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Filter Design Using Data Fusion for a Pneumatic Control Valve

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Abstract: This paper presents a filter design technique for a pneumatic valve using data fusion techniques. The objective of this paper is to examine the suppression of the effect of parameters causing deviation from normal system performance using the technique of data fusion over time. The output of a system affected by inherited noise is processed by applying operations such as finding the statistical variance, time warping, interpolation, and extrapolation. These techniques are used to compute the transfer function of the filter, which when cascaded with the system will suppress the effect of noise on the process. The operation of the control valve is affected by characteristics such as stiction, structural deformation, etc. The characteristics of the system are studied and data for multiple time instances are extracted to carry out fusion across time by dynamic time warping. Tests show that the filter presented here can suppress the effects of stiction and mechanical deformation on the output signal.

Keywords: Control valve, Data fusion, Dynamic time warping, Filter, Spline interpolation.

1 Introduction

An example of inherent system noise in the case of a control valve is the viscosity of the liquid. With a change in the temperature of the fluid, the viscosity of the fluid changes, resulting in a change in fluid flow rate; when this viscosity changes continuously, we do not obtain the desired output flow rate. The viscosity also differs greatly from one fluid to another, and this factor must also be accounted for. When the input is kept constant for each sample, the output is expected to be the same; however, in most cases, this is not the case, meaning that some amount of system noise has been introduced. This noise must be eliminated to achieve the desired output.

Many researchers have studied the removal of disturbances using several methods, and some are mentioned here. The estimation of noise variance using a wavelet threshold function is reported in [1]. In this case, noise is removed by selecting a suitable threshold value, and this method focuses on removing noise

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from random and non-stationary signals. In [2], random signal-dependent noise is eliminated from raw image sensor data by designing a Kalman filter. The suppression of coloured noise using wavelet thresholding is reported in [3]. In this case, inertial sensor errors are mainly modelled to remove noise. The authors of [4] report a filter design technique for the removal of measurement noise that involves placing a filter in the feedback loop. Evaluation of the unpredictable variation of the sensor data for the measurement of traffic noise signal is highlighted in [5]. An adaptive filtering technique is reported in [6] for removing random noise from seismic data. The determination of a modal parameter from a noisy impulsive response function is discussed in [7], and noise is removed from the data. The elimination of noise from electroencephalograph results using a feature extraction technique is reported in [8]. In [9], noise models are used for the characterisation of sensors; once a model of the noise has been obtained, it can be used in an analysis of the sensor behaviour. In [10], instances that are not part of normal operation are partially reduced, and useful instances are retained. Outliers are found in order to reduce the size of the data used for machine learning.

A noise removal technique based on infinite filters is reported in [11]. The noise included in images obtained via a sensor is filtered in order to leave only the desired signal. In [12], a covariance matrix of noise is designed to estimate the process and measurement disturbances. The filtering and correction of noisy instances using a noise scoring and ensemble filtering technique is reported in [13], and the filtering of image noise using a Kalman filtering technique is reported in [14]. In [15], an adaptive median filtering technique is presented for the detection and removal of salt-and-pepper noise from acquired images. An observer design technique is reported in [16] for a system under conditions of measurement noise, and this is claimed to be robust for measurement noise. In [17], thermal noise is removed from the acquired image using a microlens of two wavelengths as the sensor, and the quality of the image is shown to be improved. In [18], a method for mining the required data from a noisy signal is reported; this approach is referred to as a stamp method.

It is clear that a technique is required that can help to eliminate or compensate for noise arising from abnormalities in the behaviour of the system. Data fusion can be applied to this problem, and can be used to design a robust filter. In this paper, an attempt is made to eliminate the inherent system noise by designing a robust filter using data fusion techniques. Noise inherited in a control valve system is considered by introducing random noise as part of the constant term in the denominator of the control valve transfer function. The collected data are then analysed, and the behaviour of the inherent noise is estimated and used to nullify the effects of the noise.

This paper is organised as follows: this section has presented an introduction; a problem statement is given in Section 2; an analysis of the system is carried out in Section 3; the results are analysed in Section 4; and a conclusion is presented in Section 5.

2 Problem Statement

Control valves form an integral part of any flow process loop. Flow through a pipe is restricted with the help of a pneumatic control valve, in which the position of the valve is changed based on the input given by the controller. The position of the shaft is affected by numerous parameters, such as the friction between the shaft and the walls, and the friction between the fluid and the shaft, which depends on the viscosity of the fluid. The mechanical deformation of the shaft is a further parameter that can disturb the action of the control valve. In this paper, an analysis is carried out in order to understand the effects of noise by modelling its behaviour, and a filter is designed to overcome its effect.

3 Analysis of the System

In this study, a standard control valve transfer function is considered as given in (1), following the method presented in [19]. The transfer function in (1) is obtained by considering the controller output current as the input, and the fluid flow rate as output. In this transfer function, the nominal flow rate used was 120 gallons per minute.

$$TF_{A/V} = \frac{K_A K_V \, \mathrm{e}^{-\tau_{dA/V}}}{(\tau_3 s + 1)\left[\dfrac{s^2}{\omega_n^2} + \dfrac{2\zeta s}{\omega_n} + 1\right]} . \tag{1}$$

Equation (1) is a generalised formula for a control valve transfer function, where K_A, K_V are the static gain of the actuator and valve, respectively; $\tau_{dA/V}$ is the actuator and valve dead time; ζ is the damping ratio; ω_n is the natural frequency; and τ_3 is the time constant. Values of $K_A = K_V = 16.62$, $\omega_n = 11.94$, $\zeta = 0.5$, $\tau_3 = 0.215\,\mathrm{s}$ and $\tau_{dA/V} = 0.02\,\mathrm{s}$ are selected from [19] and substituted into (1), resulting in the transfer function in (2):

$$TF = \frac{3.858\,\mathrm{e}^4}{0.215s^3 + 3.567s^2 + 42.59s + 142.6} . \tag{2}$$

Inherent disturbance may arise due to modifications to any of the coefficients of the transfer function given in (2). To start with, an assumption is made that the disturbance only affects the s^0 term in the denominator of the control valve transfer function in (2). To maintain the units in SI form, flow in gallons per minute is converted to m^3/s; thus, a factor of 0.0075082 is multiplied with the numerator, and a random function is added to the constant term in (2), resulting in (3). Once the valve transfer function has been obtained, the next objective is to calculate the change in system behaviour.

$$TF = \frac{292}{0.215s^3 + 3.567s^2 + 42.59s + (142.6 + \text{rand}(1))}. \tag{3}$$

3.1 Calculation of statistical variance

A knowledge of the behaviour of noise helps in eliminating it, and thus an understanding of the fluctuations in the data values is essential. A step input was applied to the system given in (3), and 10 output samples were collected over a period of 0–2 s at intervals of 0.01 s. This resulted in a total of two hundred tuples for each sample.

To understand the behaviour of the system at different time instances, the statistical variance of these 10 samples needs to be calculated. The variance for each of the sample outputs was calculated and plotted on the graph in Fig. 1. The variance is the actual noise that needs to be eliminated to obtain the same output for the same input.

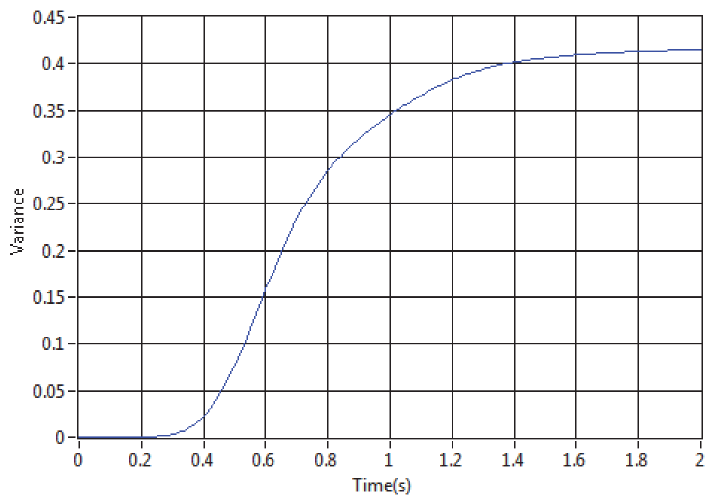


Fig. 1 – *Variance over time.*

Data fusion is a process of combining multiple data points to achieve the desired objective. In this paper, the process that is evaluated for fault diagnosis is subjected to input with varying time frames, and these signals are time wrapped in order to carry out data fusion. In this work, a distributed black-box fusion [20] framework is used for data fusion. A block diagram of this framework is shown in Fig. 2.

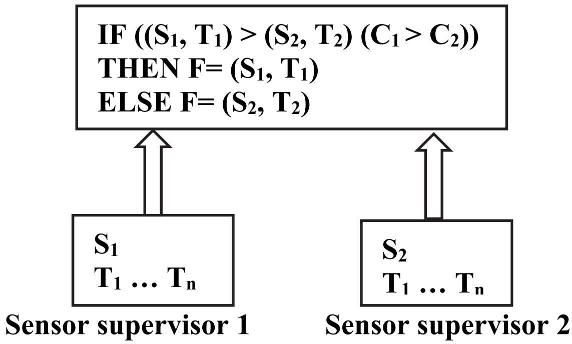


Fig. 2 – *Distributed black-box model.*

Dynamic time warping (DTW) is commonly used when the aim is to find the optimal alignment between two time-dependent sequences. In DTW, two time sequences, for example $X=(x_1,x_2,\ldots,x_p)$ of length P and $Y=(y_1,y_2,\ldots,y_p)$ of length P, are compared; these consist of P sensor observations obtained from the same sensor over different periods of time [21]. DTW is also used in data mining and speech recognition applications. From the system described by (3), 10 data points were collected at 10 time instances.

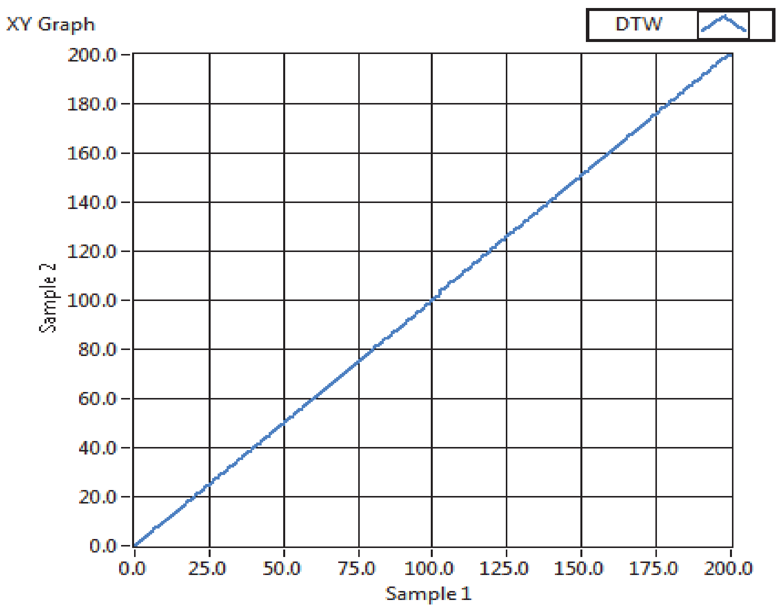


Fig. 3 – *DTW between two samples.*

Temporal alignment was then required, as the intention was that the collected data would be fused across time, and DTW was applied as part of this data fusion. The first sample was used as a reference, and graphs were obtained after applying DTW to the second sample. The DTW obtained from the first two samples is shown in Fig. 3.

Once DTW had been performed, the fault in the process behaviour needed to be estimated. To carry out this estimation, various techniques were used, of which polynomial interpolation was one. Polynomial interpolation is a method of estimating the new value by observing the variation in a given data range using a polynomial. By applying numerical analysis, a polynomial can be found that passes exactly through the available data points. We assume that the polynomial used for interpolation is as given in (4):

$$p(x) = a_n x^n + a_{n-1} x^{n-1} + \cdots + a_2 x^2 + a_1 x + a_0 . \quad (4)$$

The statement that p interpolates the data points means that

$$p(x_i) = y_i \ \text{ for all } \ i \in \{0,1,\ldots,n\} . \quad (5)$$

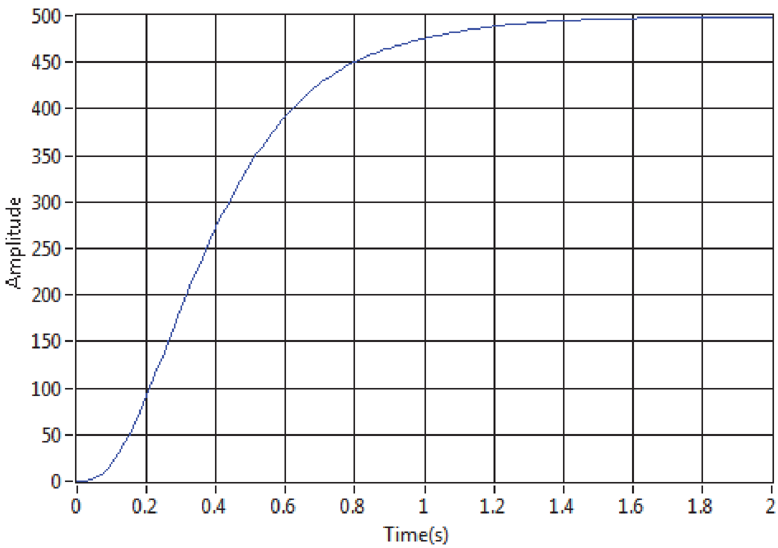


Fig. 4 – *Polynomial interpolation.*

By substituting (4) into (5), we obtain the system in a matrix-vector form, as given in (6):

$$\begin{bmatrix} x_0^n & x_0^{n-1} & x_0^{n-2} & \cdots & x_0 & 1 \\ x_1^n & x_1^{n-1} & x_1^{n-2} & \cdots & x_1 & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ x_n^{n-1} & x_n^{n-1} & x_n^{n-2} & \cdots & x_n & 1 \end{bmatrix} \begin{bmatrix} a_n \\ a_{n-1} \\ \vdots \\ a_0 \end{bmatrix} = \begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_n \end{bmatrix}. \tag{6}$$

Equation (6) needs to be solved for a_k to construct the interpolant $p(x)$. The matrix on the left-hand side of (6) is referred to as a Vandermonde matrix. The next sample is estimated from the samples that were obtained previously. Polynomial interpolation is performed to obtain this estimation, and the interpolation graph is shown in Fig. 4.

If the Vandermonde matrix is considered when computing the coefficients a_k by solving the system equation using Gaussian elimination, large errors may arise due to a large condition number. To avoid these errors, spline interpolation is used to find the next value.

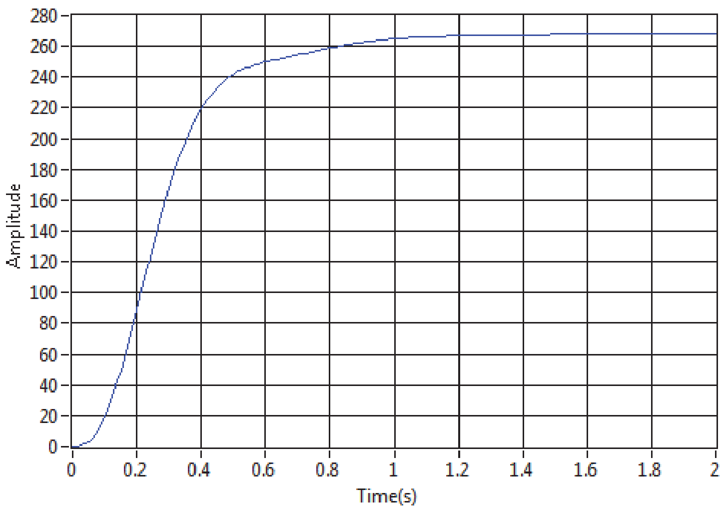


Fig. 5 – *Spline interpolation.*

A spline is a special type of piecewise polynomial used for numerical analysis. The use of spline interpolation can reduce the error, as good performance can be achieved even when the order of the polynomial is lower. The points are formed by the input arrays ***X*** and ***Y***. On the interval $[x_i, x_{i+1}]$, (7) defines the output interpolation value y:

$$y = Ay_i + By_{i+1} + Cy_i'' + Dy_{i+1}'', \tag{7}$$

where

$$A = \frac{x_{i+1} - x}{x_{i+1} - x_i}, \quad (8)$$

$$B = 1 - A, \quad (9)$$

$$C = \frac{1}{6}(A^3 - A)(x_{i+1} - x_i)^2, \quad (10)$$

$$D = \frac{1}{6}(B^3 - B)(x_{i+1} - x_i)^2. \quad (11)$$

Since polynomial interpolation does not give accurate results for a large dataset, spline interpolation was used to estimate the next sample, and the graph for this is shown in Fig. 5. From the figure, it can be observed that spline interpolation gives a better response than polynomial interpolation in terms of the settling time and the peak value.

The next aim is to obtain the original signal again after removing the noise. Three possible methods are applicable here: the Bayesian, Kalman, and extrapolation techniques. In this work, the extrapolation technique is used for the estimation of values.

Extrapolation is a process of estimation beyond the original series, in which the value of the next state is estimated based on its relationship with another variable. Initially, an impulse is given to the first row of the inverse covariance matrix, and the output is used as input for the next set of covariance; in this way, the rest of the six signals are calculated using the inverse covariance matrix. The covariance matrix was obtained from the DTW samples. The variance of all six values at the rising edge were considered to obtain the transfer function of the valve. The obtained transfer function was then cascaded with the original signal containing the random error to retrieve the filtered output.

To obtain the transfer function from the multiple polynomials given in (12–18), only the rising edges of the output signals from the inverse covariance matrix were considered.

$$\chi^1 = [-8.7E7, 6.6E8, -2.06E9, 3.1E9 - 2.6E9, 1.2E9, -2.5E8, -5.5E7], \quad (12)$$

$$\chi^2 = [-684.1, 5153.6, -15625.2, 24359.4, -20657.5, 9240.3, -1921.6, 430.3], \quad (13)$$

$$\chi^3 = [-1.4E6, 1.1E7, -3.3E7, 5.1E7, -4.3E7, 1.9E7, -4.0E6, 902089], \quad (14)$$

$$\chi^4 = [0.9, -6.8, 20.5, -32.0, 27.2, -12.1, 2.5, 0.6], \quad (15)$$

$$\chi^5 = [-1.2E10, 9.1E10, -2.8E11, 4.3E11, -3.6E11, 1.6E11, -3.4E10, -7.6E9], \quad (16)$$

$$\chi^6 = [0.1, -1.1, 3.3, -5.2, 4.4, -2.0, 0.4, 0, 0.1], \quad (17)$$

$$\chi^7 = [2.5E8, -1.9E9, 5.7E9, -9.0E9, -3.4E9, 7.1E8, 1.6E8]. \quad (18)$$

All rising edges of the output signal from inverse covariance matrix were subtracted from 1, and were given as output for the transfer function estimation block, and the input was an impulse signal of length seven. The block estimates the transfer function based on the given output. The transfer function obtained after estimation is shown in (19). All the methods discussed above were implemented using LabVIEW software.

$$TF_{filter} = \frac{(3.95222s - 2.7374)2.857}{0.0212907s^2 + 1.08348s + 1}. \tag{19}$$

To observe the response of the filter, an impulse input was applied to it, and the response is shown in Fig. 6.

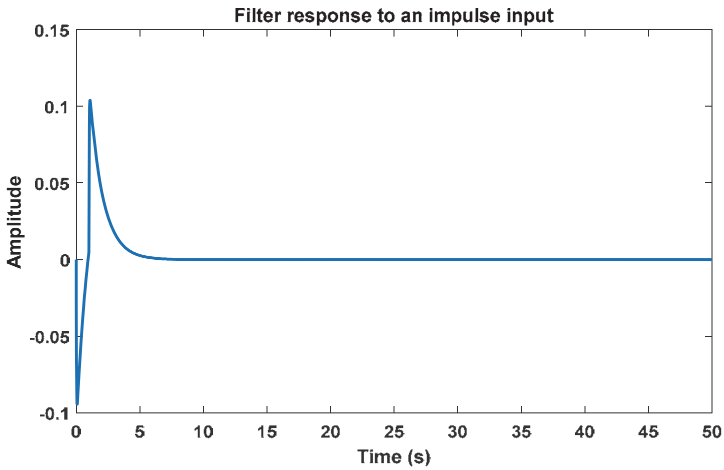


Fig. 6 – *Impulse response of the filter.*

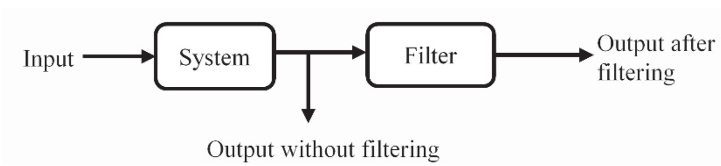


Fig. 7 – *System with filter.*

The derived transfer function was then cascaded (placed in series) with the system transfer function in (3), as shown in Fig. 7. The filter was simulated using Simulink software to remove the inherited noise.

4 Analysis of the Results

Fig. 8 shows the valve response after filtering, both without noise (*i.e.* the response from (1)), and with noise (*i.e.* the response from (2)), for a step input of amplitude one. Figs. 8a and 8b show the response of the valve for random values of 0.9110 and 0.6123, respectively. From the graphs, it can be observed that the valve response with noise gives a very high magnitude compared to the actual response. After cascading the filter with the system containing noise, the filtered response almost tracks the actual system response under noiseless conditions. The filtered response tracks the actual response, whereas the response in the system with noise is strongly deviated. This output was consistently achieved for multiple time samples.

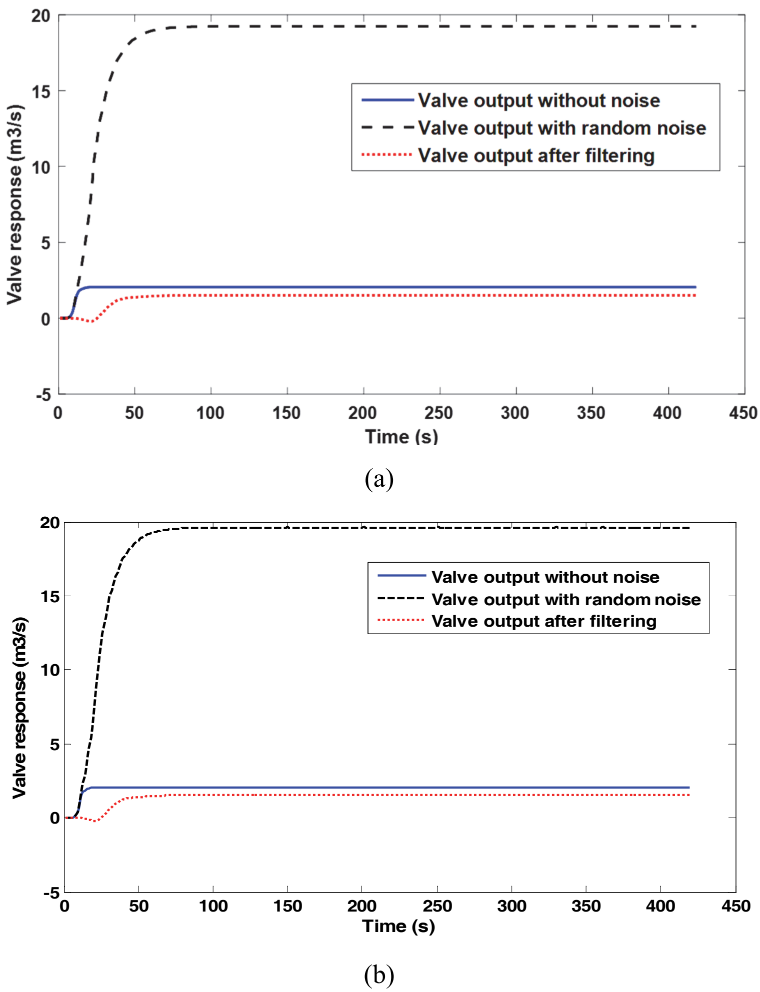
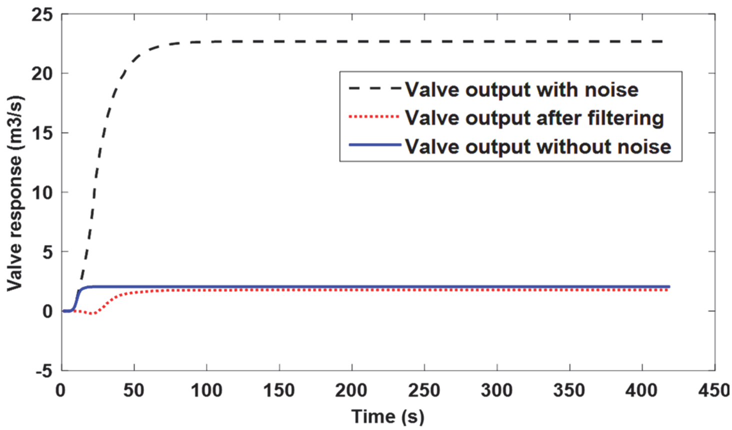
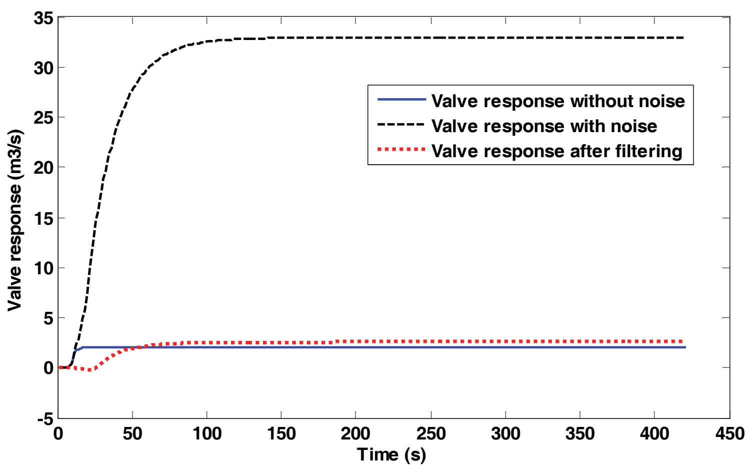


Fig. 8 – *Step response of valve without noise, with noise and with a filtered output, for a system with added random noise.*

To verify the effectiveness of the proposed filter, we multiply the rand function with the constant term of the system transfer function. The step response of the system with and without random noise and the filtered response are depicted in Figs. 9a and 9b. From these figures, it is evident that the filter can also compensate for the noise introduced due to the multiplication of a random function with the constant term of the denominator. Figs. 9a and 9b show the response of the valve for two random values of 0.9110 and 0.6123, respectively. There is a noticeable difference between these two responses, although the filter can maintain the filtered response very close to the actual response. The design of the filter is therefore validated.



(a)



(b)

Fig. 9 – *Step response of valve without noise, with noise and filtered output for a system with multiplied random noise.*

5 Conclusion

In this paper, the estimation and noise cancellation of inherited noise in a pneumatic control valve is carried out based on the concept of temporal data fusion. Data are collected from the sensor at different time instants, and are subjected to a statistical analysis technique involving the calculation of variance. To observe the change in the behaviour of the system due to the inherent noise, the statistical variance between samples at different time intervals was calculated. A disturbance was then introduced by adding a random signal to the constant coefficient of the transfer function, and DTW was used to compensate for this variance. Noise estimation was carried out by applying polynomial and spline interpolation. The rising edge of the inverse covariance matrix was considered, and the transfer function was estimated. This transfer function was cascaded with the actual system transfer function, which gave a good response by nullifying the effect of the inherent noise and making the process accurate. The proposed filter was exposed to noisy data generated by multiplying a random term with the constant term of the system transfer function, and the filter was able to compensate for this noise and to produce a filtered output that tracked the system response without noise. This demonstrates the effectiveness and efficiency of the proposed filter. In most studies in the literature, noise reduction is achieved through a variety of methods for tuning the controller; however, in this paper, an inherent noise reduction filter is designed based on a data fusion process. The process of fusion is mainly achieved through temporal alignment using DTW.

In this study, the noise was assumed to be part of the constant term of the transfer function to start with the process of filtering. This work could be extended by considering noise in any of the coefficients of the system transfer function.

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