Kalman Filtering in DeltaV

Addressing Control in Presence of Process and Measurement Noise

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1 Introduction

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

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.

Figure 1 - Kalman at the White House

The complexity of the Kalman filter algorithm is often a barrier in the application of this filtering technique in the process industry. The original Kalman filter was designed to address a general multi-variant environment where the process and measurement noise covariance are known or may be calculated.

In this paper we address the implementation of a scalar Kalman Filter for use in closed loop control of industrial process that is characterized by one manipulated input and one controlled parameter. A DeltaV linked composite is described that allows Kalman filtering to be used with the PID block in closed loop control. Also, information is provided on a DeltaV module that may be used to get more familiar with the Kalman filter in a test environment. The Kalman Filter composite and test module may be accessed through application exchange at the DeltaV Interactive Portal
– see http://www2.emersonprocess.com/en-US/brands/deltav/interactive/Pages/Interactive.aspx .

2 Background – Process Modeling

The Kalman filter is based on the fact that a model of the process may be constructed. For example, many industrial process unit are characterize by one manipulated input, U(t), and one measured process output, X(t), as illustrated below.

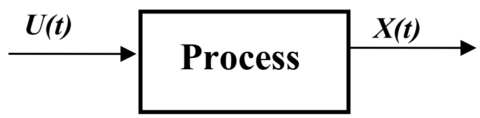

Figure 2 - Industrial Process

The model of a liner processes with one manipulated input and one measured process output may be expressed in state variable format as:

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

where

$$X_j = Process\ Output\ at\ time\ j$$

$$U_j = Process\ Input\ at\ time\ j$$

$$a\ and\ b = \ constants\ defining\ the\ process\ gain\ and\ dynamic\ response$$

For example, the state variable representation of a first order process may be expressed in this format where:

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

$$K = Process\ Gain$$

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

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

$$j = Current\ time\ instance$$

For an integrating process, the state variable representation of a first order process may be expressed in this format where:

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

When process and measurement noise and the process measurement units are taken into account, a general representation of a process may be illustrated as shown below.

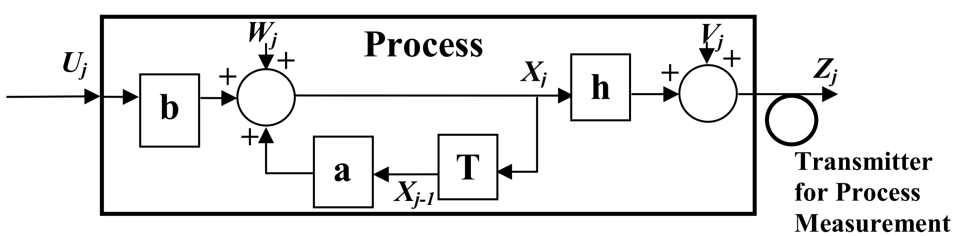

Figure 3 - Process Representation

where
$W_j = Process\ Noise.\ Assumed\ to\ be\ white\ noise\ with\ zero\ mean\ with\ \boldsymbol{covariance\ Q}$
$and\ is\ uncorrelated\ with\ the\ input.$

$V_j =$
$Measurement\ Noise.\ Assumed\ to\ be\ white\ noise\ with\ zero\ mean\ with\ \boldsymbol{covariance\ R}$
$and\ is\ uncorrelated\ with\ the\ input\ or\ with\ the\ noise\ W_j.$

$h = gain\ associate\ with\ units\ conversion$

$T = one\ unit\ of\ delay$

3 Kalman Filter

When a process is characterized by process or measurement noise then a Kalman filter may be applied to estimate the process output measurement. The impact of process or measurement noise on a control application may be reduced by utilizing the estimated process output for control as illustrated below.

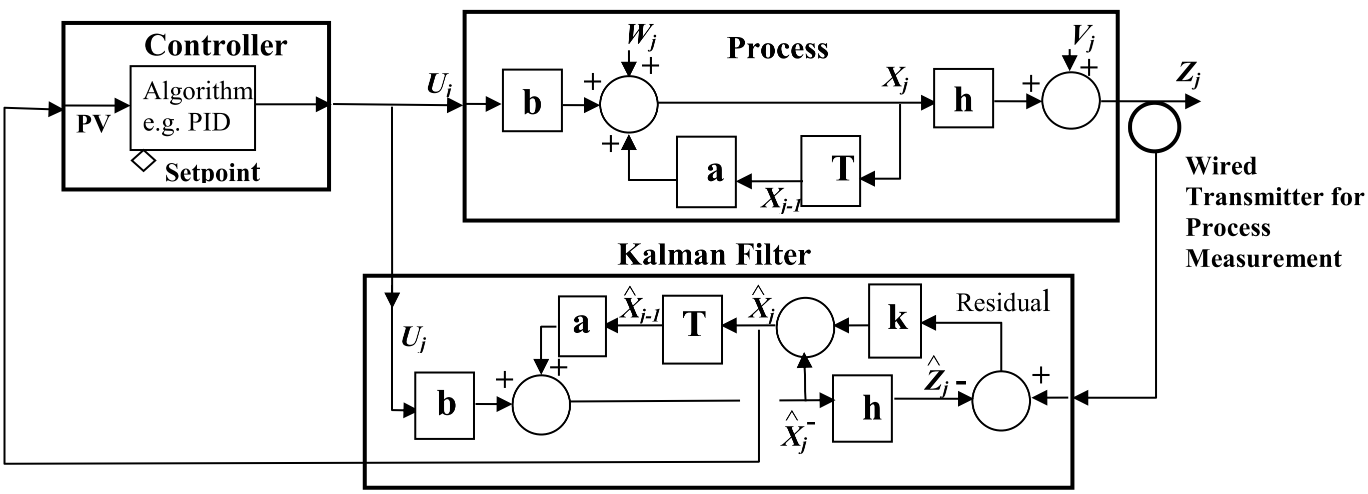

Figure 4 - Kalman Filter in Control Application

Where

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

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

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

As illustrated above, the Kalman filter includes a model of the process without process or measurement noise. In addition, the difference between the estimated process output, $\hat{Z}_i$, the measured process output , is calculated as the residual - also known as the innovation. The

Kalman gain, K, determines what portion of the residual is used in the Kalman filter model to compensate for accuracies in a, b, or h and to account for the process or measurement noise.

As is well documented in the literature, an optimal linear estimator may be achieved by dynamically calculating the Kalman gain in a recursive manner as shown below:

Input Initial Guess of previous values:

$\hat{X}_{j-1}$ = *a posteriori* state estimate

P_{j-1} = a posteriori state covariance

↓

Predictor Step

$$\hat{X}_j^- = a\hat{X}_{j-1} + bU_j$$

$$P_j^- = a^2 P_{j-1} + Q$$

↓

Correction Step

$$K_j = \frac{hP_j^-}{h^2 P_j^- + R}$$

$$\hat{X}_j = \hat{X}_j^- + K_j\left(Z_j - h\hat{X}_j^-\right)$$

$$P_j = P_j^-\left(1 - hK_j\right)$$

$$\hat{Z}_j = hX_j^-$$

Figure 5 - Dynamic calculation of Kalman gain

However, the Kalman gain may be assumed to be a constant if the covariances of the process and measurement noise are assumed to be constant. Thus, the Kalman gain in implemented as a tunable parameter in the DeltaV Kalman filter composite. The user may adjust the Kalman gain to achieve best control performance. The Kalman gain is defined to have a value of 0-1. A Kalman gain of 1 provides no filtering of the measurement used in control. A value of 0 means that the measurement prediction is only based on the process model i.e. the measurement value is not utilized.

4 Kalman Filter Modifications

The design of the Kalman filter assumes the process and measurement noise may be characterized as white noise with zero mean. If the mean value of the process and measurement noise is non-zero then for Kalman gain values less than one (1) an offset will be observed between the predicted value of the measurement and the actual measurement value as illustrate below.

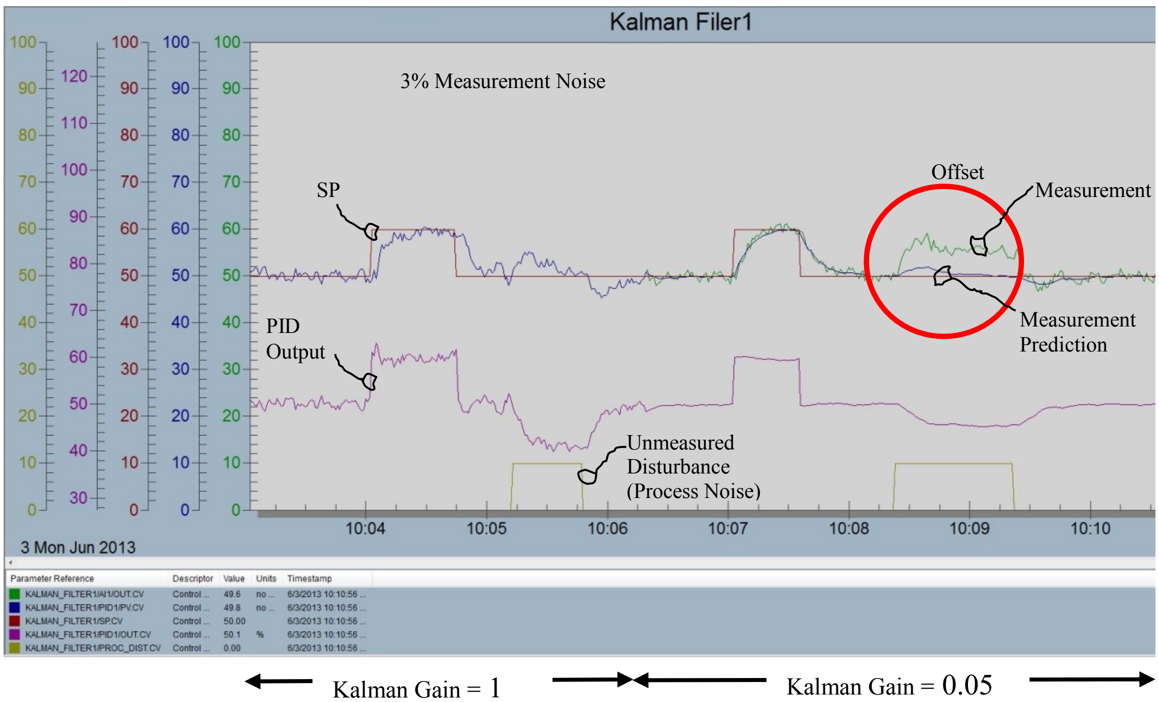

Figure 6 - Kalman Filter Response

The Kalman filter may be modified to allow the predicted measurement to correctly compensate for noise with a non-zero mean. In the following figure the required changes in the Kalman filter are shown.

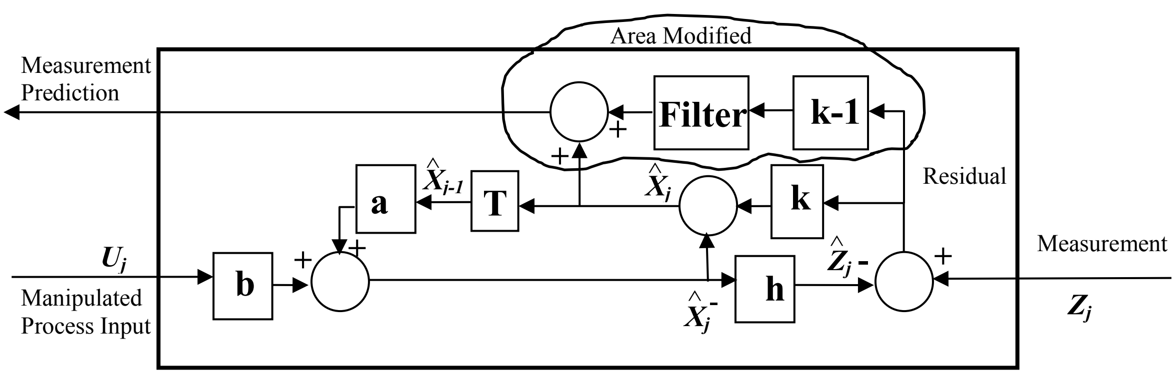

Figure 7 - Modified Kalman Filter

A first order filter acting on the calculated residual is added to the measurement prediction. The filter time constant is adjustable but it is recommended that it be set equal to the controller reset time. The improved performance of the modified Kalman filter is illustrated below.

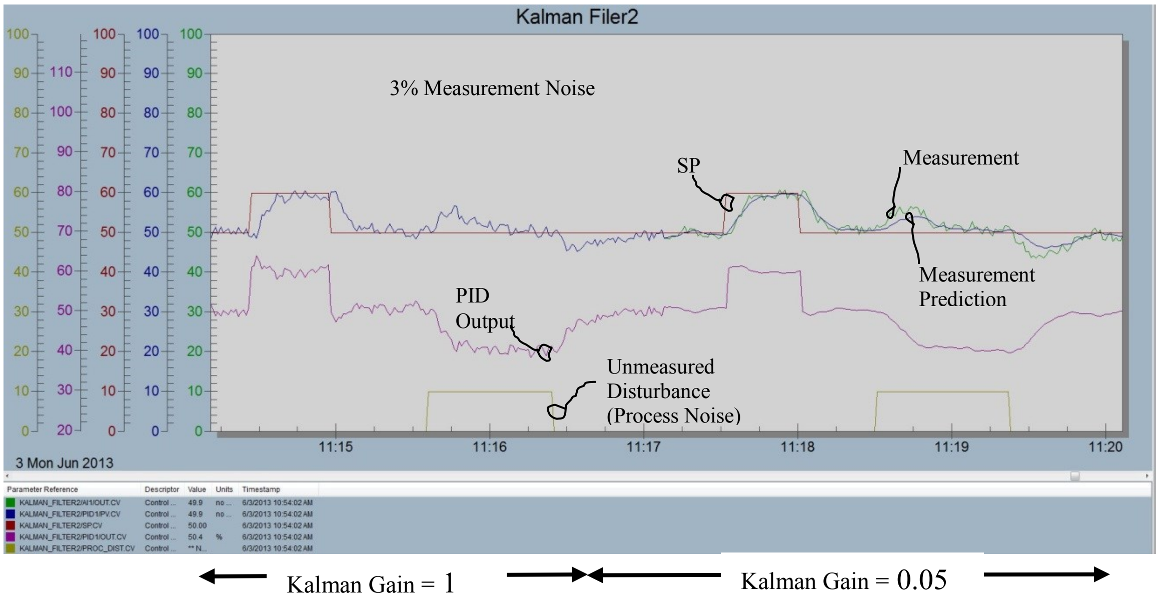

Figure 8 - Modified Kalman Filter Response

5 Kalman Filter Implementation in DeltaV

A linked composite block, KALMAN_FILTER, has been created that may be used with the PID function blocks for control of processes that are characterized by measurement or process noise. An example of the how this composite may be incorporated into a DeltaV module with the PID function block is shown below.

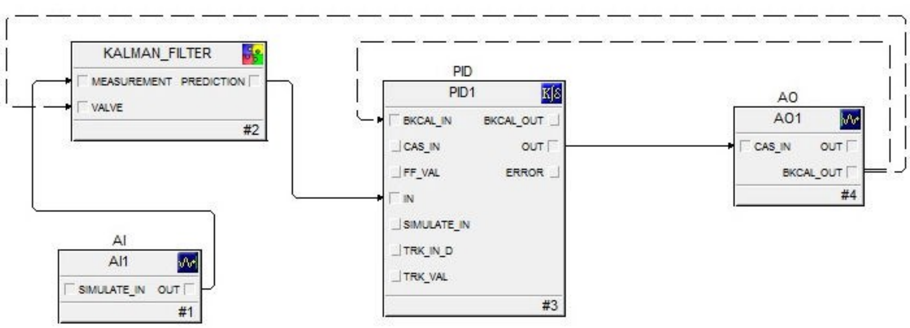

Figure 9 - Example – Kalman Filter Use with PID Function Block

The structure of the KALMAN_FILTER composite is illustrated below.

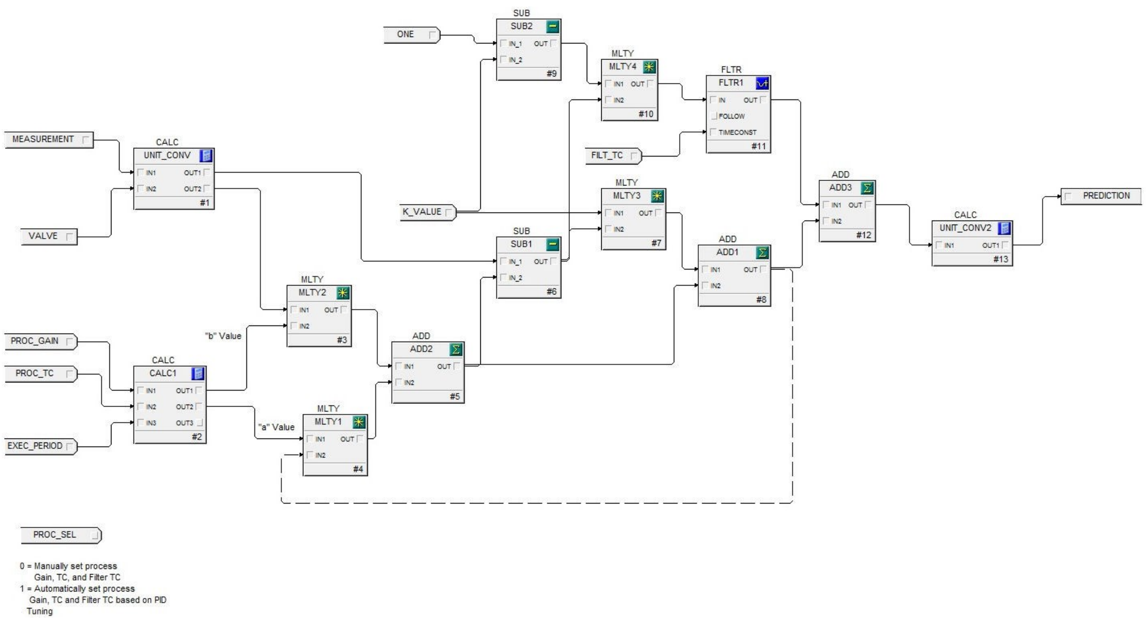

Figure 10 - Kalman Filter Composite

When using the Kalman filter composite, it is necessary to configure the following parameters:

- PROC_GAIN – The gain of the process
- PROC_TC – The time constant of the process (sec)
- EXEC_PERIOD – The execution period of the control module (sec)
- FILT_TC – The time constant of the filter used in the modified Kalman filter (sec)

When the parameter PROC_SEL is set to a value of one(1) then the CALC1 block will automatically set the process gain, time constant and the filter time constant based on the PID gain and reset.

The Kalman Filter composite may be downloaded from DeltaV Interactive Portal, Application Exchange:
– see http://www2.emersonprocess.com/en-US/brands/deltav/interactive/Pages/Interactive.aspx .

Note: The calculation blocks in the Kalman composite are designed to access PID parameters based on the PID function block instance name being PID1. When using the Kalman filter composites with the PID block, the standard PID dynamo will show the PV of the PID block i.e. the predicted measurement value. The PID dynamo should be modified to show both the measurement and predicted measurement values.

6 Test Results

The test module documented in section 7 was used to demonstrate how a Kalman filter may be used with a PID controller in closed loop control. Control performance is compared to a PI controller with PV filtering.

The process used for this comparison was a first order plus deadtime process with the following characteristics:

Process Gain = 1

Process Time Constant = 6 sec

Process Deadtime = 2 sec

The PI controller with the Kalman filtering was tuned for a lambda factor of 1.

GAIN = 1/Process Gain

RESET = Process Time Constant + Process Deadtime

The process input and output were scaled 0-100%. Thus, h = 1 in these examples. For these tests the Kalman gain was set to 0.05. The module execution rate was set at 0.5 sec.

6.1 Kalman Filter Results

The test results achieve using a modified Kalman filter with a PID controller and PID with filtered PV is summarized in the following table.

					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

Table 1 - Test Results

The modified Kalman filter provides approximately a 2X reduction in variation (as measured by IAE) over control based on PID with PV filter. This improvement stems from the fact that when using the Kalman filter the PID tuning is based only on the process dynamics and gain. However, when PV filtering is used the PID reset must be modified to account for the slower response from process plus filter.

The same changes in setpoint and unmeasured disturbance were applied for all test cases. Test were conducted for various filter setting and also where the process gain was reduced (without changing PID tuning) from 1 to 0.7. Below is a trend showing the steps introduced in testing.

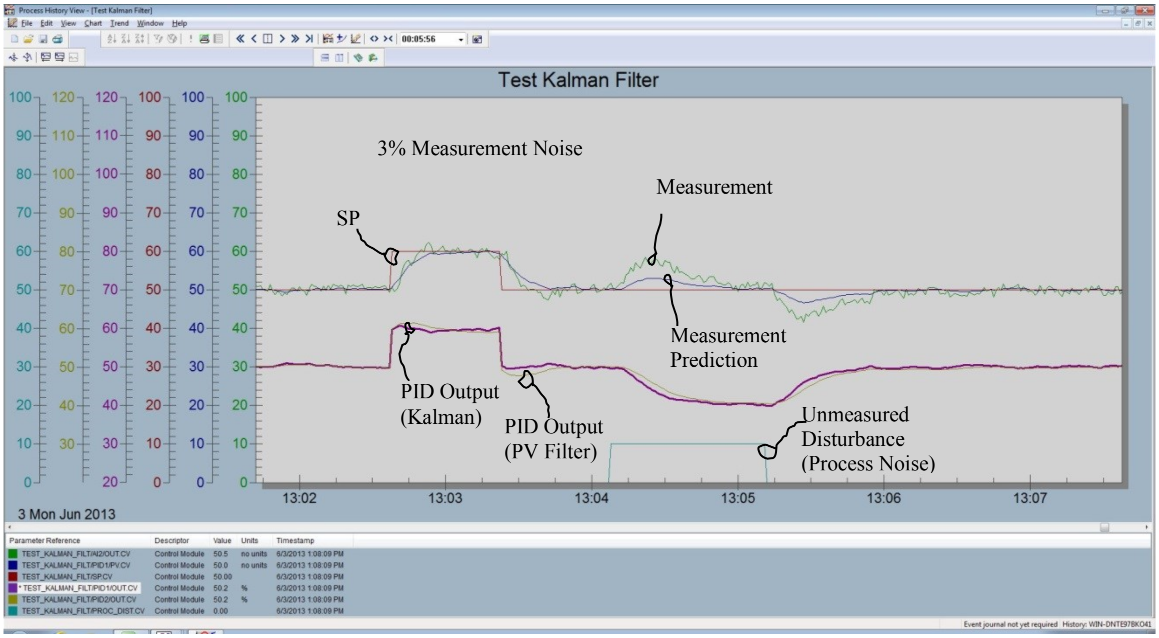

Figure 11 - Example Trend - PID with modified Kalman filter vs. PID with filtered PV

7 Test and Demonstrating Kalman Filter

The tests summarized section 6 of this report were conducted using the Kalman Filter test module. This module allows the PID control performance using Kalman filter to be compared to PID control using a PV filtering. The module is designed to allow setpoint changes to be introduced at the same time into both controllers. Also, changes in the measurement and process noise may be introduced at the same time into both of the associated processes. This module for testing and demonstrating the Kalman Filter are documented in this section.

The Kalman Filter test module and associated trend may be downloaded at the DeltaV Interactive Portal, Application Exchange:

– see http://www2.emersonprocess.com/en-US/brands/deltav/interactive/Pages/Interactive.aspx .

7.1 Test Module - Kalman Filter

The module TEST_KALMAN_FILT shown below allows PID control using the Kalman filter to be compared to PID control using PV filtering.

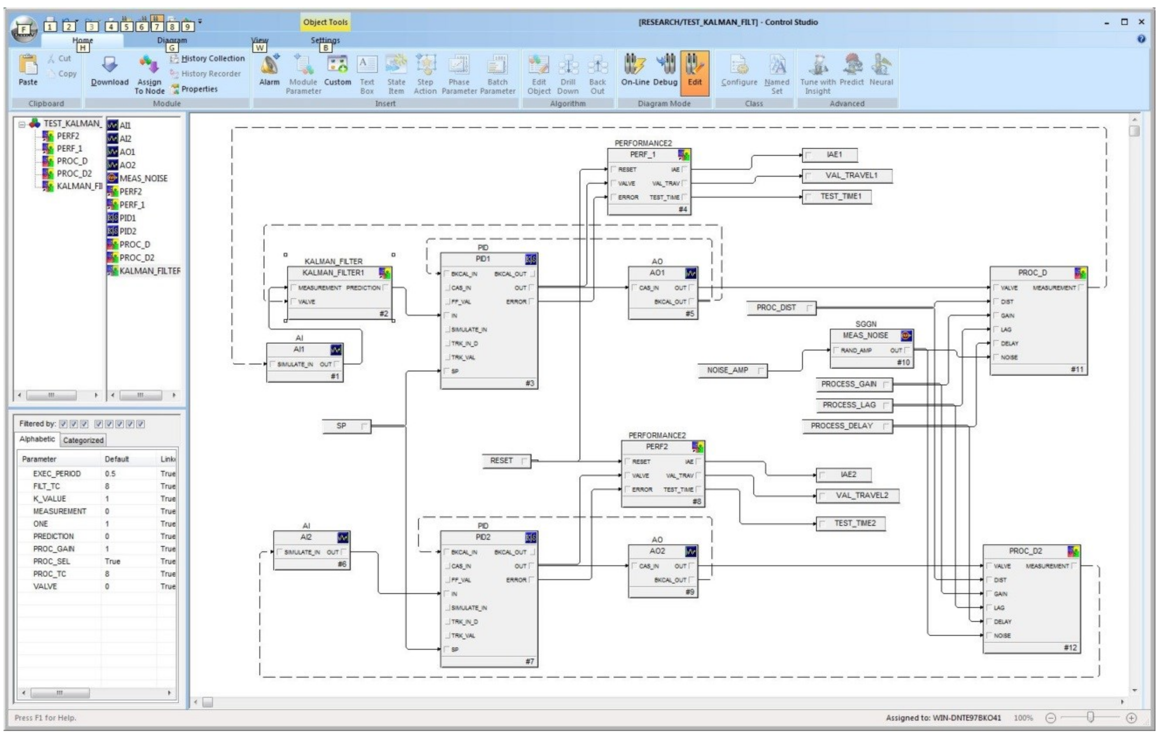

Figure 12 - Test Module

Parallel first order plus deadtime processes with PID control are simulated in this module. The amplitude of the process and measurement noise introduced into each process may be specified using the PROC_DIST and NOISE_AMP parameters respectively. Control performance as measured by Integral of Absolute Error (IAE) and valve travel are calculated and may be reset at the start of a test by changing the RESET parameter to 1 and then back to zero(0). Through the

SP parameter, the setpoint to both PID may be changed. The test response may be visualized using the trend, Test Kalman Filter, shown below.

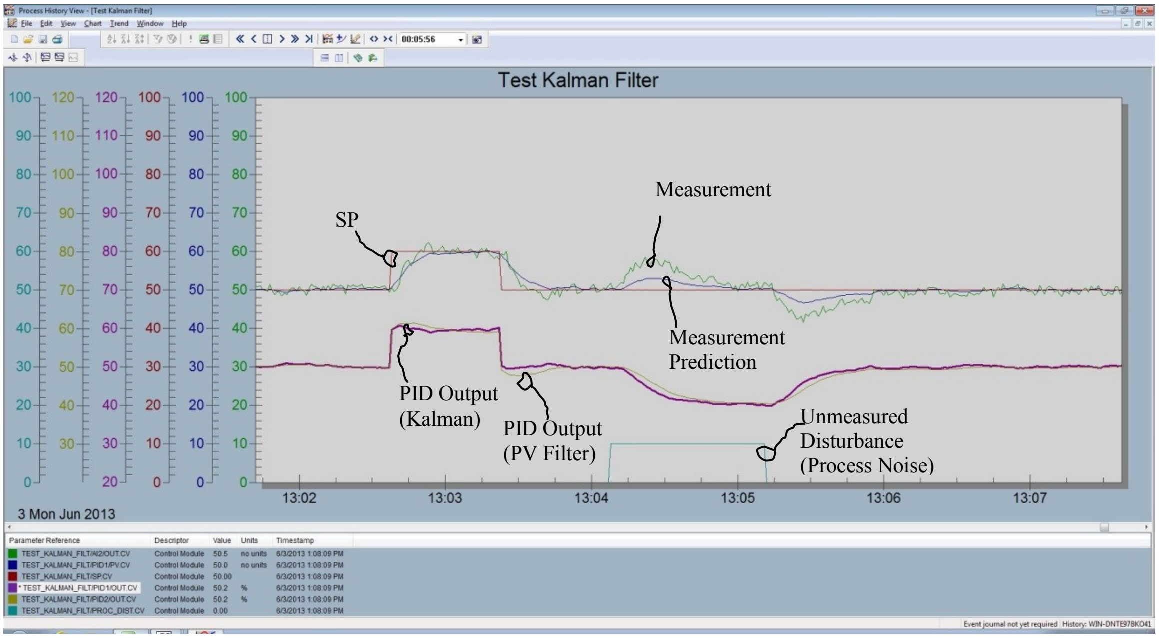

Figure 13 - Trend for Test Module