STEADY STATE AND TRANSIENT STATE

IDENTIFICATION IN AN INDUSTRIAL PROCESS

By

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Abstract:

A computationally simple method is demonstrated for automated identification of steady state and transient state in noisy process signals of an industrial-scale, single or multi-variable process. This steady state and transient state identification method uses the R-statistic method, which is a ratio of estimated variances, and independent of the process variance. It has been implemented for automated identification of steady state of a single variable water flow rate to an absorption column in the Unit Operations Lab and the multi-variable commercial scale distillation process in FRI. When there is an upset in the process the steady state identifier indicates so. Most often the visual identification of steady state agrees with the statistic-based method of identification of steady state. At the process where the noise is pronounced and confounds identification of steady state, the steady state identifier helps operators to interpret the data.

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CHAPTER I

INTRODUCTION

1.1 Overview

Identification of both steady state and transient state in noisy process signals is important to design and analyze a control system. Steady state is where the system becomes stable but may be confounded by noise. Steady state triggers the collection of data for process model adjustment, control [1], optimization [2], process analysis, fault detection [3], data reconciliation [4], neural network training, etc. Alternately, a transient state can occur because of environmental changes, upsets, changes in set point, etc. Transient state triggers the collection of data for dynamic modeling, recognition of points of change, motion, etc. [5-7] Identification of steady state is usually a visually subjective operator decision, and a statistically-based method can standardize this procedure. This study reports on an application to trigger sampling and transitions in an experimental sequence.

Engineers often run a sequence of experiments throughout a range of operating conditions to collect data, and process operators sequence to the next stage of a process. Each sampling event is initiated when the operator observes that steady conditions are met, and then the operator implements the new set of operating conditions. However, this visual method of triggering requires continual human attention, and it is subject to human error in the recognition of steady state when: measurements are noisy, process changes are slow, there are multiple dynamics, or change-of-shift timing infects the visual interpretation.

Alternately, the experimental run can be scheduled to go to the next set of conditions at pre-set time intervals. Unfortunately, this method can create inefficiency if the runs are scheduled for an unnecessarily long time, or the data can be worthless if the scheduled time is insufficient for any particular set of conditions to achieve steady state. Since the time to reach steady state varies with operating conditions, it is nearly impossible to predict the necessary hold time.

Consequently, automated online, real-time steady state identification would be useful to trigger the next stage of an experimental plan or process phase.

The Steady State Identification (SSID) and Transient State Identification (TSID) method in this study is based on the R-statistic method [8]. It has been implemented for automated identification of steady state of a single variable water flow rate to an absorption column in the Unit Operations Lab at OSU and the multi-variable commercial scale distillation process in Fractionation Research, Inc. (FRI).

The implementation has two stages: First, historical data are used off-line to choose a sample interval to eliminate autocorrelation of the data and to validate the method. Second, the SS and TS identification code is installed onto an online computer for either application (Labview software in the Unit Operation Lab, and Excel VBA running on the FRI servers at the unit). Results illustrate how this SS or TS identification can be used in real-time for online control of a test sequences.

The findings reveal: A) When there is an upset in the process the steady state identifier indicates so; B) Most often the visual identification of steady state agrees with the statistic-based method of identification of steady state; C) At the process where the noise is pronounced and confounds identification of steady state, the steady state identifier helps operators interpret the data.

1.2 Literature Survey

1.2.1 Direct Approach to Steady State Identification

The direct approach to steady state identification is to perform a linear regression of a sequence of data and test the slope of this linear regression line. If the slope is close to zero, it means the process is probably at steady state. On the contrary, if the slope is significantly different from zero, the process is probably at transient state [9].

In general, this method is an off-line technique. The online version requires large computational data storage, and user expertise to decide the data window length to clear autocorrelation. Concerning computational burden, the whole data window must be updated and the computer must calculate the linear regression slope at each of the time interval. Furthermore, the appropriate length of the data window is important. For example, the linear regression slope is temporarily equal zero in the middle of a definite oscillation, which would lead to wrong steady state identification. The length of data window could not be decided by a universal rule and any selection would require human judgment.

1.2.2 F-test Type Statistic Method

The F-test type statistic method [10] is to calculate the ratio of variances which is measured from same sequence of data using two different methods. One of the variances is the mean square deviation of data within the chosen data window. The other variance is the mean of squared differences of successive data from the same data window. Ideally, the ratio of two variances would be unity at a steady state process. However, the actual ratio will not be exactly unity because of random noise in the real process. The ratio is around unity at steady state.

The F-test statistic method is valid, but has several undesirable features. For instance, this method must also store and calculate a large number of data, which leads to it also being computationally expensive. Furthermore, this method requires user expertise to select an appropriate time interval to eliminate the autocorrelation.

1.2.3 R-Statistic Method

The R-statistic Method is styled after the F-test type static method [11]. The R-statistic method [8] calculates the ratio of variances, which are measured on the same set of data by two different methods. The detailed information of R-statistic method is presented in Chapter 2. This approach is executed using an easily implemented statistical method with defined critical values [12, 13]. It was extended to a multi-variable process and demonstrated on lab-scale and pilot-scale processes to automatically trigger an experimental sequence [14-16]. It was also demonstrated as a convergence criterion in nonlinear regression optimization [17, 18]. This work demonstrates it in a commercial scale process.

1.3 Summary

In either Steady State Identification or Transient State Identification, computers are preferred over visual inspection. The R-statistic method has advantages over direct approach identification method and F-test type statistic method. This work demonstrates two separate implementations, one in the Unit Operation Lab and the other on the FRI Unit. The method works with both off-line and online data by running in the background. It is a computationally simple method which only needs to store eight variables in each calculation. It detects steady state and loss of steady state based on time series analysis and statistical tests, which requires no process knowledge for the operators.

CHAPTER II

Method

2.1 Explanation of the R-statistic Method

This R-statistic method calculates the ratio of two variances, which are measured on the same set of data by two methods [8]. In order to reduce computational effort, exponentially weighted moving average and variances are calculated in place of the conventional average or variance. Fig 2.1 illustrates the concept. The dotted line represents the true but unknowable trend of a process. The value starts at 15, ramps to a value of 10 at a time of 50, and then holds steady. The diamond markers about that trend represent the measured data that the observer sees and constitutes all knowledge. The dashed line, the true trend is unknowable, only the measurements can be known and they are infected with noise-like fluctuations, masking the truth.

The SSID/TSID approach first calculates a filtered value of the process measurement, indicated by the curved line that lags behind the data. Then the variance in the data is measured by two methods. The deviation indicated by d_2 in the upper left of the figure is the difference between measurement and the filtered trend. The deviation indicated by d_1 in the lower right is the difference between sequential data measurements. If the process is at SS, as illustrated in the 80 to 100 time period, X_f is almost the middle of the data. Then the process variance ν^2, estimated by d_2 will ideally be equal to δ^2 estimated by d_1. Then the ratio of the variances $r = \frac{\nu^2{}_{d_2}}{\delta^2{}_{d_1}}$ will be approximately equal to unity, $r = \frac{\nu^2{}_{d_2}}{\delta^2{}_{d_1}} \cong 1$. Alternately, if the process is in a TS, then X_f is not the middle of data, the filtered value lags behind, and the variance as estimated by d_2 will be much larger than the variance as estimated by d_1, $\nu^2{}_{d_2} \gg \delta^2{}_{d_1}$, and ratio will be much greater than unity, $r = \frac{\nu^2{}_{d_2}}{\delta^2{}_{d_1}} >> 1$.

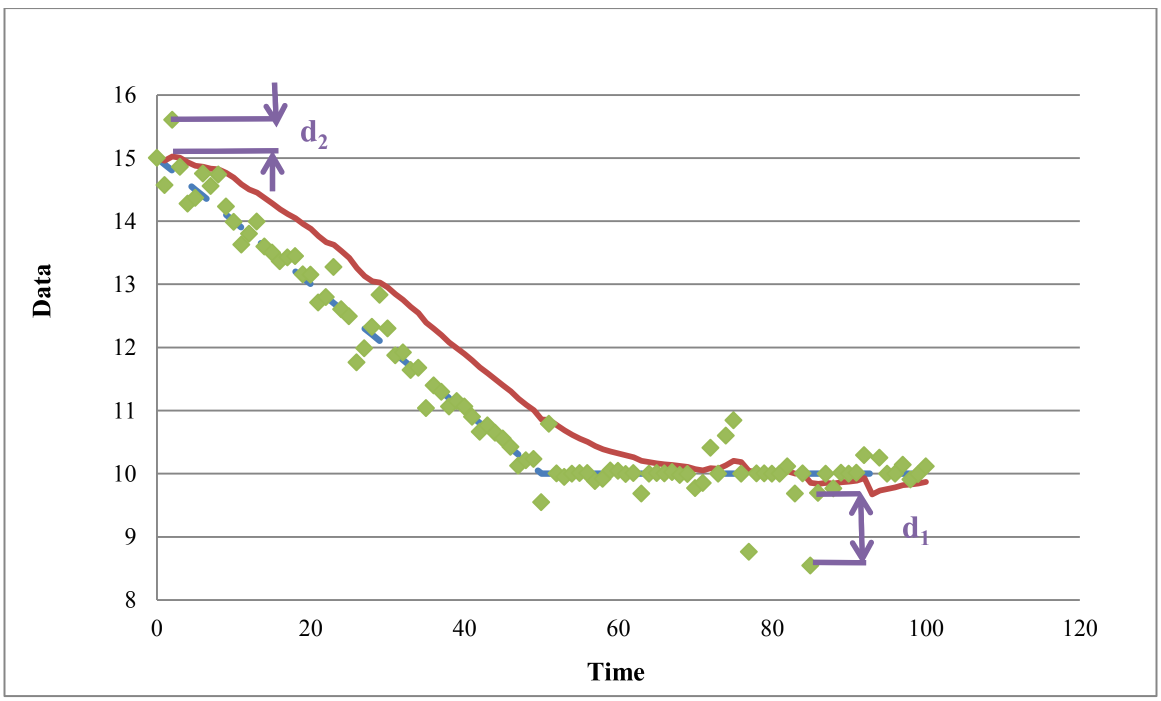

Figure 2.1: Calculated actual process, filtered data and process trend by Excel

To minimize computational burden, in this method a filtered value (not an average) provides an estimate of the data mean:

$$X_f = \lambda_1 X_i + (1 - \lambda_1) X_{f,i-1} \tag{1}$$

Where,

X = the process variable

X_f = Filtered value of X

λ_1 = Filter factor

i = Time sampling index

The first method to obtain a measure of the variance uses an exponentially weighted moving "variance" (another filter) based on the square of the difference between the data and the "average":

$$v^2{}_{f,i} = \lambda_2(X_i - X_{f,i-1})^2 + (1 - \lambda_1)v^2{}_{f,i-1} \tag{2}$$

Where,

$v^2{}_{f,i}$ = Filtered value of a measure of variance

$v^2{}_{f,i-1}$ = Previous filtered value of precious measure of variance

Equation (2) is a measure of the variance to be used in the numerator or the ratio statistic. In Equation (2) the previous value of the filtered measurement is used instead of the most recently updated value to prevent autocorrelation from biasing the variance estimate, $v^2{}_{f,i}$, keeping the equation for the ratio simple.

The second method to obtain a measure of variance is an exponentially weighted moving "variance" (another filter) based on sequential data differences:

$$\delta^2{}_{f,i} = \lambda_3(X_i - X_{i-1})^2 + (1 - \lambda_3)\delta^2{}_{f,i-1} \tag{3}$$

Where,

$\delta^2{}_{f,i}$ $=$ Filtered value of a measure of variance

$\delta^2{}_{f,i-1}$ $=$ Previous filtered value of previous measure of variance

This will be the denominator measure of the variance.

The ratio of variances, the R-statistic, may now be computed by the following simple equation:

$$R = \frac{(2-\lambda_1)v^2{}_{f,i}}{\delta^2{}_{f,i}} \tag{4}$$

The calculated value is to be compared to its critical values to determine SS or TS. Neither Equation (2) nor Equation (3) computes the variance. They compute a measure of the variance. Accordingly, the $(2 - \lambda_1)$ coefficient in Equation (4) is required to scale the ratio to represent the variance ratio. See [8] for the full derivation and analysis.

In expanding the technique for a multi-variable analysis, we choose to claim that a process is not at steady state if any process variable is not at steady state, and might be at steady state if all variables are at SS. This can be easily computed with a single statistic:

$$SS_{process} = \prod_{j=1}^{N} SS_j \tag{5}$$

Where,

N $=$ Total number of variables in process

j $=$ Variable index

$SS_j \quad = 1$ if the variable is at SS and 0 if the variable is in TS

$SS_{process} = 1$ if all variables are at SS and 0 if any one variable is in TS

2.2 Selection of Critical Value

The concept is simple but the statistical vagaries create distributions of the R-statistic values that need to be understood. Fig 2.2 represents the statistical distribution of the R-statistic values at steady state.

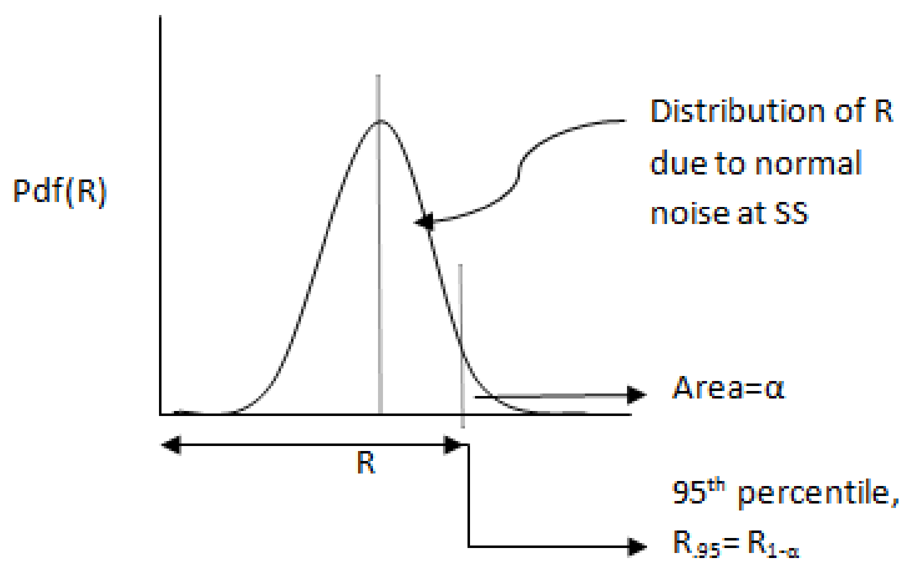

Figure 2.2: R-statistic distribution at steady state

The value of the R-statistic will have some variability because of the random fluctuations in the sequential measured data. If the value of R is less than the upper 95% confidence value, the process may be at steady state, but if it is beyond (larger than) the 95% confidence value then it is likely that the process is not at steady state. If the process is at steady state, there is a small, α = 5% chance that $R > R_{0.95}$.

Fig 2.3 includes the distribution of the R-statistic for a process that is not at steady state, one that is in a transient state, with its distribution of R-statistic values greater than unity. For a process that is not at steady state, there is a high chance that $R > R_{0.95}$. As illustrated in Fig 2.3 it is over a 70% chance.

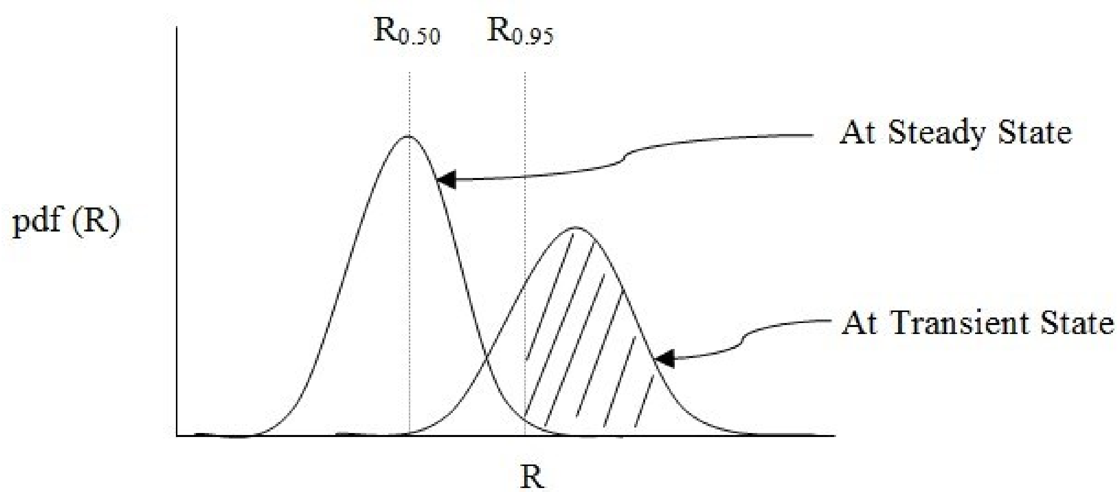

Figure 2.3: High chance of not being at steady state

So, if $R > R_{0.95}$ the likely explanation is process is in transient state. As illustrated by the shaded areas to the right of the $R_{0.95}$ value, the probability that an excessive R-value could come from the SS or the TS distribution, the odds are about 15:1 for being in the transient state.

However, if $R > R_{0.95}$ this does not indicate the process is at steady state. Fig 2.4 provides an illustration using the same two SS and TS distributions. As illustrated, the likelihood of $R < R_{0.95}$ if at steady state is 95%, and if not at steady state is 30%. Here the odds are 3:1 that the steady state conclusion is true. The 3:1 odds are not very definitive. So, to be confident that the process is at steady state, consider the left side of the distributions.

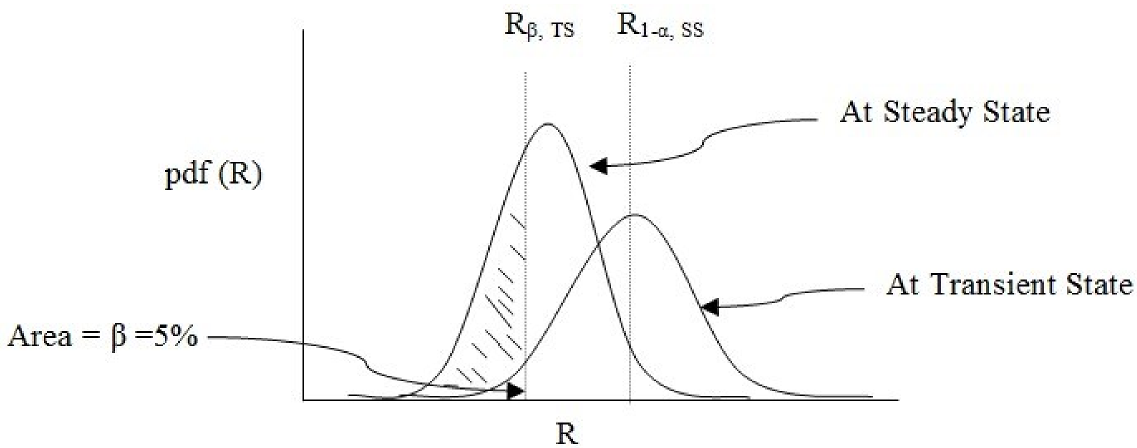

Figure 2.4: Critical value for steady state identification

For a given transient state, $R_{\beta,\,TS}$ is the lower β critical value and for a given steady state, $R_{1-\alpha,\,SS}$ is the 1-α upper critical value. If $R > R_{1-\alpha,\,SS}$, then it will reject SS (accept TS). And if $R < R_{1-\alpha,\,SS}$, it will reject TS (accept SS).

If the process is in a transient state then β is the probability of $R < R_{\beta,\,TS}$. However, if the process is at steady state then as illustrated in Fig 2.4 there is a 40% likelihood that $R < R_{\beta,\,TS.}$ However, if the process is in TS, then as illustrate in Fig 2.4 there is only a 1% chance that $R < R_{\beta,\,TS.}$ So, if $R < R_{1-\alpha,\,SS}$ the odds are 40:1 that process is at steady state.

If $R_{\beta,\,TS} \leq R \leq R_{1-\alpha,\,SS}$ then there is a likelihood of the process being either at steady state or transient state. There is no certainty that a change happened, so hold the last decision.

A Type-I error is the trigger of a 'not at steady state' claim when the process is at steady state. A Type-II error is the trigger of an 'at steady state' claim when the process is in a transient state. In any statistical test, the user needs to choose the level of significance, α, the probability of a Type-I error, and power, β the probability of a Type-II error. Once decided, the $R_{1-\alpha, SS}$ critical value can be obtained from [12] and the $R_{\beta, TS}$ critical value from [13].

However, if this is a multi-variable test, to have the overall test error probability values of α and β, the individual test values need to be shifted. Theoretically, it can be shown [14] that when there is no correlation between process variables,

$$\alpha_i = 1 - \sqrt[M]{1 - \alpha_{overall}} \tag{6}$$

Where,

M = number of variables observed in the analysis

$\alpha_{overall}$ = desired overall level of significance for the process statement

α_i = required level of significance for each individual test

For example in a SSID application that includes $M = 10$ variables and with an overall level of significance $\alpha = 0.05$ for rejecting the SS hypothesis and claiming TS, the level of significance for each individual test needs to be about 0.005.

However, it is more convenient and less dependent on idealizations to visually select data from periods that represent a transient or steady period, and to find the R-critical values that make the algorithm agree with the user interpretation.

2.3 Selection of Filter Value

Three filter factors, λ_1, λ_2 and λ_3, are used to calculate the R-statistic value. The filter factors in Equations (1-3) can be related to the number of data (the length of the time window) in the average or variance calculation. The lower the λ-value the more data are effectively averaged, and the longer a not-at-SS event will persist in the data window. This means a larger run length to claim SS after the process returns to SS. To determine an average run length (ARL), first expand the filter mechanism:

$$
\begin{aligned}
X_{f_i} &= \lambda X_i + (1-\lambda)X_{f_{i-1}} \\
&= \lambda X_i + (1-\lambda)\left[\lambda X_{f_{i-1}} + (1-\lambda)X_{f_{i-2}}\right] \\
&= \lambda X_i + (1-\lambda)\{\lambda X_{f_{i-1}} + (1-\lambda)[\lambda X_{f_{i-2}} + (1-\lambda)X_{f_{i-3}}]\} \\
&= \lambda X_i + (1-\lambda)\lambda X_{f_{i-1}} + (1-\lambda)^2\lambda X_{i-2} + \cdots + (1-\lambda)^N\lambda X_{i-N} + (1-\lambda)^{N+1}\lambda X_{i-(N+1)} \qquad (7)
\end{aligned}
$$

What value of N makes the persisting influence of the old $X_{i-(N+1)}$ trivial? If at SS for N samplings then $X_i \cong X_{i-1} \cong X_{i-2} \cdots$ and $X_{f_i} \sim X_i$. What value of N makes $(1-\lambda)^{N+1}X_{f_{old}} \ll X_{SS}$? As an estimate assume " $\ll$ " means 2%, and perhaps $X_{f_{old}} \sim 5X_{SS}$. If $\lambda = 0.1$, then $(1-0.1)^{N+1}(5X_{SS}) = 0.02X_{SS}$, and $N = \frac{Ln(\frac{0.02}{5})}{Ln(1-0.1)} - 1 = \frac{Ln(0.004)}{Ln(0.9)} - 1 \approx 50$. If we assume " $\ll$ " means 5%, $N = \frac{Ln(\frac{0.05}{5})}{Ln(1-0.1)} - 1 \approx 43$. If we assume " $\ll$ " means 5% and $X_{f_{old}} \sim 3X_{SS}$, $N = \frac{Ln(\frac{0.05}{3})}{Ln(1-0.1)} - 1 \approx 38$. So, N for the influence to be gone, to permit X_f, ν_f^2 and δ_f^2 to be at SS values is between 35 and 50 samples of steady state after an event, depending on magnitude of event and what decay fraction makes it in consequential.

When the process is at SS and the method values have reduced to their SS value, then there is a probability of $R < R_{\beta, TS}$. Assume K is average number of samples to get an R < critical value,

$$\mathrm{P(claiming\ TS\ when\ @\ SS\ in\ K\ samples)}$$

$$= \mathrm{P}\left(\text{not in } 1^{\text{st}}, \text{not in } 2^{\text{nd}}, \cdots, \text{not in } \mathrm{K}^{\text{th}}\right)$$

$$= \mathrm{P}(\text{not in } 1^{\text{st}}) * \mathrm{P}\left(\text{not in } 2^{\text{nd}}\right) \cdots * \mathrm{P}\left(\text{not in } \mathrm{K}^{\text{th}}\right)$$

$$= [\mathrm{P}(\text{not in any one})]^{\mathrm{K}}$$

$$= (1-\beta)^{\mathrm{K}} \tag{8}$$

$$\mathrm{P}(\text{claiming SS in K samples when @SS}) = 1-(1-\beta)^{\mathrm{K}} \tag{9}$$

For the multi-variable test, if we have M variables and each PV is independent,

$$\begin{aligned} \mathrm{P}(\text{claiming SS for process}) &= \mathrm{P}(\text{claiming SS for } \mathrm{PV_1}\ \&\ \mathrm{PV_2}\ \&\ \cdots \&\mathrm{PV_M}) \\ &= \mathrm{P}(\text{SS for} 1^{\text{st}}) * \mathrm{P}\left(\text{SS for } 2^{\text{nd}}\right) * \cdots * \ \mathrm{P}\left(\text{SS for } \mathrm{M}^{\text{th}}\right) \\ &= [\mathrm{P}(\text{SS for any one})]^{\mathrm{M}} \end{aligned} \tag{10}$$

$$\mathrm{P}(\text{claiming SS for process when @SS}) = [1-(1-\beta)^{\mathrm{K}}]^{\mathrm{M}} \tag{11}$$

If we assume a 50% chance of claiming SS when the process is at SS, $\mathrm{K} = \frac{\mathrm{Ln}(1-0.5^{\frac{1}{\mathrm{M}}})}{\mathrm{Ln}(1-\beta)}$. If $\beta = 0.25$ and $\mathrm{M} = 10$, then $\mathrm{K} \sim 10$. If we assume a 95% chance of claiming SS when the process is at SS, then $\mathrm{K} \sim 20$. That means that after wait of 35 to 50 samples for an event to clear, there is an additional wait of about 10 to 20 samples for the probability of R less than critical value. The average run length (ARL) to detect SS after a transient is then about 45 to 70 samples.

However, to ensure greater confidence in the SS claim [13, 15, 18], or faster identification [19], alternate values have been recommended. Larger λ values mean that fewer data are involved in the analysis, which has a benefit of reducing the time for the identifier to catch up to a process change; but, has a undesired impact of increasing the variability on the statistic, confounding interpretation. Lower λ values undesirably increase the average run length to detection, but increase precision (minimizing Type-I and Type-II statistical errors). Following the findings of [14-16] , this work uses filter values of $\lambda_1 = \lambda_2 = \lambda_3 = 0.1$ in Unit Operation Lab and $\lambda_1 = 0.2$ and $\lambda_2 = \lambda_3 = 0.1$ in FRI, balancing precision with ARL.

2.4 Selection of Sampling Intervals

The basis for this method presumes that there is no autocorrelation in the time-series process data. Autocorrelation means that if a measurement value is high (or low) the subsequent measurement value will be related to it. For example, if a real process event causes a temperature measurement to be a bit high, and the event has persistence, then the next measurement will also be influenced by the event and will also be a bit high. Autocorrelation could be related to control action, thermal inertia, filters in sensors, etc. Autocorrelation would tend to make all R-statistic distributions shift to the right, requiring a reinterpretation of critical values for each process variable.

It is more convenient to choose a sampling interval that eliminates autocorrelation. A plot of the current process measurement versus the previous sampling of the process measurement over a sufficiently long period of time (equaling several time-constants) at steady state is required to establish the presence/absence of autocorrelation. Visually choose a segment of data that is at steady state, and plot the PV value vs. its prior value. If a plot that resembles the pattern shown in Fig 2.5, there is no autocorrelation between the sequential process measurements. This pattern is also referred to as a shotgun pattern.

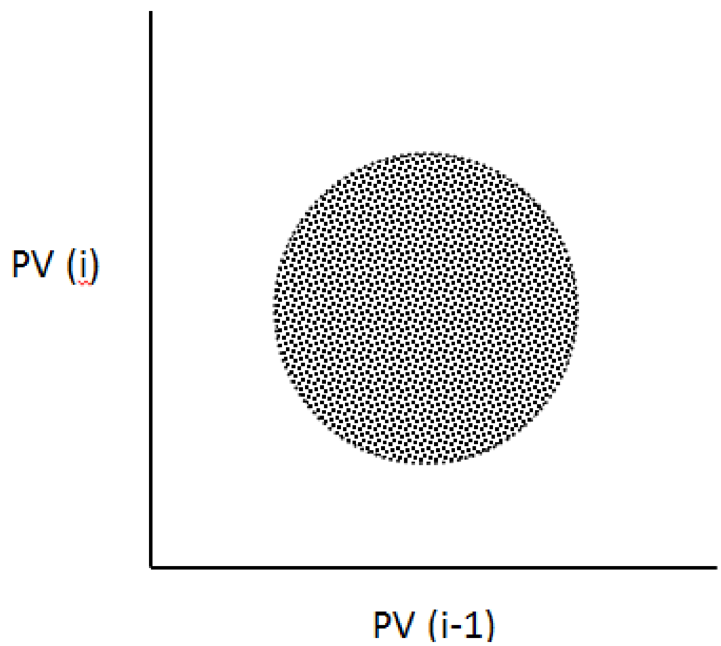

Figure 2.5: Test for autocorrelation revealing no trend

Alternately, if the plot appears as Fig 2.6 where there is a definite trend between the current measurement and the previous measurement, then there is autocorrelation. The figure illustrates a linear pattern; however, the trends can be exponential, quadratic, etc.

If autocorrelation is revealed, increase the sampling interval until it effectively disappears, leaving a shotgun pattern. Although there are statistical methods to evaluate the degree of confidence in autocorrelation, this experience reveals that visual inspection of the plots testing autocorrelation is sufficient.

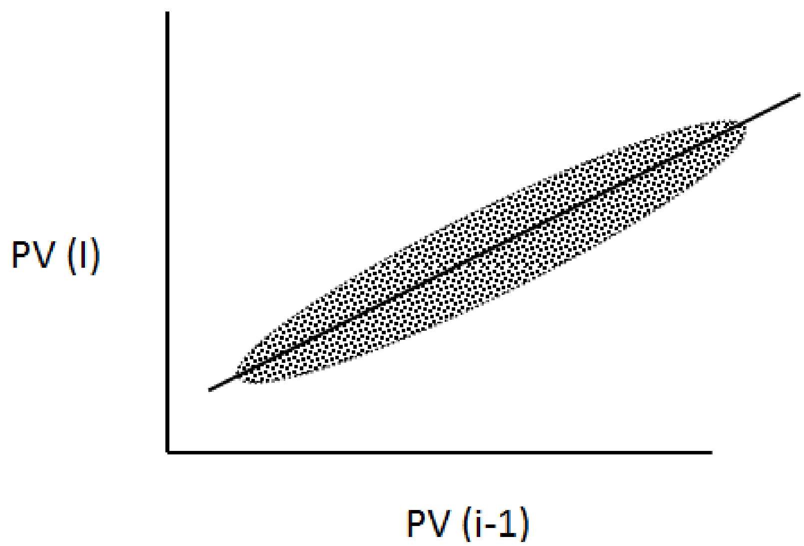

Figure 2.6: Test for autocorrelation revealing trends

In the Unit Operation Lab, data is available for each measurement on a one-second interval. Fig 2.7 shows that there is no autocorrelation at one second interval. For the single variable test in Unit Operation Lab, a sampling interval of one second is suitable for the steady state identifier and controller also.

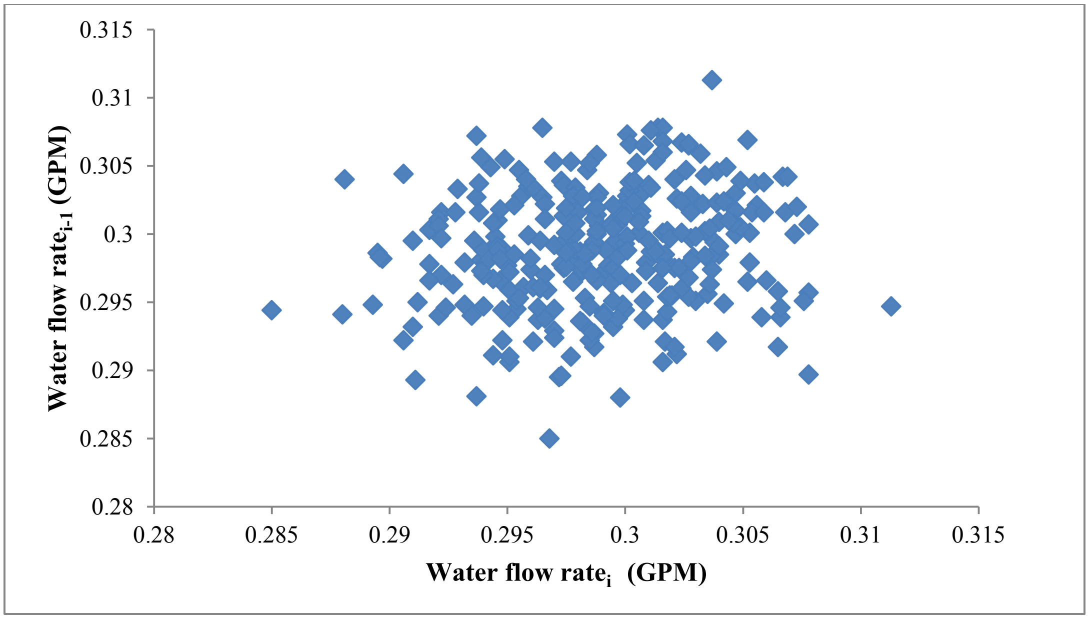

Figure 2.7: Test for autocorrelation revealing no trend in Unit Operation Lab

For the multi-variable test in the FRI distillation column, nearly all variables revealed autocorrelation at the sampling frequency of the controller. For some, a sampling interval of 20 seconds removed the autocorrelation, but for others, it required about a 50 seconds sampling interval. For instance, for the variable "FIC-2", Fig 2.8 shows the autocorrelation at one second interval, and it would change to non-autocorrelation by increasing the sampling interval, which is shown in Fig 2.9. For simplicity, we set a common sampling interval of one-minute for all variables.

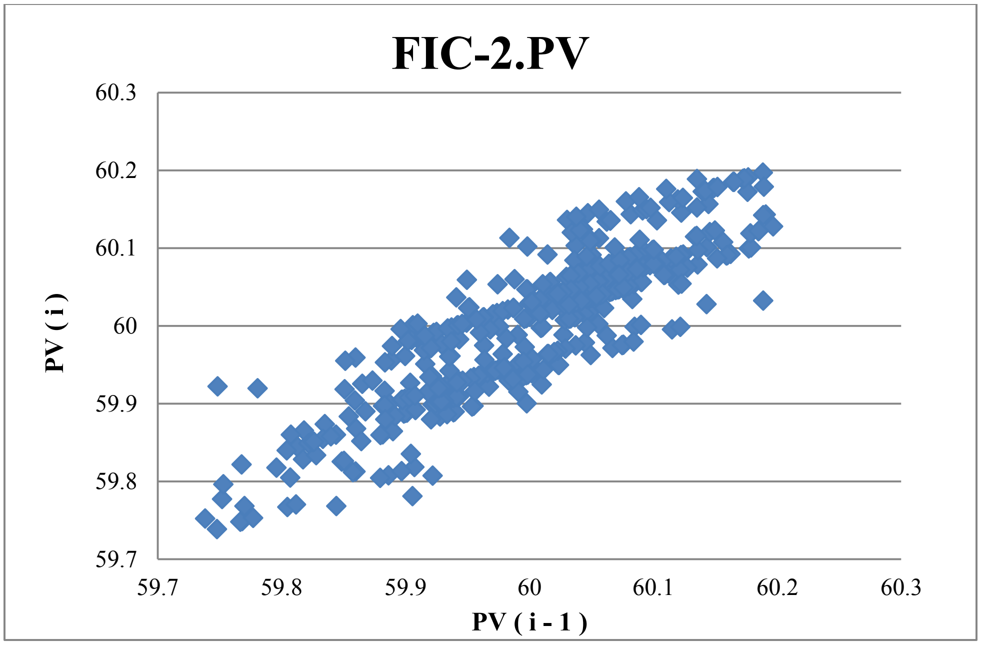

Figure 2.8: Test for auto correlation revealing trends of FIC-2 in FRI.

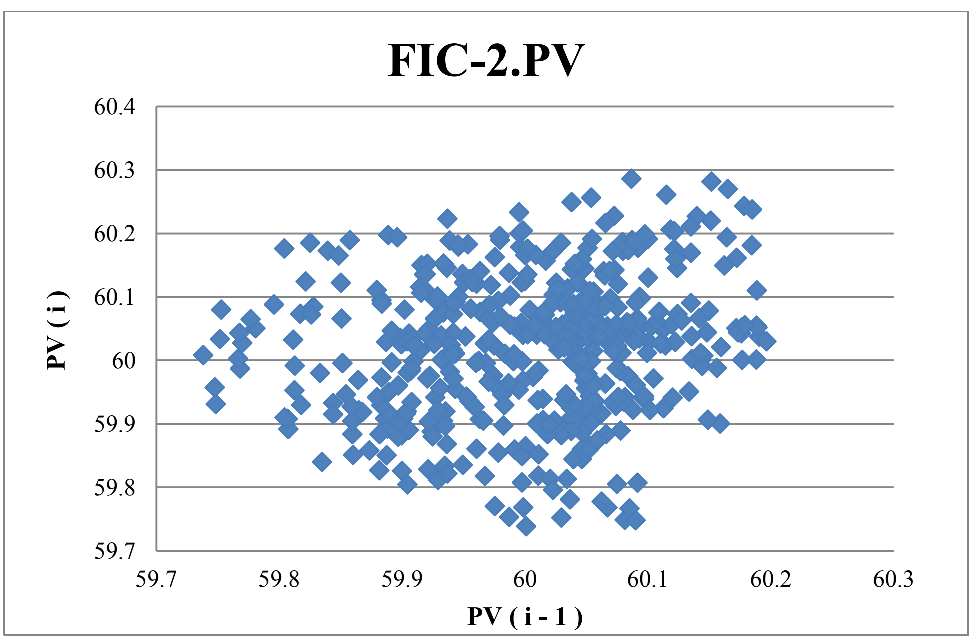

Figure 2.9: Test for autocorrelation revealing no trend of FIC-2 in FRI.

As a final aspect of the method development, recognize that this statistical method only accommodates noisy data. If the data are noiseless and at steady state, the data series will have exactly the same values, which would drive the denominator measure of variance to zero, leading to an execution error. In this application, because of discrimination error in the instrument system under some conditions, or zero flow rate under other conditions, the time series of measurements could have identical values. In order to avoid this condition, a normally and independently distributed noise signal of zero mean and small variance NID (0, σ) was added on the original data to calculate the R value. The Box Mueller formula was used to generate the perturbation. The variance was chosen to be small relative to the signal variance at normal conditions.

2.5 Summary

Upon algorithm initialization all SS_i values are set to a value of 0.5, to represent that there is no basis to state that the variable is either in a transient $SS_i = 0$ or at steady state $SS_i = 1$. Subsequently, when the process variable is at SS (if $R_i <$ lower critical value), it will set $SS_i = 1$. Alternately, if $R_i >$ higher critical value set $SS_i = 0$. When each variable becomes confidently at SS, the product of all SS_i values is 1, and the process is at SS. If the product is 0, then at least one variable is confidently in a transient, or has recently been in a transient and is not confidently at steady state, which means the process is in a transient, not at SS. If the product is between 0 and 1, it means that some labels still have the initial 0.5 value, meaning that there is not enough information to make a definite decision about the recent state of the process.

CHAPTER III

EXPERIMENTAL EQUIPMENT

3.1 Experimental Equipment in Unit Operation Lab

The absorption column in the Unit Operation Lab in the School of Chemical Engineering is approximately 12 ft. tall and 0.7 ft. in diameter. In the column, 0.7 inch Nutter rings are randomly distributed. This packing is used to increase the surface area of contact between absorbent and gas streams to improve mass transfer. National Instruments Compact FieldPoint and LabView software are used for data acquisition of 7 variables and control of 4. One represents the absorbent liquid (water or a dilute NaOH solution) flow rate into the column.

An orifice flow meter is used. Ideally, an orifice plate is a thin plate with a hole in the middle. It is placed in the pipe in which water flows. When the water reaches the orifice plate, water is forced to converge to go through the small hole. The point of maximum convergence actually occurs shortly downstream of the physical orifice, at the so-called the vena contracta. As it does so, the water flow rate changes. Beyond the vena contracta, the water flow streamlines expand and the water flow rate changes once again. The Bernoulli relation defines the pressure difference created by the differing fluid velocity. The pressure drop across the orifice then becomes an easy to measure representation of the flow rate.

Our non-ideal orifice assembly, shown in Fig. 3.1, is in a 1.25 inch line and represents the flange-tap configuration commonly used in industry. The differential pressure cell, just below and out of the photo, converts differential pressure of the orifice to a 4-20 mA transmission electric current.

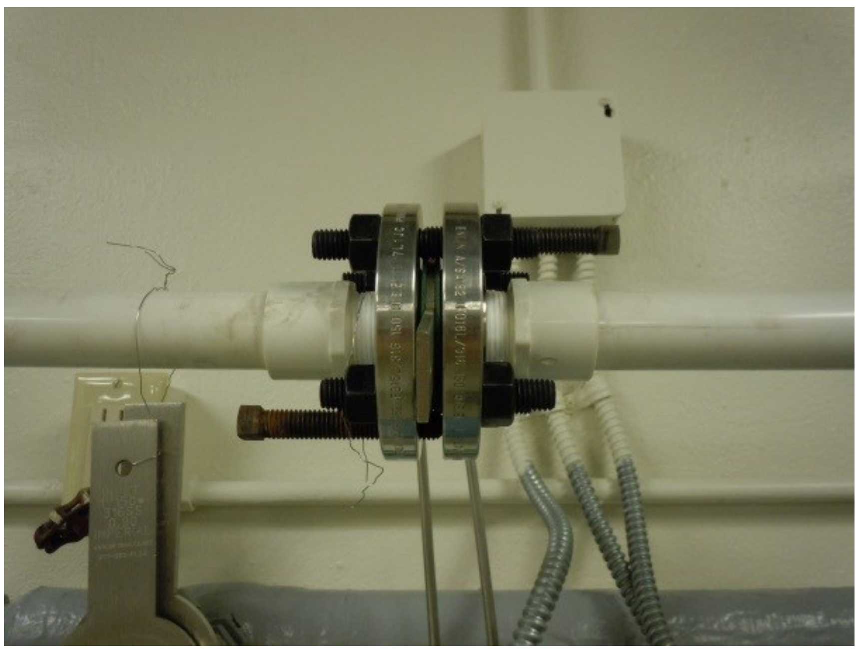

Figure 3.1: Orifice meter used in the Unit Operation Lab

As part of the nonideality of the device, turbulence in the flowing water creates pressure drop fluctuations on the pressure drop, which adds noise to the signal. Further, the intensity of the pressure fluctuations increases with flow rate. But simultaneously, the nonlinear conversion of the transmission signal to flow rate (ideally a square root) tempers the larger fluctuations, making the noise on the calculated flow rate signal appear lower at high flow rates and larger at low flow rates. In this project, water flow rate is used to demonstrate that this SS and TS identification works.

The application in the Unit Operation Lab is a pilot scale water flow process, which is single variable, but also represents industrial craft. It has the advantage of permitting a variety of tests to reveal method application.

3.2 Experimental Equipment in FRI

Fractionation Research, Inc. (FRI) [20] is a non-profit research consortium which performs distillation research in commercial scale distillation columns for its 72 member companies around the world.

The FRI unit has two distillation columns – the low-pressure (LP) column that operates from deep vacuum to 165 psia and the high-pressure (HP) column that operates from atmospheric pressure to 500 psia. Both the LP and the HP columns have a 4-ft diameter 28-ft section, and the LP column has an 8-ft diameter 12-ft section on top of the 4-ft diameter section. Binary hydrocarbon systems are typically used. The FRI unit is capable of operating from deep vacuum to a high pressure of 500 psia. Each column has its own set of auxiliary equipment (condensers, reboilers, pumps, etc.).

FRI tests distillation column internals by using hydrocarbon systems. Each test has different design conditions to perform different test requirement. All the FRI data are collected at steady state. Once the required test conditions are established and steady state is confirmed, data will start to be recorded. Once the data collection is complete, new conditions will start to be approached and wait for the steady state again.

FRI reads the real-time process data from Yokogawa® Exaquantum™ historian and it could be output to excel spreadsheet, which is installed the steady state and transient state identification code by running in VBA.

CHAPTER IV

RESULTS AND DISCUSSION

The implementation has three stages: First, historical data is used off-line to choose a sample interval to eliminate autocorrelation of the data and to validate the method. Second, the steady state and transient state identification code is installed into online computers for either application: LabView software in the Unit Operation Lab and also installed onto FRI servers, running in Excel VBA, at the unit. Third, the result from the steady state and transient state identifier would be tested whether or not it agrees with visual observation. Results illustrate how this SS or TS identification can be used to in real-time for online control of test sequences.

4.1 SSID Implementation in Unit Operation Lab

The steady state identifier has been tested on a water flow line feeding the absorption column. In this test, 1 second is chosen as sampling interval, which is as same as the operation time interval, $\lambda_1 = \lambda_2 = \lambda_3 = 0.1$ are used as the filter factor, as well as 1 is used as the lower critical value and 4 is used as higher critical value.

4.1.1 SSID Test with Set Point Change in the Unit Operation Lab

Fig. 4.1 presents the plot of water flow rate vs. time and the state identification value, SS, results vs. time. The solid line is the process measurement (water flow rate) and the dotted line is the SS-value. A value of 1 means probably or confidently at steady state. And, the value of 0 means confidently or probably transient state. It shows that the steady state identifier does respond correctly to the dynamic changes made in the system. In Fig. 4.1, all the process changes are step changes to the flow rate set point, and trigger the steady state identifier to SS=0 almost instantly. But, when the process is back to steady state, it will take almost 30 seconds (30 samples) for the R-value to go below the critical value and trigger the steady state. That is because of the filtering nature of the steady state identifier. The amount of delay depends on λ values, the nature of the process and the trigger value. For example, $\lambda_1 = \lambda_2 = \lambda_3 = 0.1$ meaning that the most recent 30 data points are used to calculate the R-statistic value. In the other words, the identifier has to wait 30 seconds to change the status. The time to claim SS, the ARL, is consistent with the N+K estimate of the prior section. For most of the processes, the amount of delay is acceptable. Step changes are made at 0, 25, 60, 100, 130, 210 seconds. Notice that at low flow rates, the measurement noise is much higher compared to high flow rates. The SSID response is independent of the noise amplitude. A visual detection would be subjective, however having a steady state identifier that has a theoretical basis helps identify steady state.

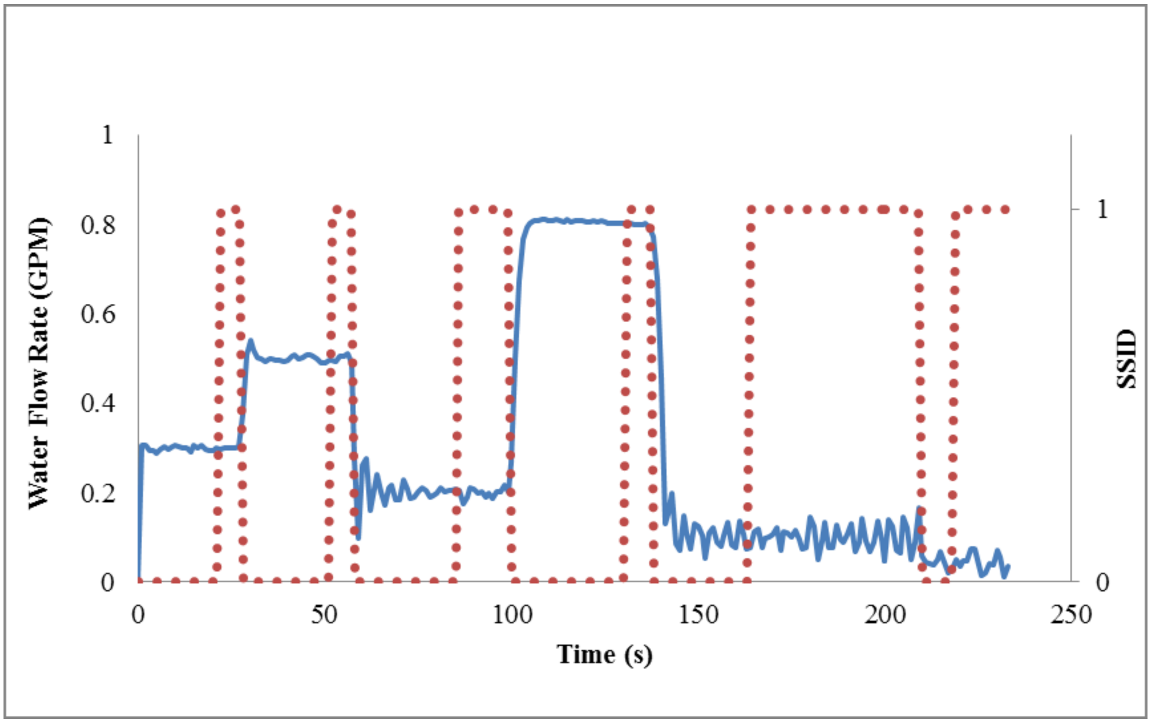

Figure 4.1: Steady state identifier results with set point changes in the water flow rate

4.1.2 SSID Test with Diverse External Upsets in the Unit Operation Lab

Similar with the Fig 4.1, Fig. 4.2 presents the plot of water flow rate vs. time and the state identification value, SS, results vs. time. The solid line is the process measurement (water flow rate) and the dotted line is the SS-value. A value of 1 means probably or confidently at steady state. And, the value of 0 means confidently or probably transient state. It shows that the steady state identifier responds to upsets and environmental disturbances. We toggled the pump off then on at t~65s and changed the signal to the valve down then up at time~130s. Fig. 4.2 reveals that the identifier recognized these changes “instantly” and then comes back to the steady state. At time~250s, we changed the set points and increased the flow controller gain, which prevented process from settling. Observe again that the steady state identifier works in spite of the noise change.

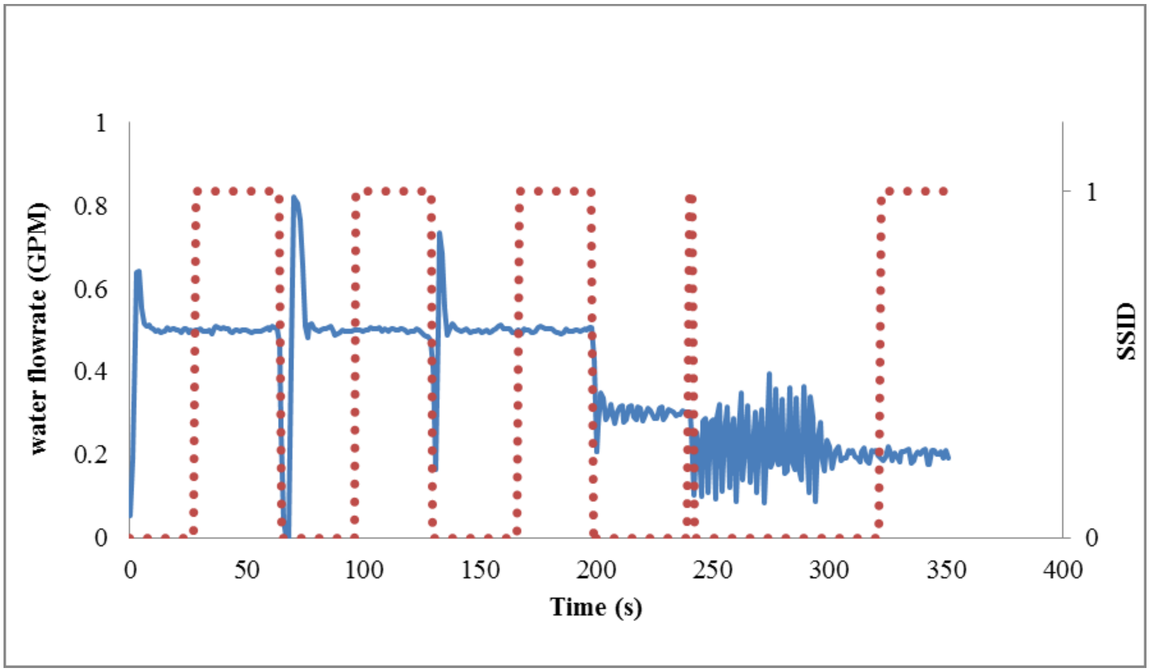

Figure 4.2: Steady state identifier results on the water flow rate with diverse external upsets

In both of these graphs, the steady state identifier agrees with a visual recognition of the system state except for one instance at a lower flow rate (Fig 4.2, time~250s) where the controller oscillation might appear as noise on the comprised time scale, which confounds identification of steady state visually.

4.2 SSID Implementation in FRI

The steady state identifier has been used to detect steady state and transient state in offline and online data at the FRI distillation unit. As we have discussed above, the value of 0.5 means that there is no basis to state that the variable is either in a transient or at steady state, the value of 1 means probably or confidently at steady state and the value of 0 means confidently or probably transient state. For every test in FRI, six to twelve key variables are chosen to monitor to decide whether the process is at steady state or transient state that is based on the nature of the distillation column. Depending on the different test objectives; the monitored key variables are changed.

4.2.1 SSID Offline test in FRI

Offline data from historian was collected to check on the working of this steady state and transient state identification method and confirmed that the 1 minute sampling interval is appropriated.

Fig 4.3 shows that the steady state identifier responds correctly to the dynamic changes to the multi-variable historical process. The solid lines reveal eight process measurements vs. time, and the dotted line is the SS-value vs. time. At first, there is no basis to state the process is at steady state or transient state so SSID value equal 0.5. In Fig. 4.3, the process changed at 23:33, and trigger the steady state identifier to SS=0 almost instantly. But similar with the SSID test in Unit Operation Lab, the process will take some time to trigger the process is back to steady state.

In this multi-variables test, $\lambda_1 = 0.2$ and $\lambda_2 = \lambda_3 = 0.1$ was used. That means we need to wait 35 to 50 samples for an event to clear and an additional 10 to 20 samples for the probability of R less than critical value for each variable. In total the identifier has to wait 45 to 70 minutes (samples) to change the status. For a commercial scale distillation process, the delay is acceptable.

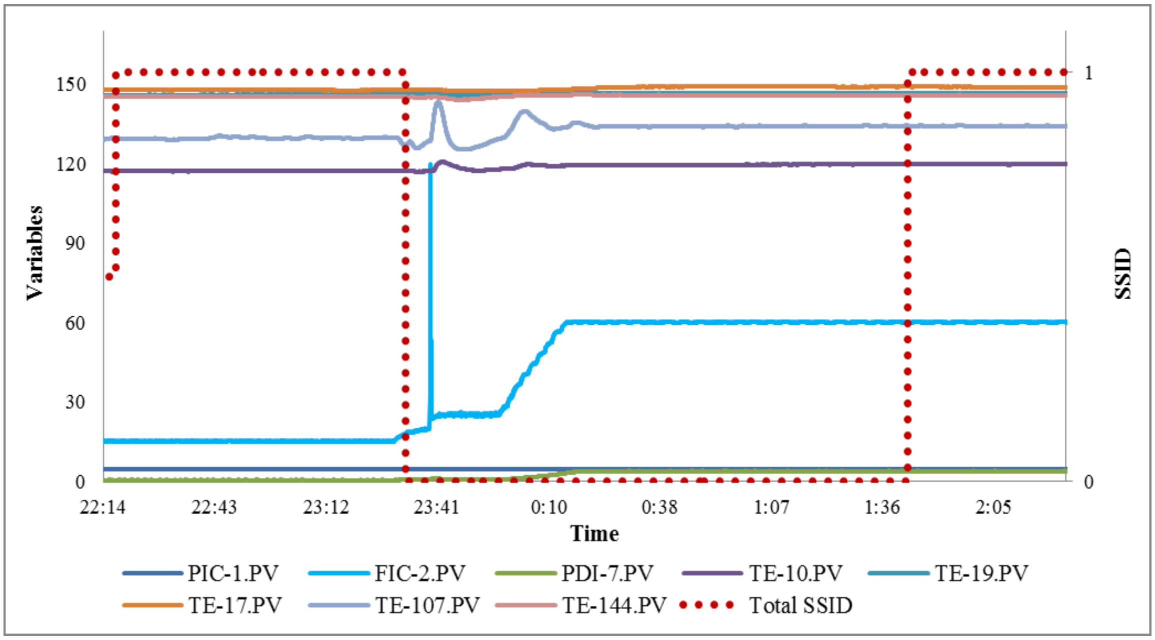

Figure 4.3: Steady state identifier offline result in FRI

4.2.2 SSID Online Test in FRI

The steady state and transient state identifier was also installed onto FRI servers, running in Excel VBA, to test online. Based on the result from offline test, 1 minute is chosen as the sampling interval, $\lambda_1 = 0.2$ and $\lambda_2 = \lambda_3 = 0.1$ is chosen as filter factor, as well as 1 is chosen as lower critical value and 4 is chosen as higher critical value.

4.2.2.1 SSID Online Test in FRI on 8/14/2012 - 8/15/2012

Fig 4.4 shows that the steady state identifier result on 8/14/2012 - 8/15/2012, which responds correctly online to the dynamic changes to multi-variable process. The solid lines reveal seven process measurements vs. time, and the dotted line is the SS-value vs. time. Step changes are made in the process at 20:25, 23:55, 3:10, and 6:05. Steady state and transient state identifier is triggered to SSID = 0 almost instantly. But similar with the SSID test in Unit Operation Lab and SSID offline test, the process will take some time to trigger the process is back to steady state. The approximately one hour delay is acceptable for FRI.

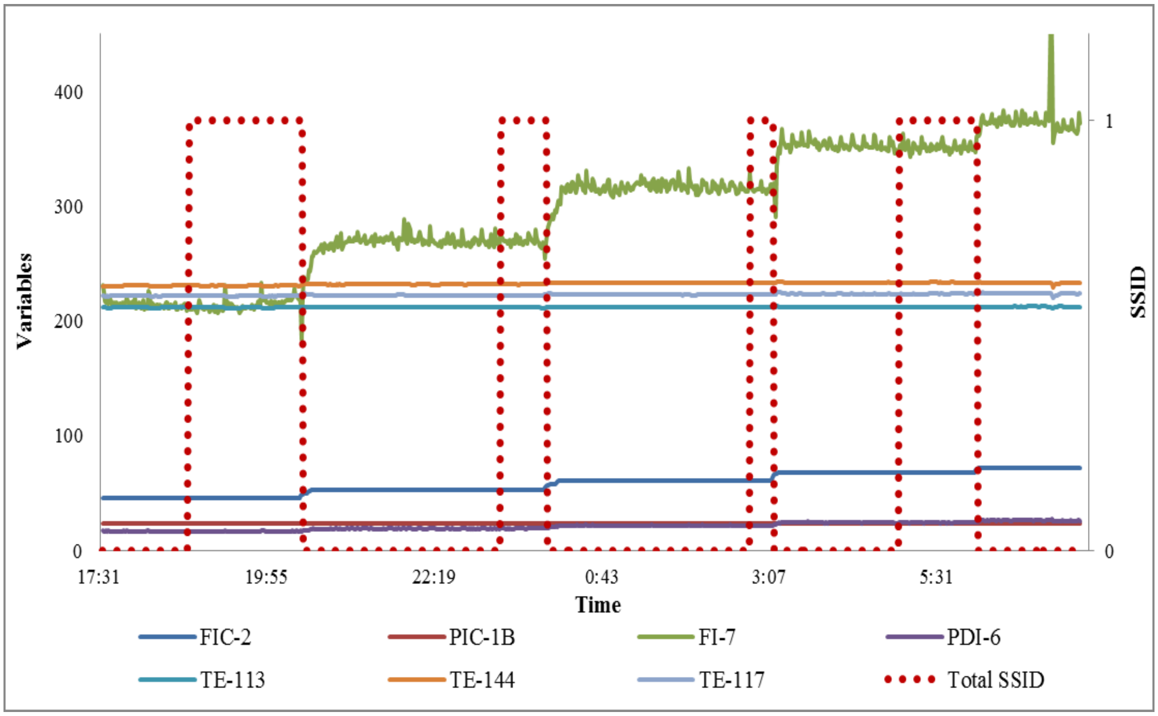

Figure 4.4: Steady state identifier online result in FRI on 8/14/2012 - 8/15/2012

4.2.2.2 SSID Online Test in FRI on 9/17/2012 - 9/19/2012

Fig 4.5 shows that the steady state identifier result on 9/17/2012 - 9/19/2012, which responds correctly online to the dynamic changes to multi-variable process. Similar with the other tests, the solid lines reveal seven process measurements vs. time, and the dotted line is the SS-value vs. time. More step changes are made in this test. The result are also similar with the SSID test in Unit Operation Lab and other offline and online tests in FRI, steady state and transient state identifier is triggered to SSID = 0 almost instantly, but the process will take some time to trigger the process is back to steady state.

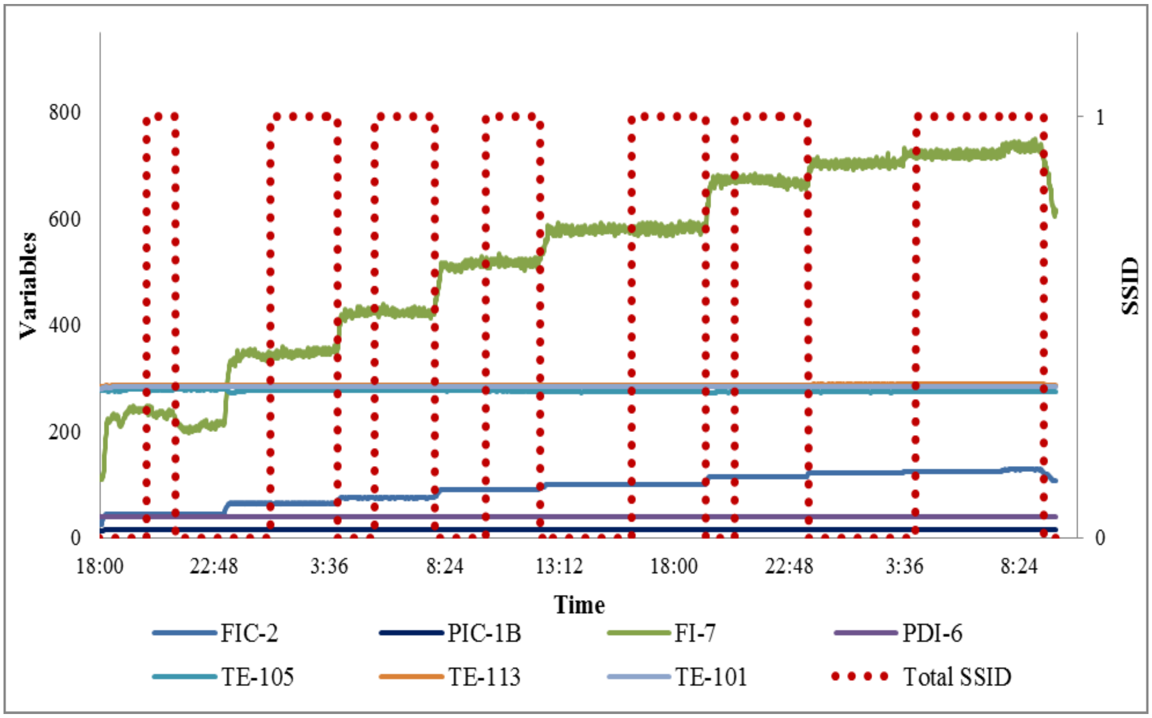

Figure 4.5: Steady state identifier online result in FRI on 9/17/2012 - 9/19/2012

4.2.2.3 SSID Online Test in FRI on 8/20/2012 - 8/22/2012

Fig 4.6 shows that the steady state identifier result on 8/20/2012 - 8/22/2012, which responds correctly online to the dynamic changes to multi-variable process with larger noise disturbance. Similar with the other tests, the solid lines reveal seven process measurements vs. time, and the dotted line is the SS-value vs. time. In this test the process is running with larger noise disturbance. The result is also similar with the SSID test in Unit Operation Lab and other offline and online tests in FRI, steady state and transient state identifier is triggered to SSID = 0 almost instantly, but the process will take some time to trigger the process is back to steady state.

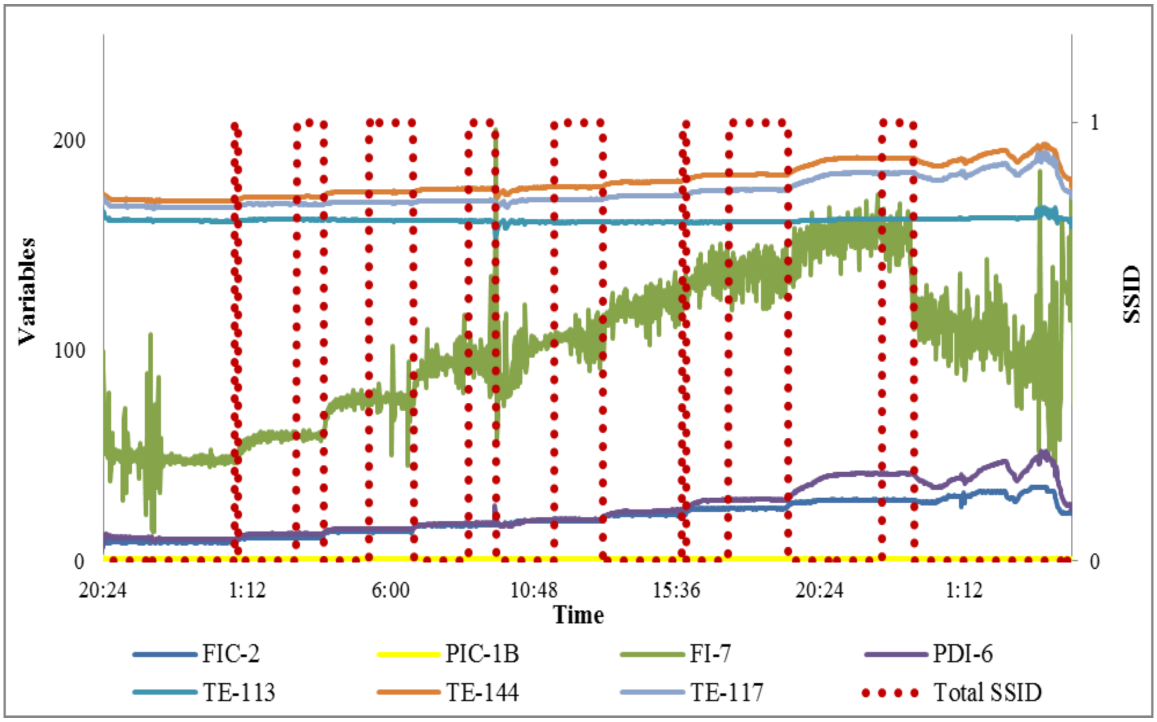

Figure 4.6: Steady state identifier online result in FRI on 8/20/2012 - 8/22/2012

4.2.3 SSID Online Test Corroborate with Visual Observation from FRI

In order to test the steady state and transient state identifier, the results from the online SSID test were compared with the visual observation from FRI operators. Table 4.1 shows the times which are the FRI operators determined steady state based on the FRI test on 10/1/2012 – 10/4/2012, as well as at that time the SSID results of each key variable. From Table 4.1, almost all the SSID test result matches with the visual observation from FRI operators except the variables of flow rate. Through the analysis of each key variable SSID result, the mismatch of flow rate variables is because the steady state and transient state identifier response later than the FRI operator. In order to decrease the response delay, the lower critical value is changed to 1.3

and the higher critical value is changed to 3.9. The sampling interval of flow rate variables is changed to 30 second, as well as sampling interval of other variables is kept at 1 minute.

FRI determined steady state	**SSID Program Predictions**						**Compare**	
Date and Time	FIC-2	PIC-1B	FI-7	TE-105	TE-113	TE-101	Overall	Overall without flows
10/1/12 4:44 PM	1	1	0	1	1	1	0	1
10/1/12 5:07 PM	1	1	0	1	1	1	0	1
10/1/12 10:26 PM	1	1	1	1	1	1	1	1
10/1/12 10:47 PM	1	1	1	1	1	1	1	1
10/2/12 2:08 AM	1	1	0	1	1	1	0	1
10/2/12 2:22 AM	1	1	0	1	1	1	0	1
10/2/12 5:10 AM	1	1	1	1	1	1	1	1
10/2/12 5:21 AM	1	1	1	1	1	1	1	1
10/2/12 8:13 AM	0	1	0	1	1	1	0	1
10/2/12 8:37 AM	1	1	0	1	1	1	0	1
10/2/12 11:47 AM	1	1	0	1	1	1	0	1
10/2/12 12:10 PM	1	1	0	1	1	1	0	1
10/2/12 3:15 PM	0	1	1	1	1	1	0	1
10/2/12 3:38 PM	1	1	1	1	1	1	1	1
10/2/12 6:17 PM	1	1	1	1	1	1	1	1
10/2/12 6:39 PM	1	1	1	1	1	1	1	1
10/2/12 9:49 PM	1	1	1	1	1	1	1	1
10/2/12 10:10 PM	1	1	1	1	1	1	1	1
10/3/12 1:05 AM	1	1	1	1	1	1	1	1
10/3/12 1:29 AM	1	1	1	1	1	1	1	1
10/3/12 4:25 AM	1	1	1	1	1	1	1	1
10/3/12 4:44 AM	1	1	1	1	1	1	1	1
10/3/12 4:37 PM	1	1	0	1	1	1	0	1
10/3/12 5:52 PM	0	1	1	1	1	1	0	1
10/3/12 7:25 PM	0	1	1	1	1	1	0	1
10/3/12 10:03 PM	1	1	0	1	1	1	0	1
10/3/12 11:17 PM	0	1	0	1	1	1	0	1
10/4/12 2:22 AM	1	1	0	1	1	1	0	1
10/4/12 3:40 AM	1	1	1	1	1	1	1	1
10/4/12 8:12 AM	0	1	0	1	1	1	0	1
10/4/12 9:27 AM	0	1	0	1	1	1	0	1
10/4/12 10:46 AM	0	1	0	1	1	1	0	1
10/4/12 12:30 PM	0	1	1	1	1	1	0	1
10/4/12 1:59 PM	1	1	0	1	1	1	0	1
10/4/12 3:08 PM	0	1	0	1	1	1	0	1
10/4/12 5:04 PM	0	0	0	0	0	0	0	0
10/4/12 6:07 PM	0	1	0	1	1	1	0	1
10/4/12 7:07 PM	0	1	0	1	1	1	0	1
10/4/12 8:02 PM	0	1	0	1	1	1	0	1
10/4/12 9:00 PM	0	1	0	1	1	1	0	1
10/4/12 10:17 PM	0	1	0	1	1	1	0	1
Percent of math compare the result from FRI and SS/TS Identifer							**34%**	**98%**

Table 4.1: Compare the result from FRI operator and steady state identifier

4.2.3.1 SSID Online Test Corroborate with Visual Observation on10/1/2012

Fig 4.7 and Fig 4.8 show that the detail steady state identifier result and FRI operator visual observation result on 10/1/2012, which responds to the dynamic changes. The operator determined the steady state times almost agree with the steady state and transient state identifier predictions. Most of the times, the steady state and transient state identifier triggered the SS = 1 quicker than the FRI operator, which is agreed with the observation of the whole process. Only few times, the steady state and transient state triggered delay. But little delay is acceptable for the operators.

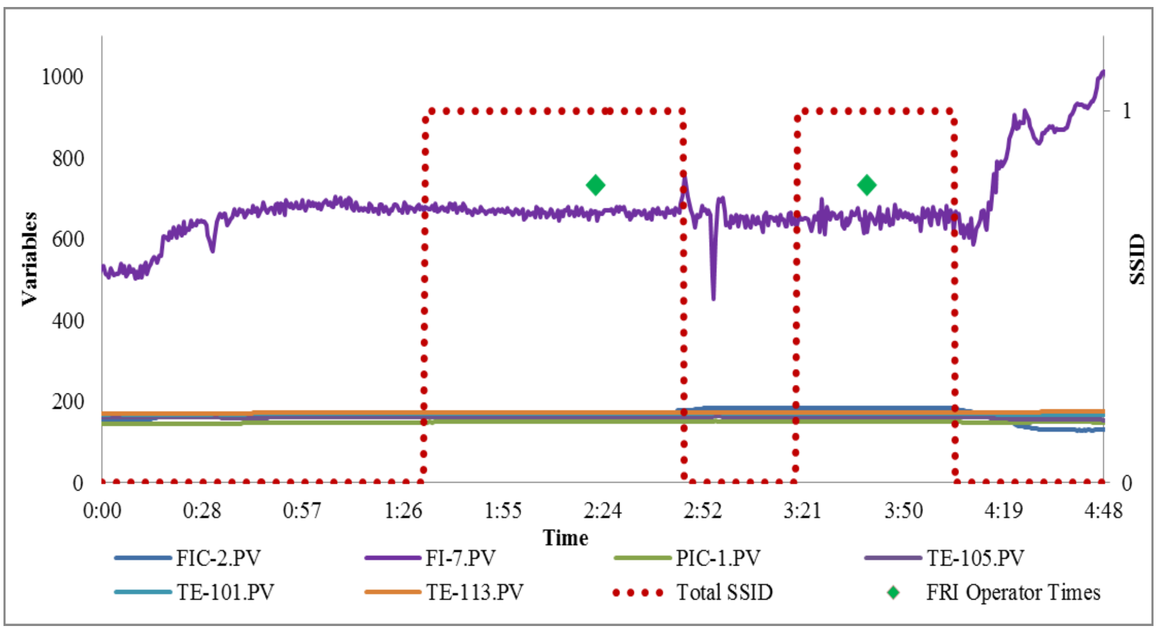

Figure 4.7: Steady state identifier online result Corroborate with Operator on 10/1/2012

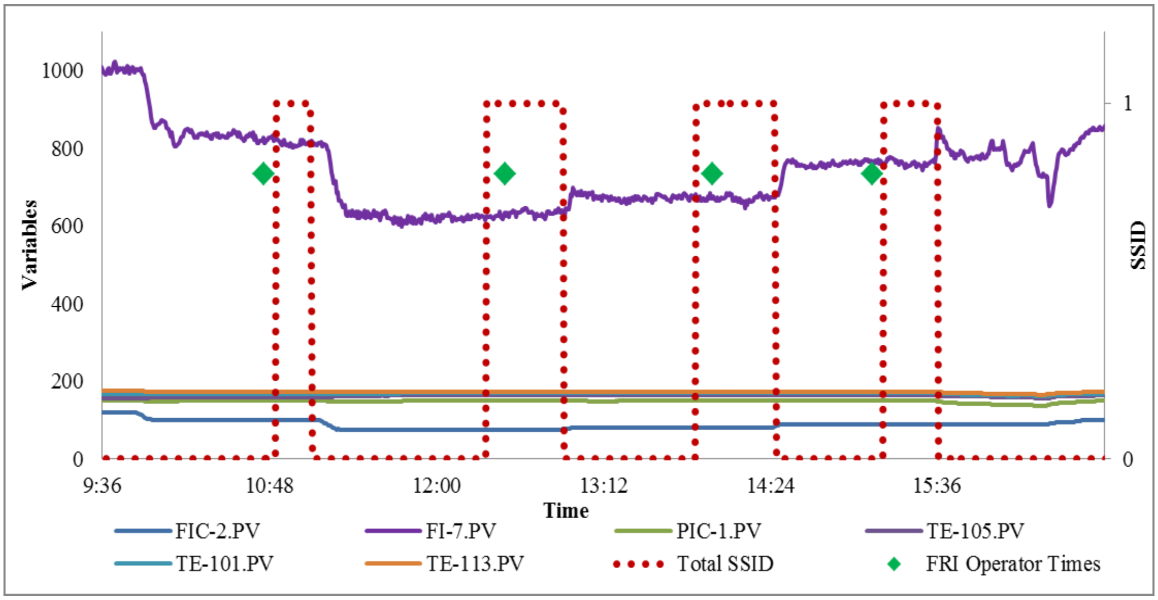

Figure 4.8: Steady state identifier online result Corroborate with Operator on 10/1/2012

4.2.3.2 SSID Online Test Corroborate with Visual Observation on 2/6/2013 – 2/7/2013

Fig 4.9 show that the steady state identifier result and FRI operator visual observation result on 2/6/2013 - 2/7/2013, which responds to the dynamic changes. The operator determined the steady state times clearly agree with the steady state and transient state identifier predictions. Most of the times, the steady state and transient state identifier triggered the SS = 1 quicker than the FRI operator, which is agreed with the observation of the whole process.

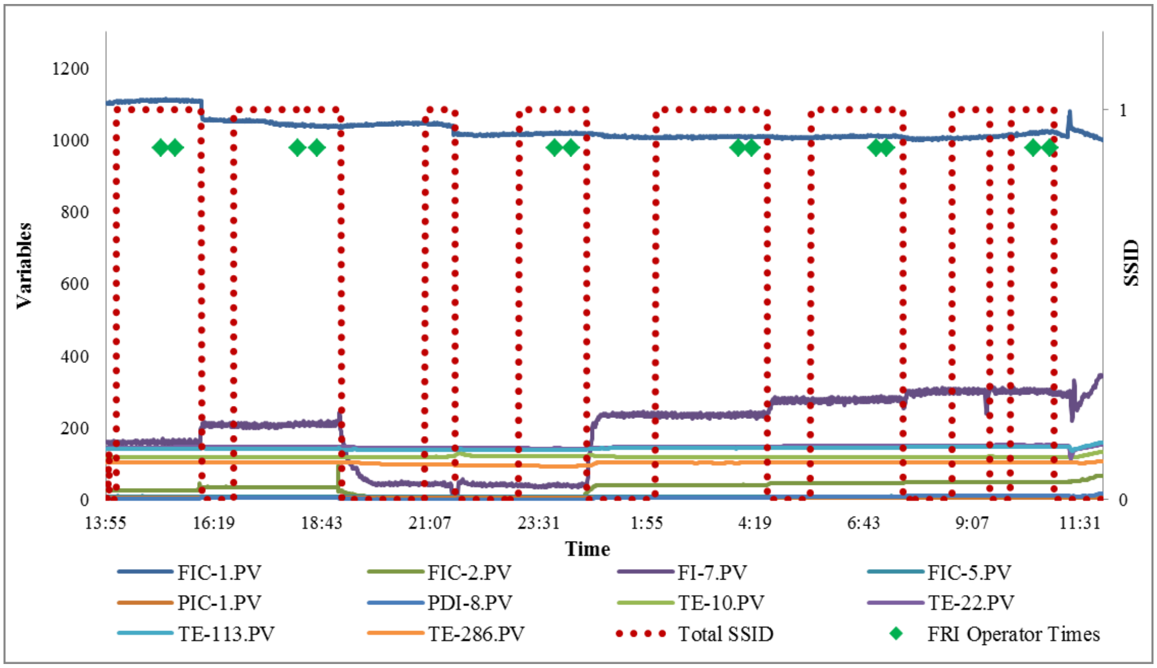

Figure 4.6: Steady state identifier online result Corroborate with Operator on 2/6/2013 – 2/7/2013

CHAPTER V

CONCLUSION AND RECOMMENDATIONS

In order to evaluate the performance of the steady state and transient state identifier, the steady state and transient state identifier has been implemented on the absorption unit in the Unit Operation Lab to do the single variable test, as well as on the FRI distillation unit to do the multi-variable test. Prior to the multi-variable test, the identifier had been tested offline to analyze the filter factor, lower and higher critical value, sampling interval, and then tested online to compare the online test results with the visual observations from the operator to optimize the identifier result.

5.1 Conclusions

1. R-statistic steady state and transient state identification method detects steady state and loss of steady state on time series analysis and statistical tests.
2. R-statistic steady state and transient state identification method requires no process knowledge, only the time series data.
3. R-statistic steady state and transient state identification method works for one variable and multi-variable.
4. The steady state and transient state identifier could work with historical or real-time data in Unit Operation Lab and FRI distillation unit.

5. The steady state and transient state identifier was implemented in the Unit Operation Lab by using LabView and FRI unit by using Excel VBA.
6. The steady state and transient state identifier would run in the background, which will not affect the other operations of the operators.
7. The steady state and transient state results are consistent with visual observations from the FRI operators.
8. The steady state and transient state identifier is computationally simple, only 8 variables are stored in the computer, which decreases the computational load and leads to a quicker computer response.
9. The steady state and transient state identifier has the potential to be easily implemented in other industrial processes.

5.2 Recommendations

Recommendations for future work are:

1. Continue to test the steady state and transient state identifier in FRI. Based on the different test objective, different key variables are used to test the identifier.
2. One of the variables is hard to eliminate the autocorrelation and always show the incorrect responds. So increase the correctness of the steady state and transient state identifier result, through the analysis of the filter factor, lower and higher critical values, sampling interval, etc.
3. Decrease the response time of the steady state and transient state identifier.

4. Evaluate the use of the steady state and transient state identifier; consider the ease of use, computational burden, robustness, understandability and other technical issues compared to other approaches.

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APPENDICES

The methodology of the steady state and transient state identifier is described in Chapter 2. This section lists the LabView cod and Excel VBA code of the simulation system.

A.1 LabView code of the application system

```
NV = lambda * (x - xf) ^ 2 + (1 - lambda) * NV          ' numerator of variance estimator

xf = lambda * x + (1 - lambda) * xf                      ' first order filter

DV = lambda * (x - xold) ^ 2 + (1 - lambda) * DV        ' denominator of variance estimator

xold = x

If (2 - lambda) * NV > Ra * DV Then

    ID = "SS"

ElseIf (2 - lambda) * NV > Rb * DV Then

    ID = "TS"

End If
```

Where lambda=0.1, α=0.01, Ra=4, β<0.05, Rb=1.

A.2 Excel VBA code of the application system

```
Option Explicit
```

```
'Declare variables

Dim lamada1 As Double          '1st filter factor
Dim lamada2 As Double          '2nd filter factor
Dim lamada3 As Double          '3rd filter factor
Dim i As Integer               'counter the variable
Dim SSID_total As Double       'total SSID result
Dim n As Long                  'counter
Dim p As Long                  'counter
Dim m As Integer               'number of columns of data - ANV
Dim x(1 To 100) As Double
Dim x_new(1 To 100) As Double
Dim xf(1 To 100) As Double
Dim xf_new(1 To 100) As Double
Dim numvar(1 To 100) As Double
```

```
Dim numvar_new(1 To 100) As Double

Dim denovar(1 To 100) As Double

Dim denovar_new(1 To 100) As Double

Dim SSID(1 To 100) As Double                    'SSID result for each variable

Dim r(1 To 100) As Double                       'R-statistic value

Dim nvar As Long                                'numble of variable

Dim nn As Long

Dim nf As Integer

Dim mm As Integer

Dim tSSID As Single                             'counter the number of SS

Dim percentage_SSID As Single                   'percentage of variables reaches SS

''

''

------------------------------------------------------------------------------------------------------------

Sub main()

'The main program calls each sub program to make events organized
```

```
Call initial                                    'input values and initialize states

For p = 1 To 10796

    nn = 0

    SSID_total = 1

    tSSID = 0

    If Sheet1.Cells(2, 1).Value > Sheet1.Cells(445, 1).Value Then

        If Sheet1.Cells(2, 1).Value - Sheet1.Cells(445, 1).Value > 0.000694444 * 5 Then

          For m = 1 To nvar Step 1

              SSID(m) = 0.5

          Next m

        End If
```

```
For m = 1 To nvar

    If m <= nf Then
    'for the flow rate variables, 30 second is chosen as sampling interval
        Call SSID_cal                       'calulate SSID for each variable
    Elseif p Mod 2 <> 0 Then
    'for the other variables, 60 second is chosen as sampling interval
        Call SSID_cal                       'calulate SSID for each variable
    End If

    Call SSID_total                         'calculate total SSID

    If SSID(m) = 1 Then
        tSSID = tSSID + 1
    End If
```

```
        Next m

        Call percentage_cal                    'calculate percent of variable reach SS
        Call GRAPH                             'graph on sheet1
        Call S2                                'echo the result to sheet2
        DoEvents
    Else
        p = p - 1
        For n = 1 To 100000
            DoEvents
        Next n
    End If

    DoEvents
    Call S2                                    'echo the result to sheet2
    Call save_file                             'automatically save the contents in sheet2
```

```
                                          'every 4 hour

Next p


End Sub

''

''

------------------------------------------------------------------------------------------------------------

Sub initial()

' This sub program is used to give the initial



lamada1 = 0.2

lamada2 = 0.1

lamada3 = 0.1



nvar = 0

nf = Sheet1.Cells(4, 2).Value
```

```
Sheet1.Range(Cells(445, 1), Cells(445, 103)).Clear

For i = 1 To 100 Step 1
    If Cells(2, i + 1) <> "" Then
        nvar = nvar + 1
    Else
        Exit For
    End If
Next i

Sheet2.Cells(1, nvar * 2 + 2).Value = "Total SSID"
Sheet2.Cells(1, nvar * 2 + 3).Value = "Percent @ SS"

For m = 1 To nvar
    SSID(m) = 0.5
Next m
```

```
Application.ScreenUpdating = True

End Sub
"
"
-----------------------------------------------------------------------------------------------------------------
Sub SSID_cal()
' This sub program is used to calculate the SSID result for each variable

Sheet1.Cells(445, 1).Value = Sheet1.Cells(2,1).value

If p = 1 Then
    x_new(m) = Sheet1.Cells(2, m + 1).Value
    xf_new(m) = x_new(m)
    numvar_new(m) = 0
```

```
    denovar_new(m) = 0
Else
    x_new(m) = Sheet1.Cells(2, m + 1).Value * (1 + 0.001 * Sqr(-2 * Log(Rnd())) * Sin(2 *
3.14159 * Rnd()))
    xf_new(m) = lamada1 * x_new(m) + (1 - lamada1) * xf(m)
    numvar_new(m) = lamada2 * (x_new(m) - xf(m)) ^ 2 + (1 - lamada2) * numvar(m)
    denovar_new(m) = lamada3 * (x_new(m) - x(m)) ^ 2 + (1 - lamada3) * denovar(m)
End If


If denovar_new(m) > 0.000000000001 Then


    r(m) = (2 - lamada1) * numvar_new(m) / denovar_new(m)


    If r(m) > 3.9 Then
      SSID(m) = "0"
      Sheet1.Cells(3, m + 1).Interior.Color = vbRed
    End If
```

```
    If r(m) < 1.3 Then

      SSID(m) = "1"

      Sheet1.Cells(3, m + 1).Interior.Color = vbGreen

    End If



Else



    SSID(m) = 0.5



End If



If SSID(m) = 0.5 Then

    Sheet1.Cells(3, m + 1).Interior.Color = vbYellow

End If
```

```
Sheet1.Cells(3, m + 1).Value = SSID(m)

End Sub

''

''

------------------------------------------------------------------------------------------------------------------

Sub SSID_total()

' This sub program is used to update the information and calculate the total SSID result



Sheet1.Cells(445, nn + 2).Value = Sheet1.Cells(2, m + 1).Value

Sheet1.Cells(445, nn + 3).Value = Sheet1.Cells(3, m + 1).Value



x(m) = x_new(m)

xf(m) = xf_new(m)

numvar(m) = numvar_new(m)

denovar(m) = denovar_new(m)
```

```
SSID_total = SSID_total * SSID(m)

nn = nn + 2

End Sub
''
''
---------------------------------------------------------------------------------------------------------------
Sub percentage_cal()
' This sub program is used to calculate how many variable at SS

percentage_SSID = Round(tSSID / nvar, 4)
Sheet1.Cells(445, 102).Value = SSID_total
Sheet1.Cells(4, 5).Value = percentage_SSID
Sheet1.Cells(445, 103).Value = percentage_SSID
```

```
End Sub

''

''

------------------------------------------------------------------------------------------------------------------

Sub GRAPH()

' This sub program is used to graph the variable vs time and SS value vs time of the recent 4 hours



For i = 6 To 444 Step 1



    For m = 1 To 103 Step 1



      Sheet1.Cells(i, m).Value = Sheet1.Cells(i + 1, m).Value



    Next m



Next i
```

```
End Sub

"

"

----------------------------------------------------------------------------------------------------------------

Sub S2()

' This sub program is used to echo the result to sheet2



Sheet2.Cells(p + 1, 1).Value = Sheet1.Cells(445, 1).Value



For m = 1 To nvar * 2

    Sheet2.Cells(p + 1, m + 1).Value = Sheet1.Cells(445, m + 1).Value

Next m



Sheet2.Cells(p + 1, nvar * 2 + 2).Value = Sheet1.Cells(445, 102).Value

Sheet2.Cells(p + 1, nvar * 2 + 3).Value = Sheet1.Cells(445, 103).Value
```

```
End Sub

''

''

-------------------------------------------------------------------------------------------------------------

Sub save_file()

' This sub program is used to save the content in sheet2 automatically every 4 hours



If p Mod 480 = 0 Then



    ActiveWorkbook.Save



    ActiveWorkbook.Worksheets(2).Copy



    ActiveWorkbook.SaveAs ThisWorkbook.Path & "\" & "130109 SSID_" & Format(Time,
    hhmmss") & "_" & Format(Date, "MMM-DD-YY") & ".xls"
```

```
    ActiveWindow.Close

End If

End Sub
```

VITA

Ting Huang

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Master of Science

Thesis: STEADY STATE AND TRANSIENT STATE IDENTIFICATION IN AN INDUSTRIAL PROCESS

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