ($\hat{x}_m$) using a set of measurements from three valve-mounted pressure sensors ($h_{in}$, $h_c$ and $h_{out}$). We then solve Equation (11) to estimate the flow rate ($q$) across a valve, for which the valve stem position estimate and the measured differential pressure across the valve ($\hat{x}_m$, $h_{in} - h_{out}$) are utilised. The 2P&Pos
flow estimation method is applied by solving Equation (11) for a flow estimate ($\dot{q}$), given a set of measurements of $x_m$, $h_{in}$ and $h_{out}$ (note: $x_m$ is measured by a stem-mounted position sensor).

THE 3P FLOW ESTIMATION METHOD AND MULTIPLE SOLUTIONS

The valve stem position estimation function (Equation (10)) for the 3P flow estimation method can have multiple roots (solutions). Multiple roots result from the hydraulic conditions defined by the valve geometry, the control loop and the resulting pressures (forces) acting upon the valve diaphragm. We demonstrate experimentally that identical datasets of three pressure signals, $\{h_{in}, h_{out}, h_c\}$, from the valve-mounted sensors can correspond to different valve stem positions and, therefore, result in multiple solutions (Figure 5) for Equation (10).

As an illustration, Figure 5(a) shows multiple steady states for the Cla-Val DN80 NGE. With relatively constant $\{h_{in}, h_{out}, h_c\}$, $h_c$ varies and reveals a non-monotonic behaviour as both the flow rate and valve stem position increase. In addition, two steady-state flows are presented with the same combination of pressure variables but different valve stem positions using a parallel coordinate plot (Figure 5(b)). Valve stem position estimation functions are plotted in Figure 6 for Cla-Val DN80 NGE for a given set of three pressure signals, $\{h_{in}, h_{out}, h_c\}$, acquired by the valve-mounted sensors.

Polynomial regression methods were applied to fit the valve stem position estimation functions with polynomials of varying degrees for $x_m$. Residual analyses were carried out to determine a suitable degree of a polynomial, which depends on the valve size, hydraulic conditions and training datasets.

The residuals are calculated as follows:

$$\text{Res} = h_c - (c_1(x_m)h_{in} + c_2(x_m)h_{out} + c_3(x_m))$$  \hspace{1cm} (12)

A random pattern in the calculated residuals indicates that a model provides a reasonable fit to the data. A fourth-degree polynomial is the lowest degree polynomial, for which a random pattern was observed between Res and $x_m$. Even if the most appropriate degree of a polynomial might not be selected, the model can still provide a reasonably accurate estimate of the valve stem position and therefore flow rate. High-degree polynomials can be applied when large training datasets are available with multiple flow combinations. Smaller training datasets could result in overfitting and consequently a failure in estimating the valve stem position reliably from new pressure data.

For the experimental datasets, which were acquired from the control valves installed in the laboratory pipe rig, the valve stem position estimation functions were

![Figure 5](https://iwaponline.com/jh/article-pdf/21/4/571/580607/jh0210571.pdf)
determined as fourth-degree (quartic) polynomials for the three investigated valve sizes. Quartics have zero to four roots and zero to three turning points (local extrema; or points, at which the derivative changes sign) and no general symmetry.

Since the model coefficients depend on valve sizes, hydraulic conditions and training datasets, the number of roots and the number of turning points within a valve stem range depend on the completeness of the training datasets. Based on the experimental datasets used for training, the valve stem position estimation functions for the Cla-Val DN100 GE and Cla-Val DN150 GE contain no more than two turning points within the corresponding valve stem position range. In comparison, the valve stem position estimation function for the Cla-Val DN80 NGE contains no more than three turning points within its stem position range. Consequently, the solution of a valve stem position estimation function (Equation (9)) results in no more than two solutions for Cla-Val DN100 GE and Cla-Val DN150 GE valves and no more than three solutions for a Cla-Val DN80 NGE valve. It should be noted that the lowest stem position solution for a Cla-Val DN80 NGE is not a correct solution. This is because the polynomial is fitted with the same high-degree polynomial using a smaller data range due to the narrow range of the valve stem movement. Furthermore, a typical operational range for diaphragm-operated globe valves is a valve stem position of up to 75% open. It is not common for these control valves to operate as fully opened (or above 75%).

We address the problem of solving the valve stem position estimation function with multiple roots, \( g(x_m; h_{in}, h_c, h_{out}) \), by applying heuristics to bind the possible solution within a specific (probable) range of the operation of a control valve. The proposed solution procedure exploits the high-frequency content of the acquired outlet pressure signal as a heuristic for isolating the root (solution) for the valve stem position estimation from multiple possible solutions. The solution procedure includes an analysis of the outlet pressure signal and a classification procedure that applies an SVM algorithm. We define an SVM-based classification procedure so that the predictor variables are able to distinguish cases for which the first solution is the correct solution, and also for which the second solution is the correct solution. The investigation for the predictor variables and SVM classifier is discussed in the next two sub-sections.

**Pressure envelope range, ER, as a predictor variable**

Bull & Lim (1968) described an increase in the measured wall-pressure fluctuations with an increase in the Reynolds number. The same phenomenon was observed in Stages 1, 2 and 3 of the completed experimental programme. Consequently, the dynamic (high-frequency) pressure fluctuations occurring at the outlet of a valve have been utilised as a root isolation heuristic to determine a region for the feasible solution.

We define the pressure envelope range (ER) variable as the difference between the upper and lower peak envelopes.
of the pressure signal acquired at the outlet of a valve (a sampling rate of 100 S/s; although a sampling rate of 10 S/s and 1 S/s was also successfully applied). The pressure envelope is calculated by a spline interpolation over local maxima/minima data points, and it is computationally efficient for implementation in embedded systems with limited resources. An alternative approach was also considered based on a short-term Fourier transform analysis but was found to be less appropriate than the ER for implementation in an SVM classifier.

The pressure ER of an experimental dataset is presented in Figure 7, and it demonstrates an increase in the pressure ER with an increase of the flow rate across a control valve. (The Spearman rank-order correlation between ER and flow across a valve for different data acquisition (sampling) rates is presented in Appendix A, available with the online version of this paper.) The pressure ER results produced slight differences for the three control valves that were tested in the laboratory pipe rig versus the same model control valves installed in operational WSNs (Figure 8). For example, the laboratory-based experimental data show that ER can be high for low flows (Figure 8(a)). In contrast, this phenomenon was not observed in operational WSNs as demonstrated in Figure 8(b) and also validated in the ‘Validation and implementation of the flow estimation methods’ section. It is likely that turbulence from the pump and the demand control valve in the relatively short experimental pipe rig created complex fluid interactions, which were the reason for the high-pressure ER at low flow rates. Consequently, the application of the 3P flow estimation method for the laboratory-based experimental tests excluded data with flow below the turning point of 5 l/s for Cla-Val DN80 NGE (Figure 8(a)). This phenomenon (and the resulting turning point) defined a feasible (or minimum) flow rate threshold for the laboratory-tested control valves; and as a result, it slightly limited the flow range, over which the 3P flow estimation method was applied under this specific experimental set-up.

![Figure 7](https://iwaponline.com/jh/article-pdf/21/4/571/580607/jh0210571.pdf)

**Figure 7** The pressure ER calculated for Cla-Val DN80 GE: (a) pressure and flow measurements; (b) a magnified outlet pressure signal, \( p_{\text{out}} \); (c) pressure ER based on \( p_{\text{out}} \) sampled at 100 S/s; (d) pressure ER based on \( p_{\text{out}} \) sampled at 10 S/s.
minimum flow rate threshold was approximately 5 l/s for the laboratory-tested Cla-Val DN100 GE and approximately 7 l/s for the laboratory-tested Cla-Val DN150 GE. Based on the extensive experimental validation, we do not anticipate that the 3P method will have a lower bound on the estimated flow in operational WSNs.

SVM classifier for identifying the valve stem position: 3P flow estimation method

Two variables have been proposed and included as heuristic predictors for identifying the correct valve stem position (root isolation); namely, the pressure ER and the differential pressure (DP = \( h_{\text{in}} - h_{\text{out}} \)). The acquired pressure data were downsampled to 100 S/s for the presented results. Sampling rates of 10 S/s and 1 S/s were also successfully applied. Sampling rates of 128 S/s and 1 S/s are now achieved with ultra low-power microcontrollers, ADC converters and pressure sensors within battery-operated IP68-rated pressure monitoring devices with a life expectancy of 5 years (as utilised and demonstrated in the ‘Validation and implementation of the flow estimation methods’ section).

In the initial stage of the 3P flow estimation method, we solve the valve stem position estimation function using \( h_{\text{in}}, h_{\text{out}}, h_{c} \) acquired from the valve-mounted pressure sensors. The outcome of this process is the roots, or the likely stem position estimates, one of which is the correct valve stem position estimate. We then identify the correct stem position estimate using an SVM classification model. The SVM classifier uses the ER and DP (the predictor variables), and the solution class for the specific data tuple (the response variable) for training. The solution classes are defined by the roots of the valve stem position estimation function and the true (correct) valve stem position estimate. If the true valve stem position estimate is the ‘lower stem position’ estimate, we define the class to be Class 1. If the true valve stem position estimate is the ‘higher stem position’ estimate, we define the class to be Class 2. In rare cases, where there might be more than two classes, a modified version of the SVM is applied for a three-class classification. To simplify the process, an SVM model maps predictors (ER and DP) to response (the solution class) in the training process. The valve stem position estimation model is then applied to predict the solution class from the continuously measured ER and DP.

Classes can either be defined from a fixed constant boundary value because the turning point is relatively constant (fixed boundary) or based on the location of the position estimate with respect to the turning point (non-fixed boundary). The non-fixed boundary approach is a preferred approach because the fixed boundary can be biased if the training datasets are non-symmetric; for example, more tuples (experimental cases) with a lower value of the turning point are collected rather than data tuples with a higher value of the turning point. This training scenario could
occur in operational networks with a confined range of flow based on the diurnal demand profiles. The output of the classification model is the true class of the position estimate (Class 1 or Class 2). Finally, the true valve stem position estimate is identified.

Classification models training and validation

The investigated SVM methods perform a non-linear non-parametric classification. Both steady-state datasets and quasi-unsteady-state datasets were used to train the SVM classifier. The experimental datasets, which had been acquired in Stages 1 and 2 (laboratory-based experimental programme), were split into non-overlapping sliding windows. All pressure variables were averaged within a sliding window to obtain a single value. The width of a sliding window was 30 s for training and validation. This is based on the response time of the flow modulating control and the utilised sampling rate.

Six SVM kernel functions were evaluated for the classification analysis, namely, Linear SVM (LSVM), Quadratic SVM (QSVM), Cubic SVM (CSVM), Fine Gaussian SVM (FGSVM), Medium Gaussian SVM (MGSVM) and Coarse Gaussian SVM (CGSVM). The SVM models were validated with a 50-fold model validation method. Different sampling rates were also studied to assess their impact on classification. The results are shown in Table 1. All SVM kernels have demonstrated a good classification performance. The data subset of 100 S/s consistently achieved the best classification performance.

For the training process, we used tuples with a sampling rate of 100 S/s (e.g. discrete periods of steady-state conditions; or quasi-unsteady-state conditions). The selected window widths were 30 s (a tuple) for the laboratory-based experimental programme, and both 10 s and 60 s for the experimental programme in operational networks. Figure 9 shows two classes of data for the three investigated control valves. The classification models used for the flow estimation were trained using the datasets plotted in Figure 9.

The number of training data tuples should be specified to define the boundary between the two classes. In order to achieve this, the turning point of the estimation function shown in Figure 6 needs to be determined. Tests were conducted to collect data at every 1 mm of the valve stem position for the full range of operational hydraulic conditions as part of the experimental investigation. The current models were trained by 188 data tuples for the Cla-Val DN80 NGE, 258 data tuples for the Cla-Val DN100 GE and 319 data tuples for the Cla-Val DN150 GE. The experimental validation in operational WSNs was based on a 24-h training dataset (1440 tuples) and validated with datasets of which window widths are 10 s (2P&Pos) and 60 s (3P). Since the boundary between the two classes is expected to be similar for the same valve type, the amount of data to train a classification model can be reduced if the data are only collected along the expected boundary area (e.g. the turning point of the valve stem position estimation function). An illustrative example based on Figure 6(b) shows a turning point of around 7 mm for the stem position estimation function for DN100 valve.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Accuracy of the SVM classification kernels applied to pressure tuples that were acquired (sub-sampled) with different sampling rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Cla-Val DN80 NGE</td>
</tr>
<tr>
<td></td>
<td>100 S/s</td>
</tr>
<tr>
<td>LSVM</td>
<td>94.4%</td>
</tr>
<tr>
<td>QSVM</td>
<td>93.9%</td>
</tr>
<tr>
<td>CSVM</td>
<td>94.4%</td>
</tr>
<tr>
<td>FGSVM</td>
<td>93.1%</td>
</tr>
<tr>
<td>MGSVM</td>
<td>93.6%</td>
</tr>
<tr>
<td>CGSVM</td>
<td>85.3%</td>
</tr>
</tbody>
</table>

The accuracy is calculated through 50-k fold cross-validation on the training datasets and is shown as a percentage of correctly classified data. The sampling rates with the best classification accuracy are labelled in bold.
Consequently, the classification model can be successfully trained with data within 7 mm (±2 mm).

VALIDATION AND IMPLEMENTATION OF THE FLOW ESTIMATION METHODS

This section validates and compares the performance of the two flow estimation methods (3P and 2P&Pos) using the extensive experimental data.

3P flow estimation vs. 2P&Pos flow estimation

The flowchart for the implementation of the 3P flow estimation method is described in Figure 10. Since all investigated SVM classification models exhibited similar performance, the LSVM was applied as it requires the least data and computational resources for both training and application. The $C_v$ curve of each valve was obtained using the acquired steady-state data from Stage 1 of the experimental programme (Figure 4).

The flow estimation accuracy of the 3P method using the laboratory experimental set-up is summarised in Figure 11 for the three tested control valves (Cla-Val DN80 NGE, Cla-Val DN100 GE and Cla-Val DN150 GE). For all laboratory experiments, the sampling rate is 1200 S/s and downsampled to 100 S/s for the flow estimation. The performance is analysed for flow rates that are expected in typical operational scenarios. The distribution of flow estimation errors, which includes the minimum, first quartile, median, third quartile and maximum, is compiled in Figure 11. As a comparison, Figure 12 summarises the performance of the 2P&Pos method for the same set of control valves and experimental data. The median percentage error for the 3P is between 9% of a reading for a flow rate of 5–10 l/s and 2% of a reading for a flow rate of 15–20 l/s for Cla-Val DN80 NGE. The interquartile range varies between 6% for a flow rate of 5–10 l/s range and 3% for a flow rate of 15–20 l/s for Cla-Val DN80 NGE. In comparison, the median percentage error for the 2P&Pos is between 0.5% of a reading for a flow rate of 5–10 l/s and 0.2% of a reading for a flow rate of 15–20 l/s for Cla-Val DN80 NGE. The interquartile range varies between 1% for a flow rate of 5–10 l/s and 0.5% for a flow rate of 15–20 l/s for Cla-Val DN80 NGE. These results show that (i) the accuracy of the 3P flow estimation method is comparable to the performance of a typical turbine flow meter used in WSNs and (ii) the direct sensing of the valve stem position, which is applied in the 2P&Pos method, provides a greater accuracy that exceeds the performance of a turbine flow meter and it is comparable with the performance of an electromagnetic flow meter.

Figure 9 | Data categorised by an estimation function turning point. Data of three valves are shown separately in (a–c).
Continuous flow estimation for robust pressure control (FM) in an operational WSN

We investigate and compare the applicability of both the 3P and the 2P&Pos flow estimation methods for the implementation of flow modulating control in WSNs. This experimental validation includes control valves (two Cla-Val DN100 GE and one Cla-Val DN150 GE) installed in an operational WSN, which we refer to as ‘Field Lab’ and show in Figure 13, and also control valves installed in a laboratory pipe rig (Cla-Val DN 80 NGE, Cla-Val DN100 GE and Cla-Val DN150GE). The ‘Field Lab’ has 10,000 customer connections, and it is jointly operated by Bristol Water, InfraSense Labs (Imperial College London) and Cla-Val (Wright et al. 2014, 2015). The ‘Field Lab’ contains three PMAs with three FM-based automatic control valves (ACVs) and two automatic boundary control valves. The FM control profiles for the ACVs, which are also displayed in Figure 13, include the ‘fail-safe’ settings and error bounds in the FM curves.

The ‘Field Lab’ and the experimental pipe rig allow us to carry out a systematic and extensive investigation of the performance of the considered flow estimation methods under a wide range of operational conditions and control valve sizes. The 3P flow estimation method was implemented in non-overlapping moving windows with a fixed time interval of 10 s for all valves and experiments presented in this section. The pressure is continuously sampled at 128 S/s (‘Field Lab’). The 2P&Pos flow estimation was computed every 1 s for the laboratory experimental set-up and every 60 s for the valves in the operational WSN (‘Field Lab’). The 60 s time interval was applied because of sampling constraints for the stem position sensor for the valves installed in the ‘Field Lab’. ABB electromagnetic flow meters (full bore) were used for each control valve to acquire flow validation data. ABB WaterMaster FEX100 is installed in the ‘Field Lab’ and ABB ProcessMaster FEP500 is installed in the laboratory test rig. The accuracy of the ABB flow meters is 0.2% of a reading.

The operational WSN (Figure 13) includes valves with different control functions. Three ACVs are set as flow modulating valves, and these are labelled SKL (Cla-Val DN100 GE), WLW (Cla-Val DN150 GE) and LCW (Cla-Val DN100 GE). The parametric force-balance functions for these control valves were derived from a 24-h dataset.

Figure 10 | A flowchart for the implementation of the 3P flow estimation method.
The results of applying and comparing the two flow estimation methods for a laboratory-tested control valve (Cla-Val DN100 GE) are plotted in Figure 14. The laboratory experiments include rapid changes in the flow conditions simulated by the demand valve (shown in Figure 2). In the ‘Field Lab’, there is a pre-defined relationship (a flow modulating control curve) for each control valve, which is derived from an optimisation algorithm for minimising the average zone pressure in a multi-feed PMA as outlined in Pecci et al. (2017). The application of the two flow estimation methods in the ‘Field Lab’ for Cla-Val DN100 GE is shown in Figure 15.

The flow estimation for the robust flow modulating control in the ‘Field Lab’ is done for three separate control profiles for each control valve in order to observe their performance under a wide range of hydraulic conditions (Figure 16). The flow estimation errors for the 3P and 2P&Pos methods are shown in Table 2. The impact of these flow estimation errors on the implementation of the flow modulating control profiles is illustrated in Figure 17.

The results obtained through both estimation methods are compared with direct flow measurements from the electromagnetic flow meters. The performance of the 2P&Pos flow estimation method is identical to the flow data acquired...
from the electromagnetic flow meter with an RMSE (root-mean-squared error) of 0.3 l/s for the laboratory-based experiments (Figure 14(b)). The 3\textit{P} method produced estimates that are slightly worse than the flow data acquired from the electromagnetic flow meter with an RMSE of 2.14 l/s for the laboratory-based experiments (Figure 14(a)).

The applications of the 3\textit{P} and 2\textit{P}\&\textit{Pos} methods for continuously estimating the flow in an operational WSN for a Cla-Val DN100 GE control valve are displayed in Figure 15(a) and 15(b), respectively. The results show a typical 24-h diurnal profile with a flow range of 25 l/s. The RMSE for the 3\textit{P} flow estimation method is 0.7 l/s with a mean absolute percentage error, MAPE, of 9\%, in comparison with the flow data measured by the electromagnetic flow meter. The RMSE for the 2\textit{P}\&\textit{Pos} flow estimation method is 0.3 l/s with an MAPE of 3\%. These results demonstrate that both the 3\textit{P} and 2\textit{P}\&\textit{Pos} flow estimation methods perform well within the uncertainty bounds for the
implementation of a flow modulating profile in an operational WSN, as shown in Figure 16. The distribution of the error in the outlet pressure based on the flow estimates from the various methods as implemented in the ‘Field Lab’ is summarised in Figure 17(a) as a boxplot and in Figure 17(b) as a beeswarm plot.

CONCLUSIONS

In this paper, we investigate methods for the redundant (and reliable) flow estimation, which support the implementation of robust pressure control in WSNs. A novel flow estimation method (the 3P method) is presented, which utilises advances in pressure monitoring with high sampling rates (10–100 S/s) and computationally efficient algorithms for their implementation in low-power embedded electronic systems. Three pressure measurements are continuously acquired at valve inlet pressure, valve outlet pressure and control chamber pressure within a diaphragm-actuated globe valve. The 3P flow estimation method applies a data-driven force-balance relationship for the valve stem estimation, an accurate \( C_v \) relationship and a classification model for solving the non-linear stem position estimation function with multiple solutions. Heuristics, based on characterising the envelope range of the high-frequency outlet pressure signal, was proposed to bind the possible solution for the valve stem position estimation within a specific (probable) range of the operation of a control valve.

An extensive experimental programme has been conducted to acquire data from multiple control valves under laboratory conditions. The same model control valves...
were then installed in an operational network (the ‘Field Lab’) to validate the performance of the developed 3P flow estimation method and benchmark it against an alternative flow estimation method, the 2P&Pos method.
which uses measurements of the valve stem position and the pressure differential across a valve.

The RMSE for the $3P$ flow estimation method in an operational network (‘Field Lab’) has been consistently within $2\, l/s$ when compared with the flow data measured by an electromagnetic flow meter (0.2\% of a reading). The RMSE for the $2P&Pos$ flow estimation method has been consistently within $0.7\, l/s$. The $3P$ and the $2P&Pos$ flow estimation methods were then applied and analysed for the robust pressure control implementation in an

![Figure 15](https://iwaponline.com/jh/article-pdf/21/4/571/580607/jh0210571.pdf)
The deviations for the outlet pressure setting based on the flow estimates were within the uncertainty bounds for the implementation of an FM profile in an operational WSN. The results showed that both the 3P and the 2P&Pos flow estimation methods can be successfully applied for redundant flow estimation to support the implementation of robust pressure control in WSNs. Furthermore, each of these methods can also be applied as a primary flow estimation method for control applications where a flow meter is not available (e.g. pressure-managed areas with closed-loop control from a remote critical point as this method depends on reliable wireless communication with the remote critical point).

Advanced pressure control methods, which dynamically adapt their settings, are becoming increasingly attractive for utility operators to manage their WSNs. The implementation is driven by regulatory and financial pressures to extend the life cycle of ageing infrastructure and

<table>
<thead>
<tr>
<th>Valve site</th>
<th>Control profile</th>
<th>RMSE (l/s)</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>3P</td>
<td>2P&amp;Pos</td>
</tr>
<tr>
<td>SKL 1</td>
<td></td>
<td>0.7</td>
<td>0.3</td>
</tr>
<tr>
<td>SKL 2</td>
<td></td>
<td>0.6</td>
<td>0.3</td>
</tr>
<tr>
<td>WLW 1</td>
<td></td>
<td>3.6</td>
<td>0.9</td>
</tr>
<tr>
<td>WLW 2</td>
<td></td>
<td>3.7</td>
<td>0.6</td>
</tr>
<tr>
<td>LCW 1</td>
<td></td>
<td>0.7</td>
<td>–</td>
</tr>
<tr>
<td>LCW 2</td>
<td></td>
<td>0.2</td>
<td>–</td>
</tr>
</tbody>
</table>

Errors are shown in l/s and %. Valves have the following size and type: SKL is DN100 GE, WLW is DN150 GE and LCW is DN100 GE. It should be noted that high errors on the WLW valve come from the fact that the valve in the ‘Field Lab’ operates in a narrow range of pressure combination through the model training process.
reduce leakage while maintaining an agreed quality of service within a wide range of operational conditions. However, the high reliability of advanced control methods is a prerequisite for maximising their benefits and minimising their whole life cost. The redundant flow estimation methods, which were presented and extensively experimentally tested in this paper, enable the robust implementation of flow modulating control in water supply systems in order to maintain and enhance the benefits of advanced pressure control.
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