

RUN LENGTH-BASED CONTROL PERFORMANCE MONITORS: A Comparison Between Two Techniques

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Abstract:

This work compares two techniques of controller performance monitoring. Both are based on the sequences (or Run Lengths) of signs of the actuating errors of a single controlled loop variable. One technique defines Run Length as a state, and transition probabilities between states are then modeled as a Markov Chain. The other technique observes the distribution of Run Lengths. Both techniques were tested with experimental data and found to be equivalent in their ability to detect poor control loop performance

Introduction

Controller performance often changes during plant operations and since the performance is important to process safety, product quality, and manufacturing costs, it would be desirable for operators to notice these performance changes as soon as possible.

The industrial need for efficient controller performance assessment tools is supported by research efforts aimed at such techniques [1-9]. Most of these methods utilize either the actuating error and or control output signal. It is generally desired that assessment of control loops should utilize routine plant operating data and be noninvasive (i.e. should not disturb routine operations of the processes). It is also desired that the performance assessment algorithm should be simple, user friendly, and require minimal process knowledge.

Here, one approach uses a Markov Chain and binomial statistics to monitor controller performance [1]. In it, the probabilities of transition between states are compared with control limits, which have been determined beforehand from a user-defined period of good control.

This work demonstrates the application of the monitor on experimental data, and compares the technique to an earlier version [2], in which the authors used the distribution of actuating errors between consecutive zero crossings.

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1. Control Performance Monitoring Based on Markov Chains and Binomial Statistics

Summarizing [1], first define a historical period of good control, then analyze the run length transitions in the data. Run length is a state in a Markov Chain. If there is a sequence of data with three positive values in a row, then the state is +3. If there are five sequential negative values of the actuating error then the state is -5. Determine the probability of transitioning from one run length to another. Conveniently, this is a binary probability, since; for instance, a run of +4 can only transition to a state of +5 if the next error is "+" or transition to a state of -1 if the next error is "-". Before beginning the analysis, the user makes two initial selections of (i) an upper limit for the number of states (6 to 12 seems reasonable) and (ii) a sampling frequency for the monitor which populates the low numbered states. then the monitor determines the window length of samples that will be used for test analysis.

The flow chart in Figure 1 summarizes the steps for determining the window length of samples for test analysis.

Figure 2 is a schematic diagram showing a Markov Model of state transitions. In general, let n_{+i} denote the number of samples (transitions) entering a state of +i say, which is the same as the number of samples in that state. The only exception to this involves the state of ± 1 and the extreme state of $\pm E$. For the general case above, let P_{+i} denote the transition probability of the number of samples exiting the state of +i and entering the state of -i. Similarly, let P_{-i} denote the transition probability of the number of samples exiting the state of -i and entering the state of +i. Consider only the positive side of Figure 4 for this part of the analysis. Let the number of samples leaving the positive penultimate state (+E-1) and entering the positive extreme state (+E) be denoted by n_{+E} . For this Figure +E = 4 for simplicity and n_{+E} = the total number of samples in the extreme state (samples that entered from (+E-1) + those that persisted in the extreme state i.e. those that re-entered the extreme state). For the extreme state, the probability of making a transition to a state of -1 is given by:

$$P_{+E} = \frac{n_{+E-1}}{n_{+E}}$$

Hence the probability of making a transition from the extreme state back into the extreme is given by:

$$1 - P_{+E} = \frac{n_{+E} - n_{+E-1}}{n_{+E}}$$

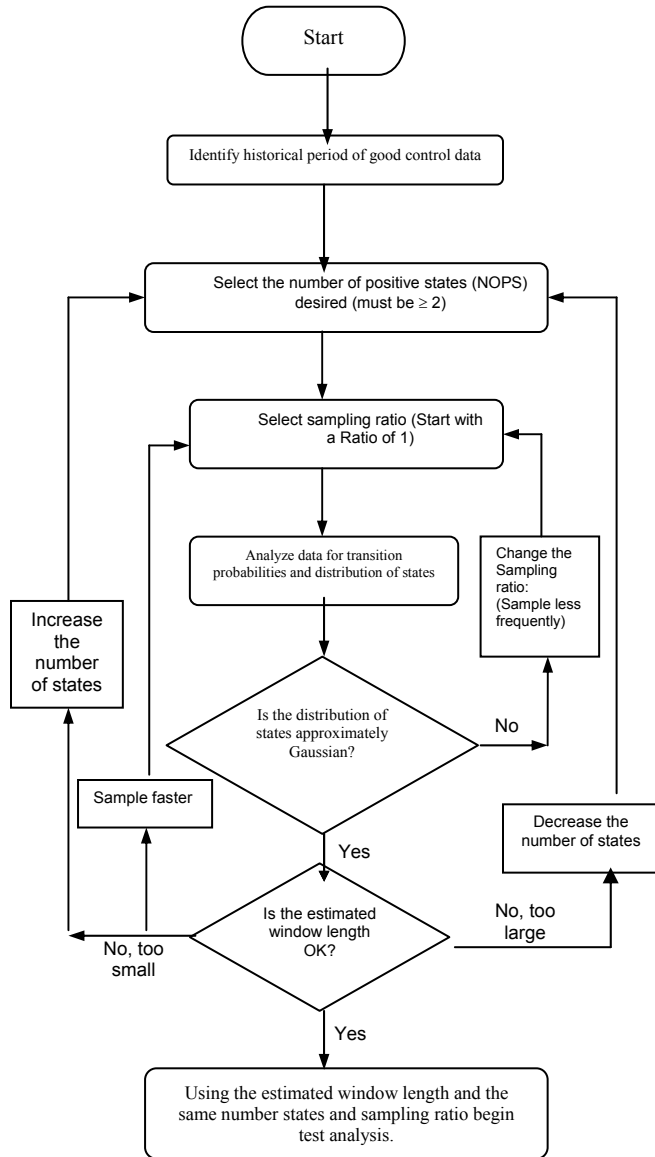


Figure 1. Flow Chart for Analyzing Historical Good Data

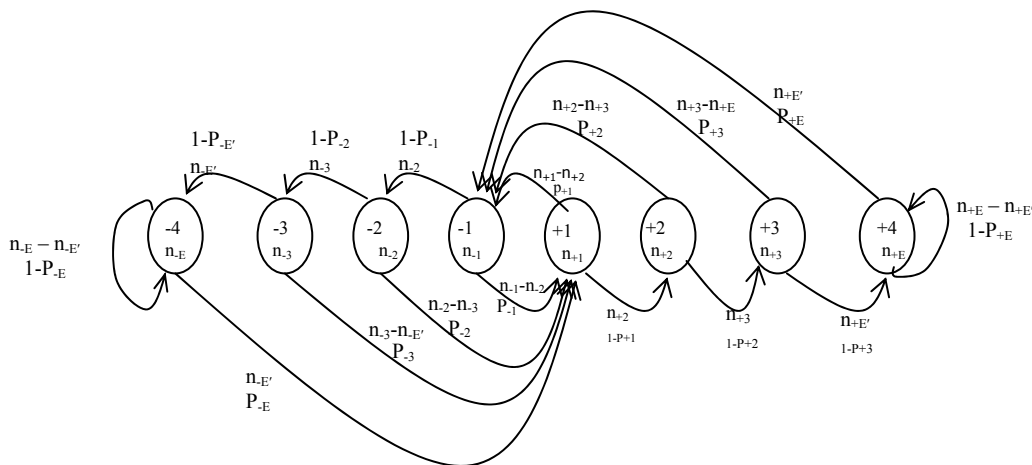


Figure 2. Schematic Diagram of Markov Process with 8 Total states

All the state transition probabilities can be easily determined and using the data from a good control period the monitor determines the window length necessary for test performance analysis.

The user provides the overall level of significance α [1]. The monitor then uses this together with the total number of state to determine the level of significance that will be associated with each state. Figure 3 summarizes the flow procedures for performing test analysis.

During analysis of normal operating data, if any transition probabilities lie outside the control limits, a violation is registered and a grace period counter invoked. The grace period allows time for the controller to recover good control after an upset. If after the grace period, the violation is still registered, then the monitor raises a flag retroactively to indicate the start of the problem. Once the disturbance that caused the problem is removed, flagging stops and the violation counter is reset.

Data from a two-phase flow experimental unit was collected and the monitor used to analyze the data. The aim was to test the ability of the monitor to detect durations when there were control problems. The experimental unit consisted of a vertical column through which water and airflow upward, co-currently. The unit is designed with individual PID-Type control loops to manipulate both water and the airflow valves to sustain either flow rate or pressure drop.

Process data is collected during a good control period, preferably just after the controller is well tuned. The performance of the monitor using three different control schemes follows.

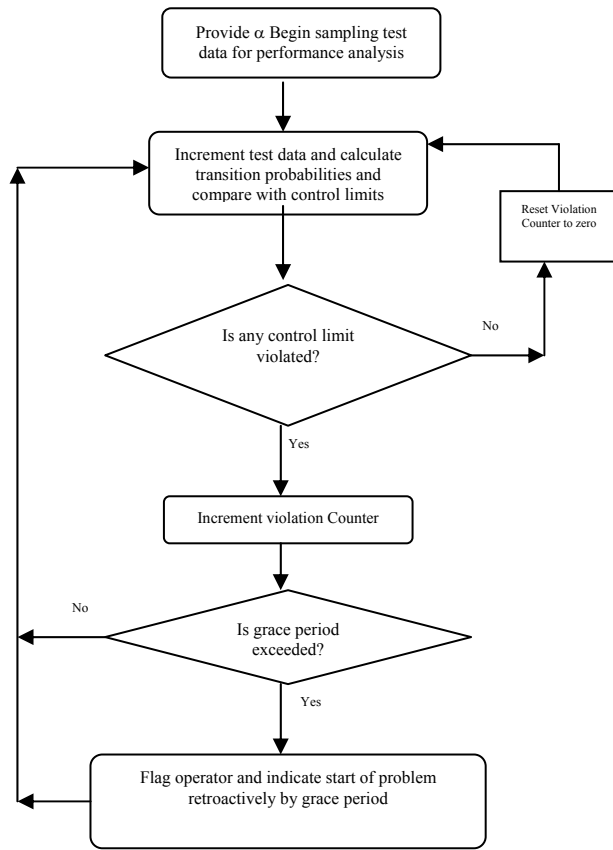


Figure 3. Summary Flow Chart for Conducting Performance Test Analysis

Process data is collected during a good control period, preferably just after the controller is well tuned. The performance of the monitor using three different control schemes follows.

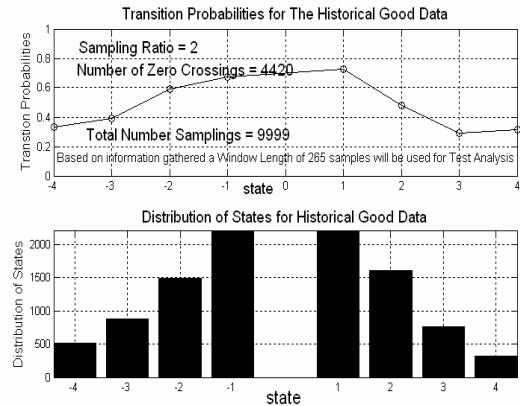
Once control was judged to be optimum after tuning, data was collected at a rate of 10 Hz, which was the fastest rate at which data could be logged for the system we used. After collecting good data, various disturbances such as setpoint and gain changes were introduced into the loop to disturb it.

Test 1: Controlling Pressure by manipulating signal to the water control valve

Figure 4 illustrates the statistical analysis of the good control data and it shows 2 plots consisting of the transition probabilities versus state and a histogram of the distribution of state. The number of positive state used was 4 (i.e. 8 total state) at a sampling rate of 5 Hz. The window length is 265 samples.

The test level of significance is 0.3%, and monitor results are shown in Figure 5. There are six individual plots in Figure 5. The top horizontal graph displays the process variable with respect to time. The second from

the top graph, the manipulated variable, and the third, the



violation counter and the flag.

Figure 4. Transition Probabilities and Histogram of Distribution of state for Historical Good Data

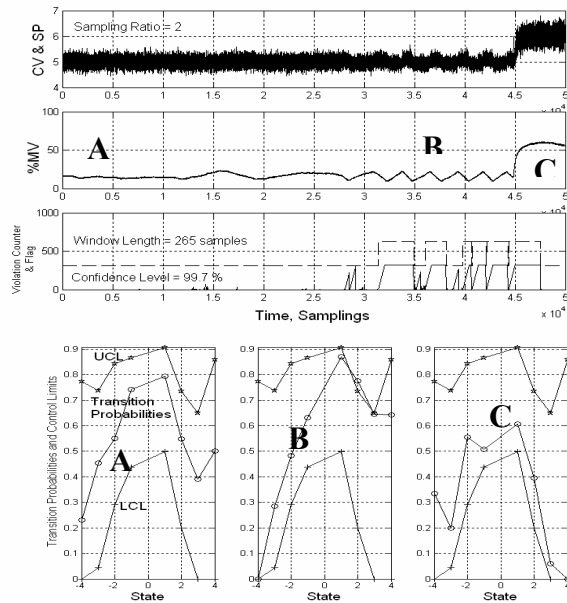


Figure 5. Control Loop Performance Output (Window Length = 265 Samples, Closed Loop Settling Time (CLST) = 50 samples, level of Significance = 0.003, Grace period = 265 + CLST)

The counter shows a saw tooth pattern, and the flag shows the square wave pattern. The lower three graphs show the probability transitions, and control limits from the three time regions marked as “A”, “B”, and “C”.

During the time period indicated by the letter “B” the water control valve revealed sticktion - evidenced by the rectangular shape on the CV plot as well as the saw tooth behavior on the MV plot. The monitor detected this anomaly and raised a flag after the grace period was exceeded.

Test 2: Controlling Pressure by manipulating signal to the air control valve

This experiment manipulated the signal to the airflow control valve to control pressure drop between the top and bottom of the column. Analysis of the test data revealed that monitor was able to detect all periods during which control was bad.

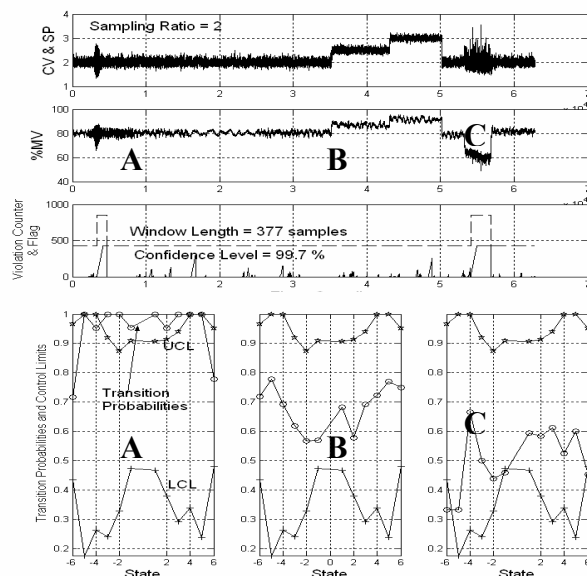


Figure 6. Control Loop Performance Output (Window Length = 377 Samples, Closed Loop Settling Time (CLST)= 50 samples, level of Significance = 0.003, Grace period = 377 + CLST

Between about 5 to 8% through data sampling, the controller gain was doubled. The monitor detected the change in controller performance and raised a flag after the grace period was exceeded. Setpoint changes that were made 50 to 70% through the sampling were not flag as expected. Between 75 to 85% through the sampling, the water flow rate was increased slightly. This disturbed the loop as evidenced on the first and second plots in Figure 6, which represents the process variable output and the controller signal output respectively. The monitor detected the anomaly in the loop and flagged when it registered the continuous persistence of the problem after the grace period was exceeded. It is worthy to note that in all three instances, there were durations when the violation counter was invoked but there were no obvious disturbances in the loop. These could be attributed to the occurrence of type-I errors and by the proper choice of window length (i.e. number of state and sampling ratio), the occurrence of these errors were significantly reduced.

2. Control performance Monitoring based on Run Length Distributions and Chi Squared Distribution

The reference Run length distribution is built from the actual data (controlled variable CV and setpoint SP) collected during good control period, usually just after the controller is well tuned. The control performance monitor flags when statistical tests indicate that there is a sustained period with significant changes in the distribution compared to the reference distribution [2]. A flow chat of the process is shown in figure 7.

1. At each sampling time, measure the process controlled variable (CV) and setpoint (SP), and calculate the error (SP – CV).
2. Calculate the RL distribution from a window of the past N error values. The choice of the window length N will be discussed in detail later.
3. Apply the statistical goodness-of-fit test (to be discussed later) to determine whether the obtained RL distribution is significantly different from a reference RL distribution, which have previously been built from data collected during a good control period.
4. If the goodness-of-fit test indicates that the two RL distributions are significantly different, increment a counter, called a violation counter VC, which records the length of the time period during which the goodness-of-fit tests continuously indicate significant differences between the obtained RL distribution and the reference distribution. Otherwise, if the test does not indicate significant differences, reset the violation counter to zero.
5. Compare the violation counter with the pre- selected grace period (to be discussed later), which is the time period allowed for a good controller to respond to changes in setpoint or non-random disturbances plus the time period needed for a window length of data used to build current RL distribution. If the violation counter becomes greater than the grace period, then the control performance monitor flags poor control performance. Otherwise, it does not flag.
6. At the next sampling time, repeat the whole procedure.

Before Running the performance monitor and doing a chi-square test, the following steps must be done: (1) build the reference RL distribution, (2) divide the RL range of the reference distribution into several class intervals, and (3) choose a sampling window length N to build the current RL distribution. Each step will follow a specific choice-free procedure and can be fully automated after being provided with data collected during a representative good control period, and the closed-loop settling time after the control loop is well tuned. The window length is determined such that each

grouped bin in the chi-square test will have at least five expected observations. The grace period is chosen as the closed loop settling time plus the window length.

Figure 8 tests the distribution based monitor with the same data as in Figure 5. During the instance of valve sticktion, the run length distribution (RLD) technique was also able to detect the anomaly and flagged after a grace period was exceeded.

Lastly, Figure 9 compares with Figure 6. During the period when increased water flow rate made the loop unstable, the RLD technique was able to detect the nuisance and flagged it after it persisted beyond the grace period.

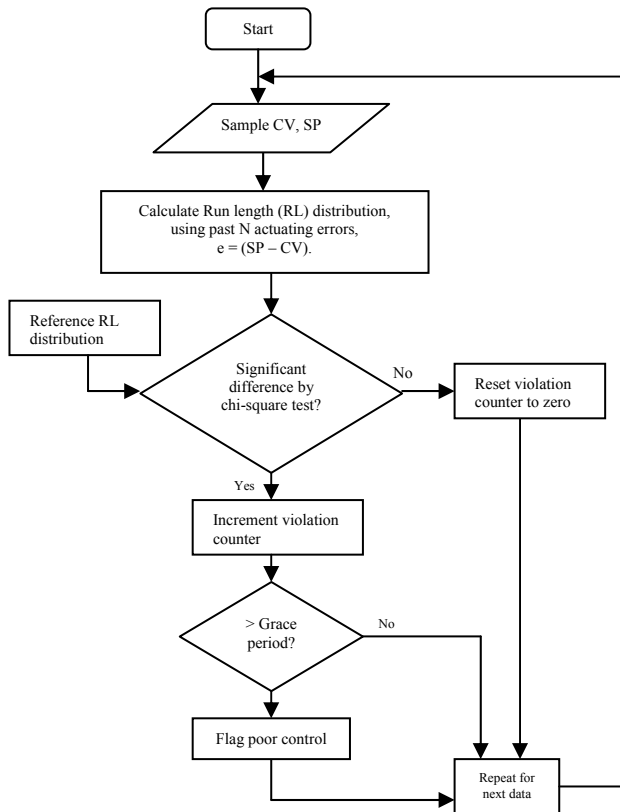


Figure 7. Flow Chart of the Control Performance Monitor

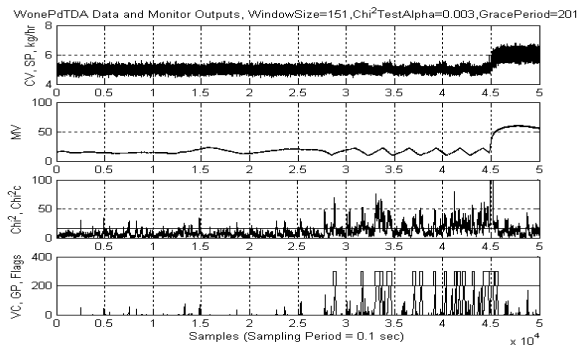


Figure 8. Controlling Pressure by manipulating signal to the water control valve

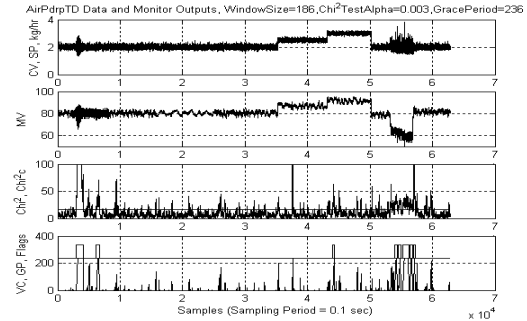


Figure 9. Controlling Pressure by manipulating signal to the air control valve

3. Comparisons Between the Two Techniques

3.1. Similarities

The two approaches have many things in common. Both are based on lengths of Runs of signs of actuating error samples. Only the signs of the samples, not the values of the samples, are used in both monitors, so the algorithms need few storage spaces in memory and can be very efficient.

Both approaches use a moving window of the sample data to build the Run length distributions or state transition probabilities. Both need to choose an appropriate window size before starting monitoring and both use a heuristic rule, for example, the RLD technique requires at least of 5 expected observations in each bin while the state transition probability (STP) technique requires at least 5 observations in each of the extreme state, to determine the window size. Both allow a grace period of violation before flagging poor control. The grace period is chosen as the closed loop settling time plus the window size.

Both monitors compare the RL information with a reference case, which is represented by the data collected during a good control period, judged so by an expert.

Very fast linear time algorithms can be designed to implement both monitors. The major memory storage requirements for both monitors are very small: one array of integers with the same size as the window size, and one array of integers with the same size of the bins or twice the number of state.

Experiments show that both monitors can catch common poor control performance due to too sluggish control, constrained control, too aggressive control, or stiction.

3.2. Differences

Although the RLD and STP methods use similar information (and can almost be derived from each other), they process it a bit differently. While the RLD method is more intuitive, the state transition method uses more ideal statistical analysis. The major functional difference seems to be consistency of flagging. In these

experiments, RLD flags on and off during a bad period, while STP flags on more continuously. But, this might be due to choice of sampling rate and window length more than some fundamental property of the techniques..

3.3. Perspective

Two feasible control loop-monitoring techniques capable of identifying changes in control behavior in real time have been developed. At this time neither of the two methods provides indication of exactly what and where a problem could be, the moment a flag is raised. It is worthwhile to mention that this is effort is work in progress and future work will embody fault location as well. Nevertheless, the instant a violation is registered is an indication that there could be a loop degradation some where and once a flag is raised, then it means operator attention is required. Also, although, both schemes have been developed for a single controlled variable (CV), they are applicable to all multivariable systems as well

4. Conclusion

Two different techniques for controller and control loop performance assessment have hereby been developed. Both methods were developed with different statistical approaches. Experimental tests reveal that, although computational difficulty involved in each method (i.e. number of calculations carried out at each monitor sampling) is different, both methods are found to be significantly equivalent in their ability to detect and flag violations in controller and control loop performance.

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