Measured and Scaled Signals: Issues and Calculations
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1. Introduction

This is an introduction to an article about scaled information transmission signals (for example 4-20 mA, 3-15 psig, etc.), the actual sensed signals (like using orifice dP to infer flow rate, or temperature to infer composition), and reconstruction of the process variable of interest (like the flow rate or composition) from the scaled transmission signal. This document is aimed at those who will be structuring the signal processing and calculations within data acquisition and control systems. Readers should understand the interpretation and reconstruction of the Process Variable (PV) value from the transmission received in the control room, which is related to the Sensed Variable (SV) value, the actual measurement by the sensor. And, readers should understand the associated issues associated with device calibration and digital discretization.

Consider a classic orifice flow measurement. The process variable (PV) is volumetric flow rate, $\dot{Q}$, perhaps it has a value of 430.1 gal/min. The orifice creates a pressure drop, dP, which ideally is proportional to flow rate squared. The corresponding dP might be 3.602 psig. The flow sensor measures the dP not the $\dot{Q}$. But, ideally, from the dP one can infer the flow rate, one can calculate $\dot{Q}$ from dP using the orifice equation. The orifice device creates a Sensed Variable (SV) which is easily measured. Then the transducer transmits a mA current signal to the control room; but, the i value is between 4 and 20 mA, ideally, and it may have a value of 11.145 mA, representing the 3.602 psig value. Finally, the analog to digital devices convert the i to a digital count, perhaps between 200 and 800, the ideal count of 467.9375 must be truncated to 467, which will be reported as 11.120 mA, which will become a distortion of the calculated PV value, even if every other calibration idealization were true. But, none of the calibrations are exactly perfect, and the model relating the SV to the PV is not exactly true either.

The questions are about how to convert the digital representation of the transmission scaled signal value back to the PV value for display/monitoring/control, how to calibrate the several devices in the signal transmission steps, how to determine the impact of the digital discretization and calibration imperfection, and how does all this shape the calibration protocol and selection of digital devices.

The situation is not exclusive to flow rate measurement. Composition is not directly measured, but a related property is, the Sensed Variable. This SV might be near-infrared light intensity, electrical conductivity, or electrical millivolt; and the transducer (sensor/transmitter) will be reporting a signal that is ideally proportional to the SV, not the composition. Similarly, level is not measured, but the consequential differential pressure or electrical capacitance might be. Temperature is not measured, but the associated SV, thermocouple mV or RTD resistance, is. Density is not measured, but the related vibration harmonic frequency can be. Some of the relations between the PV and the sensed property are linear, but many are nonlinear.

Additionally, the situation is not exclusive to systems that transmit electric current signals as 4-20 mA. If the transmission signal is pneumatic it has a nominal 3-15 psig range of values, if volts it has a nominal 1-5 V range, and many digital transmissions are reported in the 0-100% ideal range. Such transmitted signals are usually linearly related to the sensed property, the SV. There may be several linear transmission conversions in the path between sensor and control room.

The not-too-difficult challenge is inverting the several stages of signal conversion to translate the control room signal back to the PV value. Part of the challenge is including the nonidealities of the multiple calibrations in the signal conversion sequence. Signal reconstruction can be divided into two stages: The first is the sequence of linear translations to reconstruct the SV value from the scaled signal received in the control room. The second is using the inverse of the measurement device model to convert the SV to the PV. In all, making choices to minimize uncertainty due to calibration imperfection and the distortions related to digital discrimination are important.

The rest of this article contains examples and how-to steps. It is accessible in the digital version of CONTROL magazine. The topics are Sensed Variables, Transmission Signals, PV Reconstruction, Absolute and Relative Variables, Propagation of Uncertainty Due to Noise on a Signal, Digital Discretization Effects, and Calculations with Scaled Signals if the transmission signals are not first converted to PV values.

2. Definitions

In conceptual order:

- Process Variable (PV) – The variable that you use to monitor, assess, control the process.
- Sensed Variable (SV) – The value that is actually measured. As an example, flow rate, $\dot{Q}$, is inferred by an orifice that creates a pressure drop, dP. The SV, the actual measurement is dP, not $\dot{Q}$. The SV might be called transmitter measurement, secondary variable, inferential variable, indirect measurement, etc.

- Digitization – The conversion of a variable to discretized values for digital storage and processing. The variable might be a continuum-valued one or a previously digitized one.
- Digital Discretization – The value interval caused by digital devices when values are truncated for storage. It might be called measurement deadband, or instrument resolution. Truncating creates an error in value.
- Scaled Signal – The communication signal (mA, %, counts, psig, etc.) that is transmitted and usually has a 1:1 relation to the SV.
- Reconstruction – Conversion of the transmission signal back to the SV or to the PV value.

3. Sensed Variables

Many process variables (PV) are difficult to measure directly, but they can be associated with another variable that is easily measured with an inexpensive and reliable sensor. For instance, liquid level is often "measured" by differential pressure between the bottom of the tank and the free space above the liquid. Since the pressure at the tank bottom is related to liquid level, or height, h:

$$P_{bottom} = P_{free\ space} + \rho g h / g_c \tag{1}$$

Then level, h, can be directly related to the sensed differential pressure (dP or ΔP).

$$h = \frac{(P_{bottom} - P_{free\ space}) g_c}{\rho g} = \frac{\Delta P\ g_c}{\rho g} = a\ \Delta P \tag{2}$$

This happens to be a linear relation between ΔP, the Sensed Variable (SV), and the PV of interest, h. Assuming density is constant, the coefficient a combines all constants, and becomes the calibration coefficient for the measurement device model.

Another common example is orifice flow measurement. The orifice creates a pressure drop, which ideally, is related to the flow rate squared. For volumetric flow rate, the ideal orifice relation is:

$$\dot{Q} = \frac{\pi}{4} {d_0}^2 \sqrt{\frac{2 g_c \Delta P}{\rho(1-\beta^4)}} = a\sqrt{\frac{\Delta P}{\rho}} \tag{3}$$

Here a is a combination of the several constants for a particular application, and ΔP is again the sensed property, or SV. In this example I did not restrict density to be a constant.

However, investigation of the measurement device might reveal that it is not an ideal orifice, and the square root relation could be relaxed to a power law [1]. Now there are two calibration coefficients to relate the SV to the PV.

$$\dot{Q} = a\left(\frac{\Delta P}{\rho}\right)^b \tag{4}$$

Perhaps, this orifice is a gas flow meter, with changes in gas density being the result of changes in upstream pressure and temperature. But, density is relatively difficult or expensive to measure compared to pressure and temperature. So, using the ideal gas law, $PV = nRT$, and molecular weight of the gas, M, density is calculated as:

$$\rho = \frac{MP}{RT} \tag{5}$$

Then by inserting density of Equation (5) into Equation (4), ideally converting to standard conditions, and combining constants, volumetric flow rate would be determined by three Sensed Variables (orifice ΔP, and the upstream measured P and T).

$$\dot{Q}_{STP} = a\left(\frac{\Delta PRT}{MP}\right)^b \left(\frac{T}{P}\right)_{Std} \left(\frac{P}{T}\right) = a'\Delta P^b \left(\frac{T}{P}\right)^{1-b} \tag{6}$$

Of course, if molecular weight changed, and could be measured, there could be four SVs in the relation.

The ideal gas law is not exactly true, and the nonideal power, b, may also adapt the combination of ideal relations to adequate accuracy over the range of variables.

Note: Equation (6) reveals that a PV could be reconstructed by more than one SV.

Note: The ideal functional structure of the SV to PV relation can be relaxed make it match the reality. There is no need to pursue full modeling thermodynamic or phenomenological rigor. Nor is there a need to stick to the ideal relation and use a complicated empirical correction. Often an appropriation of the ideal functionality is fully adequate to relate the PV to the SVs.

Note: What are termed Soft Sensors or Inferential Variables, would be similar to Equation (6), in that several SVs are used to reconstruct or predict a PV. In Equation (6) the data model is grounded in first principles. By contrast, in Soft Sensors the models are usually empirical. But, the purpose to reconstruct a difficult-to-measure variable with easily measured associated variables is the same. Equation (6) is not exactly the ideal square root relation. The power, b, will be determined with data. In this sense Equation (6) has an empirical component making it partly a soft sensor.

Note: The value of the calibration coefficients could be determined from the mechanistic relations. Such as $a' = \frac{\pi}{4} {d_0}^2 \sqrt{\frac{2g_c}{(1-\beta^4)}} \sqrt{\frac{R}{M}}$. In such a case, the accuracy of the calibration coefficient would be dependent on the accuracy of several geometric device measurements and the model idealizations. Alternately, the calibration coefficients could be determined by experimental tests. Either is a valid choice. If the experimental testing is easy, inexpensive, safe, and does not violate overriding protocol, testing would be preferred; because determining coefficient values from experimental data would minimize errors. However, in some situations testing might not be feasible. Then one must accept the use of values in some theoretical confluence of variables that compose the calibration coefficients.

Note: I encounter a range of terms for what I have labeled the Sensed Variable. It could be called an Inferential Variable, because from it you can infer the PV value. It could be termed the Primary Measurement because it is the actual measurement, or the Secondary Measurement because it is a cascaded consequence of the PV, or Auxiliary Variable. I chose to use the term Sensed Variable, because the other terms seem to infringe on other concepts.

Note: SV and PV need a 1:1 relation. Any value of the PV should calculate a unique value of the SV and vice versa. A simple example or this undesirable aspect is a quadratic relation: $SV = a + b\ PV + c\ PV^2$.

Here, the reconstruction of PV given the SV leads to two PV values. I have encountered this using index of Refraction, IR, to measure Methanol/Water liquid composition. IR would be the SV, and it has a parabolic-like response to the composition, which does not provide a unique inverse.

Note: The sensitivity of SV to PV should not approach either the extreme of zero or infinite slope. If it does, then many values of the PV would effectively lead to a common value of the SV which is masked by measurement noise or digitization. Or vice versa. The effect of sensitivity, the derivative of PV w.r.t. SV times the noise or discretization interval in the PV should be small relative to any sources of uncertainty on the SV. And vice versa.

Note: One would prefer that the functional form of the model has an explicit calculation of the PV from the SV, as opposed to having to use a root-finding approach in an implicit functionality.

The next two examples of inferential measurements are both related to composition. Here is the first: The concentration of a species in a gas would be difficult to measure. Perhaps one wants to measure the CO_2 content in N_2. A common approach is to compress a sample of the gas to a convenient pressure and temperature and run the sample through a glass cell with near-infrared light shining through it. The CO_2 molecules absorb and scatter some of the light at a particular wavelength, and the diminished pass-through light intensity can be easily measured. The Beer-Lambert law ideally relates gas CO_2 composition, y, and intensity I.

$$I = I_0\left(1 - e^{-\lambda y}\right) \tag{7}$$

Inverting this device model, the CO_2 composition can be inferred from the light intensity

$$y = -\frac{1}{\lambda} ln\left(1 - \frac{I}{I_0}\right) \tag{8}$$

Here, there are two calibration coefficients. I_0 is the light intensity with zero CO_2 in the gas sample, and λ is the extinction coefficient. These are normally determined from a two-point calibration: Accept the truth of the logarithm functionality of the model, and use the I from two y-values to determine values for I_0 and λ. In use, the PV, y is calculated from the SV, I.

As the second (and last specific) example, consider the need to measure liquid composition on a distillation column tray. Composition can be inferred by the much more easily measured temperature. Here is how: For a binary mixture, the inferential model can be constructed from a relation between vapor pressure of a pure liquid, such as the Antoine relation, an ideal Raoult's law, and ideal gas properties. The partial pressures provided by the two components are:

$$p_1 = x_1 A_1 e^{-\frac{B_1}{T+C_1}} \tag{9}$$

$$p_2 = x_2 A_2 e^{-\frac{B_2}{T+C_2}} = (1 - x_1) A_2 e^{-\frac{B_2}{T+C_2}} \tag{10}$$

Here x_i is the liquid mole fraction of the ith component, p_i is the partial pressure of the vapor of the ith component, (A_i, B_i, C_i) are coefficients of the vapor pressure relation for each component, and T is the temperature of the liquid mixture on the tray.

In an ideal binary situation (two components, no non-condensable gases), the absolute pressure on the tray is the sum of the partial pressures, $P = p_1 + p_2$. If the static pressure, P, on the tray is known, then the liquid composition of the light key, x_1, can be calculated as

$$x_1 = \frac{P - A_2 e^{-\frac{B_2}{T+C_2}}}{A_1 e^{-\frac{B_1}{T+C_1}} - A_2 e^{-\frac{B_2}{T+C_2}}} \tag{11}$$

This is dependent on many idealizations, so it may not be perfectly accurate. But, like more rigorous modeling, it reveals a one-to-one relation between the PV, x_1, which is calculated from the two SVs, P and T, which are easily measured.

For a given choice of component coefficients and tray pressure, a graph of Equation (11) also reveals a generally exponential inverse relation between x_1 and T.

$$x_1 \cong e^{-\frac{T-a}{b}} \tag{12}$$

The coefficients in this empirical model (a, b) could be obtained with relatively simple two-point calibration tests, and this appropriation of the Equation (11) first-principles model might be adequately precise and as good as any rigorous model attempt.

This model could also be locally approximated by a linear relation, applying a truncated Taylor Series to Equation (11) (or any more rigorous version) if the SV range is not extreme.

$$x_1 \cong x_{1,r} + a(T - T_r) + b(P - P_r) \tag{13}$$

There are many other examples of Sensed Variables. Conductivity is used to infer ionic concentration in water, resonant frequency is used to infer density, capacitance is used to infer level, temperature is used to infer extent of reaction in a catalytic reactor, dP and flow rate are combined to infer fluid viscosity, etc.

Note: One could certainly move to the next level of detail in the measurement mechanics, and consider the internal working of a sensor to identify the SV. For instance, temperature is not actually measured, but is inferred by the mV generated by a thermocouple, or by the black body radiation received by an optical pyrometer, or by measuring the resistance of an RTD. As another example, in orifice flow rate measurement, the orifice creates a dP, which might be considered the SV. But the dP creates a force on a flexible diaphragm. Then its displacement creates capacitor change, and capacitance is actually sensed. Or, maybe a drill down into the electronic circuitry may reveal an additional cascade of electrical responses until the actual measurement. The bottom line is that the sequence of variable translations within a sensor can be complicated. The true sensed variable is deeper into the sensor device. But, all that detail is unnecessary because the transmission signal is designed to have a convenient mathematical relation to the SV.

Note: Regardless of the level of detail in modeling, inversion of the sensor measurement to the PV often requires nonlinear models. These could be based on first-principles (elementary phenomenological concepts), rigorous models (futile attempts to be perfect), convenient functional approximations, or something more empirical like neural networks or polynomials.

Note: Appropriated first-principles models, such as Equation (6), or empirical models, such as Equation (12), are more convenient than rigorous modeling attempts. And considering nonidealities, they are usually as accurate as rigorous modeling attempts.

Note: The models that relate the PV to the SVs could be termed a data model or a measurement device model.

4. Transmission Signals

The sensor-transmitter (transducer) measures the value of the Sensed Variable from the process. For instance, an orifice dP sensor measures differential pressure, which might have the units of psig. But, the signal it transmits is not the SV value in its engineering units. The signal may be a direct current with milli-Amperes, mA, as its value. The transmission signal is a scaled value, ideally linearly proportional to the SV value.

Here is a representative plot of the scaled transmission signal with respect to (w.r.t.) the SV value. The transmission signal is mA and the device has it linearly respond to the SV, which might be orifice dP with the units of psig. The dots on either end of the line could indicate an ideal two-point calibration. At zero flow rate, the dP is zero, ideally corresponding to a transmission signal of 4 mA. At the maximum flow rate in this example, the dP is 12 psig, and the transducer zero and span are ideally adjusted to make the device transmit 20 mA.

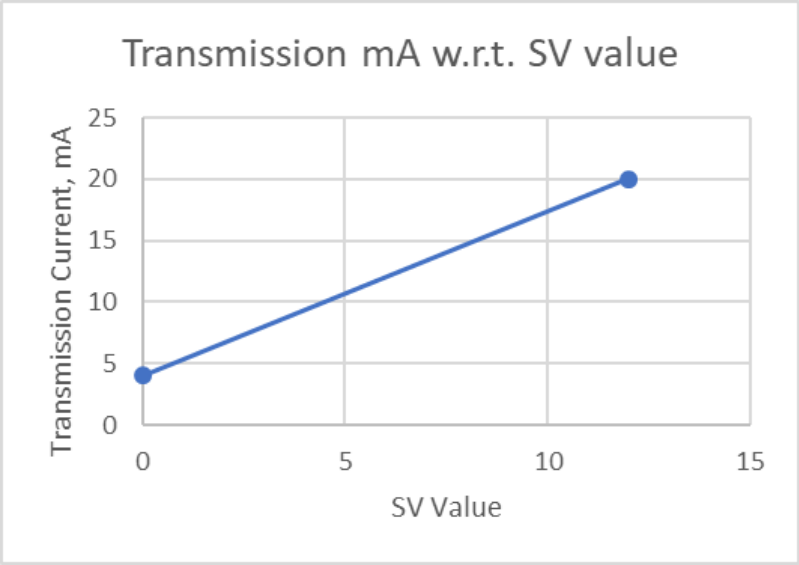

Figure 1 – The linear relation between transmission signal and the SV

Common transmission signals are nominally 4-20 mA, 1-5 V, 3-15 psig, 0-100%, etc.

The lower value of the transmission signal (for instance 4 mA) might indicate zero flow rate, or zero level, an absolute zero. However, it might refer to zero gage pressure, meaning atmospheric pressure, or it might refer to the lowest temperature expected (15 °F), which is not absolute zero.

Traditionally the transmission signal has a 5:1 range, with the upper value (for instance 20 mA) relating to the normal maximum PV value.

The transmission signal has an elevated "zero"; so that if a communication line was broken and the received value was 0 mA or 0 psig, you can tell that there is a communication error, that the received transmission signal does not reflect the process.

However, the transmission signal has a range which includes zero, and about 20% more than the nominal maximum. So, mA could range from 0 to about 24, and psig from 0 to about 20. Controllers have a nominal output of 0 to 100%, but the actual range could be -6% to 106%. A 10-bit digital device has $2^{10} = 1024$ possible values, a count in binary from 0000000000 to 1111111111 (in base ten, 0 to 1023 counts) but the nominal range associated with the minimum PV and maximum PV might be 200 to 800 counts. This signal range beyond the nominal low to high PV values permits communication function within the imperfection of calibration; and in case, during calibration, there was an underestimation of the maximum PV value.

Usually there is a sequence of scaled transmission signals from start to finish (from field to the control room or from control room to field). For instance, a digital controller wanting to change the valve position has a digital-to-analog (D/A) device that converts a digital value of % to a mA, the i/p (current-to-pneumatic) device converts the mA to a psig, and the valve actuator converts the psig to stem position. Ideally, if the controller wants the valve at 50%, the mA signal will be 12 (half-way between 4 and 20 mA), the psig signal will be 9 (halfway between 3 and 15 psig), and the resulting stem will be 0.5 of stroke. However, if any one device in the sequence is not perfectly calibrated, the valve will not be exactly at 0.5 stroke.

As an example of the sequence of scaled transmission signal values, consider that mA is transmitted from a transducer at the process, and converted to digital counts in the control room, in two linear conversions. The transducer converts the inferential property, SV, to i, and the A/D device converts i to counts, c. The ideal relations might be:

$$i = 4 + (SV - SV_{min})\frac{(20-4)}{(SV_{max}-SV_{min})} = i_{min} + (SV - SV_{min})\frac{i_{range}}{SV_{range}} \qquad (14)$$

$$c = 200 + (i - i_{min})\frac{(800-200)}{(20-4)} = c_{min} + (i - i_{min})\frac{c_{range}}{i_{range}} \qquad (15)$$

Ideally, $i_{min} = 4\,mA$ and $i_{range} = (20 - 4) = 16\,mA$, but probably the calibration is not exactly that. Perhaps when i_{min} was adjusted, a value of $3.8mA$ was deemed close enough, or the PV was not exactly at zero (or its minimum), or the SV did not exactly correspond to the PV because of a bit of condensation in one pressure tap. Similarly, the range might not have the ideal value because the span adjustment might only be able to reach $17.3mA$ (because the transducer SV range was oversized for the measurement device), making the true $i_{range} = 13.5mA$. So, I am not showing the ideal values in the second stage of each equation. Instead, I use symbols for the actual minimum and range values.

In reconstruction, the first objective is to convert c back to SV. Solve Equation (15) for i, then Equation (14) for SV, and substitute. The result is:

$$SV = SV_{min} + \frac{SV_{range}}{c_{range}}(c - c_{min}) \tag{16}$$

At first, the sequential inverse and successive substitution to get Equation (16) might seem complicated, but most of the terms are constants, and it reduces to a simple linear relation.

$$SV = \alpha c + \beta \tag{17}$$

Although this was derived from two sequential signal conversions, the simple Equation (17) model is the same regardless of the number of linear signal conversions along a communication path between the SV and c.

The α and β values in Equation (17) could be calculated from knowledge of the minimum and range of the first and final stages in the signal conversion

$$\alpha = \frac{SV_{range}}{c_{range}} \tag{18}$$

$$\beta = SV_{min} - \frac{SV_{range}}{c_{range}} c_{min} \tag{19}$$

Likely, the count value would not be displayed in the control room. The A/D (analog-to-digital) device will convert the incoming mA to a digital count; but, pretending perfect A/D calibration, will probably display mA in the control room. So, what you'll use is

$$\alpha = \frac{SV_{range}}{i_{range}} = \frac{SV_{max} - SV_{min}}{i_{max} - i_{min}} \tag{20}$$

$$\beta = SV_{min} - \frac{SV_{range}}{i_{range}} i_{min} = \frac{SV_{min} i_{range} - SV_{range} i_{min}}{i_{range}} = \frac{i_{max} SV_{min} - i_{min} SV_{max}}{i_{max} - i_{min}} \tag{21}$$

Alternately, if the true minimum and maximum values are not known with certainty, the α and β values could be determined from a two-point test on the transducer-to-control-room values.

$$\alpha = \frac{SV_2 - SV_1}{i_2 - i_1} \tag{22}$$

$$\beta = SV_1 - \alpha i_1 = \frac{i_2 SV_1 - i_1 SV_2}{i_2 - i_1} \tag{23}$$

Note: I think that this two-point calibration is better for accuracy than accepting nominal minimum and maximum values for the transmission signals, because 1) the devices used for calibration are not the same devices used for control room A/D signal value reporting, and 2) the calibration might not have achieved the nominal minimum and maximum signal values. If translation of communication signals is linear, then one only needs to know two points of the initial and final signal values to reconstruct the initial from the final. Seeking perfection in all zero and span adjustments along the signal transmission path takes time. However, installed system testing may not be feasible or convenient, and Equations (20) and (21) with ideal or nominal values might have to be accepted for the calibration reconstruction of the SV from the control room display.

Note: See Section 6 of this report for an analysis of uncertainty, to estimate the impact of inexact, nominal, values.

Note: However, don't let my preference for sufficiency override standards, institutional procedures, or legal requirements. Contractually, calibration procedures might be specified in custody transfer applications. Or, ideality might have become custom if instrument techs want to show craftsman skill or work quality, or where their performance might be measured by closeness to perfection in calibration. Alternately, calibration may be done off-line with control-room calculations based on ideal conditions.

There is one more step – The PV reconstruction.

5. PV Reconstruction

The second objective in signal reconstruction is to convert the calculated value of the sensed property, SV, back to the PV value. This needs the knowledge of the measurement device, and the model is often nonlinear. For example, the ideal orifice relation between pressure drop and flow rate is:

$$\dot{Q} = \frac{\pi}{4} {d_0}^2 \sqrt{\frac{2 g_c \Delta P}{\rho(1-\beta^4)}} = \sqrt{\frac{\gamma\, \Delta P}{\rho}} = \sqrt{\frac{\gamma\, SV}{\rho}} \tag{24}$$

Where γ is a combination of the several constants for a particular application, and ΔP is the sensed property, SV. γ is the same as $\sqrt{\alpha}$ in Equation (3).

The final signal reconstruction stage is to substitute Equation (17) into the ideal (24)

$$\dot{Q} = \sqrt{\frac{\gamma(\alpha c - \beta)}{\rho}} = \sqrt{\frac{\delta c - \varepsilon}{\rho}} \tag{25}$$

This could be a simple two-point calibration. At zero flow rate, Point 1, $\delta c_1 - \varepsilon = 0$. At any other calibrated flow rate, Point 2, $\delta c_2 - \varepsilon = \rho {\dot{Q}_2}^2$. These are easily solved to get the two coefficients: $\varepsilon = \delta c_1$ and $\delta = \rho {\dot{Q}_2}^2 / (c_2 - c_1)$.

Alternately, of course, the ideal model for the device (constituency model) could be relaxed to account for nonidealities such as $\dot{Q} = \left(\frac{\delta c - \varepsilon}{\rho}\right)^{\theta}$, and then a three-point calibration or a multipoint calibration with nonlinear regression could be used to determine the coefficients.

There are many variants to a calibration procedure: The measurement device might be calibrated off-line, separately from the instrument system signal translations, then the results combined to translate the control room signal to the PV.

Note: Some flow measurement devices have a square root extractor at the sensor transmitter (transducer) and transmit a linear translation of mA to $\dot{Q}$, ideally. If so, ideally, no phenomenological model would be required in the control room to convert mA to $\dot{Q}$. A linear relation would be appropriate, if the ideal square root functionality was acceptable. In any case, know what features are on your instruments.

Note: Some SV values need to be time coordinated (lagged, leaded, or delayed) prior to being combined in the PV reconstruction model. For instance, if temperature and pressure are part of a flow rate measurement, the T sensor might be in a thermowell with a significant lag. If the P and dP sensors can respond quickly, then one might need to lag the P and dP values so that they match the T. Or, lead the T value so that it matches the P and dP values. As another example, SV measurements may be sequential in a pipeline. If the downstream SV value has a transport delayed response relative to the upstream one, the reconstruction should use the equivalently delayed upstream SV value with the downstream value.

6. Absolute and Relative Variables

Some signals are absolute, such as flow rate, which might go from 0 to 10 gpm, where the zero really means zero. But, many other signals provide a relative difference, or a deviation from a base case. For instance, a temperature of 0°C does not mean absolute zero, and zero psig in a H_2S cylinder does not mean that there is no H_2S in it. It means that the remaining H_2S in it has the same P as the atmosphere.

Absolute signals include those expressed in psia or °R. Associated deviation signals include those with the units of psig or °F.

If the signal is relative (alternately called a deviation variable) you cannot use the zero as a value of quantity. Again, zero psig in a H_2S cylinder does not mean that there is no H_2S in it, and zero °F does not mean there is no heat in it. In a kinetic model, for instance $r = ke^{E/RT}[c]$, the temperature must be absolute, not relative. When using pressure to calculate density of a gas or composition of a vapor, absolute pressure, not relative, is required.

Before doing any calculations with relative (deviation) variables, my choice is to first convert them to absolute variables.

However, deviation variables for temperature and pressure are commonly used in language; so for communication, perhaps the deviation variables should be what the control system displays to the users.

7. Propagation of Uncertainty Due to Noise on a Signal

This section explores the impact of SV noise or systematic calibration bias (model coefficient value uncertainty) on the calculated value.

Note: Noise is random continually changing fluctuation. It relates to repeatability or precision. Systematic bias is a consistent, repeatable error that relates to accuracy. Both noise and bias are often termed error, or uncertainty, or deviation. And, methods to quantify the impact of the noise or systematic bias are similar.

Note: A person could propagate the maximum possible deviation (error) in a calculation, or you could propagate variance to determine a probable error on a calculated value. Propagation of maximum error and propagation of variance are similar, but the propagation of variance does not presume that all deviations are at their maximum value, and that all deviations are conspiring to push the error in the same direction. Assuming that the many error sources are independent and have normally distributed values,

I think that propagation of variance is a better representation of the reality. So, I'll use the propagation of variance method.

Note: There are also analytical and numerical procedures for propagation of uncertainty. The analytical procedure might seem more scientific because it is stated with calculus derivatives, but it presumes that there are many, independent, random influences, and each with a small enough magnitude to be modeled with a linear effect. Although the numerical methods do not require such limiting conditions, the analytical method is both more familiar and easier to present. Details can be found in many applied statistics texts or Handbook Chapters [2, 3].

Here is the basis of the method:

The general equation for propagation of error (uncertainty), from the propagation of variance method, for a single I/O relation, $y = f(x)$, is Equation (26).

$$\sigma_y = \frac{df(x)}{dx}\sigma_x \tag{26}$$

If there are several input variables with uncertainty, then it becomes an orthogonal or hypotenuse-type calculation (square root of a sum of squared terms).

$$\sigma_y = \sqrt{\sum_{i=1}^{N}\left[\frac{df(x_i)}{dx_i}\sigma_{x_i}\right]^2} \tag{27}$$

Although represented as a calculus derivative, the meaning of $\frac{df(x)}{dx}$ is simply the sensitivity of y with respect to (w.r.t.) x. With a small change in x, measure the y change. Then divide the change in y by the change in x to get the value for $\frac{df(x)}{dx} \cong \frac{y(x+\varepsilon)-y(x)}{\varepsilon}$. If you can perform the analytical derivative using calculus, great. If not, use this numerical change/change approach.

To use Equation (27), one must also estimate the standard deviation of the variation of the x-values. This could come from observing the x-signal, or by estimating uncertainty by any of several methods. One is to relate the range of uncertainty to sigma at steady-state. If for instance, x could be within 31.2 and 31.6, then the range is 0.4, and the possible "maximum" error is the half-range, ± 0.2. If the variation is normal, then about 99.5% of the values will be within the $\pm 2.5\sigma$ range of the middle. Consequently, an estimate of σ_x would be

$$\sigma_x \cong \frac{half\ range\ of\ variation}{2.5} \tag{28}$$

In this example $\sigma_x \cong \frac{0.2}{2.5} = 0.08$.

Once σ_y has been estimated from either Equation (26) or (27), to estimate the 95% probable error on y, consider that the variation is normally distributed and use:

$$\varepsilon_{y,95\%} \cong 2\sigma_y \tag{29}$$

Note: The ideal value for the 2 in Equation (29) is about 1.96. But, considering the uncertainty associated with estimating σ_y, the 2% error in using 2 instead of 1.96 is inconsequential to the convenience of using the value of 2.

Note: Estimation methods like this would have strong objections to those seeking statistical, mathematical, scientific perfection. But, the basis for many estimates of σ_x, even replicate testing, have significant uncertainty within the practicality of a limited number of measurements. And, the analytical propagation of variance method idealizes several issues (independent effects, locally linear); so, even the method for propagating uncertainty is not the absolute truth. However, a crude approximation is fully adequate. My experience is that errors as high as 20% on the magnitude of uncertainty have little impact on the decision consequences. Here is why: A 10% error on σ_y means that the uncertainty on y is uncertain in its second decimal digit. Consider that a PV value is 17.381 and that the estimate of uncertainty is 0.6789. This means that the PV value of 0.3 is uncertain and the PV would be rounded and reported as 17.4. A 20% variation in the uncertainty, of 0.56575 to 0.81468 does not change the legitimately reported PV value of 17.4. So, for practice, I like sufficiency of a method over scientific perfection.

As a first example of the impact of signal noise, I'll use the orifice relation. I'll use an elementary model for pressure, P, fluctuation, $rms_P = kv^2$ (rms is the acronym for root-mean-of-squared values), and use $\sigma_P = rms_P$. Since P_1 (upstream) and P_2 (at the orifice discharge) have different fluid velocities, this means $\sigma_{P_1} = k{v_1}^2$ (upstream) and $\sigma_{P_2} = k{v_2}^2$ (at the orifice discharge). Since $\Delta P = P_1 - P_2$, then propagation of variance on ΔP estimates $\sigma_{\Delta P} = k{v_1}^2\sqrt{1 + 1/\beta^4} = k'\dot{Q}^2$, where β is the diameter ratio of the orifice to the pipe. Then propagation of variance on the calculated $\dot{Q}$ from Equation (26) indicates $\sigma_{\dot{Q}_{calculated}} = \frac{d\dot{Q}}{d\Delta P}\sigma_{\Delta P}$, then $\sigma_{\dot{Q}_{calculated}} = k''\dot{Q}$. The exact value of k'' is not needed to recognize that the fluctuation in the calculated value of $\dot{Q}$, the noise on $\dot{Q}_{calculated}$, will increase proportionally to the flow rate.

Figure 2 represents a characteristic example of how a noisy signal would change as orifice-measured flow rate changes in time. The flow rate starts at about a value of 2, then at a time of 5 eases up to a flow rate of 5, then at a time of 12 eases up to a flow rate of 10. You can see how the noise level increases with flow rate.

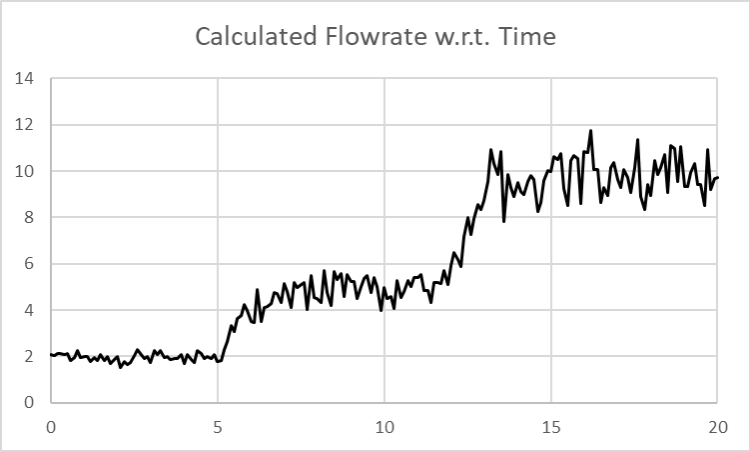

Figure 2 – One example of how nonlinearity affects noise

Figure 2 is a general characterization, representing the model $\sigma_{\dot{Q}_{calculated}} = k''\dot{Q}$; so I did not place units on the axes.

Implications for this relate to 1) controller tuning and signal filtering to alleviate the impact of the noise (more filtering is required at the noisier higher flow rates), and 2) the impact of digital discrimination (see Section 8 of this article).

Note: A Coriolis or vortex flow device could make the low flow rate and measurements be the noisier region.

Note: About noise filtering, I've explored several approaches to automatically adjust filter coefficients by monitoring the amplitude of the noise, and my favorite is a CUSUM filter which is grounded in Statistical Process Control principles [4, 5, 6].

As a second example of propagation of noise, along the same type of analysis, use the $x_1 \cong e^{-\frac{T-a}{b}}$ relation, Equation (12), for calculating composition from tray T. x_1 is purity, and for a binary situation, $x_2 = (1 - x_1)$ is impurity. Since T is the standard controlled variable in distillation, invert the constitutive relation to see how T responds to the impurity. $T = a - b\, ln(1 - x_2)$. If fluctuation on impurity is proportional to the impurity amount, then $\sigma_{x_2} = k\, x_2$. Propagating the composition variation to T, $\sigma_T = \frac{dT}{dx_2}\sigma_{x_2} = \frac{b}{1-x_2}kx_2 = k'\frac{x_2}{1-x_2}$. Figure 3 characterizes how σ_T changes with T (as a deviation variable).

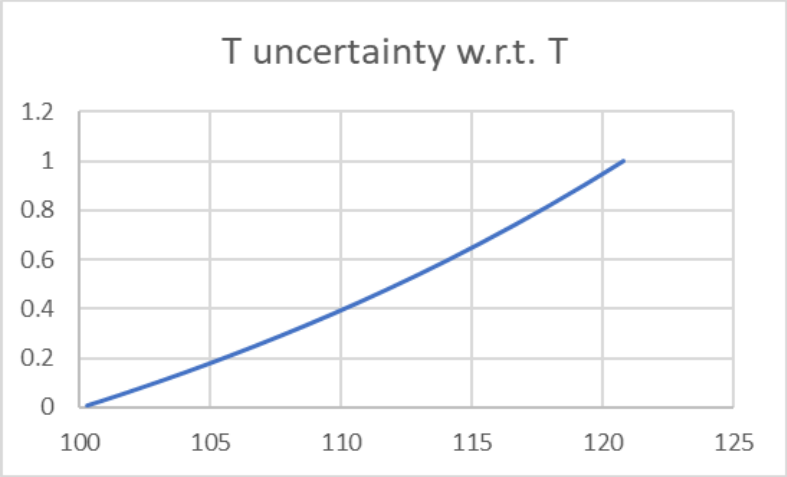

Figure 3 – How uncertainty scales with measured temperature due to composition variation

Figure 4 is an example of how the measured T would change as composition changes in time. The impurity starts with a value of 0.2, which has a corresponding temperature of about 150. Then begins to drop to 0.05 at a time of 60, to a corresponding T of about 100. You can see how the noise level drops in time as the purity increases (temperature decreases).

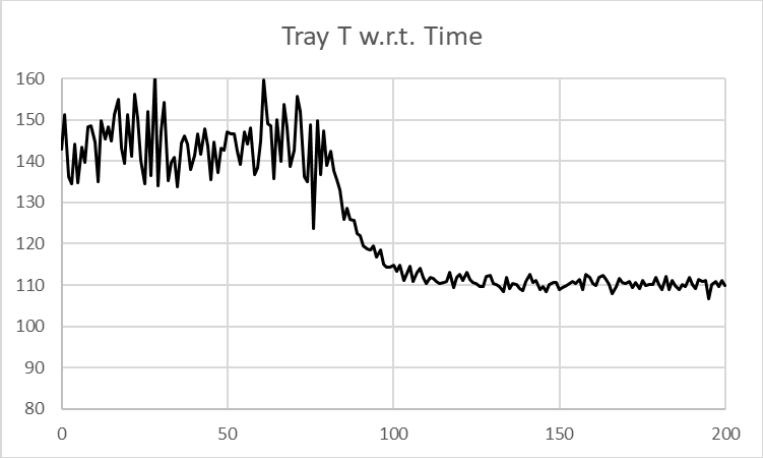

Figure 4 – A second example of how nonlinearity affects noise

Again, implications for this relate to 1) controller tuning and signal filtering to alleviate the impact of the noise, and 2) the impact of digital discrimination (see Section 8).

The previous examples considered noise, random fluctuation in the process. As a final analysis of uncertainty, consider bias or systematic error in a coefficient value because of how the series of transmission devices are calibrated.

Ideally Equation (17) represents the reconstruction of the SV from the signal as interpreted in the control room. $SV = \alpha i + \beta$. Here, I changed counts to mA, because the measured mA is likely what is displayed in the control room. If the signal is electrical current, mA, then Equations (20) and (21) show how coefficients α and β would be calculated from knowledge of the calibration of the transmission signal. However, it is unlikely that the calibration would exactly make i_{min} and i_{max} have their ideal values of 4 and 20 mA when the SV truly corresponds to its limits of SV_{min} and SV_{max}. At SV_{min}, perhaps with the flow rate turned off, condensation in a supposedly dry pressure tap, or an immiscible oil in a supposedly full tap, would corrupt the supposedly exact 4 mA that ideally corresponds to the SV_{min}. Similarly, an iterative calibration procedure might be stopped when the low and high values are perceived to be close enough to 4 and 20 mA. Alternately, the sensor instrument might not have enough adjustment range and the maximum mA might be 17.3, not 20. However, even if the calibration could be exactly performed in the lab, the lab mA meter would not be the same as the A/D device in the control room, and the control room may report 20.3 mA when the lab meter indicated it was 20 mA. These situations are each about a systematic bias in the calibrations, not random noise from the process, as were the two prior examples.

Propagation of uncertainty on the calculated SV value due to a systematic error (bias) on the i_{max} with all other values presumed exactly right leads to $\varepsilon_{SV} = \frac{SV_{range}}{{i_{range}}^2}(i - i_{min})\varepsilon_{i_{max}}$. With ideal values presumed, except for an actual calibration deviation of $\varepsilon_{i_{max}} = 1$ mA, $\varepsilon_{SV} = \frac{SV_{range}}{16^2}(i - 4)1$. With i near to the upper value of 20 mA, the error on the reconstructed SV value, $\varepsilon_{SV} = \frac{SV_{range}}{256}(20 - 4)1$ is about 1/16th of its range.

On the other hand, if the calibration is not presumed to be exactly known, and coefficients α and β would be calculated from the two-point values as reported in the control room, then the small imprecision in the one A/D conversion might be on the order of 0.1 mA. Now, propagation of uncertainty of one of the i-values, perhaps i_2 to the $SV = \alpha i + \beta$ reconstruction, given all other values are exactly known leads to $\varepsilon_{SV} = \frac{SV_\Delta}{i_\Delta{}^2}(i - i_1)\varepsilon_{i_2}$. Here the Δ means the difference between Points 2 (the higher value) and 1. If the two points are nearly at the minimum and maximum SV values, then this is essentially the same relation as the prior one, but with a much smaller uncertainty on the i_2 value, with i near to the upper value of 20 mA, the error on the reconstructed SV value is about 1/160th of its range.

If the calibrations are ideally performed with ideal instruments, either the off-line or two-point methods have equivalent accuracy. But, if there are discrepancies in the presumed max and min values, then the two-point use of the control room displayed values are going to be more accurate when reconstructing the translation of the signal to the SV.

8. Digital Discretization Effects

Digital versions of a signal cause discretization error. As a familiar example, your digital clock reads 8:23 then later 8:24. As the time moves from 8:23.000000 to 8:23.0000001 to 8:23.0000002 to eventually 8:23.9876543 to 8:23.999999999 the clock reads 8:23, then finally at 8:24000000 the clock display changes. This makes the reading constant at the value of 8:23 for a minute, until the end of the minute interval, even though time is increasing during the interval.

Many industrial signals are digital, and a 12-bit digital machine would only be able to support 2^{12}=4096 possible integer values. If the signal represented weight, with a range from 0 to 1,000 lbs, and the 800 to 4,000 count values matched that PV range, then essentially, the discretized value would only change by counting in 0.3125 lb increments (a 1,000 lb range covered by a 3,200 count range). For example, If the PV value were 893.51 lbs, the counts would ideally be 3659.232 [=800+(893.51/1000)*3200]. But counts would be truncated to an integer 3659 and the signal would show 893.44 lbs, until the weight increased to 893.75 lbs when the truncated counts would jump to 3660, and the reported weight value would jump to 893.75. The next higher digital value would be 894.06 lbs. Between these incremental values, the display cannot show the true value.

It does not matter where the digital truncation happens. Whether within the smart sensor, in the wireless communication system, within a relay in the local area network, in the control room A/D, or on the display; the impact of digital discrimination will be dominated by the lowest bit device relative to its signal range. Similarly, it does not matter whether the digitized variable is an integer, or single precision, or double precision floating point. The discretization error depends on the weakest link in the chain. If a 10-bit sensor is in a system, and all of the other processors in the system (wireless, controller, and display devices) are 32-bit, the PV resolution is limited by the 10-bit device, the device with the least precision.

Although I used a 12-bit processor as an example in the weight calculation above, the digital discretization is just less with higher bit-count devices. Digital discretization might be inconsequential in a system in which all devices have a 32-bit processor, but discretization it is not eliminated.

I've seen this digital discretization effect in temperature, flow rate, and composition readings. An example was a thermocouple that was calibrated over a very wide temperature range. The device resolution was 1.5 ^{o}C, which was inadequate for the precise control needed.

Note: Alternate terminology for this "digital discretization" concept, might be "Instrument Resolution", "reconstructed PV resolution", "digital discrimination", or "measurement deadband".

Nonlinear measurement devices, such as orifice flow meters, may reveal the discretization in one operation region, but not another. As an example, for the orifice with the square root conversion, the discretization is not obviously visible in the upper flow ranges, but it can be very distinct in the low ranges.

Figure 5 characterizes the impact of digital discretization with a square root function representing an orifice model. The situation modeled is that a mA signal representing the orifice dP is sent to the control room, and the flow rate is reconstructed. The smooth curve represents the ideal continuum (analog) situation, and the curve with steps represents what happens when the mA value is discretized (either because of the transducer, a relay, the A/D conversion, or the display device). Here the digital interval is very coarse to clearly reveal the consequence.

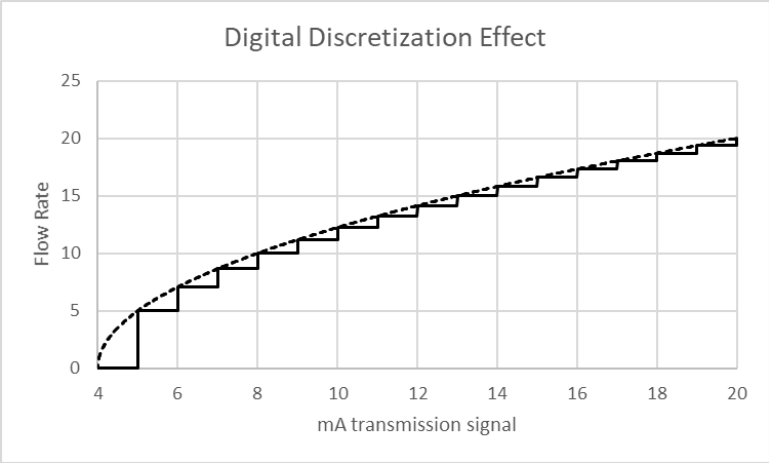

Figure 5 – An illustration of the impact of digitization on a nonlinear reconstruction – an orifice

In Figure 5, the step tread (horizontal distance) is uniform for all steps but the step rise (the vertical distance) is not uniform. The rise, the reconstructed flow rate value, is much higher in the low flow rate range than in the high range.

Figure 6 reveals the same data as in Figure 2, but with a digital discretization.

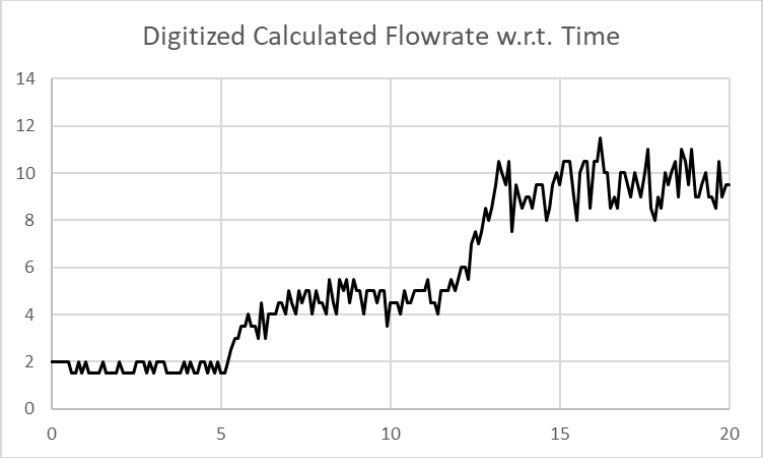

Figure 6 – Digitization impact on the data from Figure 2

Notice in Figure 6, at the higher flow rates, the signal looks like the original (superficially). But, in the lower flow rates it is distinctly different; it only has two values, with flat spots in between.

Similarly, reconsider the temperature data in Figure 4, when digitized in Figure 7. Digital discretization in the low purity region (the left-hand portion of the graph) is not so obvious. But, in the high purity region, which has low temperature sensitivity to composition, the T signal makes discrete steps between two values. On the right-hand portion of Figure 7, T is obviously discontinuous, not noisy.

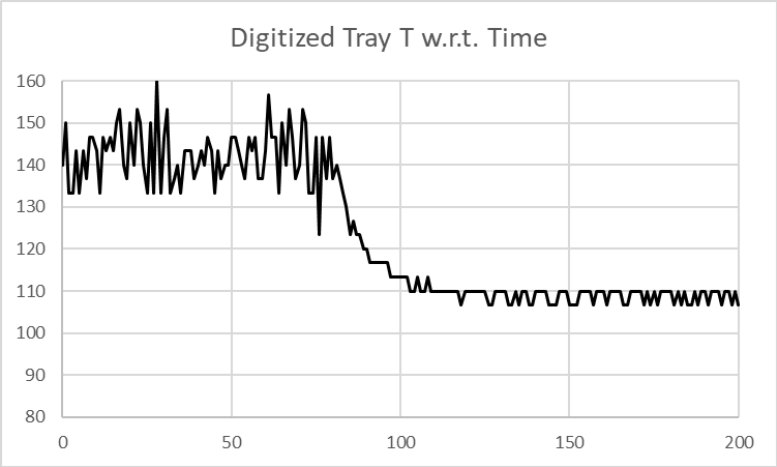

Figure 7 – Digitization impact on the data from Figure 4

And what's the problem with this? If discretization is coarse, it has the same impact as deadband or valve sticktion in control, leading to persistent oscillation. Or, if the unit is automating signal interpretation, such as identifying steady state periods, the periodic flat-lining or non-normal data distribution, can confound the observer algorithm. Or, if the flat spot continues for a while, the operators may misread the situation as a sensor fault and invest unnecessary maintenance.

A higher bit-count device can make the digitization inconsequential. But, even with a higher bit-count device, if the sensor is reporting over a very large SV range (perhaps one device to include startup as well as normal operating conditions) then the normal range of operating might not have many discretized values.

Note: You need to choose high enough bit count for each device with a digital processor in the communication sequence, and a low enough calibration range to make discretization inconsequential.

9. Calculations with Scaled Signals

My recommendation is to convert scaled signals to the SV then to the PV they represent prior to using them in calculations. There are two reasons for this: First, using scaled signals in the calculations can be a confusing procedure. Second, grounding calculations in the conservation laws (inventory relations) or constitutive relations (such as the orifice) preserves process fundamentals for those that follow.

First, consider some examples to reveal how scaled signals can be misleading.

There are two tanks. How much is the total inventory? The answer is easy, add the volume in the two tanks: $V_{Total} = V_1 + V_2$. This is the inventory equation in engineering units. It indicates a simple addition. However, one might see the scaled signals. $s_i = s_{i,0} + \frac{s_{i,max} - s_{i,min}}{V_{i,max} - V_{i,min}}(V_i - V_{i,min})$, where i represents Tank 1 or Tank 2. If one tank is ½ full and the other is ¾ full the answer is not achieved by simple addition of the scaled signals. The total is not ½ + ¾ = $^5/_4$ = 125% full. To do a calculation directly with scaled signals, first use the inverse of the signals to get the PVs, $V_i = V_{i,0} + \frac{V_{i,max} - V_{i,min}}{s_{i,max} - s_{i,min}}(s_i - s_{i,min})$, then insert these inverses into the engineering inventory equation:

$$V_{Total} = V_{1,0} + \frac{V_{1,max} - V_{1,min}}{s_{1,max} - s_{1,min}}\left(s_1 - s_{1,min}\right) + V_{2,0} + \frac{V_{2,max} - V_{2,min}}{s_{2,max} - s_{2,min}}(s_2 - s_{2,min}) \qquad (30)$$

Adding the scaled signals does not represent the total inventory. Yet, a block diagram might indicate doing so.

Similarly, mixing equal parts of a 70% solution and a 50% solution does not result in a 120% solution. But, one might make that mistake when using scaled signal values. The engineering inventory relation for composition is $x_{mix} = (V_1 x_1 + V_2 x_2)/(V_1 + V_2)$. This models the case in which general amounts V_1 and V_2 are mixed. If two flows are being mixed, then $x_{mix} = \left(\dot{Q}_1 x_1 + \dot{Q}_2 x_2\right)/(\dot{Q}_1 + \dot{Q}_2)$. If flow rates are in scaled signals of mA, and the ideal square root orifice relation is used, substitute the PV reconstruction equation into the inventory relation to calculate the mixed composition. Here the PV reconstruction equation is $\dot{Q}_j = \sqrt{\frac{\gamma_j \frac{\Delta P_{j,range}}{i_{j,range}}(i_j - i_{j,min})}{\rho}}$, where the index j is used to indicate Flow 1 or Flow 2, to distinguish the flow item from the mA transmission signal, i. It might be algebraically entertaining to formulate the equation to calculate x_{mix} from i_1 and i_2. But, the result violates the K.I.S.S. principle.

As other examples, consider that many controllers use a 0 to 100% input, and one must scale the PV and SP, or the transmission signal to % of full range. The relation is $\% = 100\frac{s-s_{min}}{s_{max}-s_{min}}$, where s represents any of the variable types.

Here is an example of set point (SP) for secondary controller in a cascade structure that uses the PV value for measurement and setpoint, but the output from the primary controller is in common % notation, 0-100%. If the SP is in engineering units, first convert the % OP signal from the primary back to the PV range for it to become the set point for the secondary: $SP = PV_{min} + OP\frac{PV_{range}}{100}$. Here PV_{min} and PV_{range} represent the secondary controlled variable. Alternately, if the SP for the secondary controller is in the 0-100% range, convert the secondary CV to like units: $CV = 100\ \frac{PV-PV_{min}}{PV_{range}}$.

As another example: Multiplying the scaled signals does not represent the setpoint in ratio, yet a block diagram might indicate doing so. If the primary flow signal is 50% and the OP from the ratio controller is 80% the set point for the secondary flow controller is not the product 4,000%^{2} or the product 0.5x0.8=0.40=40%. If ratio values are in the 0.02 range (meaning the metered flow should be about 2% of the wild flow), then the ratio controller output might only vary between 1 and 3%. To permit full range, the ratio controller output of 0 to 100% might represent a flow rate ratio of 0 to 0.04. Here $r = \frac{\%-\%_{min}}{100-0}(0.04-0.00) = \frac{\%}{100}0.04$. The setpoint for the secondary flow controller, in engineering units, would be the wild flow times the ratio,

$$SP_{secondary} = r\dot{Q}_{wild} \tag{31}$$

Equation (31) is simple and meaningful. However, if the wild flow is represented by the incoming signal from an orifice dP, then $SP_{secondary} = \%_{primary}\frac{0.04}{100}\sqrt{\frac{\gamma\frac{\Delta P_{range}}{i_{range}}(i-i_{min})}{\rho}}$, and if the secondary controller is using % for the PV, then the setpoint needs to be converted to %. In scaled signals the same calculation would be

$$SP_{\%} = \frac{100}{PV_{range,secondary}}\left[\%_{primary}\frac{0.04}{100}\sqrt{\frac{\gamma\frac{\Delta P_{range}}{i_{range}}(i-i_{min})}{\rho}}\right] \tag{32}$$

Equation (32) is much more complicated than what it represents. This means setting it up is prone to algebra or coding errors. It also obscures the fundamental ratio principle, which can confuse others.

Additionally, sometimes the sequence of the calculations, if kept in scaled variables, such as that in Equation (32), need to be rearranged to prevent excessive (overflow values). For example, algebraically, $(x+y)/b$ is the same as $(x/b+y/b)$, but the first sequence (add x and y, then divide by b) may create an $x+y$ signal that exceeds the count capacity and would be truncated to a maximum count. The second arrangement (divide x by b, then divide y by b, then add) might avoid the overflow error.

So, again, my recommendation is to convert scaled signals to the SV then to the PV they represent. Then use the PV values in calculations. Don't try to construct the calculations with the scaled signal values.

Acknowledgments

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Author's Bio

Russ Rhinehart, has experience in both industry and academe. He was Head of the School of ChE at OK State U., President of the American Automatic Control Council, and Editor-in-Chief of ISA Transactions. He is a Fellow of both ISA and AIChE, a CONTROL Automation Hall of Fame inductee, and received numerous teaching and innovation recognitions. Russ authored textbooks on engineering statistics and nonlinear regression modeling, and engineering optimization. Now "retired" his focus is on professional education; supported by a web site to disseminate best-in-class techniques for modeling, optimization, and control. You are invited to visit www.r3eda.com, or contact him at russ@r3eda.com.