Addressing Control in the Presence of Process and Measurement Noise

Application of the Kalman Filter in DeltaV

Presenters

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Introduction

In this workshop we address how the Kalman Filter may be applied in DeltaV to reduce the impact of process or measurement noise.

- Background on Kalman filter, its use in industry
- Design of digital scalar Kalman filter, enhancements
- DeltaV Implementation, commissioning
- Test Results, expected improvement in performance
- Business Results
- Summary
- Where To Get More Information

Kalman Filtering

- A paper published in 1960 by Rudolf Kálmán “A New Approach to Linear Filtering and Prediction Problems” is the basis for the Kalman Filter.
- The Kalman filter uses a dynamics model, measured control input(s) and process measurement(s) to estimate the process output.
- A wide variety of applications have successfully utilized Kalman filtering:
  - The guidance of commercial airplanes
  - Seismic data processing,
  - Nuclear power plant instrumentation,
  - Vehicle navigation and control (e.g. the Apollo vehicle),
  - Radar tracking algorithms for ABM applications
  - Process control

Kalman Filtering (Cont)

- On 7 October 2009 U.S. President Barack Obama honored Kalman in an awards ceremony at the White House when he presented him with the National Medal of Science, the highest honor the United States can give for scientific achievement.
- The Kalman filter has played a vital role in the implementation of the navigation systems used in U.S. Navy nuclear ballistic missile submarines, cruise missiles such as the U.S. Navy's Tomahawk missile , NASA Space Shuttle and the International Space Station

Implementation Challenges

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The Discrete Kalman Filter

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1},$$

$$z_k = Hx_k + v_k.$$

$$p(w) \sim N(0, Q),$$

$$p(v) \sim N(0, R).$$

$$e_k^- \equiv x_k - \hat{x}_k^-, \text{ and}$$

$$e_k \equiv x_k - \hat{x}_k.$$

$$P_k^- = E[e_k^- e_k^{-T}]$$

$$P_k = E[e_k e_k^T].$$

$$\hat{x}_k = \hat{x}_k^- + K(z_k - H\hat{x}_k^-)$$

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$$

x is state estimate

z measurement noise

w_k process noise

Q *process noise covariance*

R *measurement noise covariance*

A $n \times n$ matrix relates the state at the previous time step $k-1$ to the state at the current step k

B $n \times l$ matrix relates the optional control input u to the state x.

H $m \times n$ matrix relates the state to the measurement z_k.

$\hat{x}_k^-$ *a priori* state estimate at step k

$\hat{x}_k$ *a posteriori* state estimate at step

P_k^- *a priori* estimate error covariance

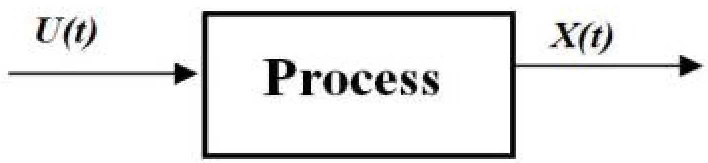
P_k *a posteriori* estimate error covariance

K $n \times m$ matrix *gain* or *blending factor* that minimizes the *a posteriori* error covariance

$$\lim_{R_k \to 0} K_k = H^{-1} \qquad \lim_{P_k^- \to 0} K_k = 0$$

- The complexity of the Kalman Filter algorithm may be a barrier in implementation
- Original design addressed a general multi-variant environment
- Process and measurement noise covariance may not be known in many industrial application.

Scalar Kalman Filter



$$X_j = aX_{j-1} + bU_j$$

where

X_j = *Process Output at time j*

U_j = *Process Input at time j*

a *and* b = *constants defining the process gain and dynamic response*

- Many industrial process units are characterized by one manipulated input, U(t), and one measured process output, X(t). The scalar Kalman Filter addresses these applications and is easier to understand and implement.
- The model of a liner process with one manipulated input and one measured process output may be expressed in state variable format.

Example - State Variable Representation

A first order process may be expressed in this format where:

$$a = e^{\frac{-\Delta T}{\tau}} \qquad b = K\left(1 - e^{\frac{-\Delta T}{\tau}}\right)$$

$$K = Process\ Gain$$

$$\tau = Process\ Time\ Constant$$

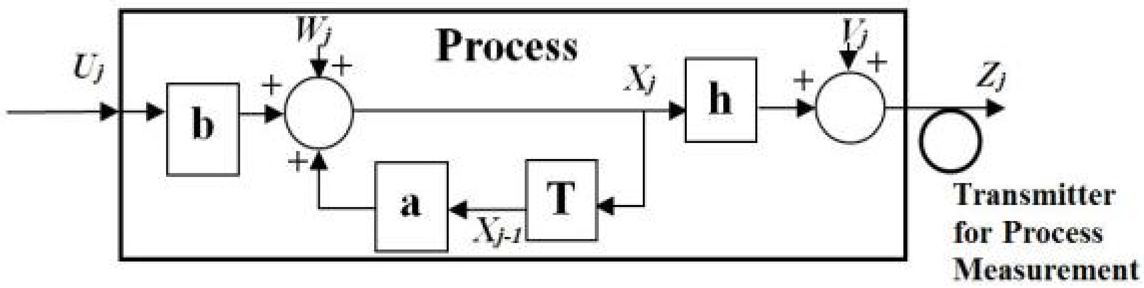
$$\Delta T = Period\ of\ Execution\ of\ the\ process\ model$$

$$j = Current\ time\ instance$$

An integration process may also be expressed in this format:

$$a = 1 \qquad b = \Delta T * K_I$$

General Process Representation



where

W_j = *Process Noise. Assumed to be white noise with zero mean with* ***covariance Q*** *and is uncorrelated with the input.*

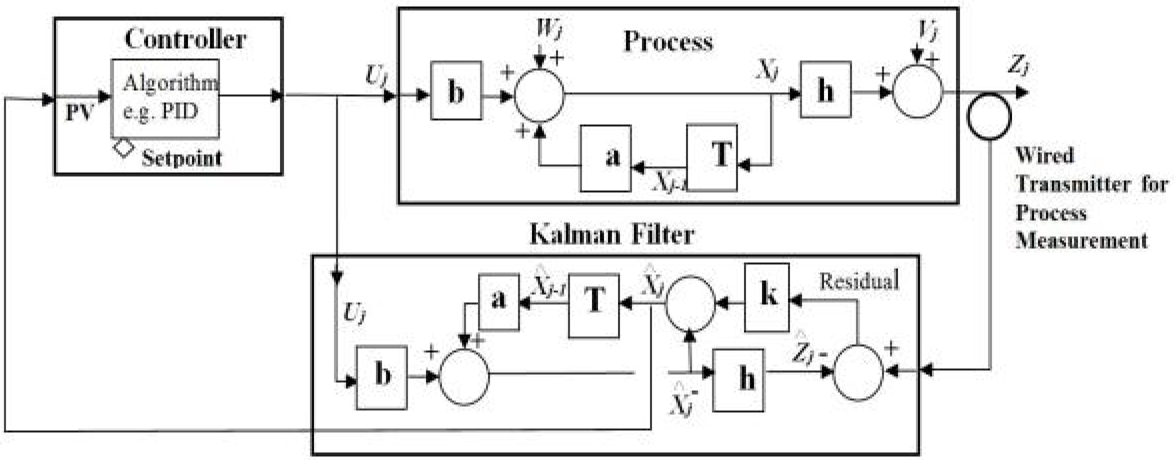
V_j = *Measurement Noise. Assumed to be white noise with zero mean with* ***covariance R*** *and is uncorrelated with the input or with the noise* W_j.

h = *gain associate with units conversion*

T = *one unit of delay*

- The Kalman filter is based on the assumption that the process and measurement noise have **zero mean.**
- Later we will see the impact of this assumption and the way the Kalman filter can be modified to accommodate a non-zero mean (common in process industry control applications)

Application of Kalman Filter with PID



Where:

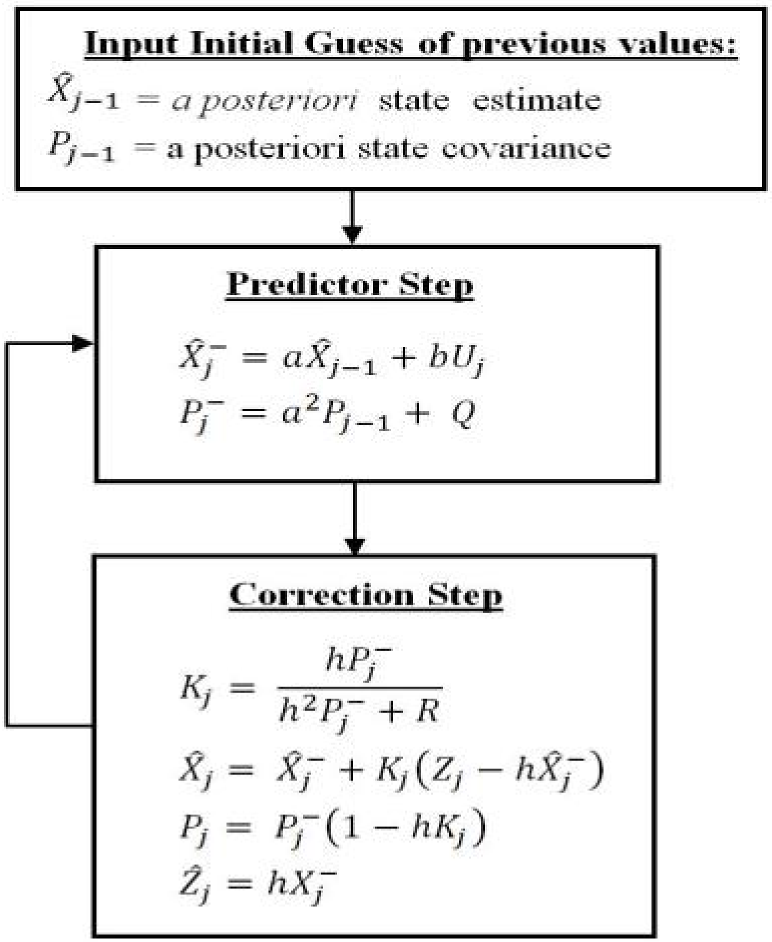
$\hat{X}_j^-$ = the *a priori* estimate of the state

$\hat{X}_j$ = the estimate of the state

$\hat{Z}_j$ = the estimate of the output

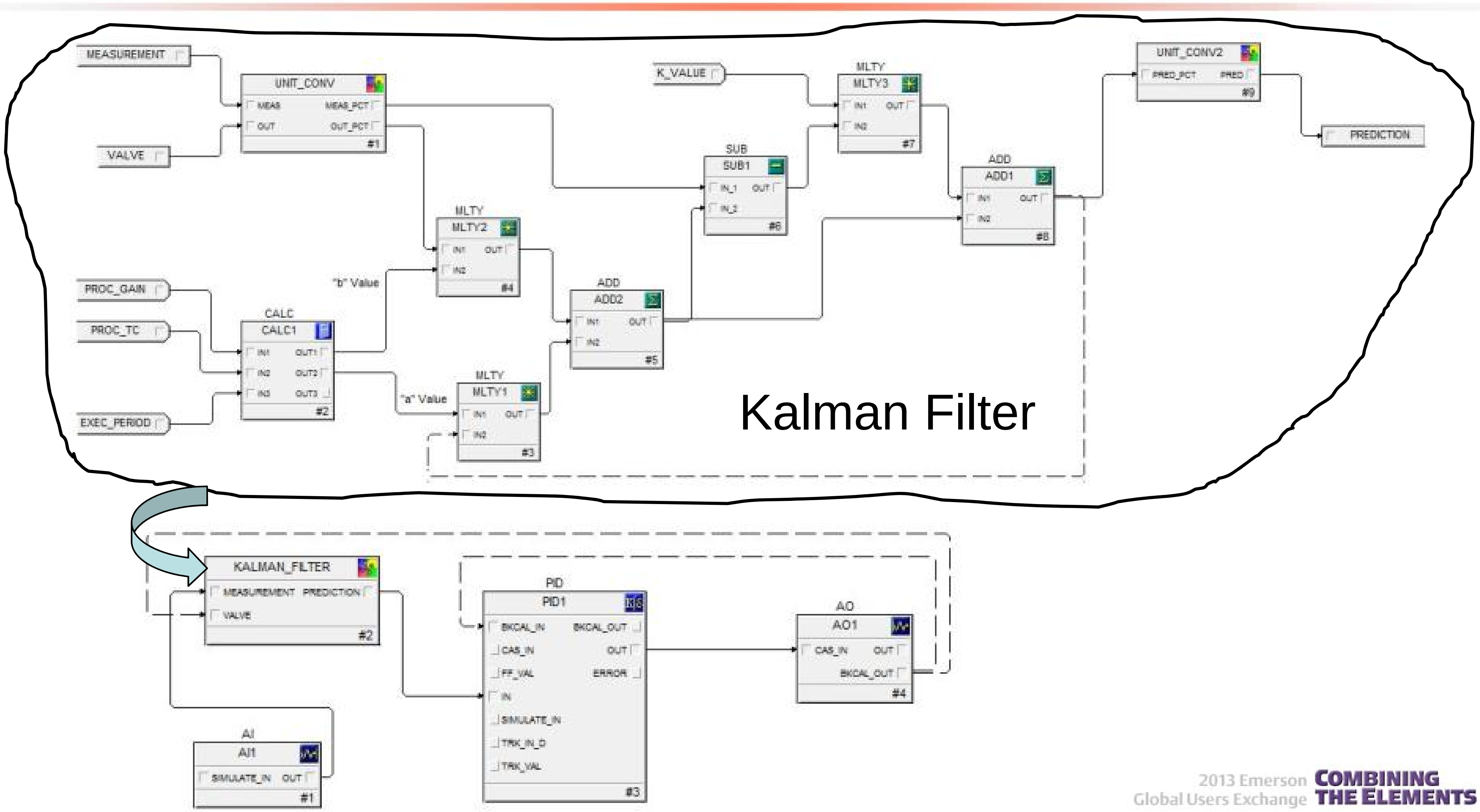
- For the case where input and output are in % of scale then h=1.
- If process gain and dynamics are known then only the Kalman gain, K, must be calculated.

Kalman Gain Calculation

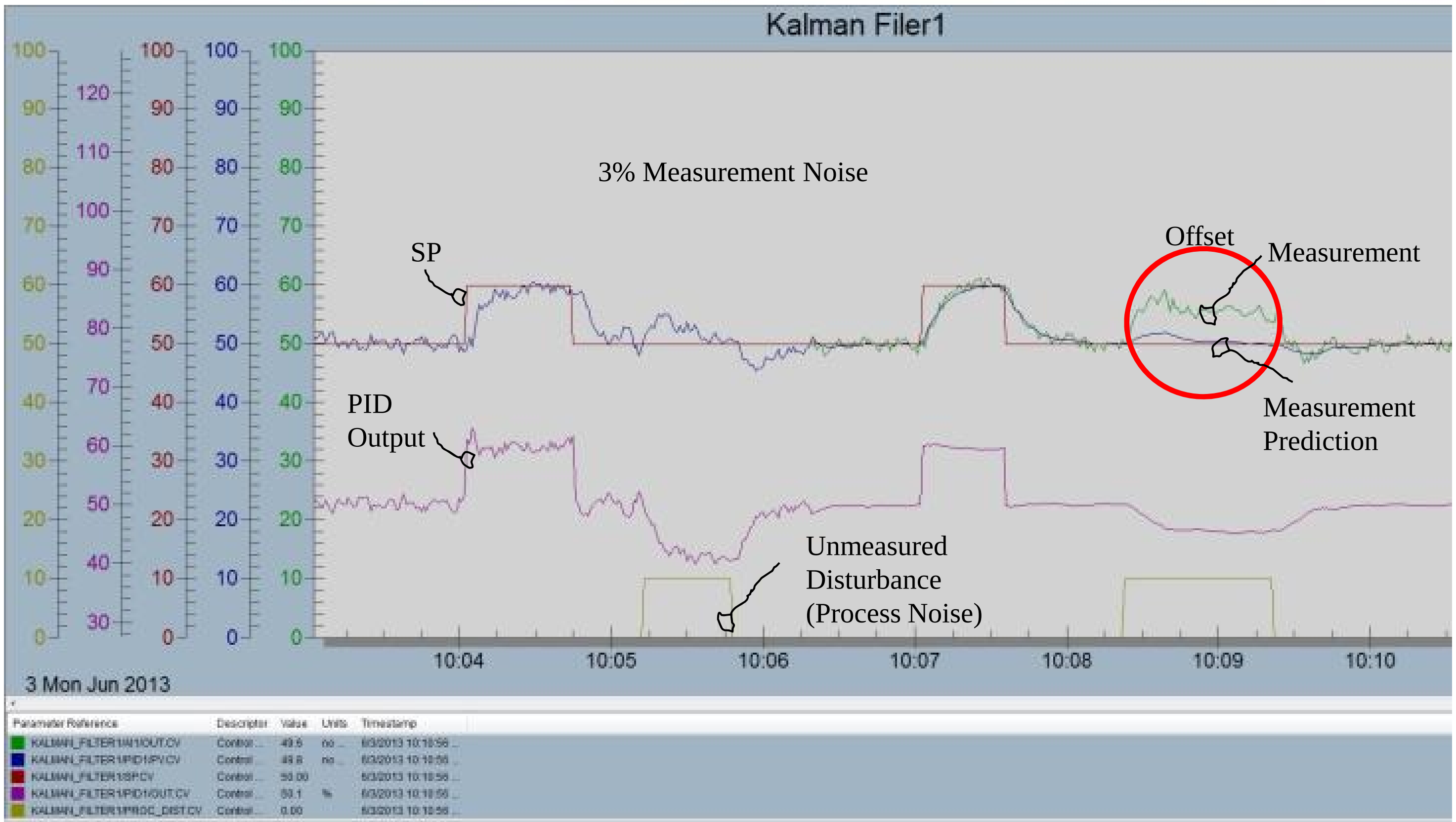


- If the process and measurement noise covariance are assumed to be constant, then K is a constant.
- When the measurement noise is negligible then the Kalman gain, K = 1/h
- Thus, <u>K may be implemented as a tuning parameter</u> that is adjusted by the user (rather than being calculated)

Kalman Filter - DeltaV Implementation



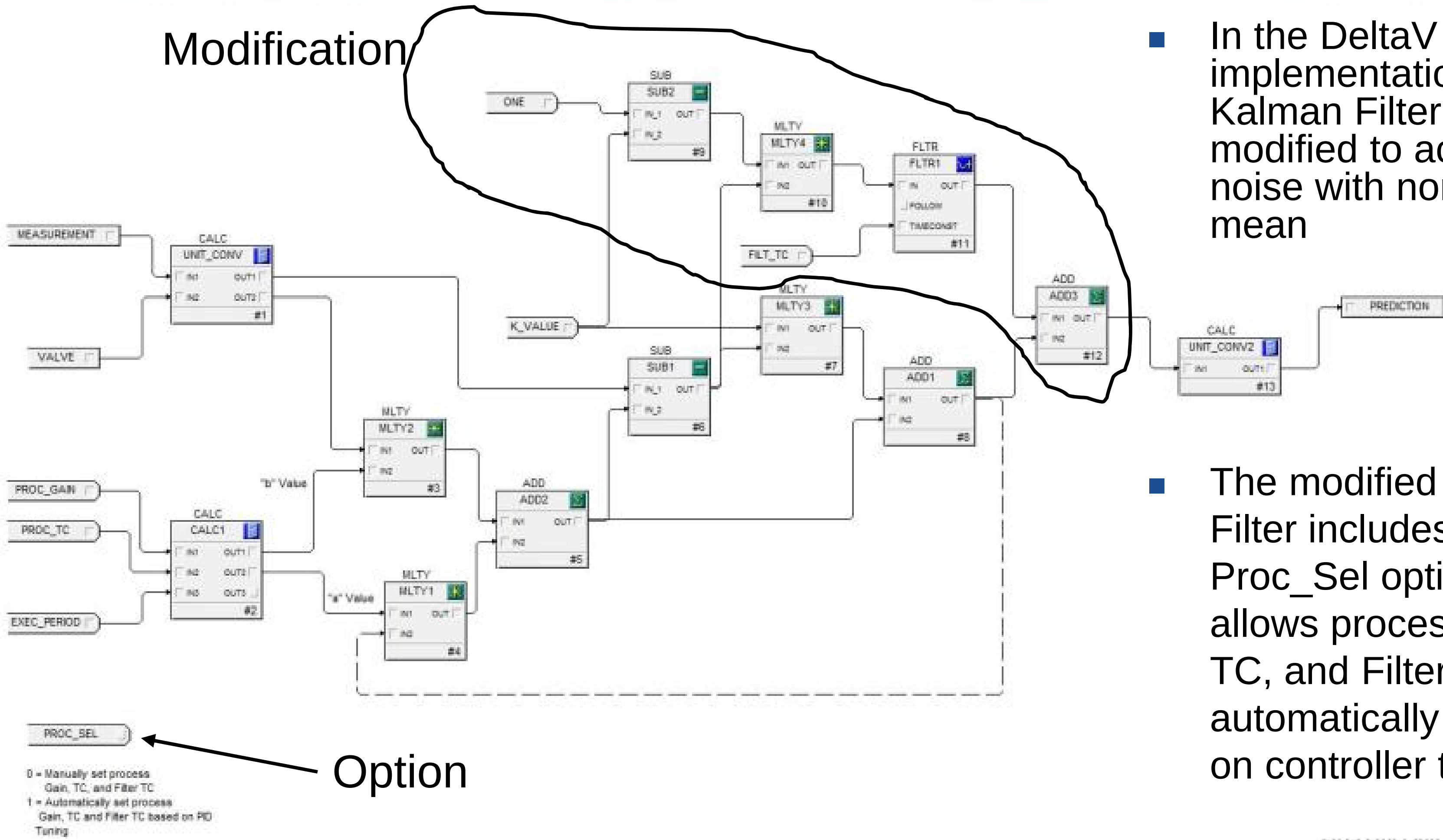
Kalman Filter Performance



← Kalman Gain = 1 →← Kalman Gain = 0.05 →

- Attenuation of process noise is provided by adjusting Kalman Gain
- Process noise with non-zero mean causes an offset in predicted and actual measurement value for Kalman gain values of K<1.

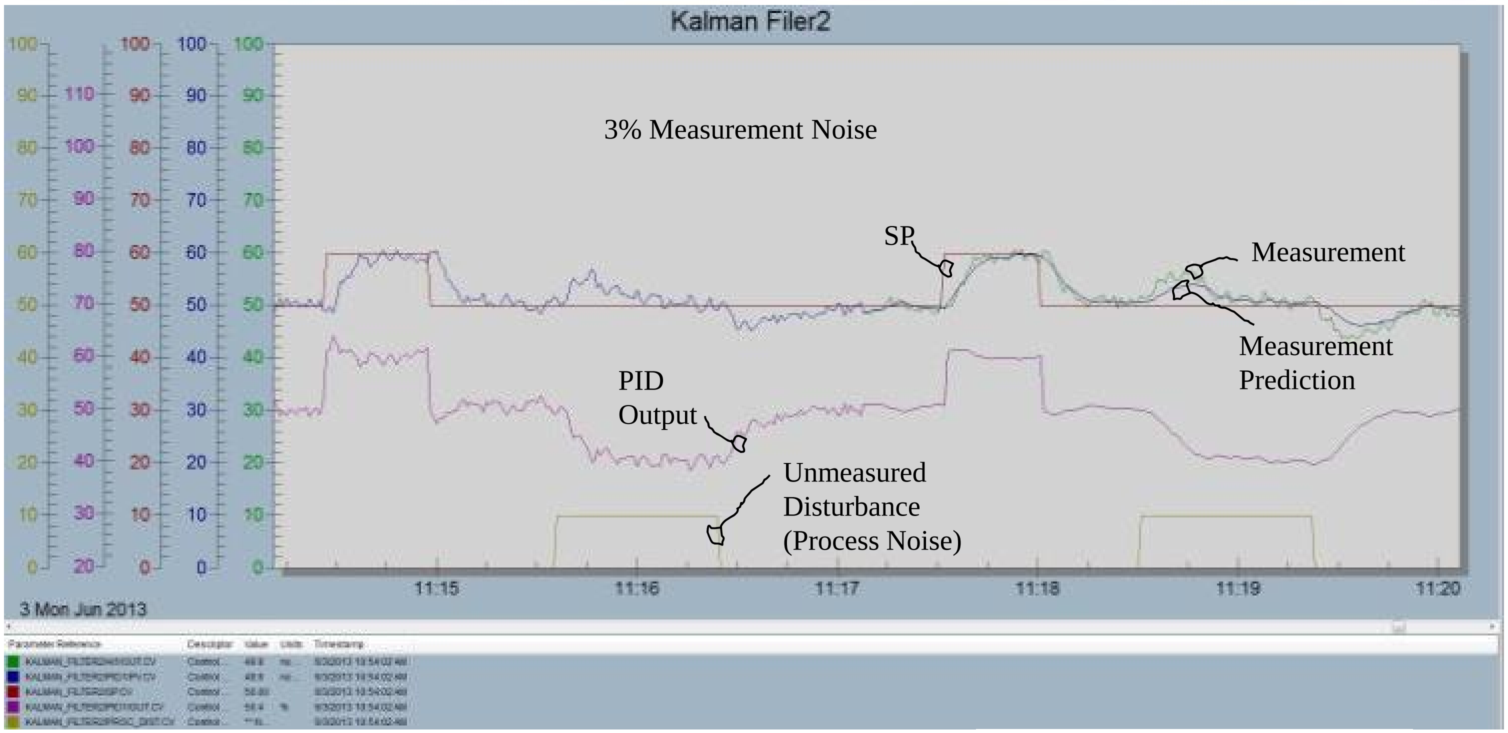
Modified Kalman Filter



- In the DeltaV implementation, the Kalman Filter has been modified to account for noise with non-zero mean

- The modified Kalman Filter includes a Proc_Sel option that allows process gain, TC, and Filter TC to be automatically set based on controller tuning

Modified Kalman Filter Performance



← Kalman Gain = 1 →← Kalman Gain = 0.05 →

- Attenuation of process noise is provided by adjusting Kalman Filter Gain
- Process noise with non-zero mean is fully addressed i.e. no off-set as observed with the standard Kalman filter

Kalman Filtering vs DeltaV PV Filtering

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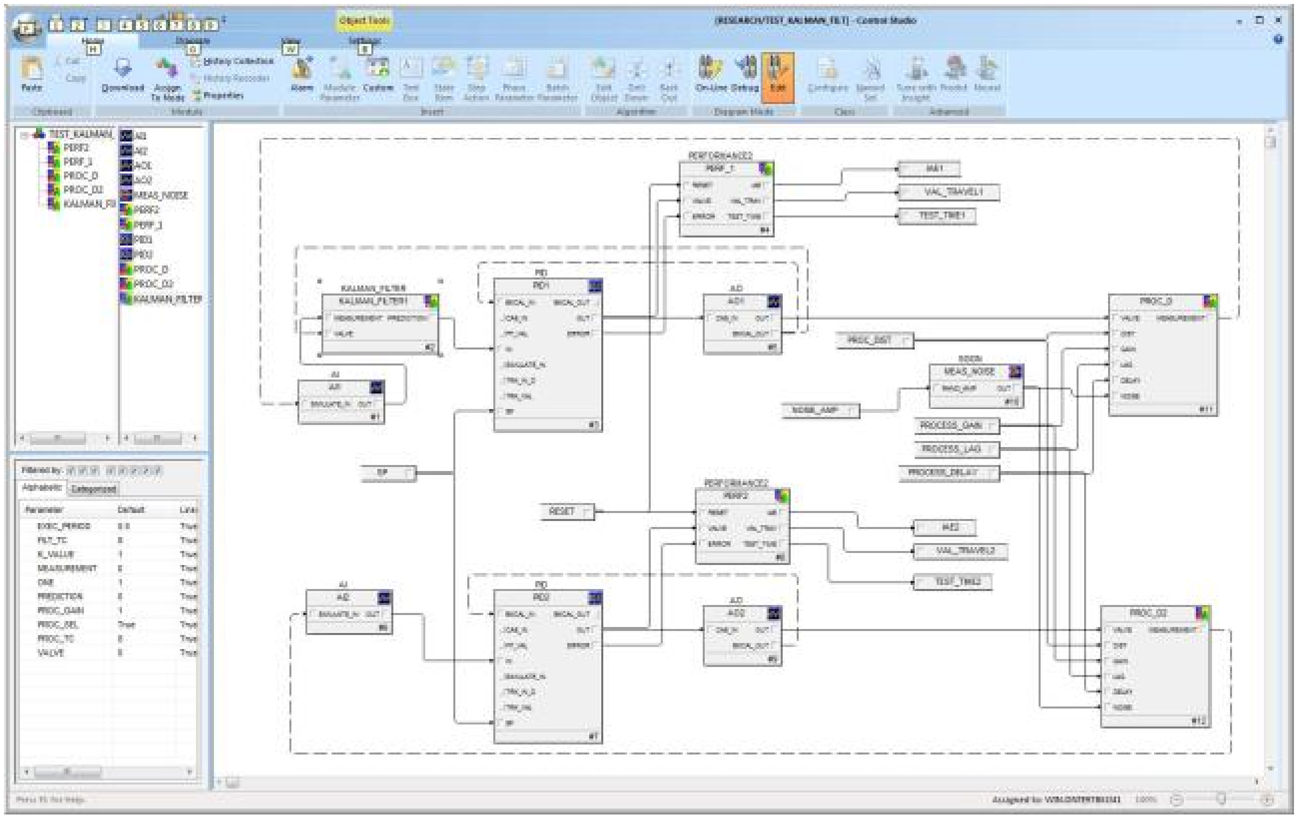
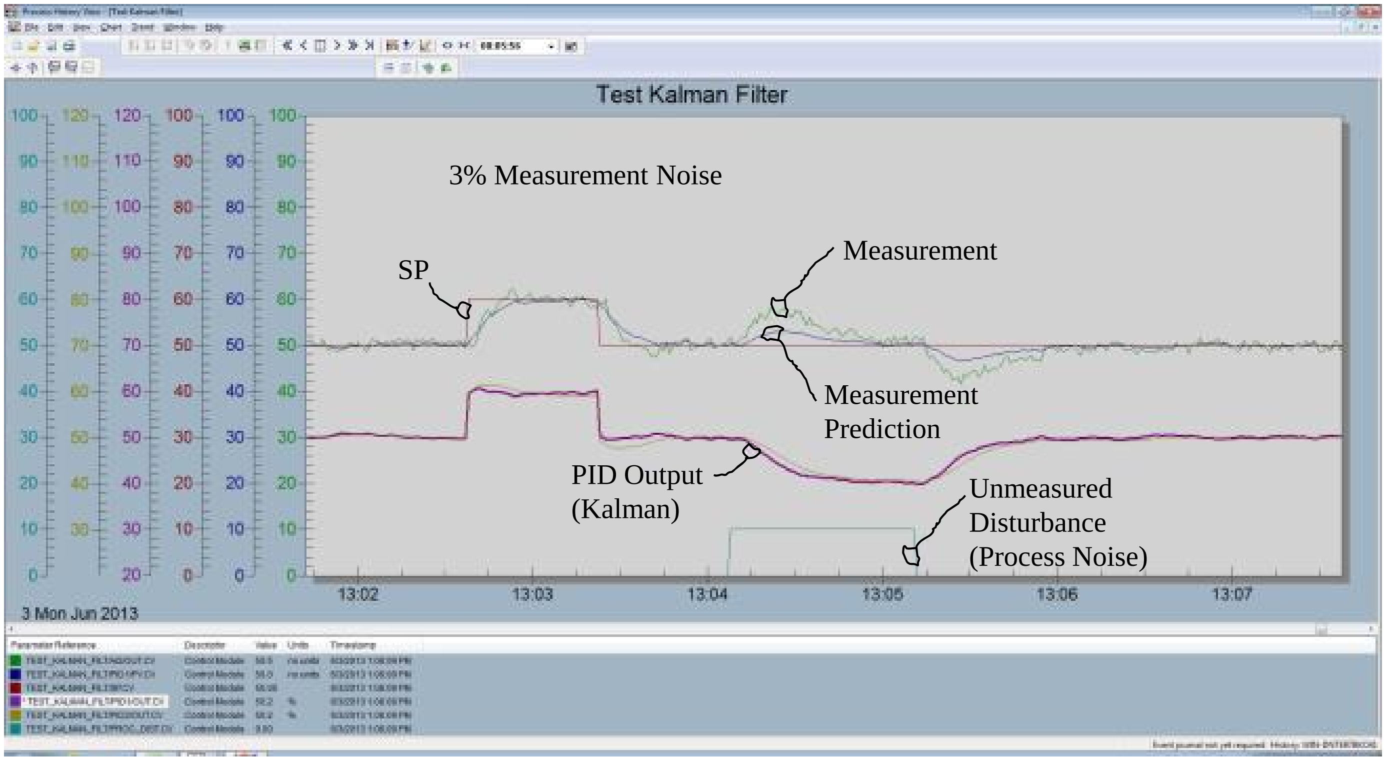


- A test module was created to compare PID control performance (IAE and total valve travel) using the Kalman Filter vs PID with PV filtering
- In this test module, measurement and process noise may be injected into the simulated process
- Default Process: Gain = 1, TC = 6 sec, DT = 2 sec

Example – Performance Test



- Kalman Gain = 0.05, filter TC =16
- PID PV filter TC = 16sec, Reset = 18 sec
- Process gain = 1, TC =6 sec, DT = 2 sec

Test Results

- The test results show the modified Kalman filter provides approximately a 2X reduction in variation (as measured by IAE) over control based on PID with PV filter.
- Improvement stems from the fact that when the Kalman filter is used, the PID tuning is based only on the process dynamics and gain. When PV filtering is used then the PID reset must be modified to account for the slower response seen by the PID as a result of the PV filter.

					PID – Kalman Filter		PID – PV Filter	
Test	PV Filter (sec)	Kalman Filter (sec)	Process Gain	Duration (sec)	IAE	Valve Travel (%)	IAE	Valve Travel (%)
1	0	8	1	91	143	70	320	167
2	8	8	1	102	140	69	232	62
3	16	16	1	95	133	58	302	50
4	8	8	0.7	100	162	69	276	58
5	16	16	0.7	109	156	59	356	48

PID Tuning: Gain = 1, Reset = Process TC + Process DT + PV Filter TC

Kalman Gain = 0.05

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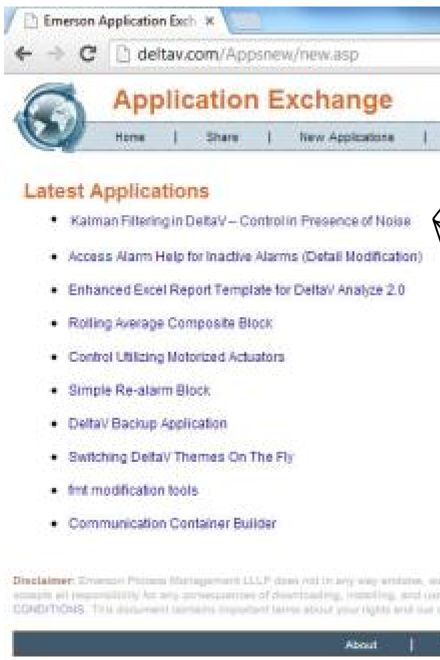
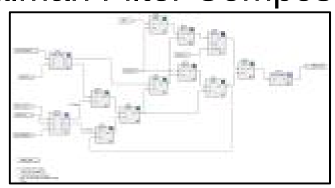
Applying Kalman Filtering in DeltaV



Documentation

Kalman Filter Composite



Module for Testing/Demo

Trend for Testing/Demo

- The Kalman Filter composite, documentation, a test module and plot are available through Application Exchange.
- The composite and test module may be utilized in any version of DeltaV.
- The documentation provides detailed information on the background, design, implementation and the test module and tend for demonstrating and testing this capability.

Business Results Achieved

- When a process is characterized by significant process or measurement noise then the kalman filter may be used with the PID to reduce variation in the controlled parameter by a factor of 2X over the application of PV filtering.
- In many application the reduction in variation achieved using the Kalman filter leads to:
  - Less off-spec product, product may be more easily maintained within specification.
  - Greater throughput when production is limited by operating constraints, by operating closer to the constraint limit.

Summary

- A DeltaV composite for the implementation of a scalar Kalman filter is freely available through the Application Exchange. The composite may be imported into any DeltaV version.
- In the DeltaV implementation, the Kalman filter accounts for process noise that is characterized by non-zero mean.
- The Kalman filter composite is designed to work with the DeltaV PID block. When the PROC_SEL option is selected (value of 1) , then only the user must only adjust Kalman gain.
- A module and trend are available in Application Exchange that may be used to demonstrate and test the modified Kalman filter.

Where To Get More Information

- Workshop 12-4381, Emerson Exchange 2013, Nixon and Blevins, “Control Using Wireless Measurements” (Using Kalman Filter)
- E. Cheever. “Introduction to Kalman Filter”, http://www.swarthmore.edu/NatSci/echeeve1/Ref/Kalman/ScalarKalman.html
- Application Exchange, “Kalman Filtering in DeltaV – Control in the Presence of Noise”, http://www2.emersonprocess.com/en-US/brands/deltav/interactive/Pages/Interactive.aspx

Thank You for Attending!

Enjoy the rest of the conference.

COMBINING THE ELEMENTS

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