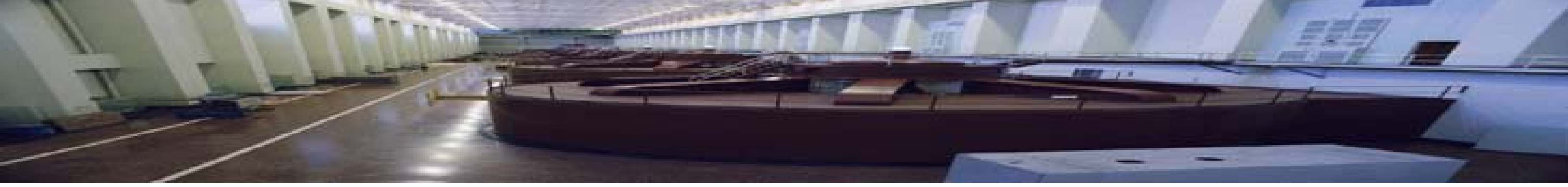

Performance Monitoring Fundamentals:
Demystifying Performance Assessment Techniques

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ABSTRACT

Real-time performance monitoring to identify poorly or under-performing loops has become an integral part of preventative maintenance. Among others, rising energy costs and increasing demand for improved product quality are driving forces. Automatic process control solutions that incorporate real-time monitoring and performance analysis are fulfilling this market need. While many software solutions display performance metrics, however, it is important to understand the purpose and limitations of the various performance assessment techniques since each metric signifies very specific information about the nature of the process.

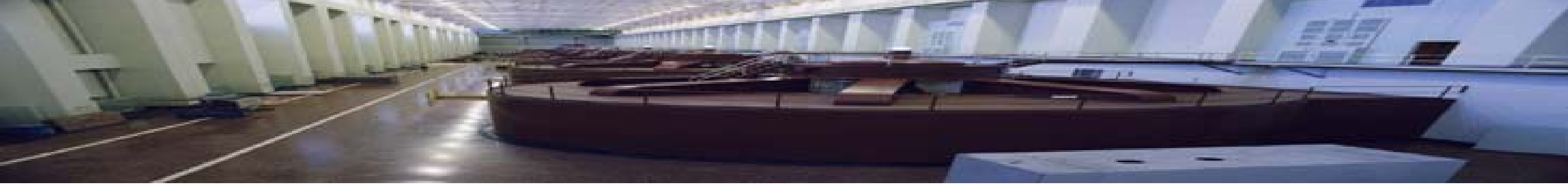
This paper reviews performance measures from simple statistics to complicated model-based performance criteria. By understanding the underlying concepts of the various techniques, readers will gain an understanding of the proper use of performance criteria. Basic algorithms for computing performance measures are presented using example data sets. An evaluation of techniques with tips and suggestions provides readers with guidance for interpreting the results.

INTRODUCTION

Over the past two decades, process control performance monitoring software has become an important tool in the control engineer's toolbox. Still, the number of performance tests and statistics that can be calculated for any given control loop can be overwhelming. The problem with controller performance monitoring is not the lack of techniques and methods. Rather, the problem is the lack of guidance as to how to turn statistics into meaningful and actionable information that can be applied to improve performance.

The performance analysis techniques discussed in this paper are separated into three sections. The first section details methods for identifying process characteristics using batches of existing data. The second section outlines methods used for real-time or dynamic analysis of streaming process data. These are vital techniques for the timely identification and interpretation of changing process behavior and deteriorating loop performance. The third section outlines techniques that aid in the identification of interacting control loops.

The techniques presented in this paper use Microsoft Excel® to calculate corresponding performance measures. Readers may obtain a complimentary copy of the Excel worksheet by contacting Bob Rice via email at bob.rice@controlstation.com.



IDENTIFYING PROCESS CHARACTERISTICS

Set Point Analysis

There are a number of techniques for analyzing closed loop process data that is collected during a Set Point response experiment. These techniques permit an orderly comparison of process response shapes and characteristics. When analyzing a Set Point response, the criteria used to describe how well the process responds to the change can include Peak Overshoot Ratio, Decay Rate, Set Point Crossing Time, Rise Time and Settling Time. These criteria can be used both as specifications for commissioning of control loops as well as for documenting changes in performance due to the adjustment of the controller or process parameters.

Figure 1 below shows a closed loop response to a Set Point change. To calculate the Set Point criteria mentioned above, we assign the following definitions:

A = Size of the Set Point step
B = Size of the first peak above the new Set Point or steady state
C = Size of the second peak above the new steady state

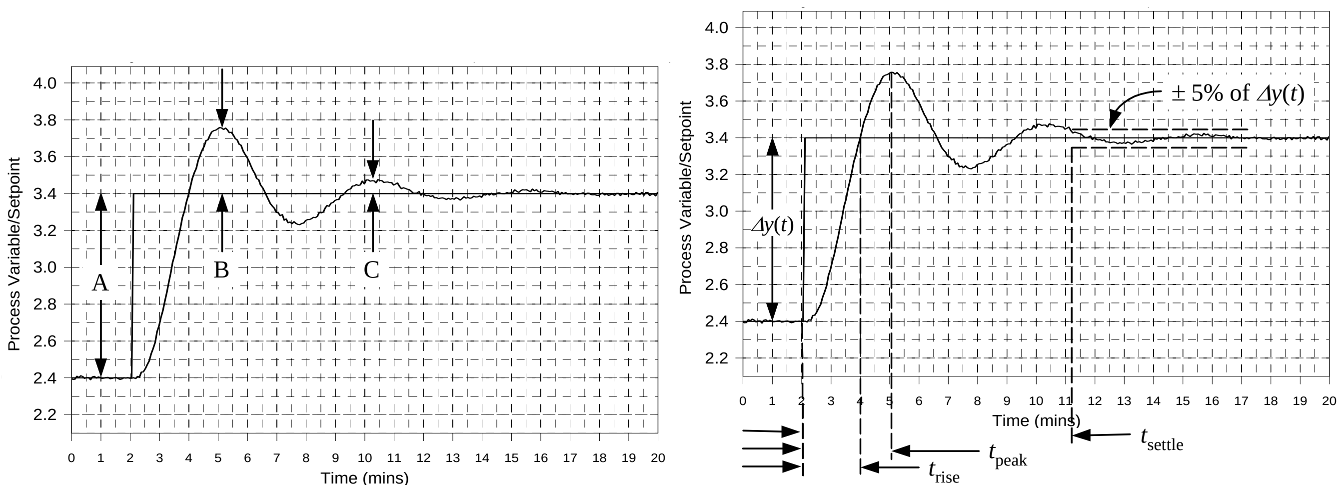
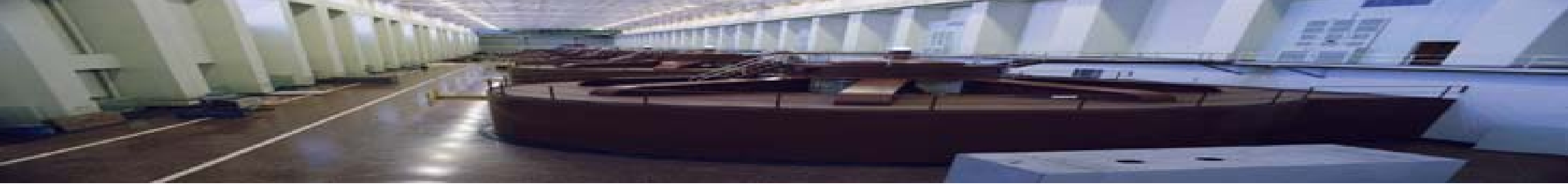


Figure 1 - Process response to a Set Point change with labels indicating response features

As shown in Figure 1, the time when the measured process variable first crosses the new Set Point and the time at which it reaches its first peak are used to describe controller performance. This performance metric is called Set Point Crossing Time and it provides insight into the relative speed with which the process responds to change. Another popular measurement is Settling Time. Settling Time describes the time required for the measured process variable to first enter and then remain within a band whose width is computed at a specified range of the total change in $y(t)$. In our example, a range of $\pm$ 5% is shown.



Additional criteria are summarized in Table 1 below. Popular values include a 10% Peak Overshoot Ratio and a 25% decay ratio. It is important to note that these criteria are not independent. A process with a large decay ratio will likely have a long Settling Time whereas a process with a long Rise Time will likely have a long peak time. The acceptability of these metrics is subjective and will be closely tied to your process and overall control objective.

Criteria	Interpretation	Calculation
Peak Overshoot Ratio (POR)	The POR is the amount by which the process variable surpasses Set Point. An aggressive controller can increase the amount of overshoot associated with a Set Point change.	(POR) = B′/A
Decay Rate	A large Decay Rate is associated with an aggressive controller, and visible oscillations are present in the Set Point response. The smaller the Decay Rate, the faster the oscillations will be dampened.	Decay Ratio = C/B
Peak Time & Rise Time	These measurements gauge the time response to a change in the Set Point. A large peak and Rise Time could be the result of a sluggish controller.	Rise Time = t_{rise} Peak Time = t_{peak}
Settling Time	The Settling Time is the time for the process variable to enter and then remain within a band. Time spent outside the desired level generally relates to undesirable product. Therefore, a short Settling Time is sought.	Settling Time = t_{settle}

Table 1 - Interpretation of Set Point Response Criteria

Other closed loop performance metrics include the integral of error indexes which focus on deviation from Set Point. The Integral Squared Error (ISE) is very aggressive because squaring the error term provides a greater punishment for large error. The Integral Time Absolute Error (ITAE) is the most conservative of the error indexes; the multiplication by time gives greater weighting to error that occurs after a longer passage of time. The Integral Absolute Error (IAE) is moderate in comparison to these two. Additional indexes can be derived depending on the system requirements. Integral Time Squared Error (ITSE) combines the time weighting with the exaggerated punishment for larger error.

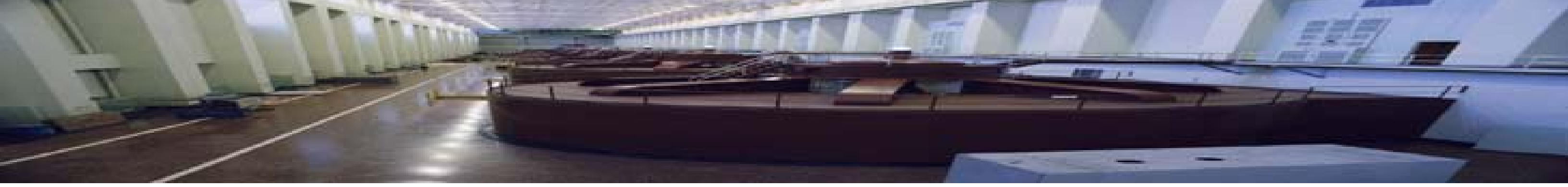
The formula for calculating the Integrated Error indexes are listed below.

$$IAE = \int_0^T |e(t)|\, dt \qquad (1)$$

$$ISE = \int_0^T e^2(t) dt \qquad (2)$$

$$ITAE = \int_0^T t\,|e(t)|\, dt \qquad (3)$$

$$ITSE = \int_0^T te^2(t) dt \qquad (4)$$



Often the above indexes are used as criteria in controller tuning. Typically, users will choose one of the above metrics and define optimal control as the tunings that achieve the minimum value of the index. Figure 2 shows the process variable's response to a Set Point change under various controller tunings ranging from poor/unstable to conservative. The results are summarized in Table 2.

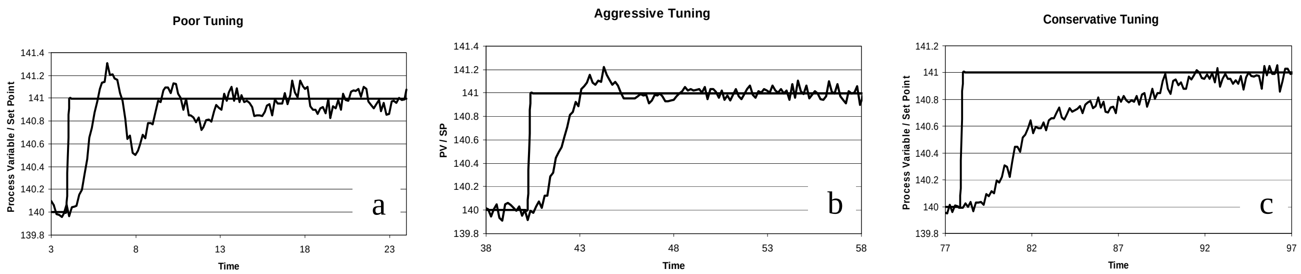


Figure 2 - Set Point Response of a a) poorly, b) aggressively, c) conservatively tuned PI controller

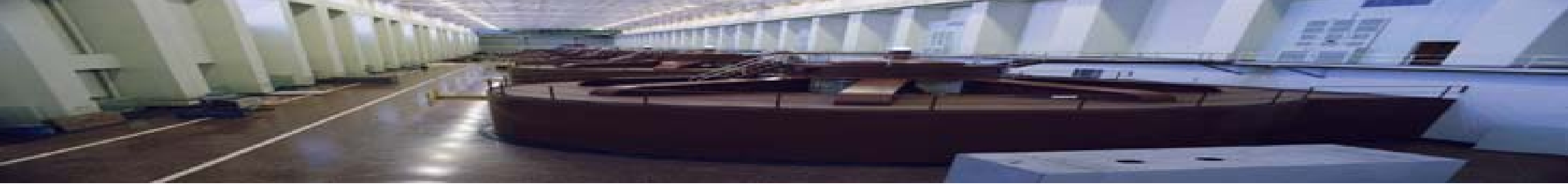
		Poorly Tuned	Aggressively Tuned	Conservatively Tuned
Set Point Bump Criteria	POR	33%	21%	0
	Decay Rate	44%	24%	0
	Rise Time	2.0 min	2.9 min	13.7 min
	Peak Time	2.4 min	4.1 min	13.7 min
	Settling Time	10.8 min	6.5 min	14.7 min
Integral of Error	IAE	3.10	2.28	5.49
	ISE	1.24	1.23	3.17
	ITAE	17.69	8.64	25.40
	ITSE	2.97	1.21	7.85

Table 2 - Results of Set Point Response Criteria, and Integral of Error calculations for Figure 2

Disturbance Analysis

A disturbance is defined as anything other than the controller output signal that affects the measured process variable. In an interacting plant environment, each control loop can have many different disturbances that impact performance. By understanding the type of disturbance and its impact on the control loop, engineers, operators and technicians can more easily identify the cause and work towards an appropriate solution.

Auto-correlation is a method that is used to determine how data in a time series are related [1]. By comparing current process measurement patterns with those exhibited in the past, the nature of disturbances and how they affect a system can be analyzed.



The equation for calculating the auto-correlation relationship is:

$$r(k)=\frac{\sum_i[(y(i)-\bar{y})(y(i-k)-\bar{y})]}{\sum_i (y(i)-\bar{y})^2} \tag{5}$$

Where: y = measured process data
$\bar{y}$ = the Set Point or the series average if there is an offset
k = time delay in samples
i = sample number (or sample time)

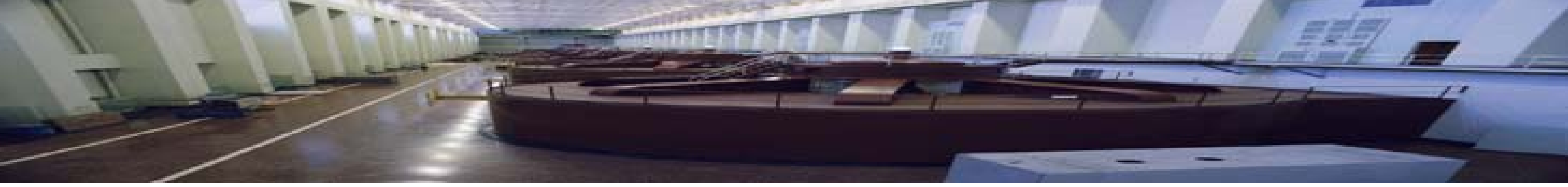
Auto-correlation values will always range between negative one and one. If data is random, the values will be approximately zero for all time. Any value that is significantly "non-zero" will indicate that the data is non-random. A strong auto-correlation will have an initial value near one or negative one and the trend will be linear, and this demonstrates a patter where each measurement dictates the next. A moderate auto-correlation is one in which the plot begins below one (or above negative one) and decreases magnitude towards zero but displays noise. An auto-correlation of closed loop data can also give an estimate of the response time for an isolated disturbance.

Another performance statistic that can prove useful with the identification of trends in data is the Power Spectrum. Power Spectrum is calculated by computing the discrete Fourier transform of the process data. A Fourier transform is a mathematical expression of the data represented by a series of two-dimensional sine waves, and the Power Spectrum is computed by squaring the complex coefficients determined by those sine waves. The Power Spectrum shows the frequency at which change is occurring and the magnitude of the change [9].

The shapes and heights of each peak on Power Spectrum plots provide relevant information about the system and its performance. Specifically, the shape of the Power Spectrum curve yields information about the nature of the disturbances by displaying its frequency. Similarly, an increase in peak heights compared to historical data indicates that the process has greater deviation from Set Point or from its historical mean. Low powers and low frequencies are most desirable, as they are associated with small deviations from Set Point and lower average values.

Figures 3-6 provided on the following pages show four different scenarios in which the auto-correlation and Power Spectrum can be useful in understanding the nature of the disturbance impacting the system. Only the single pulsed disturbance shown in Figure 3 is noticeable from a casual evaluation of the process data. By using the auto-correlation and Power Spectrum tools, however, one can identify characteristics for all four disturbances.

In Figure 3, the process is upset with a single pulsed disturbance. The auto-correlation shown in Figure 3c shows an initial peak where the process is responding to the step up then the negative peak occurs approximately 10 minutes later when the disturbance steps back down. This is characteristic of an isolated disturbance. If a second pulse had occurred, another similar pattern would be expected to



appear on the auto-correlation plot. The Power Spectrum of the process data is shown in Figure 3d. Since the frequency of change corresponds to the frequency of the disturbance, an isolated disturbance is located at approximately zero frequency on the Power Spectrum plot. There is no other disturbance occurring at any other frequency, so the power quickly drops off and the remaining values are close to zero.

Figure 4 shows the process with no disturbance impacting the system. Neither the auto-correlation nor the Power Spectrum contains any obvious peaks. In fact, both trends show random values close to zero. This indicates the control loop is undisturbed and performing well.
The oscillating disturbance depicted in Figure 5 yields an oscillating auto-correlation. The Power Spectrum analysis shows that the oscillating disturbance is a single cycle sine wave since there is one strong dominant peak at the wave's frequency. If a second disturbance was acting on the system a second peak would appear.

The continuously pulsed random disturbance depicted in Figure 6 is difficult to identify since the magnitude of the disturbance is within the range of noise. The disturbance is not impacting the system at a regular frequency because the length of time associated with the disturbance pulses is not constant. Therefore the Power Spectrum does not show any significant peaks outside the range of the noise. The auto-correlation gives an indication of a disturbance that is not associated with the process noise because there is a strong peak at 25 minutes. Also, there are slight clusters above and below the x-axis, especially close to zero. These clusters are not as regular as the oscillating disturbance. In this situation a comparison to historical data and familiarity with the process is vital.

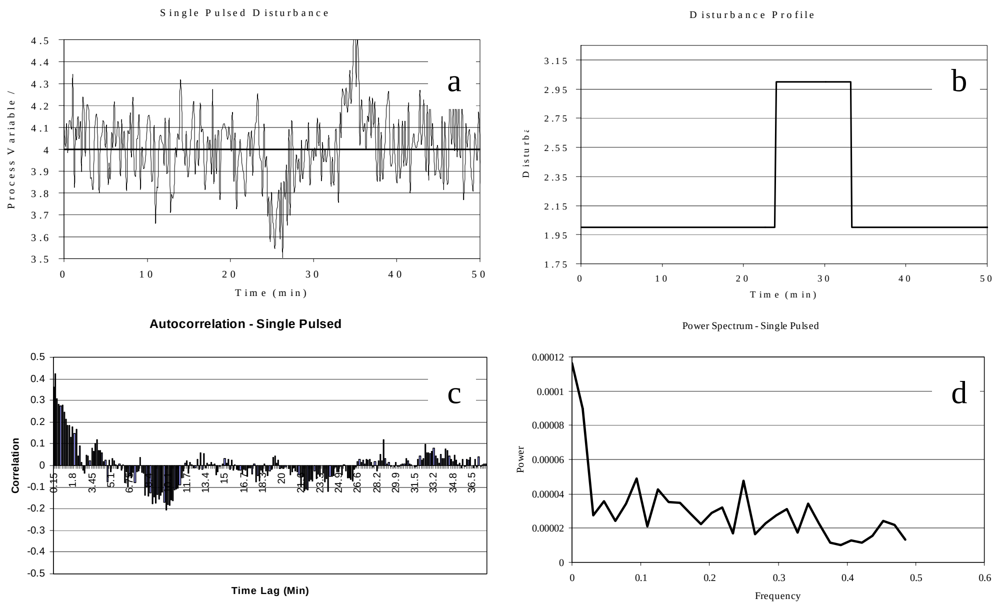
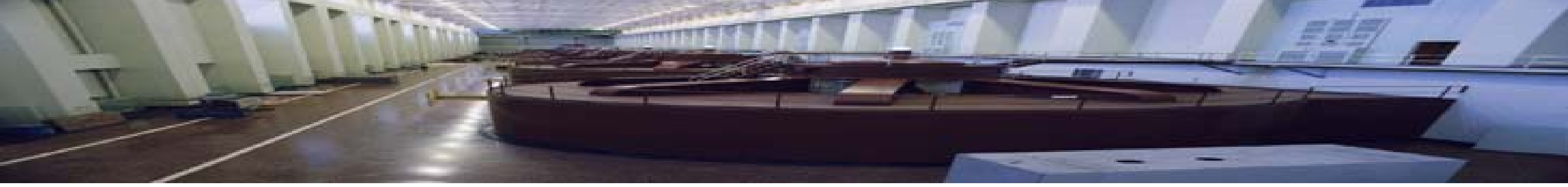


Figure 3 - For a process subjected to a pulsed disturbance here are the a) process variable response b) disturbance profile c) auto-correlation and d) Power Spectrum plots



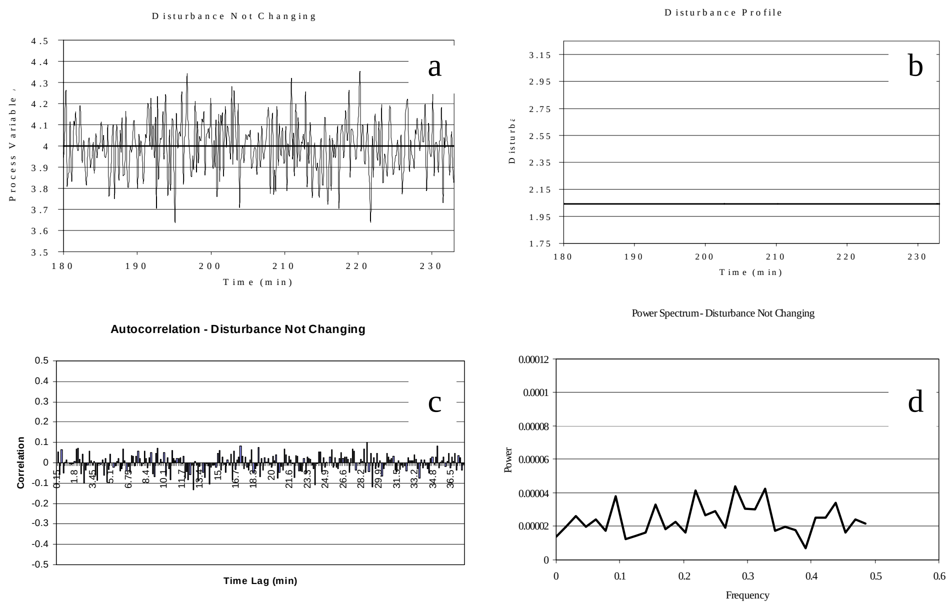


Figure 4 - For an unchanging process here are the a) process variable response b) disturbance profile c) auto-correlation and d) Power Spectrum plots

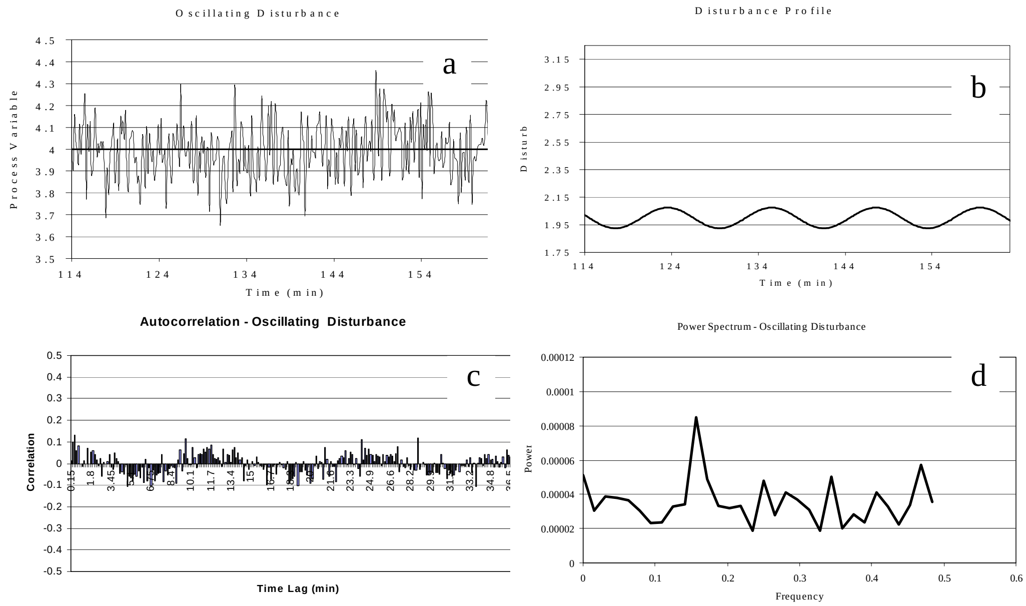
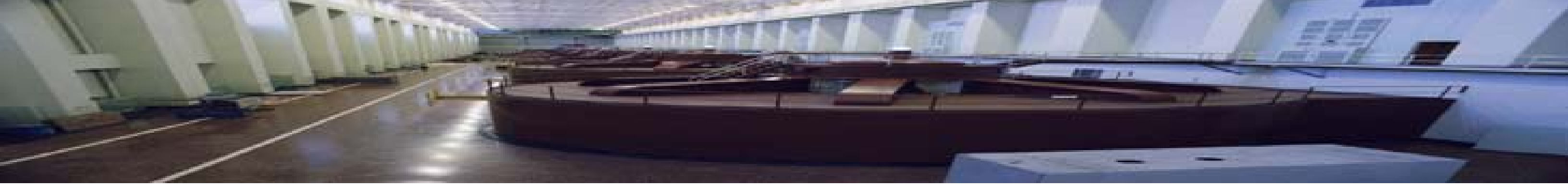


Figure 5 - For a process subjected to an oscillating disturbance here are the a) process variable response b) disturbance profile c) auto-correlation and d) Power Spectrum plots



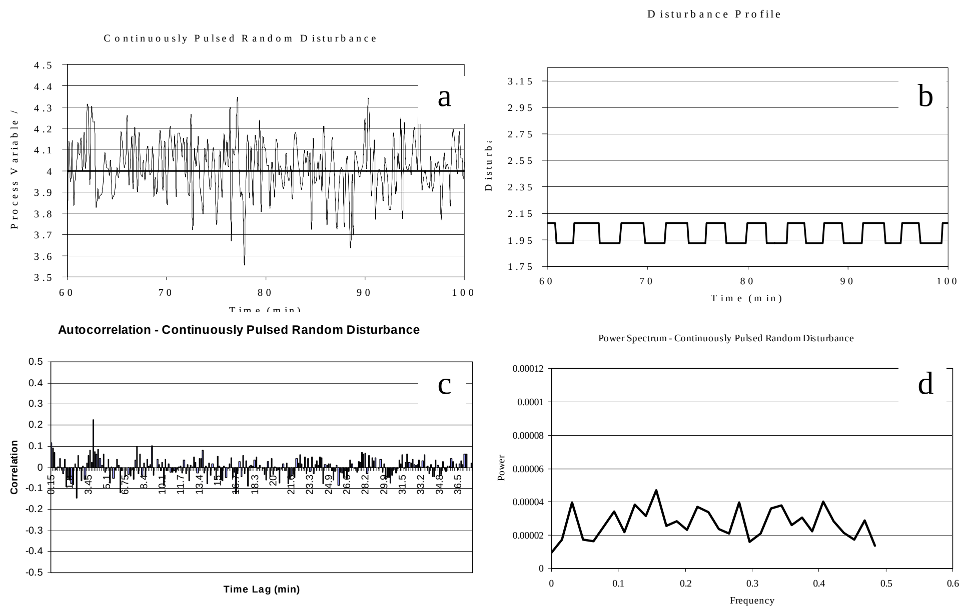


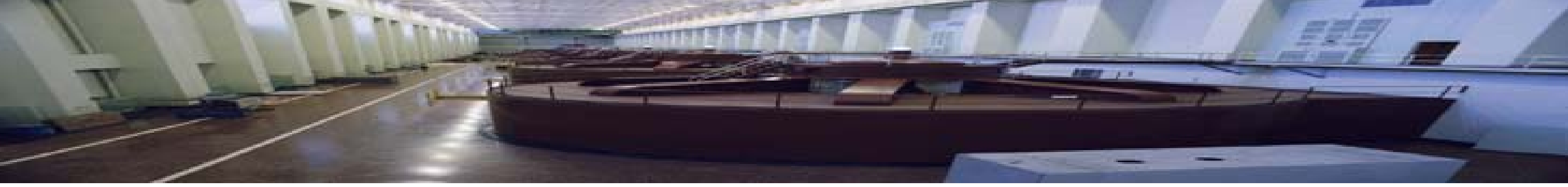
Figure 6 - For a process subjected to a continuously pulsed random disturbance here are the a) process variable response b) disturbance profile c) auto-correlation and d) Power Spectrum plots

REAL-TIME PERFORMANCE MONITORING

With growing access to plant-wide process data, real-time control loop monitoring has become increasingly popular. Many employ the Harris Index, based on minimum variance control principles, as the preferred strategy. At the heart of every performance monitoring system is the ability to identify a problem within the control loop as soon as possible. Presented in this paper is a comparison of the Harris Index to simpler strategies for monitoring controller performance.

Descriptive statistics are separated into three categories: measures of central tendency, measures of spread, and measures of shape. The mean is the most common measure of central tendency, providing insight into the location of a process' center or average state of operation. In contrast, the measures of spread provide information about the degree to which individual values are clustered or to which they deviate from the mean value in a distribution. The minimum and maximum are the simplest measures of spread and give only a range of values. The Variance and Standard Deviation are other popular measures of spread that provide a more useful numerical value based upon their deviation from the mean. Lastly, measures of shape are used to describe the distribution of data values. The skewness of these values refers to the degree of asymmetry present in the data set. Each of these descriptive statistics can provide insight into how the control loop is functioning. These statistics are most commonly calculated for the process variable, controller output, and controller error.

Shown in Equation 6, the Harris Index is a value based on the comparative performance of current control to minimum variance control, MVC. In calculating the minimum variance, an autoregressive moving average model is fit to the process data. This is a predictive model that represents the action a minimum variance controller would take. If the disturbances that affected the process can be predicted



by MVC, then the current controller is performing poorly in comparison. If the disturbances are determined to be random, then the controller is performing as well as MVC. The Harris Index is difficult to calculate. It is important to note that under MVC the auto-correlation of the data is zero after the initial process delay. Therefore, auto-correlation can be used to assess whether or not the system is displaying minimum variance.

Equation 6 - The Harris Index is computed as [4]:

$$I_H = \frac{\sigma_y^2}{\sigma_{mv}^2} \tag{6}$$

Where: I_H = the Harris Index

σ_y^2 = the Variance of the process data

σ_{mv}^2 = the minimum Variance

When the process displays minimum variance, the Harris Index is one. To establish a baseline, the Harris Index should be calculated while the system is in peak performance and then used for comparison purposes against future values. The Harris Index is useful for assessing the output variance due to stochastic disturbances. It cannot give specific information about Set Point changes, known disturbance variables, Settling Time, decay ratio or stability [10].

The reliability of the Harris Index depends on the strength of the model and the estimation of the process dead time. The parameters for the model need to be determined using the Box and Jenkins' method [1], prior knowledge, or trial and error. Poor model selection or erroneous dead time estimations will result in misleading values of the Harris Index.

An additional performance metric introduced in this paper is Standard Variation. The Standard Variation is a normalized measure of deviation of the measured process variable from the Set Point of a process. It is detailed in Equation 7 as shown below.

$$\text{Standard Variation} = \frac{\left(\dfrac{\sum |PV - SP|}{n-1}\right)}{Average(PV)} \cdot 100\% \tag{7}$$

Where: PV : Measured Process Variable

SP : Set Point

n : Number of Data Points

Using this method a smaller Standard Variation will represent less deviation from Set Point. Some factors that can impact the Standard Variation include the number of Set Point changes as well as the number of disturbances that impact the process. The Standard Variation can be used to gauge performance improvement relative to retuning a loop. If the value for Standard Variation is smaller after retuning, then performance has been improved. It should be noted that when comparing a before and after performance index, the data needs to be collected for a sufficient period of time such that the number of disturbances impacting the system are approximately equal.

Two alternative approaches for computing performance include both moving and static calculations. Moving calculations are computed on a moving subset of the complete data set. Static calculations, however, are computed based on the performance measurements of the entire data set. The results of the moving subset calculation are graphed with the performance measure plotted along the vertical axis and time along the horizontal axis. By using a moving subset in lieu of a complete batch calculation, it is possible to identify the point in time when loop performance begins to change. This in turn signals where, or at what point in time, to begin an investigation into causes. Because of the ability to identify real-time changes to performance, the moving subset method is recommended for control loop monitoring.

Figure 7 shows the process variable and controller output traces for a time-variant process. A time-variant process is a system whose dynamic behavior changes with time. This change in behavior can be the result of degrading valve performance, heat exchanger surface fouling, catalysts deactivating, or even fluctuating weather conditions. In the example shown, the system is under PI control and the tuning values are constant during the process transition. By using a moving calculation, the time at which the process began to shift was clearly identifiable.

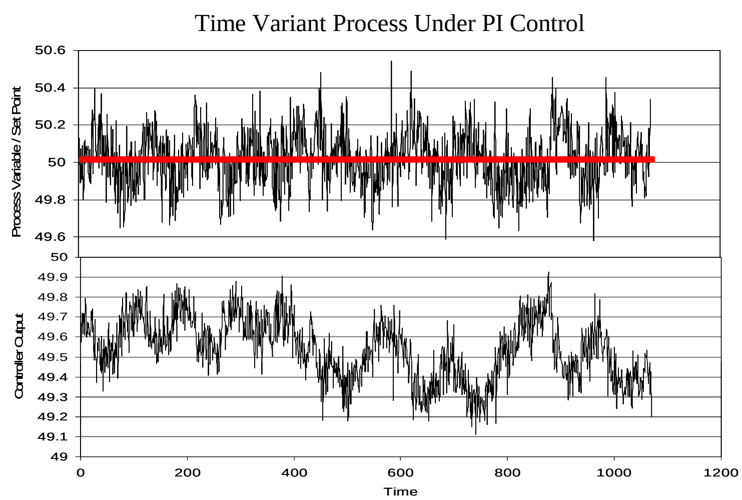


Figure 7 – Process Data and Controller Output

Visual inspection of the process trends shown in Figure 7 does not indicate a significant change in controller performance. However, the plots that follow based on methods just discussed reveal that something in the process indeed has changed. By detecting this change before it has a significant impact on controller performance, solutions including updating controller tunings can be considered before alarms are triggered.

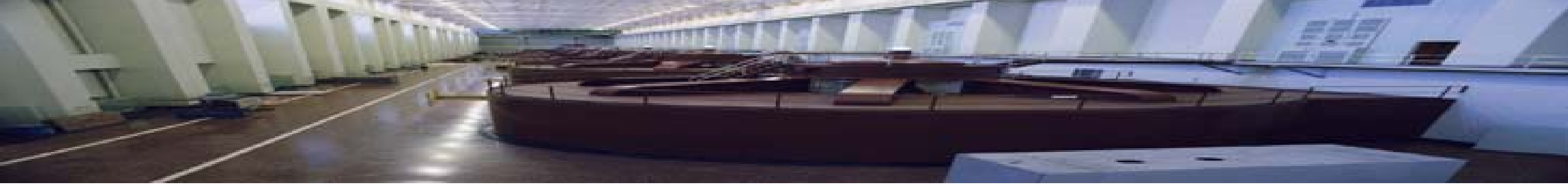


Figure 8 shows side-by-side comparison of the Harris Index, Standard Deviation, Variance and Standard Variation of a moving subset of data for the time-variant process. The dotted line in each trace represents the pre-defined baseline value. Since no two processes are alike, each process should have its own baseline or acceptable performance limit as determined by measurements collected under normal operating conditions when the system is understood to be running under good control. If the value for any performance criteria moves outside its performance limit for a specified amount of time, then that system has drifted to a warning situation. All four methods show that the process begins to drift from its baseline value at about 550 minutes.

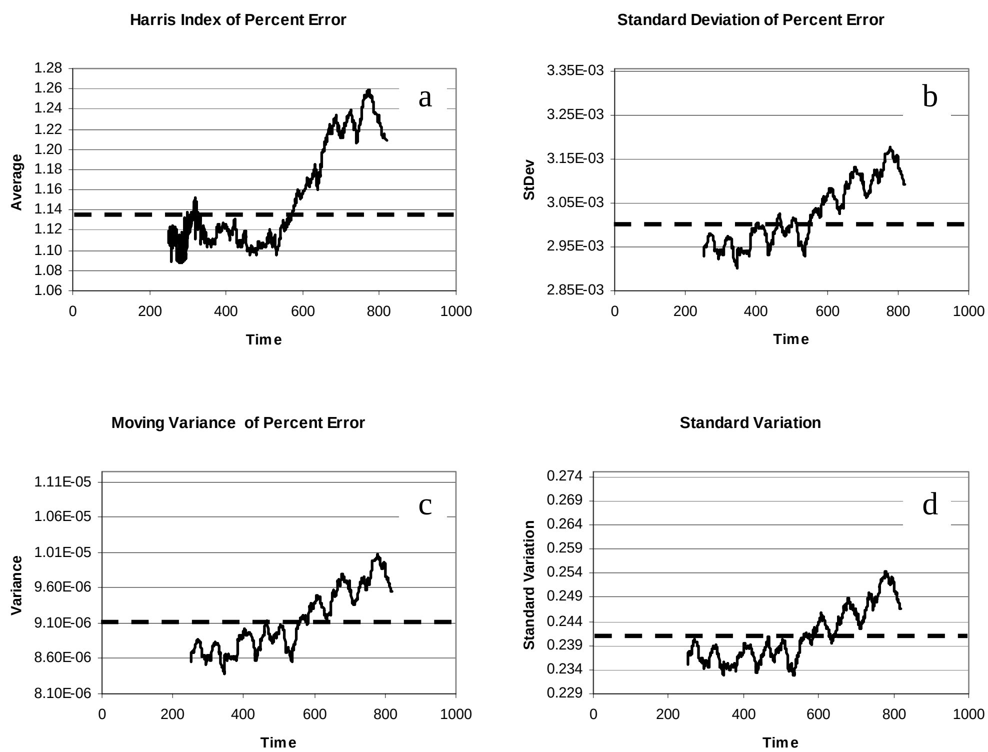
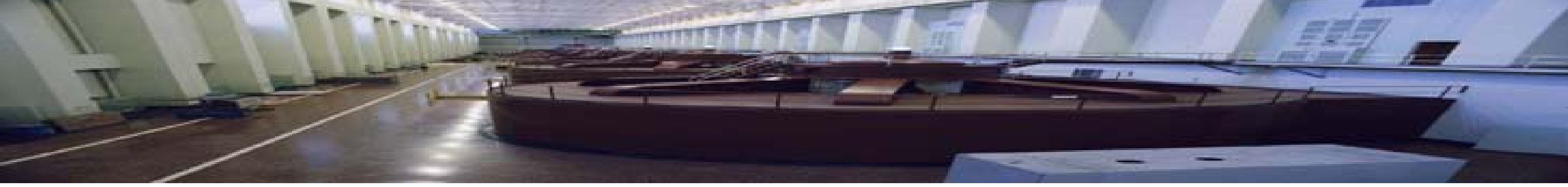


Figure 8 - a) Harris Index, b) Standard Deviation, c) Variance, and d) Standard Variation are calculated by the moving subset method. The time when the process model begins to change is apparent in all plots.

IDENTIFYING INTERACTING PROCESSES

Interacting processes can be troublesome in any manufacturing process. By identifying which systems interact, the disturbances can be counteracted rather than perpetuated throughout the system. Even if an upstream disturbance cannot be eliminated, by identifying the source, a feed-forward controller can be used to mitigate the impact of disturbances and improve downstream loop performance.



Cross-correlation analyzes the relationship between two data series. By calculating a set of correlation values at increasing time delays, a picture develops that shows how the data series are related through time. The cross-correlation is calculated as:

$$r(k) = \frac{\sum_i [(y_a(i) - \bar{y}_a)(y_b(i-k) - \bar{y}_b)]}{\sqrt{\sum_i (y_a(i) - \bar{y}_a)^2}\sqrt{\sum_i (y_b(i-k) - \bar{y}_b)^2}} \quad (8)$$

Where: y_a and y_b = process data

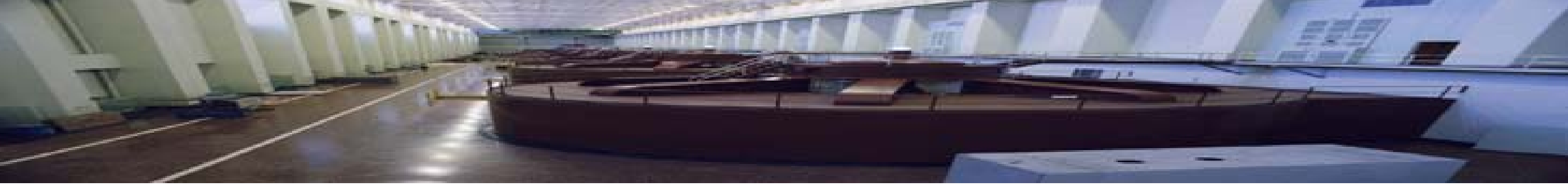
$\bar{y}_a$ and $\bar{y}_b$ = the Set Point values (or the series averages)

k = time delay in samples

i = sample number (or sample time)

Cross-correlation values are always between negative one and one. Positive values indicate that process A directly affects process B, so that an increased deviation from average in process A causes an increased deviation in B. Negative values indicate an inverse relationship such that an increased deviation in process A causes a decreased deviation in process B. If there is no relationship between the data sets, then the cross-correlation values will be close to zero. In addition to revealing the level of interaction between control loops, cross-correlation can also be used to determine exactly how much time elapses before the downstream process will be impacted. At the point when there is greatest impact on the downstream loop, there will be a peak in the cross-correlation trend. Additionally, cross-correlation is used to identify when disturbances are being caused by a recycle stream. If a recycle stream occurs within a single control loop, an auto-correlation can be used to identify how the recycle influences the system.

Power Spectrum is also employed to identify and analyze interacting loops. Interacting loops are affected by the same events and therefore have Power Spectrum peaks at the same frequencies. Power Spectrum cannot identify how long it takes for a change in one system to reach another like cross-correlation can, but it can be more useful when there are many processes separating the suspected interacting loops. Cross-correlation can be muddled when there are many processes with varying relationships, but the Power Spectrum is more sensitive. If processes are affected by events occurring at the same frequencies, Power Spectrum will identify the interaction.



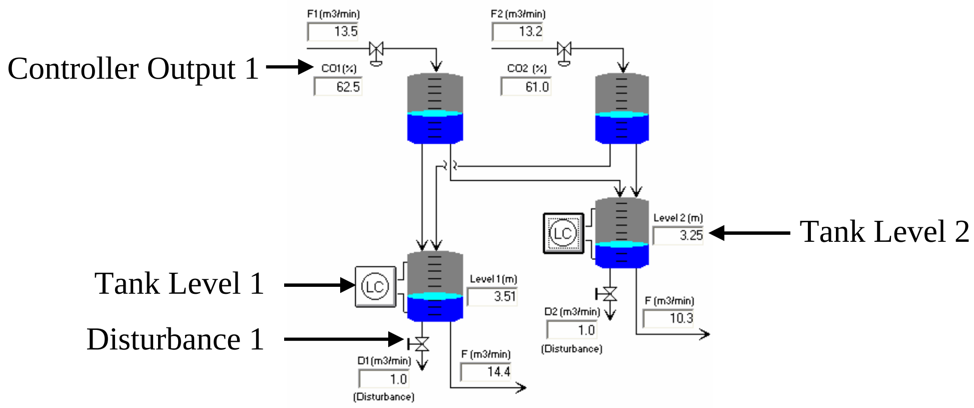


Figure 9 - The interacting tanks process used to demonstrate Power Spectrum and cross-correlation

To explore the abilities of cross-correlation and Power Spectrum to identify interacting loops, consider the array of tanks shown in Figure 9. The two upper tanks each drain into the two lower tanks. Two controllers connect lower tanks to the upper tanks. If the level controllers on the bottom tanks are put into automatic, a disturbance in one of the lower tanks will affect all four tanks. If the level controllers are left in manual, the tank connectivity is broken and disturbance impact remains local to the particular tank affected.

Now consider the system of tanks when they are operated in manual mode. Figures 10a, 10b, and 10c show the process data when a step to controller output 1 increases the flow to upper tank 1. Figures 11a and 11b show the cross-correlation of controller output 1 and the levels in lower tanks 1 and 2, respectively. The large peaks on the graphs signify a strong correlation for both and that the maximum effect takes approximately 15 minutes to impact tank level 1 and 30 minutes to impact tank level 2. Figures 12a, 12b, and 12c show process data collected during a step disturbance in lower tank 1. From the auto-correlation plots shown in Figures 13a and 13b, it is clear the disturbance has an almost instantaneous negative effect on the level in tank 1 and no effect on tank 2.

Figure 14a shows the Power Spectrum of controller output 1, tank level 1, and tank level 2 scaled so they can be displayed on the same graph. All three systems share peaks at the same frequencies and this indicates they are interacting. Figure 14b shows the relationship between a disturbance in tank 1 and the levels in tanks 1 and 2. Disturbance 1 shares similar peaks with tank level 1, indicating they are interacting. Tank level 2 has a unique Power Spectrum, indicating it is responding to different stimuli.

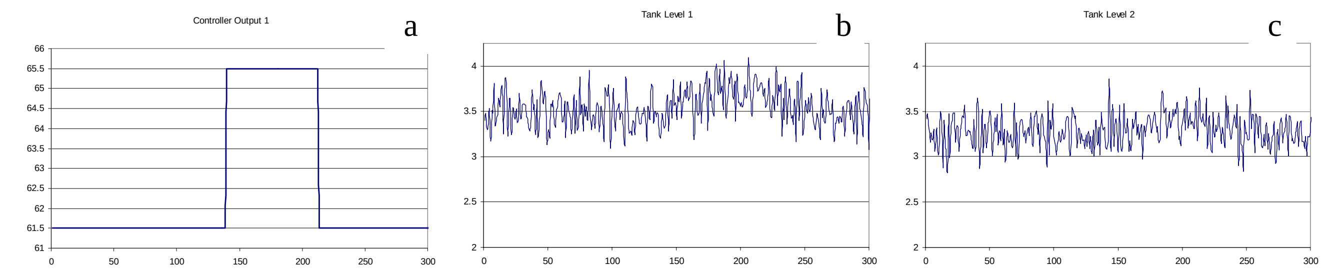
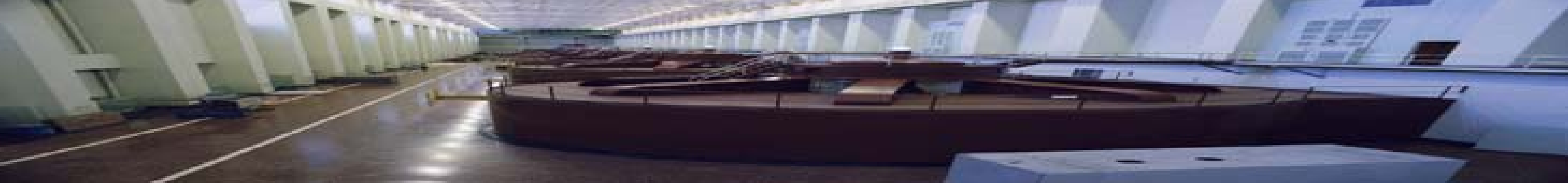


Figure 10 – Process data during a step change of controller output 1 a) controller output 1 b) tank level 1 c) tank level 2



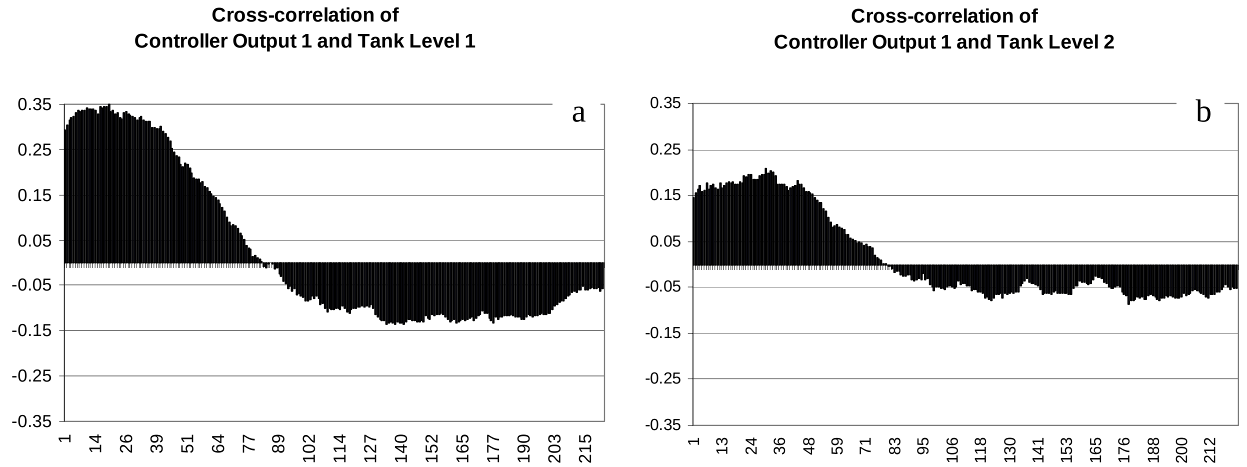


Figure 11 - Cross-correlation diagrams of the relationship between controller output 1 and a) tank level 1 b) tank level 2

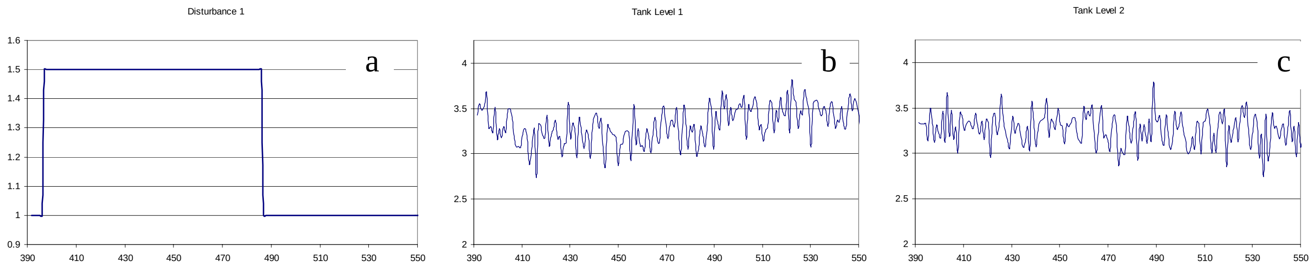


Figure 12 – Process data during a pulse disturbance in tank 1 a) disturbance 1 b) tank level 1 c) tank level 2

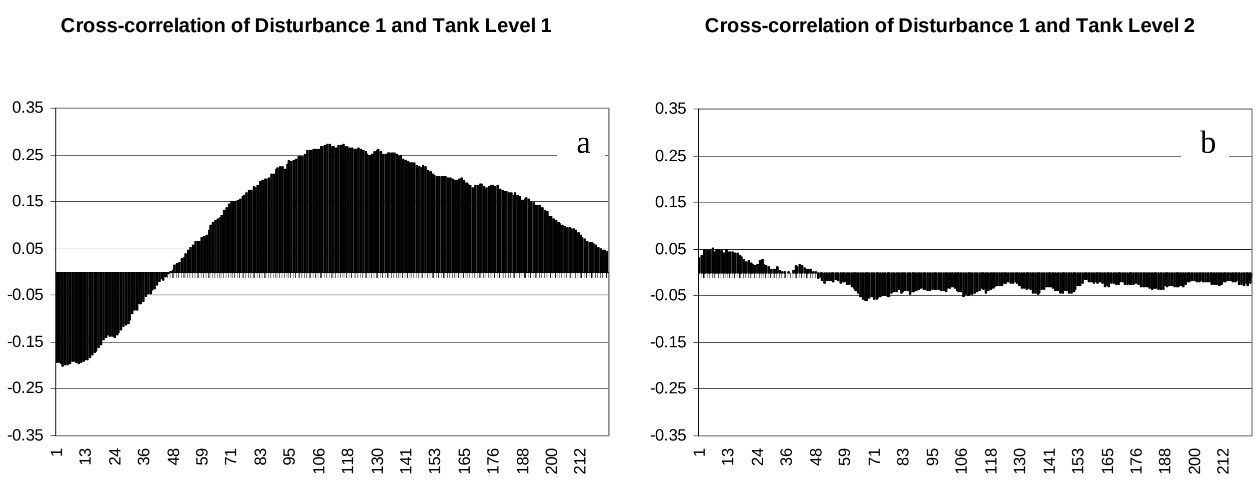
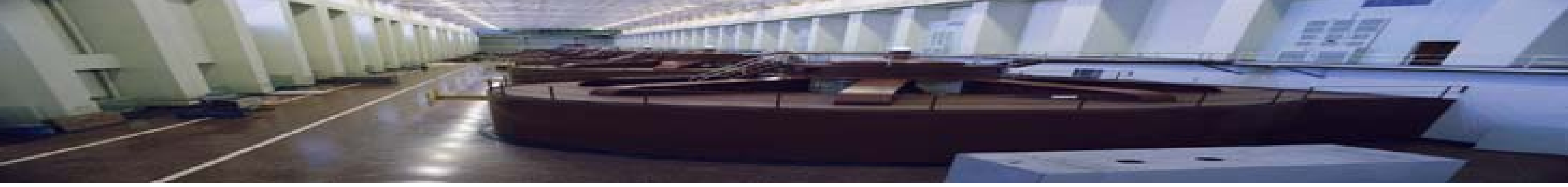


Figure 13 - Cross-correlation diagrams of the relationship between disturbance 1 and a) tank level 1 b) tank level 2



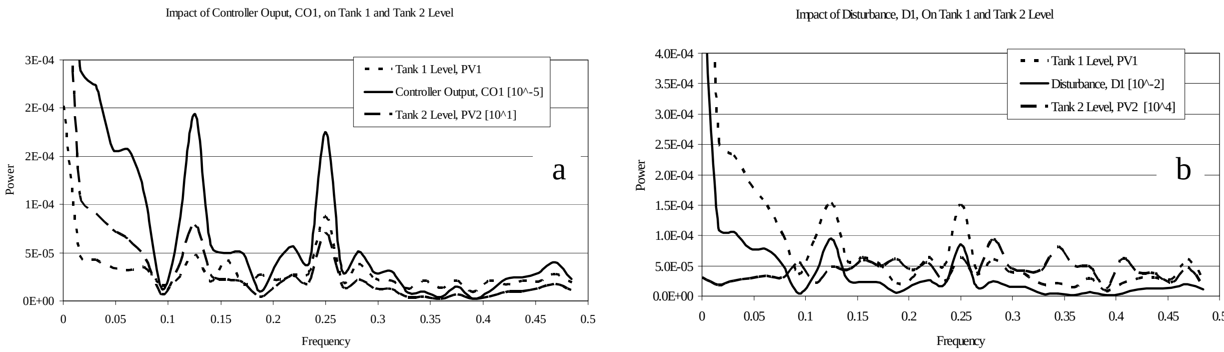


Figure 14 - Power Spectrums of a) controller output 1 and tank levels 1 and 2 and b) disturbance 1 and tank levels 1 and 2. The spectrums have been scaled so that they can be view on the same graph.

CONCLUSIONS

Performance measures are an integral part of optimizing and maintaining system performance. Industry and academia are constantly deriving new methods for performance assessment, but the methods are only useful when they can be fully understood and used properly. It is important to understand the theory, purpose and limitations of the measures before relying on their information. In many cases, the performance assessment methods only identify the start of a problem, not the source. By understanding the basic principles and disturbances that impact your system, engineers will know what to expect during normal operation and will be able to identify more quickly what is abnormal operation.

This paper addressed a wide variety of commonly used performance assessment techniques in an attempt to demystify them for better application in monitoring. The techniques detailed in this paper for tackling real-time process monitoring are twofold. First one can identify when a process starts to drift away from baseline operation and towards triggering an alarm. Once a problem is identified, the use of auto-correlation, cross-correlation, and Power Spectrum can be used for detect the root-cause.

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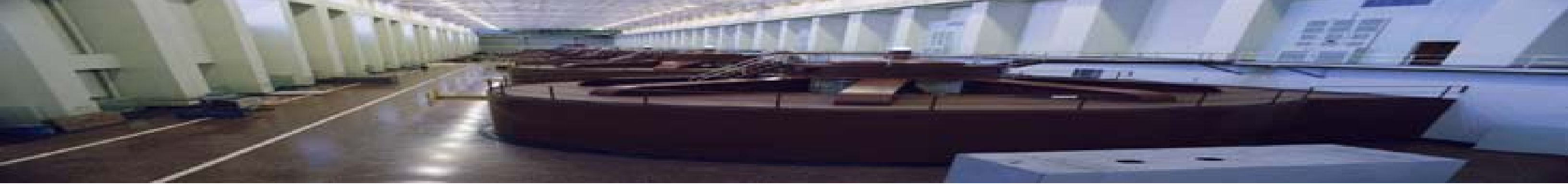

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