Root Cause Diagnosis of Plantwide Disturbance Using Harmonic Analysis

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Abstract: Disturbances in the form of oscillations are usually originated in process plants due to various faults such as sensor faults, valve faults, process faults and controller tuning faults. Many of these faults can be represented as nonlinearities. Faults in the form of nonlinearities may produce oscillations with a fundamental frequency and its harmonics. This study presents a novel method based on the estimated frequencies, amplitudes and phases of the fundamental oscillation and its harmonics to troubleshoot or isolate the root-cause of plantwide or unit-wide disturbances. Once the root cause is known, the oscillations can be eliminated, and the process can be operated more economically and profitably. The successful application of the method has been demonstrated both on simulated and industrial data sets.

Keywords: Plantwide oscillations, nonlinearity, harmonic, control performance, stiction

1. INTRODUCTION

Modern process plants are designed based on the concept of energy and material integration in order to minimize the energy requirements and pollution levels. Large process plants, such as oil refineries, power plants and pulp mills, are complex integrated systems, containing thousands of measurements, hundreds of controllers and tens of recycle streams. The integration of energy and material flow, required for efficiency, results in the spread of fluctuations throughout a plant. The fluctuations force the plant to be operated further from the economic optimum that would otherwise be possible, and thus cause decreased efficiency, lost production and in some cases increased risk. Because of the scale of operation of process plants, a small percentage decrease in productivity has large financial consequences. It can be extremely difficult to pinpoint the cause of these fluctuations. In the most difficult case, the fluctuations are in the form of oscillations. The problem is that oscillations have no defined beginning and end, and so the cause cannot be isolated by standard techniques. Finding the cause of oscillations is a tedious, labor-intensive, often fruitless task. Once the cause is understood, removal of the oscillations is usually straightforward. Therefore, it is important to detect and diagnose the causes of oscillations in a chemical process.

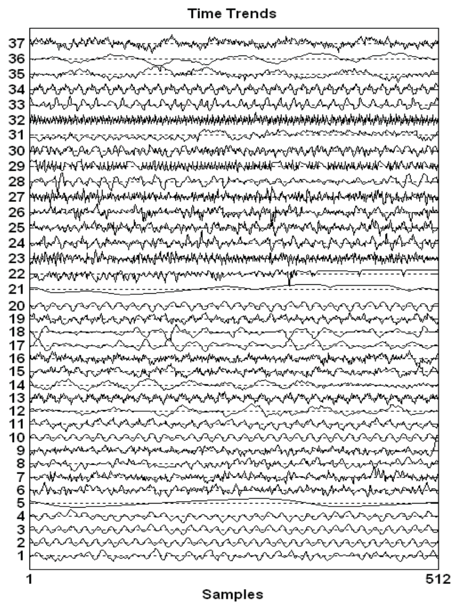
Most of the available techniques for oscillation detection focus on a loop by loop analysis (Hagglund, 1995). Thornhill and co-workers have presented some detection tools that consider the plant-wide nature of oscillations (Thornhill *et al.*, 2003). To detect oscillations in process measurements and identify signals with common oscillatory behavior, use of spectral principal component analysis (Thornhill *et al.*, 2002) or autocorrelation functions (acf) (Thornhill *et al.*, 2003) is suggested. Xia and Howell (2003) have proposed a technique that takes into account the interactions between control loops. Thornhill and Horch (2007) provided an overview of the advances and new direction for solving plantwide oscillation problems. A recent book (Choudhury *et al.*, 2008) provides two chapters on the state of the art technologies for plantwide oscillation detection and diagnosis. This paper demonstrates a method for detecting plantwide oscillations and isolating the root causes of such oscillations.

2. WHAT ARE PLANTWIDE OSCILLATIONS?

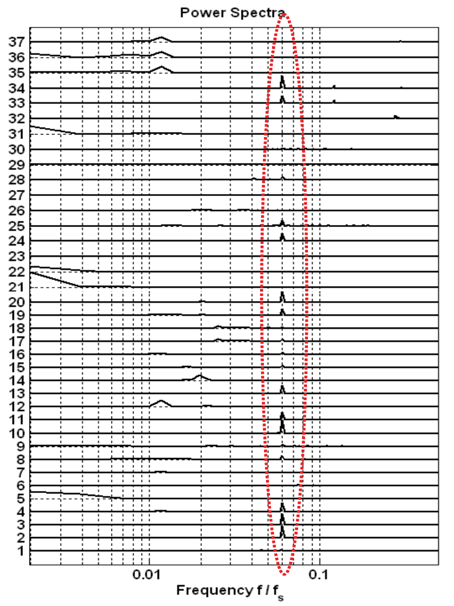
When one or more oscillations is generated somewhere in the plant and propagates throughout a whole plant or some units of the plant, such oscillations are termed as plantwide or unitwide oscillations. Oscillation may propagate to many units of the process plants because of the tight heat and mass integration in the plant as well as the presence of recycle streams in the plant. Figure 1 shows an example of a plant-wide oscillation problem. The top panel shows the time trends of 37 variables representing a plant-wide oscillation problem in a refinery (courtesy of South-East Asia Refinery). The bottom panel shows the power spectra of these variables. A common peak in the power spectra plot indicates the presence of a common disturbance or oscillation at a frequency of 0.06 or approximately 17 samples/cycle in many of these variables. The presence of such plant-wide oscillations takes a huge toll from the overall plant economy.

3. DETECTION OF PLANTWIDE OSCILLATIONS

Detection of plantwide oscillation is relatively an easy problem. Often times the plant operators notice some oscillations in the plant, which leads to a deeper investigation of the problem and may cause the invention of a plantwide oscillation of a larger nature. Over the last few years, some studies were carried out to detect plantwide oscillations (Tangirala *et al.*, 2005; Jiang *et al.*, 2006) and to group the similar oscillations together. The following are the brief description of some of these techniques that can be used for detecting plant-wide oscillations.



(a) Time Trends



(b) Power Spectra

Fig. 1. Time trends and their power spectra for the South-East Asia Refinery data set

3.1 High Density Plot - An Excellent Visualisation Tool

This plot describes time series data and their spectra in a nice compact form in one plot. From this plot, one can easily visualize the nature of the data and the presence of common oscillation(s) in the data. However, this method is not automated and cannot provide a list of the commonly oscillating variables. Figure 1 is an example of a high density plot.

3.2 Power Spectral Correlation Map (PSCMAP)

The power spectral correlation index (PSCI) is defined as the correlation between the power spectra of two different measurements. It is a measure of the similarity of spectral shapes, i.e., measure of the commonness of frequencies of oscillations. The PSCI for any two spectra $|X_i(\omega)|^2$ and $|X_j(\omega)|^2$ is calculated as

$$PSCI = correlation(|X_i(\omega)|^2, |X_j(\omega)|^2) = \frac{\sum_{\omega_k} |X_i(\omega_k)|^2 |X_j(\omega_k)|^2}{\sqrt{|X_i(\omega_k)|^4 |X_j(\omega_k)|^4}} \quad (1)$$

The PSCI always lies between 0 and 1. In the detection of plantwide oscillations, the objective is to collect variables with similar oscillatory behaviour.

For multivariate processes, the PSCI is a matrix of size $m \times m$, where m is the number of measured variables. In order to provide an effective interpretation of the PSCI, the matrix is plotted as a colour map, which is termed as the power spectral correlation map. An important aspect of this colour map is its ability to automatically re-arrange and group variables together with similar shapes, i.e., variables, which oscillate at a common frequency and have therefore similar values of PSCI. For a detailed discussion on this method, refer to (Tangirala *et al.*, 2005).

3.3 Spectral Envelope Method

In (Jiang *et al.*, 2007), the spectral envelope method has been used to troubleshoot plantwide oscillations.

Let $\mathbf{X}$ is a data matrix of dimension $n \times m$, where n is the number of samples and m is the number of variables. If the covariance matrix of $\mathbf{X}$ is $\mathbf{V_X}$ and the power spectral density (PSD) matrix of $\mathbf{X}$ is $\mathbf{P_X}(\omega)$, then the spectral envelope of $\mathbf{X}$ is defined as:

$$\lambda(\omega) \triangleq \sup_{\beta \neq 0} \left\{ \frac{\beta^* \mathbf{P_X}(\omega) \beta}{\beta^* \mathbf{V_X} \beta} \right\} \quad (2)$$

where ω represents frequency and is measured in cycles per unit time, for $-1/2 < \omega \leq 1/2$, the $\lambda(\omega)$ is the spectral envelope at the frequency ω, $\beta(\omega)$ is the optimal scaling vector that maximizes the power (or variance) at the frequency ω, the '*' represents conjugate transpose. The quantity $\lambda(\omega)$ represents the largest portion of the power (or variance) that can be obtained at frequency ω from a scaled series. Jiang et. al (2007) provided a detailed description of this method.

4. DIAGNOSIS TECHNIQUES FOR PLANTWIDE OSCILLATIONS

In a control loop, oscillations arises due to the following primary reasons:

(1) Presence of a poorly tuned controller
(2) An oscillatory external disturbance
(3) Presence of a faulty valve, e.g., a sticky valve or saturated valve.
(4) A highly nonlinear process
(5) Model-plant mismatch for an active MPC controller.

As described, the detection of plant-wide oscillation is relatively an easy problem compared to the diagnosis of its root-cause. Recently a number of papers appeared in the literature describing a few techniques to perform root-cause diagnosis of plant-wide oscillation (Thornhill *et al.*, 2001; Thornhill and Horch, 2007; Choudhury *et al.*, 2007; Jiang *et al.*, 2007; Zang and Howell, 2007; Choudhury *et al.*, 2008).

Oscillations originated in process plants due to various faults such as sensor faults and valve faults may be represented as nonlinearities. Faults in the form of nonlinearity produce oscillations with a fundamental frequency and its harmonics. It is well known that the chemical processes are low-pass filters in nature. Therefore, when a fault propagates away from its origin or source, the higher order harmonics get filtered out.

4.1 Oscillation and Harmonics

Sinusoidal fidelity states that if a sinusoidal input passes through a linear system, the output of the linear system is a sinusoid with the same frequency, but with a different magnitude and phase. A linear system does not produce any new frequency. On the other hand, when a sinusoidal signal with a certain frequency passes through various types of nonlinear systems or functions such as a square function, an exponential function, a logarithmic function and a square-root function, nonlinear systems may generate harmonics in addition to the original fundamental frequency of the input sinusoid. Therefore, nonlinearity induced oscillatory signals generally contain a fundamental frequency and its harmonics. Harmonics are oscillations whose frequencies are integer multiples of the fundamental frequency.

4.2 Fourier Series and Harmonics

Fourier series states that any signal can be represented as a summation of sinusoids. Therefore, any time series, $y(t)$, where, $t \in \Re$ can be represented as

$$y(t) = \sum_{i=0}^{\infty} A_i \, cos(\lambda_i \, t + \phi_i) \tag{3}$$

For a signal containing harmonics, Equation 3 can be rewritten as:

$$y(t) = \sum_{i=0}^{M} A_i \, cos(i * \lambda \, t + \phi_i) + \varepsilon(t) \tag{4}$$

where λ is the fundamental frequency. Each term of equation 4 contains three unknowns namely, amplitude, frequency and phase. The basic idea is to estimate the amplitudes, frequencies and phases for each term of equation 4 for any time series and then examine the relationships among the frequencies to find whether they are harmonically related.

From the experience of the author, for useful application of the harmonic analysis of chemical process data, it suffices to use $M = 5$.

4.3 Total Harmonic Content (THC)

A new index called Total Harmonic Content (THC) can be defined as:

$$THC = n * WHM \tag{5}$$

where n is the number of harmonics found and WHM is the Weighted Harmonic Mean. WHM is defined as

$$WHM = \frac{\sum_{i=1}^{M} w_i}{\sum_{i=1}^{M} \frac{w_i}{A_i}} \tag{6}$$

where w_i is weights and is defined as $w_i = i / \sum_{i=1}^{M} i$ so that the summation of the weights are equal to 1 and the weights for the higher harmonics are large. More weights are given to the higher harmonics because due to the low-pass filtering effect of the chemical processes the higher harmonics get filtered out gradually as the signal propagates away from the source or the root cause.

For plant-wide oscillations, the amplitudes, frequencies and phases of first five term of Equation 4 are estimated. For all tags or variables which have the same fundamental frequency are identified and the Total Harmonic Contents (THC) are calculated using Equation 5. After calculating the THCs, the variables are ranked according to the descending order of THC. The variable with the highest THC is likely to be the root cause. Plant information such as Piping and Instrumentation (P&I) diagrams, Process Flow Diagrams (PFD) and operators' knowledge should be utilised in conjunction with the information provided by THC to confirm the root cause. The chance of being right first time is high. However, if the variables with the maximum value of THC is not the root cause, the variable with the second highest value of THC should be investigated as a root cause. Thus maintenance effort should be started from variable with the maximum value of THC to the variables in the descending order of THC.

Thornhill *et al.* (2001) described a similar method using a distortion factor, which was defined as the ratio of the total power of the signal except the power at the fundamental frequency to the power of the fundamental frequency. They used power spectrum to estimate the distortion factor. The method was successful to a limited extent because the power spectrum is heavily affected by the signal noise. On the other hand, the method described here uses only the amplitudes of the harmonics and the fundamental frequency, therefore the THC is not influenced by the signal noise except some small contamination occurs during the frequency and amplitude estimation.

5. SIMULATION EXAMPLE

This simulation example describes a hypothetical process where a nonlinear function, a square function, followed by some linear filters are present. The simulink block diagram is shown in figure 2. The process was excited by a sinusoid

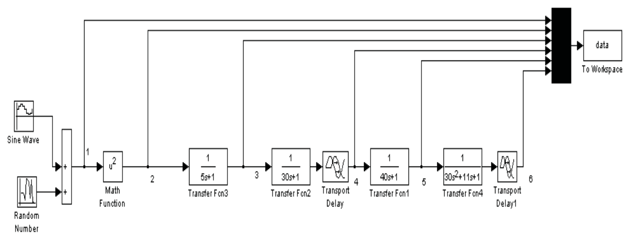


Fig. 2. Simulink block diagram for simple oscillation propagation

with frequency 0.25 rad/sec. Random noise with variance 0.05 was added to the sinusoid. The simulated time series data with their power spectra are shown in Figure 3. From the power spectra, it is hard to see the harmonics generated by the square function because the fundamental frequency has high power. It is interesting to note that for tags 4, 5 and 6, a low frequency oscillation has been developed due to the low pass filtering of the random noise by the process. The fundamental oscillation and its harmonic are gradually filtered out as the signal propagates through the system.

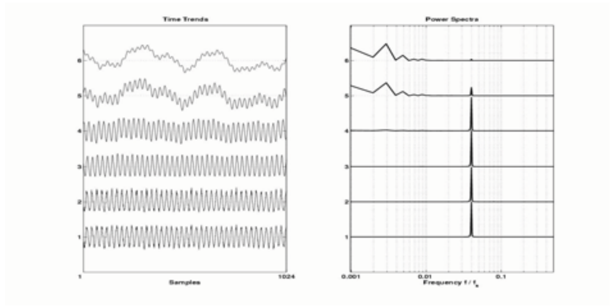


Fig. 3. Simulated data and their power spectra

Table I shows the harmonic analysis of the simulated data. The algorithm correctly identifies the presence of sinusoids in the signal. Five sinusoids are estimated for each signal. For the first signal (tag 1), the magnitude of the first sinusoid is much larger (more than 50 times) than the other sinusoids. The other sinusoids came into play due to the addition of random noise which has power in all frequencies. Research is undergoing to formulate a statistical hypothesis test to detect the presence of true sinusoids. The current algorithm correctly estimates the frequency of the main sinusoid as 0.25 rad/sec. Two dominant sinusoids with frequencies 0.25 and 0.5 rad/sec are estimated for tag 2. For tag 3, the sinusoid with frequency 0.5 rad/sec is present but its power has been decreased because of its attenuation by the first order filter. For tag 4, 5 and 6, the fundamental frequency sinusoid (0.25 rad/sec) has become gradually weak and has been masked with the noise, as evident from the estimated magnitudes shown in the table. The Total Harmonic Content (THC) was calculated for each tag where oscillation with fundamental frequency and its harmonic are found. The maximum THC corresponds to tag 2 indicating the source or root-cause of the propagated oscillation.

6. CASE STUDIES

6.1 Simulation Example - A Non-Linear Dynamic Vinyl Acetate Process

This example describes a simulation case study for root-cause diagnosis of plantwide oscillations using a non-linear dynamic model of a Vinyl Acetate process. The nonlinear dynamic model of the Vinyl Acetate process is published by (Chen *et al.*, 2003) and is freely available from the authors' website. Figure 4 shows a simplified schematic of the Vinyl Acetate Process. The process model contains 246 state variables, 26 manipulated variables and 43 measurements. The process takes approximately 300 minutes time to reach steady state. For details, refer to (Chen *et al.*, 2003).

After the process reached steady state, a 5% stiction ($S = 5$, $J = 2$) in the manipulated variable corresponding to the cooling water flow rate for the separator jacket temperature cooling valve was introduced using the stiction model developed in (Choudhury *et al.*, 2005). Simulation data set consisted of 1000 minutes of data with a sampling time of 15 seconds containing a total of 4000 observations for each variable. The last 1024 data points were used in this analysis in order to avoid transient behaviour due to the sudden introduction of stiction. Figure 5 shows the time trends and power spectra of the manipulated variables of the Vinyl Acetate process. The power spectra show that the variables 1, 2, 4, 5, 6, 7, 8, 9, 11, 12, 14, 19, 21, 22 and 23 are oscillating with a common oscillation at

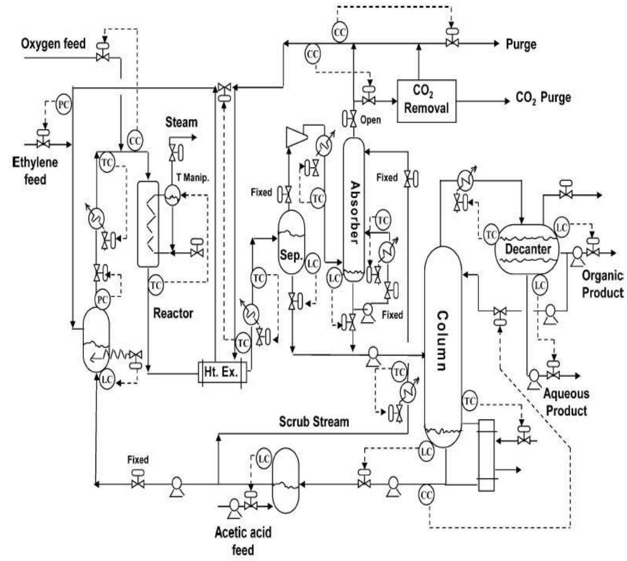


Fig. 4. Schematic of the Vinyl Acetate Process

a normalized frequency of 0.0505. Total Harmonic Content (THC) was calculated for these variables. Figure 6 shows the calculated THC values against the variable or tag number. The maximum THC corresponds to the tag 9 correctly indicating the root-cause of the plantwide oscillation because stiction was introduced in this variable during simulation.

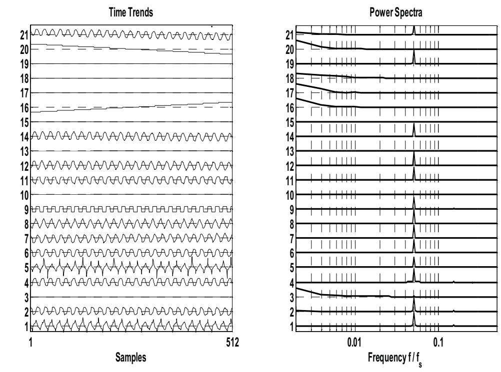


Fig. 5. Time trends and power spectra for the Vinyl Acetate Process Variables

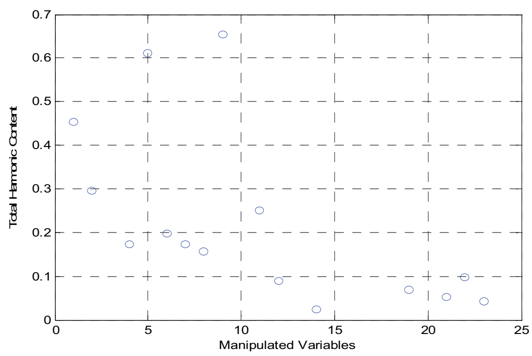


Fig. 6. THC values for the Vinyl Acetate Process Variables

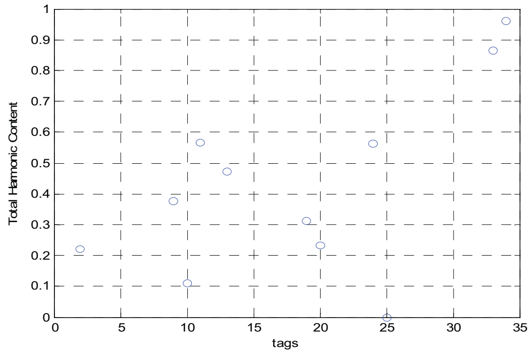


Fig. 7. Total Harmonic Contents (THC) Results for SEA data sets

6.2 An Industrial Example - Application to a Refinery Data Set

The proposed method was applied to a benchmark industrial data set for plantwide oscillations study appeared in the literature such as (Tangirala *et al.*, 2007; Tangirala *et al.*, 2005; Thornhill *et al.*, 2001). The data set, courtesy of a SE Asian Refinery, consists of 512 samples of 37 measurements sampled at 1 min interval. It comprises measurements of temperature, flow, pressure and level loop along with some composition measurements. The time trends of the controller errors are shown in Figure 1(a) and the corresponding power spectra are shown in Figure 1(b). From these figures or using the technique of power spectral correlation map (PSCMAP) described in (Tangirala *et al.*, 2005), it can be found that the tags 2, 3, 4, 8, 9, 10, 11, 13, 15, 16, 17, 19, 20, 24, 25, 28, 33 and 34 are oscillating together with a common frequency of 0.0605 or 17 samples/cycle approximately. All data corresponding to the variables with the common frequency were first normalized so that they had zero-mean and unit variance. Then the amplitudes, frequencies and phases for first five sinusoids were estimated and THC were calculated for these variables. The calculated THC values are plotted against the tag number in Figure 7. The highest THC value corresponds to the tag no. 34, which is the first candidate for the possible root-cause of this plantwide oscillation. In real plant investigation if this tag is not found to be the root cause, then the tag corresponding to next highest value of THC should be investigated. For this case, earlier studies (Thornhill *et al.*, 2001; Tangirala *et al.*, 2005; Tangirala *et al.*, 2007) found tag 34 as the root-cause. Therefore, the proposed THC index correctly detected the root-cause of this plantwide oscillations.

7. CONCLUSIONS AND FUTURE WORKS

This study describes a method to troubleshoot plantwide oscillation using harmonic information present in the signal. The amplitudes, frequencies and phases of the fundamental signal component and its harmonics are estimated and used for the diagnosis of the root-cause of plantwide oscillation. A new index called Total Harmonic Contents (THC) has been defined and used for isolating the root-cause. The method can be automated to facilitate troubleshooting of plantwide oscillation.

8. ACKNOWLEDGEMENTS

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Table 1. Harmonic analysis results for simple oscillation propagation example

Tags	λ_1	λ_2	λ_3	λ_4	λ_5	A_1	A_2	A_3	A_4	A_5	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	RESS	λ_1/λ_1	λ_2/λ_1	λ_3/λ_1	λ_4/λ_1	λ_5/λ_1	THC
1	**0.25**	**1.25**	2.88	1.95	1.22	**1.394**	**0.028**	0.027	0.023	0.023	2.06	0.39	2.17	-2.85	-0.74	24.40	1.0	5.0	11.5	8.0	4.9	3.91
2	**0.25**	**0.50**	2.88	**1.25**	1.99	**1.387**	**0.130**	0.028	**0.028**	0.023	2.06	-2.13	2.27	0.33	-3.01	26.67	1.0	2.0	11.5	5.0	8.0	8.96
3	**0.25**	**0.50**	0.02	0.06	0.03	**1.409**	**0.079**	0.028	0.026	0.024	1.15	2.96	2.46	2.79	0.98	6.08	1.0	2.0	0.1	0.2	0.1	1.91
4	**0.25**	0.02	0.03	0.00	0.05	**1.367**	0.206	0.132	0.110	0.100	-0.5	3 2.17	0.82	-0.95	1.98	21.30	1.0	0.1	0.1	0.0	0.2	0.73
5	0.02	0.25	0.00	0.03	0.02	0.864	0.688	0.545	0.407	0.301	1.66	-1.97	-1.20	0.04	-1.06	83.98	1.0	15.2	0.3	1.8	1.4	
6	0.02	0.00	0.03	0.02	0.25	0.953	0.682	0.454	0.336	0.264	1.30	-1.17	-0.33	-1.31	1.13	88.34	1.0	0.2	1.7	1.4	15.1	