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Characteristics of Instrumentation

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1.1 Simple Instrument Model
Passive and Active Sensors • Calibration • Modifying and Interfering Inputs • Accuracy and Error • Sensor Fusion • Estimation

In addressing measurement problems, it is often useful to have a conceptual model of the measurement process. This chapter presents some of the fundamental concepts of measurement in the context of a simple generalized instrument model.

In abstract terms, an *instrument* is a device that transforms a *physical variable* of interest (the *measurand*) into a form that is suitable for recording (the *measurement*). In order for the measurement to have broad and consistent meaning, it is common to employ a standard system of *units* by which the measurement from one instrument can be compared with the measurement of another.

An example of a basic instrument is a ruler. In this case the measurand is the length of some object and the measurement is the number of units (meters, inches, etc.) that represent the length.

1.1 Simple Instrument Model

Figure 1.1 presents a generalized model of a simple instrument. The physical process to be measured is in the left of the figure and the measurand is represented by an observable physical variable X. Note that the observable variable X need not necessarily be the measurand but simply related to the measurand in some known way. For example, the mass of an object is often measured by the process of *weighing,* where the measurand is the mass but the physical measurement variable is the downward force the mass exerts in the Earth's gravitational field. There are many possible physical measurement variables. A few are shown in Table 1.1.

The key functional element of the instrument model shown in Figure 1.1 is the *sensor,* which has the function of converting the *physical variable input* into a *signal variable output.* Signal variables have the property that they can be manipulated in a transmission system, such as an electrical or mechanical circuit. Because of this property, the signal variable can be transmitted to an output or recording device that can be remote from the sensor. In electrical circuits, voltage is a common signal variable. In mechanical systems, displacement or force are commonly used as signal variables. Other examples of signal variable are shown in Table 1.1. The signal output from the sensor can be displayed, recorded, or used as an input signal to some secondary device or system. In a basic instrument, the signal is transmitted to a *display* or recording device where the measurement can be read by a human observer. The observed output is the measurement M. There are many types of display devices, ranging from simple scales and dial gages to sophisticated computer display systems. The signal can also be used directly by some larger
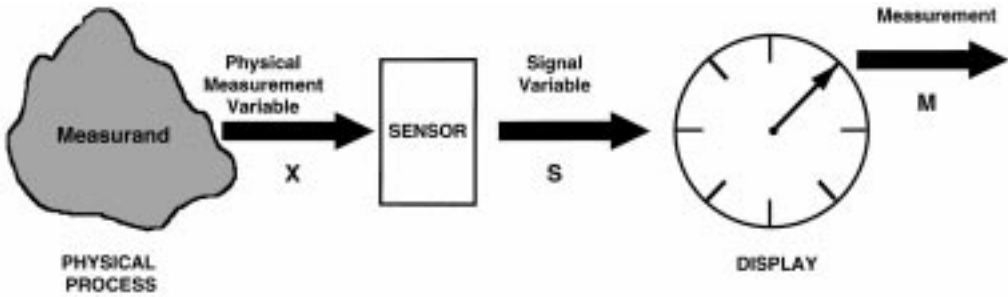
FIGURE 1.1 Simple instrument model.

TABLE 1.1

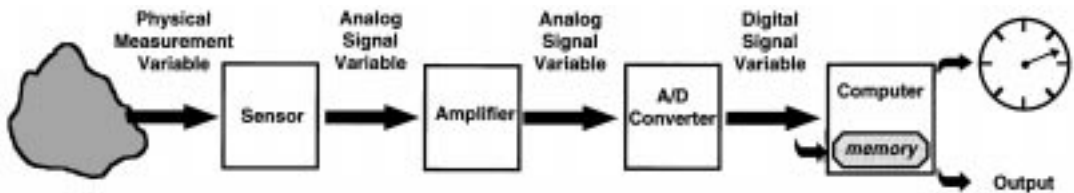| Common physical variables	Typical signal variables
• Force	• Voltage
• Length	• Displacement
• Temperature	• Current
• Acceleration	• Force
• Velocity	• Pressure
• Pressure	• Light
• Frequency	• Frequency
• Capacity	
• Resistance	
• Time	
• …	

FIGURE 1.2 Instrument model with amplifier, analog to digital converter, and computer output.

system of which the instrument is a part. For example, the output signal of the sensor may be used as the input signal of a closed loop control system.

If the signal output from the sensor is small, it is sometimes necessary to amplify the output shown in Figure 1.2. The amplified output can then be transmitted to the display device or recorded, depending on the particular measurement application. In many cases it is necessary for the instrument to provide a digital signal output so that it can interface with a computer-based data acquisition or communications system. If the sensor does not inherently provide a digital output, then the analog output of the sensor is converted by an analog to digital converter (ADC) as shown in Figure 1.2. The digital signal is typically sent to a computer processor that can display, store, or transmit the data as output to some other system, which will use the measurement.

Passive and Active Sensors

As discussed above, sensors convert physical variables to signal variables. Sensors are often transducers in that they are devices that convert input energy of one form into output energy of another form. Sensors
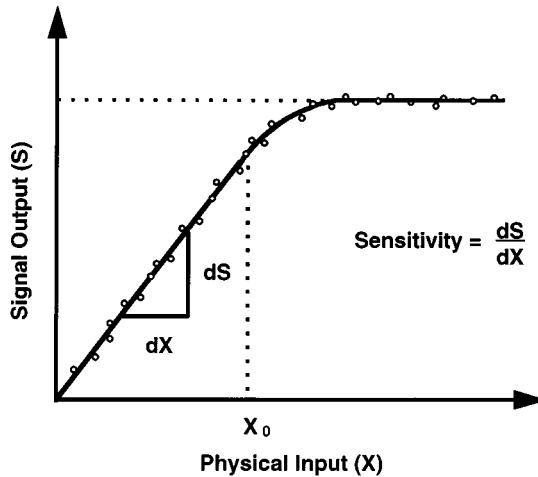

FIGURE 1.3 Calibration curve example.

can be categorized into two broad classes depending on how they interact with the environment they are measuring. *Passive sensors* do not add energy as part of the measurement process but may remove energy in their operation. One example of a passive sensor is a thermocouple, which converts a physical temperature into a voltage signal. In this case, the temperature gradient in the environment generates a thermoelectric voltage that becomes the signal variable. Another passive transducer is a pressure gage where the pressure being measured exerts a force on a mechanical system (diaphragm, aneroid or Borden pressure gage) that converts the pressure force into a displacement, which can be used as a signal variable. For example, the displacement of the diaphragm can be transmitted through a mechanical gearing system to the displacement of an indicating needle on the display of the gage.

Active sensors add energy to the measurement environment as part of the measurement process. An example of an active sensor is a radar or sonar system, where the distance to some object is measured by actively sending out a radio (radar) or acoustic (sonar) wave to reflect off of some object and measure its range from the sensor.

Calibration

The relationship between the physical measurement variable input and the signal variable (output) for a specific sensor is known as the *calibration* of the sensor. Typically, a sensor (or an entire instrument system) is calibrated by providing a known physical input to the system and recording the output. The data are plotted on a calibration curve such as the example shown in Figure 1.3. In this example, the sensor has a linear response for values of the physical input less than X_0. The *sensitivity* of the device is determined by the slope of the calibration curve. In this example, for values of the physical input greater than X_0, the calibration curve becomes less sensitive until it reaches a limiting value of the output signal. This behavior is referred to as *saturation,* and the sensor cannot be used for measurements greater than its saturation value. In some cases, the sensor will not respond to very small values of the physical input variable. The difference between the smallest and largest physical inputs that can reliably be measured by an instrument determines the *dynamic range* of the device.

Modifying and Interfering Inputs

In some cases, the sensor output will be influenced by physical variables other than the intended measurand. In Figure 1.4, X is the intended measurand, Y is an *interfering input*, and Z is a *modifying input.* The interfering input Y causes the sensor to respond in the same manner as the linear superposition of Y and the intended measurand X. The measured signal output is therefore a combination of X and Y,
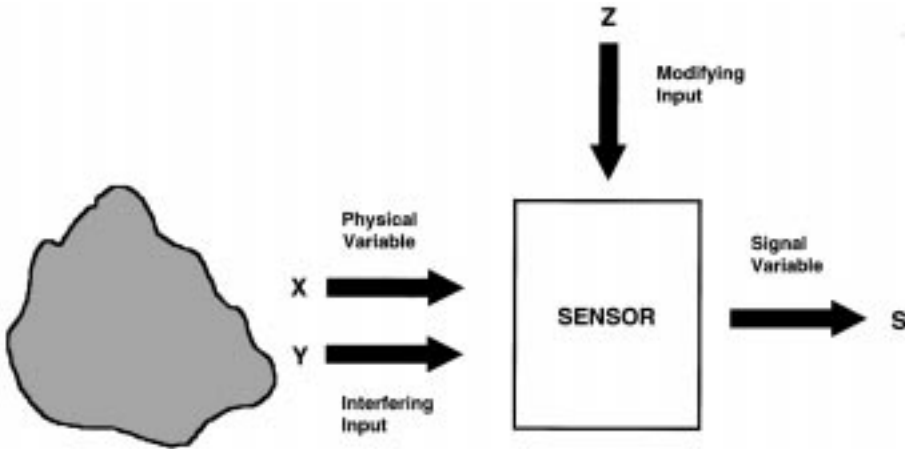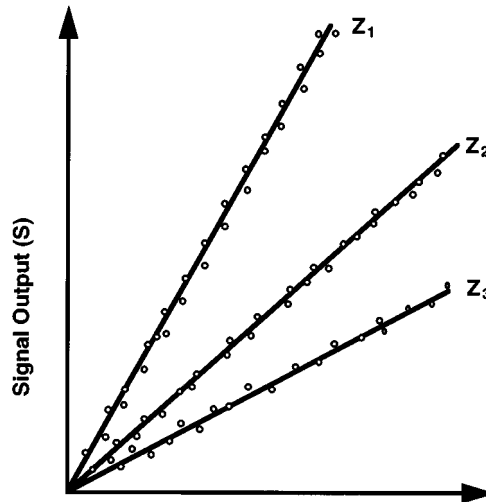
FIGURE 1.4 Interfering inputs.

FIGURE 1.5 Illustration of the effect of a modifying input on a calibration curve.

with **Y** interfering with the intended measurand **X**. An example of an interfering input would be a structural vibration within a force measurement system.

Modifying inputs changes the behavior of the sensor or measurement system, thereby modifying the input/output relationship and calibration of the device. This is shown schematically in Figure 1.5. For various values of **Z** in Figure 1.5, the slope of the calibration curve changes. Consequently, changing **Z** will result in a change of the apparent measurement even if the physical input variable **X** remains constant. A common example of a modifying input is temperature; it is for this reason that many devices are calibrated at specified temperatures.

Accuracy and Error

The *accuracy* of an instrument is defined as the difference between the *true value* of the measurand and the *measured value* indicated by the instrument. Typically, the true value is defined in reference to some absolute or agreed upon standard. For any particular measurement there will be some error due to
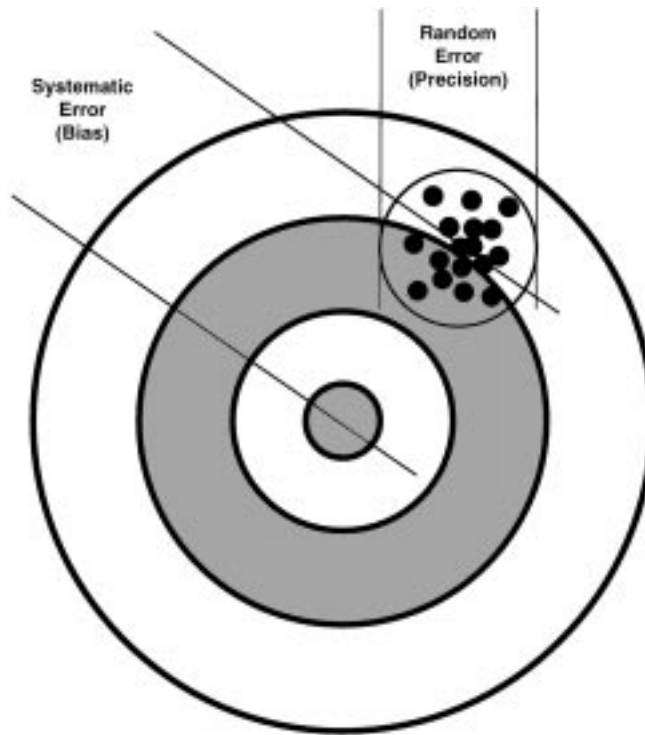
FIGURE 1.6   Target analogy of measurement accuracy.

systematic (*bias*) and *random* (*noise*) error sources. The combination of systematic and random error can be visualized by considering the analogy of the target shown in Figure 1.6. The total error in each shot results from both systematic and random errors. The systematic (bias) error results in the grouping of shots being offset from the bulls eye (presumably a misalignment of the gunsight or wind). The size of the grouping is determined by random error sources and is a measure of the *precision* of the shooting.

Systematic Error Sources (Bias)

There are a variety of factors that can result in systematic measurement errors. One class of cause factors are those that change the input–output response of a sensor resulting in miscalibration. The modifying inputs and interfering inputs discussed above can result in sensor miscalibration. For example, if temperature is a modifying input, using the sensor at a temperature other than the calibrated temperature will result in a systematic error. In many cases, if the systematic error source is known, it can be corrected for by the use of *compensation methods*.

There are other factors that can also cause a change in sensor calibration resulting in systematic errors. In some sensors, aging of the components will change the sensor response and hence the calibration. Damage or abuse of the sensor can also change the calibration. In order to prevent these systematic errors, sensors should be periodically recalibrated.

Systematic errors can also be introduced if the measurement process itself changes the intended measurand. This issue, defined as *invasiveness,* is a key concern in many measurement problems. Interaction between measurement and measurement device is always present; however, in many cases, it can be reduced to an insignificant level. For example, in electronic systems, the energy drain of a measuring device can be made negligible by making the input impedance very high. An extreme example of invasiveness would be to use a large warm thermometer to measure the temperature of a small volume of cold fluid. Heat would be transferred from the thermometer and would warm the fluid, resulting in an inaccurate measurement.
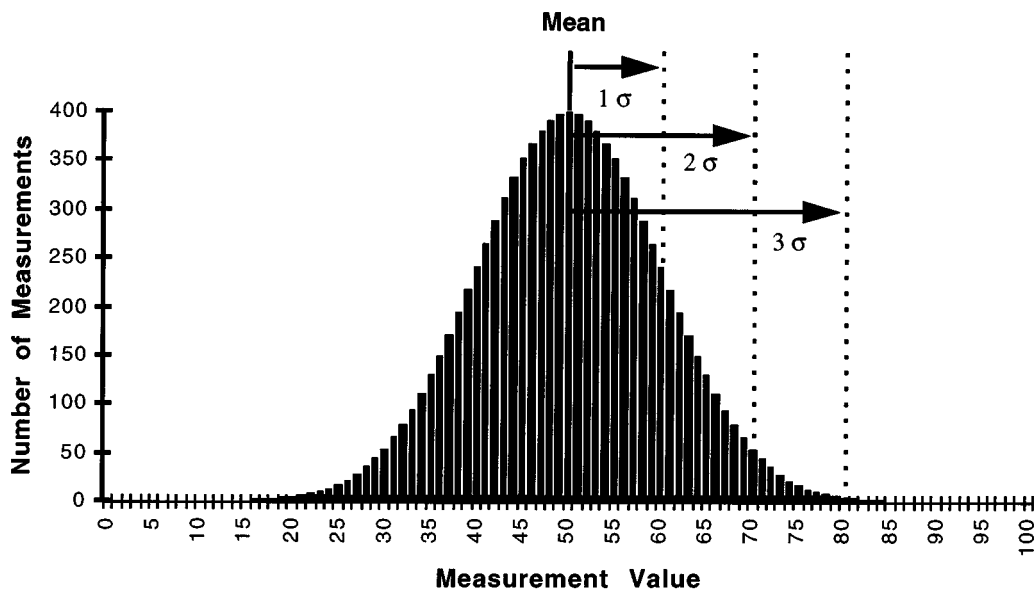
FIGURE 1.7 Example of a Gaussian distribution.

Systematic errors can also be introduced in the signal path of the measurement process shown in Figure 1.3. If the signal is modified in some way, the indicated measurement will be different from the sensed value. In physical signal paths such as mechanical systems that transmit force or displacement, friction can modify the propagation of the signal. In electrical circuits, resistance or attenuation can also modify the signal, resulting in a systematic error.

Finally, systematic errors or bias can be introduced by human observers when reading the measurement. A common example of observer bias error is *parallax error*. This is the error that results when an observer reads a dial from a non-normal angle. Because the indicating needle is above the dial face, the apparent reading will be shifted from the correct value.

Random Error Sources (Noise)

If systematic errors can be removed from a measurement, some error will remain due to the random error sources that define the precision of the measurement. Random error is sometimes referred to as *noise,* which is defined as a signal that carries no useful information. If a measurement with true random error is repeated a large number of times, it will exhibit a *Gaussian distribution,* as demonstrated in the example in Figure 1.7 by plotting the number of times values within specific ranges are measured. The Gaussian distribution is centered on the true value (presuming no systematic errors), so the mean or average of all the measurements will yield a good estimate of the true value.

The precision of the measurement is normally quantified by the standard deviation (σ) that indicates the width of the Gaussian distribution. Given a large number of measurements, a total of 68% of the measurements will fall within $\pm 1\sigma$ of the mean; 95% will fall within $\pm 2\sigma$; and 99.7% will fall within $\pm 3\sigma$. The smaller the standard deviation, the more precise the measurement. For many applications, it is common to refer to the 2σ value when reporting the precision of a measurement. However, for some applications such as navigation, it is common to report the 3σ value, which defines the limit of likely uncertainty in the measurement.

There are a variety of sources of randomness that can degrade the precision of the measurement — starting with the repeatability of the measurand itself. For example, if the height of a rough surface is to be measured, the measured value will depend on the exact location at which the measurement is taken. Repeated measurements will reflect the randomness of the surface roughness.
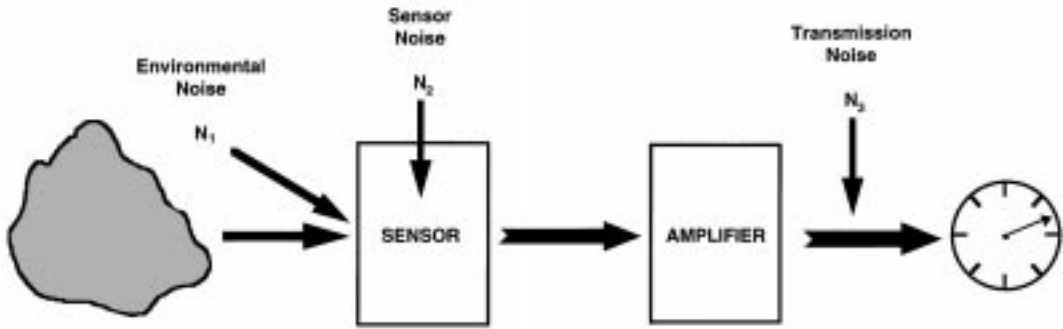
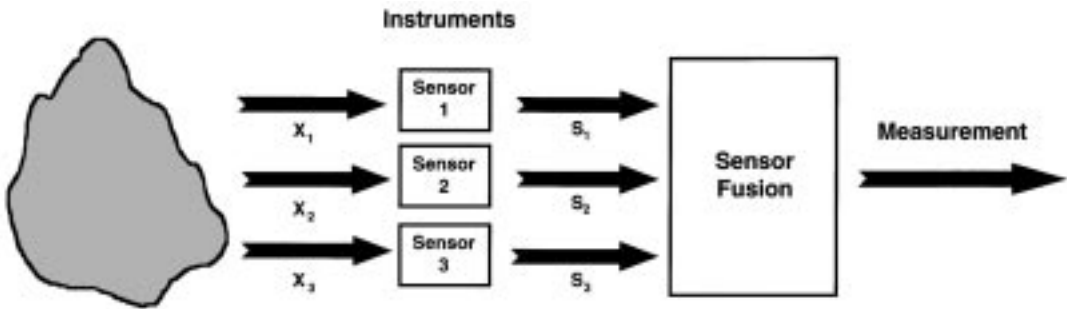**FIGURE 1.8**   Instrument model with noise sources.

FIGURE 1.9   Example of sensor fusion.

Random error generating noise can also be introduced at each stage in the measurement process, as shown schematically in Figure 1.8. Random interfering inputs will result in noise from the measurement environment N_1 that are introduced before the sensor, as shown in the figure. An example would be background noise received by a microphone. Sensor noise N_2 can also be introduced within the sensor. An example of this would be thermal noise within a sensitive transducer, such as an infrared sensor. Random motion of electrons, due to temperature, appear as voltage signals, which are apparently due to the high sensitivity of the device. For very sensitive measurements with transducers of this type (e.g., infrared detectors), it is common to cool the detector to minimize this noise source.

Noise N_3 can also be introduced in the transmission path between the transducer and the amplifier. A common example of transmission noise in the U.S. is 60 Hz interference from the electric power grid that is introduced if the transmission path is not well grounded, or if an inadvertent electric grand loop causes the wiring to act as an antenna.

It is important to note that the noise will be amplified along with the signal as it passes through the amplifier in Figure 1.8. As a consequence, the figure of merit when analyzing noise is not the level of the combined noise sources, but the *signal to noise ratio* (*SNR*), defined as the ratio of the signal power to the power in the combined noise sources. It is common to report SNR in decibel units.

The SNR is ideally much greater than 1 (0 dB). However, it is sometimes possible to interpret a signal that is lower than the noise level if some identifying characteristics of that signal are known and sufficient signal processing power is available. The human ability to hear a voice in a loud noise environment is an example of this signal processing capability.

Sensor Fusion

The process of *sensor fusion* is modeled in Figure 1.9. In this case, two or more sensors are used to observe the environment and their output signals are combined in some manner (typically in a processor) to

provide a single enhanced measurement. This process frequently allows measurement of phenomena that would otherwise be unobservable. One simple example is thermal compensation of a transducer where a measurement of temperature is made and used to correct the transducer output for modifying effects of temperature on the transducer calibration. Other more sophisticated sensor fusion applications range to image synthesis where radar, optical, and infrared images can be combined into a single enhanced image.

Estimation

With the use of computational power, it is often possible to improve the accuracy of a poor quality measurement through the use of *estimation techniques*. These methods range from simple averaging or low-pass filtering to cancel out random fluctuating errors to more sophisticated techniques such as Wiener or Kalman filtering and model-based estimation techniques. The increasing capability and lowering cost of computation makes it increasingly attractive to use lower performance sensors with more sophisticated estimation techniques in many applications.