

An Integrated Approach to Oscillation Propagation Identification and Source Locating in Process Multi-loop Systems*

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Abstract An integrated method for identifying the propagation of multi-loop process oscillations and their source location is proposed in this paper. Oscillatory process loop variables are automatically selected based on the component-related ratio index and a mixing matrix, both of which are obtained in data preprocessing by spectral independent component analysis. The complex causality among oscillatory process variables is then revealed by Granger causality test and is visualized in the form of causality diagram. The simplification of causal connectivity in the diagram is performed according to the understanding of process knowledge and the final simplest causality diagram, which represents the main oscillation propagation paths, is achieved by the automated cutting-off threshold search, with which less significant causality pathways are filtered out. The source of the oscillation disturbance can be identified intuitively through the final causality diagram. Both simulated and real plant data tests are presented to demonstrate the effectiveness and feasibility of the proposed method.

Keywords multi-loop system, process oscillation, spectral independent component analysis, Granger causality test, causality diagram, propagation path simplification, source locating

1 INTRODUCTION

Plant-wide persistent disturbances, such as loop oscillations, are common problems in process industry. The root causes of loop oscillations may be process or actuator (control valves) non-linearity, poorly tuned controllers, oscillatory disturbance, *etc.* Because of the interconnection of process equipment, the disturbances may widely propagate, influence process variables and finally lead to a plant-wide problem. The performance deterioration of numerous process control loops makes it difficult to identify the source of disturbances. Traditional methods for performance evaluation of control loops are mainly based on some transient process indices, such as overshoot, subsidence ratio and settling time. More advanced methods for performance assessment are mainly based on minimum variance control (MVC) [1, 2]. Other methods utilize multivariate statistics process control (MSPC), principal component analysis (PCA) or partial least square method (PLS), *etc.*, to try to find process variables that make dominant contributions to abnormal disturbances. These methods focus on the performance monitoring of control systems, with less intention to the identification of disturbance propagation and root-cause localization of a plant-wide perturbed system.

In many cases, the root cause of process oscillations is isolated to a specific valve. With the operation hour increasing, control valves may develop various problems such as large deadband, stiction, saturation, backlash, seat corrosion, and diaphragm wear. Further signal analysis for valve non-linearity test is usually carried out. Researches focused on the valve stiction are reviewed by Thornhill and Horch [3]. Different

methods and models have been proposed, such as those stiction models [4, 5].

Normally the disturbance propagation paths have to be determined partial manually by the inspection of process schematic model, which blocks the widely use of such propagation analysis technologies. Attempts to provide automated model-free propagation analysis and root-cause diagnosis tools are of great research interests. Many data-driven methods have been developed for root cause analysis of persistent dynamic disturbances, as reviewed in [3]. Based on the spectral decomposition method, principal component analysis, independent component analysis and non-negative matrix factorization have been intensively studied [6–8]. In combination with process knowledge, data-driven methods can be improved and lead to more efficient root cause diagnosis [9]. Bauer *et al.* proposed a method to find the propagation paths *via* the application of transfer entropy based on the conditional probability density functions that measures directionality of variation and found it effective even when the time delay information was not available [10]. Bauer and Thornhill used a cross-correlation function to estimate the time delay between process measurements and provided a qualitative model of the propagation path, which was derived in the form of a causal map, for the analysis of plant-wide disturbances [11].

In the current data-driven approach, PCA-based methods can only indirectly separate multiple oscillation sources. Spectral independent component analysis (spectral ICA) based methods can localize the place of root cause, but in some cases, especially in tight coupling systems, these methods are easily influenced by similar characteristics of the oscillation sources and

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result in wrong answers. All these methods mentioned above have not yet considered the propagation path of oscillations.

Causality test describes the interactions among process variables through causalities, with natural advantages in root-cause reasoning and propagation path identification. The understanding of process knowledge can effectively simplify the disturbance propagation paths. Therefore, the method proposed in this paper first calculates the complex causality among automatically selected oscillatory loop variables by Granger causality test. Then the causality is visualized in the form of causality diagram and further simplified by the understanding of process knowledge. Only dominant oscillation propagation paths remain after cutting off less significant causality pathways by an automated threshold search. The source of oscillation disturbances is identified by tracing back to the origin of the final simplified causality diagram. The paper describes the procedures for these analysis steps that are generally applicable, and illustrates them with both simulated and industrial cases.

In our previous study, a first attempt to locate the root-cause *via* Granger causality test showed some success [12]. Further improvement is made in this study as follows. (1) Perturbed process loop variables are automatically selected through the combined study on component-related ratio (CRR) index and mixing matrix, both of which are achieved by spectral ICA. (2) Granger causality analysis procedure is presented in detail, and the reason why causality diagram is weakly connected is discussed according to graph theory. (3) Cutting-off threshold for diagram simplification is automatically done based on a depth-first search (DFS), which is used to determine the termination condition of the search.

2 METHODS

The whole procedure contains 3 parts: (1) data preprocessing, (2) Granger causality test, and (3) causality diagram simplification. The details of the procedure are shown in Fig. 1.

2.1 Data preprocessing

2.1.1 Process variables selection

When oscillatory disturbances propagate throughout a plant, many control loops may be perturbed in various degrees. Significantly influenced loop variables with similar dominant components are normally sufficient to be selected as a subset for oscillatory source locating. In this paper, spectral ICA (see [7]) is utilized to select the candidate oscillatory process loop variables for further analysis.

Data matrix X is decomposed as follows

$$X = AS \quad (1)$$

where matrix $X = [x_1, x_2, \dots, x_m]'$ represents power

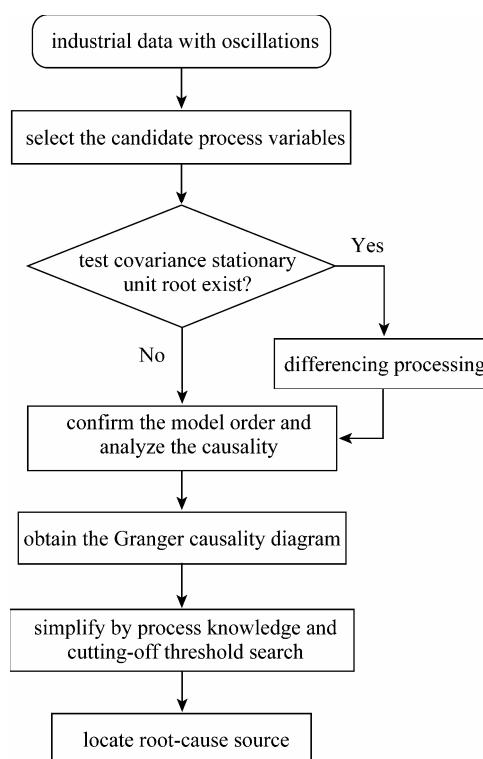


Figure 1 Flow diagram of the integrated approach for oscillation source locating

spectra of all loop process variables, with the power spectrum of a signal estimated by applying discrete Fourier transform (DFT) methods or the averaged periodogram method [13] to the mean centred time trends, $S = [s_1, s_2, \dots, s_n]'$ is the matrix containing all independent sources with single-peak spectral-like component, and $A = [a_1, a_2, \dots, a_n]$ is the mixing matrix. Matrix X can be further represented as

$$\begin{bmatrix} x'_1 \\ x'_2 \\ \dots \\ x'_m \end{bmatrix} = [a_1, a_2, \dots, a_n] \cdot \begin{bmatrix} s'_1 \\ s'_2 \\ \dots \\ s'_n \end{bmatrix} = [a_1 s'_1 + a_2 s'_2 + \dots + a_n s'_n] \quad (2)$$

From Eq. (2), the distribution of each spectral-like independent component s'_j to matrix X is determined by corresponding coefficient column vector a_j . The matrix element a_{ij} determines the quantity of corresponding independent component s'_j that exists in the i th process variable. The larger the a_{ij} value, the larger quantity of s'_j .

The CRR defined in [7] is used to reveal the magnitude of each independent component (IC).

The definition of CRR for the j th dominant IC is

$$\text{CRR}(j) = \left\{ \frac{\sum_{i=1}^m a_{ij}}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}} \right\} 100\% \quad (3)$$

The larger the $\text{CRR}(j)$ value, the greater the influence of the j th IC on the whole perturbed plant.

Ordinarily, only the IC corresponding to the largest $\text{CRR}(j)$ value is considered because other ICs normally have significantly less influence [*i.e.* the corresponding $\text{CRR}(j)$ values are much smaller than the maximum one]. The combination of two ICs corresponding to the largest and the second largest values occurs only if the two values differ not much (*e.g.* the second largest value is larger than 90% of the maximum one) and the spectral peak positions of the two ICs are close to each other in the power spectrum (here the interval of the two spectral positions less than 1% of the total spectral band is used as a criteria). Here, combination means to add the two $\mathbf{a}_j$ in the mixing matrix $\mathbf{A}$ together into a new coefficient column vector $\mathbf{a}'$.

The criteria for the selection of perturbed process loop variables are as follows: (1) the significant-valued element of $\mathbf{a}_j$ (or $\mathbf{a}'$) corresponding to the largest $\text{CRR}(j)$ value (or the combination case) is marked sequentially from the largest-valued one, until the sum of the marked elements is more than 95% of the whole sum of $\mathbf{a}_j$ (or $\mathbf{a}'$), and (2) the loop variables corresponding to the marked elements are selected as the perturbed oscillatory variables for further analysis. This step is optional. If candidate process variables are clearly correlated, this selection step can be omitted.

2.1.2 Time series normalization

The selected loop variables are normalized to be zero mean and unit variance.

2.1.3 Covariance stationary test

Application of Granger causality analysis requires that each time series is covariance stationary (CS), *i.e.*, its mean and variance do not change with time. In this paper, CS is tested by augmented Dickey-Fuller test (ADF) [14–16], which checks the existence of unit root in a time series sample. The existence of one or more unit roots implies that the assumption of CS is violated. In that case, CS can be induced by differencing, *i.e.*, by transforming the time series as follows

$$\Delta x(t) = x(t) - x(t-1) \quad (4)$$

2.2 Granger causality analysis

2.2.1 Model order search

The model order, *i.e.*, the number of ‘lagged’ observations that the regression model takes into account should be appropriate. Different model orders may lead to very different results, even for the same data. If the chosen model order is too low, the regression model is unlikely sufficient to capture dynamic rela-

tions in the data. If it is too high, there will be a danger of ‘over-fitting’. In this paper Bayesian information criteria (BIC) [17], which makes a trade-off between model accuracy and the number of model parameters estimated, is chosen to determine a sensible model order.

The BIC is an asymptotic result derived under the assumptions that the data distribution is in the exponential family. The formula for the BIC is as follows under the assumption that the model errors or disturbances are normally distributed.

$$\text{BIC} = n \ln \left(\frac{\text{RSS}}{n} \right) + k \ln(n) \quad (5)$$

where RSS is the residual sum of squares from the estimated model, k is the number of free parameters to be estimated, and n is the sample size. Lower BIC implies either fewer explanatory variables, or better fitting, or both. Hence, testing within a range of model order (2 to 15 in this paper) is needed, and the one that minimizes the BIC is preferred.

2.2.2 Causality analysis

Granger causality test is a technique for determining whether one time series is useful in forecasting another [18]. Hacker and Hatemi-J [19] developed a new method for Granger causality that is not sensitive to the normal distribution of the error term. This new method is especially useful in financial economics since many financial variables are non-normal.

To illustrate Granger causality, consider two time series X_t and Y_t . We establish regression equations including X_t and Y_t as follows, with assumption that white noise u_{1t} and u_{2t} are uncorrelated.

$$y_t = \sum_{i=1}^q \alpha_i x_{t-i} + \sum_{j=1}^q \beta_j y_{t-j} + u_{1t} \quad (6)$$

$$x_t = \sum_{i=1}^s \lambda_i x_{t-i} + \sum_{j=1}^s \delta_j y_{t-j} + u_{2t} \quad (7)$$

where q is the maximum number of past values (lags) of time series y_t , and s is the maximum number of past values (lags) of time series x_t . The model order is the larger one between q and s . x_t Granger-causes y_t if all the coefficients in α_i ($i = 1, \dots, q$) are jointly significantly different from zero. y_t Granger-causes x_t if all the coefficients in δ_j ($j = 1, \dots, s$) are jointly significantly different from zero. The procedures of Granger causality test are as follows.

(1) Build a regression of y_t on all the lags y_{t-j} ($j = 1, \dots, q$) and other lags of other variables if they exist in the regression equations, except for x_{t-i} ($i = 1, \dots, q$). Calculate the residual sum of squares RSS_R of this regression.

(2) Build the regression again with the addition of lags x_{t-i} ($i = 1, \dots, q$). Calculate the residual sum of squares RSS_{UR} of the new regression.

(3) Perform an F -test of the null hypothesis that $H_0: \alpha_i$ ($i = 1, \dots, q$), *i.e.* the regression of y should not consider the lags x_{t-i} ($i = 1, \dots, q$). The formula for an

F -test is

$$F = \frac{(\text{RSS}_R - \text{RSS}_{UR})/q}{\text{RSS}_{UR}/(n-k)} \quad (8)$$

where n is the sample size, and k is the number of estimated parameters in the first regression in Step 1. Here F is distributed as an F -distribution, with $(q, n-k)$ degrees of freedom. If the F value exceeds the threshold F_α for the given level α of significance, reject the null hypothesis H_0 , i.e., the regression with the addition of lags x_{t-i} ($i = 1, \dots, q$) is correct, indicating that x_t Granger-causes y_t .

It should be pointed out the given level α of significance should be adjusted by Bonferroni correction [20] to maintain the significance level for the entire series of tests, because if n tests are performed and each of them is significant with probability β , the probability that “at least one of them comes out significant” is (by Boole’s inequality) $\leq n \cdot \beta$. In statistics, the Bonferroni correction states that if the significance level for the whole family of tests needs to be (at most) α' , each of the individual tests should be tested at a significance level of ($\alpha = \alpha'/n$). In this paper, the family-wise error rate α' is set to be 0.01.

The magnitude of a given Granger causality interaction can be estimated by the logarithm of the corresponding F -statistic. In this paper, $\ln F_{y \leftarrow x}$ denotes the magnitude of x Granger-causing y .

The concept of Granger causality can be readily extended to the multivariate case by estimating an N -variable vector-autoregression (VAR) model. In this case, x_t Granger-causes y_t if knowing that x_t shall reduce prediction error of y_t when the activities of all other variables are taken into account.

2.2.3 Visualization of causal connectivity

A given Granger causality interaction can be represented as edges in a graph, allowing the application of graph-theoretic techniques. On the causality diagram in this paper, vertices represent process variables, and directed edges represent the Granger causality interaction. If X_2 Granger-causes X_1 , the corresponding directed edge is from X_2 to X_1 and the magnitude $\ln F_{X_1 \leftarrow X_2}$ is marked next to the directed edge.

If X_1 and X_2 Granger-cause each other, the corresponding edge is bidirectional. A Granger causality diagram looks like the one shown in Fig. 2.

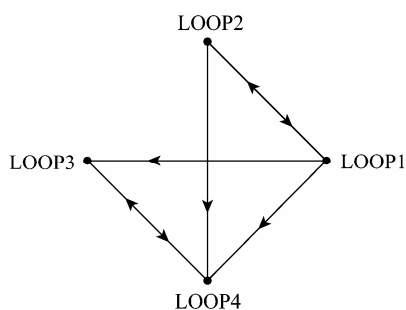


Figure 2 Qualitative causality among four loops

A graph is called connected if every pair of distinct vertices in the graph can be connected through some path. The vertex “origin” represents the source of the oscillation disturbance and every other vertex representing the influenced process loop variables is consequentially connected through some path. Hence, every pair of vertices u and v can be connected through the path u -origin- v . If the vertex $u(v)$ is just the origin, the path is u - v .

A directed graph is called weakly connected if replacing all of its directed edges with undirected edges produces a connected (undirected) graph. Obviously the Granger causality diagram is weakly connected in the real industrial cases. This indicates that all the oscillatory process loop variables are influenced by the source of one or more oscillation disturbances. Thus it should be always successful in the subsequent simplification process.

2.3 Causality diagram simplification and source locating

2.3.1 Simplification of cascade loops

The understanding of process knowledge helps simplify cascade control loops. If one vertex on a Granger causality diagram represents an outer-loop variable and another vertex simultaneously represents the relevant inner-loop variable for the same cascade control loop, the two raw vertices can be merged in to a new vertex, which retains the larger Granger causality interactions between raw vertices and other process variables in each causal direction. The Granger causality interaction between the outer-loop variable and the inner-loop variable can be ignored temporarily and considered only if the root-cause is finally located in the corresponding merged vertex. Process knowledge about cascade control loops is used for reducing the number of nodes. It makes Granger causality diagram clearer and a better judgment in the next steps.

2.3.2 Cutting-off threshold search

There are still so many edges left on the Granger causality diagram, including main and less significant causality pathways that can be traced through directed edges. Less significant causality pathways are filtered out by cutting-off threshold searching. The discrete scope of the alternative cutting-off thresholds is the aggregate of all $\ln F$ left on the Granger causality diagram. The order of searching different cutting-off thresholds is from the maximal $\ln F$ to the minimal $\ln F$. The edges whose corresponding $\ln F$ is lower than the cutting-off threshold tried will be cut down. The termination condition of cutting-off threshold searching is that the Granger causality diagram becomes a weakly connected graph. In this paper, the depth-first search (DFS) technique is used to determine if the termination condition is matched. A DFS algorithm is implemented based on references [21, 22] for traversing a tree, tree structure, or graph. The number of visited vertices determines the termination of the search.

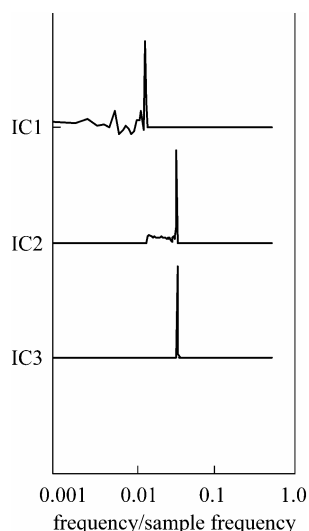


Figure 5 Normalised ICs extracted from simulated plant data in Case 1

Table 2 CRR values of ICs

IC	CRR
1	0.0001
2	0.06037
3	0.93962

Table 3 a_{ij} values of 3rd IC

Process variable	a_{ij} values
LOOP1	1.0000
LOOP2	0.8787
LOOP3	0.4644
LOOP4	0.0103

3.1.2 Integrated method

It can be seen from the model that process variables are all tightly coupled, so the selection procedure is omitted and all of them are chosen for further analysis. (1) Normalize the process variables and do the CS test by ADF. The result is that all process variable time series is not covariance stationary, hence all variables are differenced. (2) Search the model order by BIC analysis, and the result is 12. (3) Perform Granger causality analysis and correct the statistical significance level based on Bonferroni correction. (4) Plot the Granger causality diagram as shown in Fig. 6.

The difference between Figs. 4 and 6 is that secondary causalities exist in Fig. 6. The indirect Granger causalities are degeneratively passed on to the indirectly linked control loops through system coupling. Since the filtering of process propagation paths attenuates under normal circumstances, the secondary causalities shall be less significant and can be cut down by DFS-based cutting-off threshold search procedure.

The final cutting-off threshold after DFS-based search is 3.7207, and the simplified Granger causality

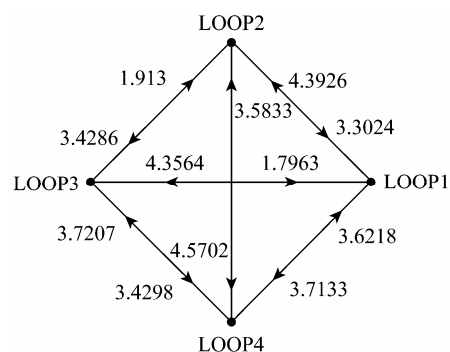


Figure 6 Granger causality diagram of Case 1

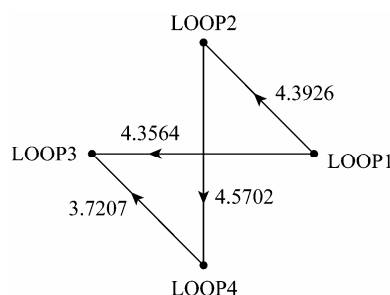


Figure 7 Simplified Granger causality diagram

diagram shown in Fig. 7 is achieved after filtering out the less significant secondary causality pathways. The candidate oscillatory source variable is pointed to LOOP1 intuitively after tracing the directed edges. The proposed approach is justified by the successful localization of the oscillation disturbance in LOOP1.

3.2 Case 2: Real plant data analysis

Real plant operation data from a vinyl chloride monomer (VCM) production plant, courtesy of Shanghai Chlor-Alkali Chemical Co., are also tested by the proposed method. The plant contains 5 units: direct chlorination unit (No. 100), oxychlorination unit (No. 200), ethylene dichloride refining unit (No. 300), dichloroethane cracking unit (No. 400) and vinyl chloride refining unit (No. 500). Tight coupling exists within these units. It is found that the plant control loop performance degrades with time and oscillations appear in many process variables. However, it is difficult to diagnose the exact origin of the oscillatory disturbances in the process according to distribution control system (DCS) monitoring tools. The proposed method is used to pinpoint the candidate source location.

Process data from No. 300 and 500 units are analyzed, since most of oscillation variables are within these loops and these units have a relatively high level of automation and system complexity. The schematic diagram is shown in Fig. 8.

High spot data samples from 34 process measurements (tags) in units 300 and 500 are recorded for analysis. The objective of the analysis is to find the

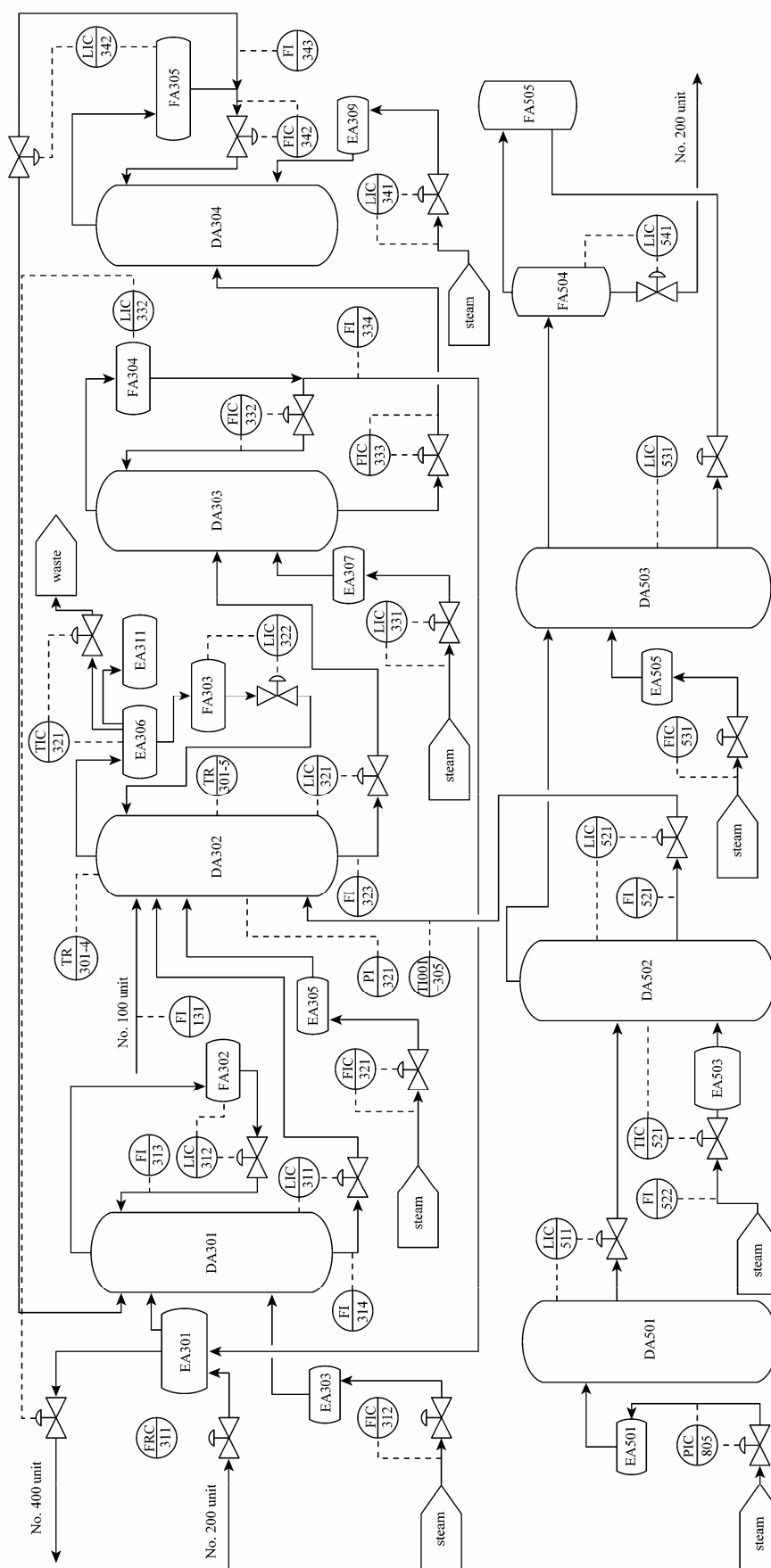


Figure 8 Schematic diagram of the process of No. 300 and 500 units

sources of dominant oscillation disturbances in the process system and provide suggestions for equipment maintenance.

3.2.1 Spectral ICA method

This method is a step as the integrated method for filtering a large number of process variables in this case. Procedures and results can be seen in the next part.

3.2.2 Integrated method

Step (1): process variable selection by performing spectral ICA on 58 process variables. Nine spectral-like ICs are extracted (see Fig. 9), and their CRR values are shown in Table 4. The IC3 has the largest CRR value 0.2166. The IC5 has the second largest CRR value 0.1906, larger than 85% of the largest one. It can be seen from Fig. 9 that the spectral peak positions of the two ICs are all close to 0.002 normalized frequency, so that they are combined and considered as one dominant oscillation. The combined a_{ij} values are given in Table 5.

Table 4 CRR values of ICs

IC	CRR
1	0.1766
2	0.0894
3	0.2166
4	0.1681
5	0.1906
6	0.0302
7	0.0153
8	0.0839
9	0.0293

Thirteen process variables from No. 300 and 500 units match the selection criteria, and are selected for further analysis. These process variables are numbered from point 1 to 13 as follows: FI522, LIC322, TIC521, LIC342, FI343, TI001-305, LIC521, PI321, TR301-5, FI521, LIC332, FI334, and TIC321. Fig. 10 shows the time trends and power spectra of these process vari-

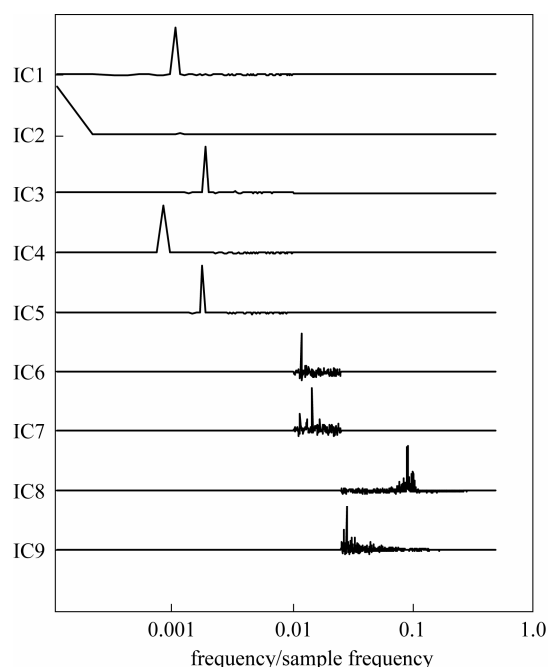


Figure 9 Normalised ICs extracted from real plant data in Case 2

ables. FI522 is thought as the oscillation root by using spectral ICA method, but there exists physical back-flow in the plant and couplings between different loops are strong. LIC322 and TIC521 have slightly smaller a_{ij} values than FI522, so they also need to be considered. The method proposed in this paper will be used for some further study on dealing with this situation.

Step (2): normalization and CS test by ADF. The CS test result is that not all variables are covariance stationary, hence all variables are differenced.

Step (3): model order search and Granger causality analysis. The calculated model order is 6, and the obtained Granger causality diagram is shown in Fig. 11. The quantitative indexes of Granger causality interaction is listed in Table 6, where the raw variable Granger causes the column variable.

Step (4): diagram simplification and source locating. According to process knowledge, no cascade

Table 5 a_{ij} values of combination of 3rd and 5th ICs

PV	a_{ij}	PV	a_{ij}	PV	a_{ij}	PV	a_{ij}
FRC311	-0.0141	LIC331	0.0686	PI321	0.4895	LIC521	0.4912
FIC312	-0.0024	LIC332	0.3477	TI001-305	0.5385	TIC521	1.2168
LIC311	-0.0017	FIC342	0	TR301-4	0.1484	FIC531	0.0062
LIC312	0.0187	LIC341	-0.0542	TR301-5	0.469	LIC531	-0.0784
FIC321	-0.0028	LIC342	1.0582	FI334	0.2497	LIC541	0.0487
LIC321	0.0633	FI313	-0.0472	FIC333	0.0219	FI521	0.3928
LIC322	1.4113	FI314	-0.0028	FI343	0.7178	FI522	1.6047
TIC321	0.2271	FI131	0.0022	LIC511	0.0607		
FIC332	0.2256	FI323	0.1246	PIC805	-0.0761		

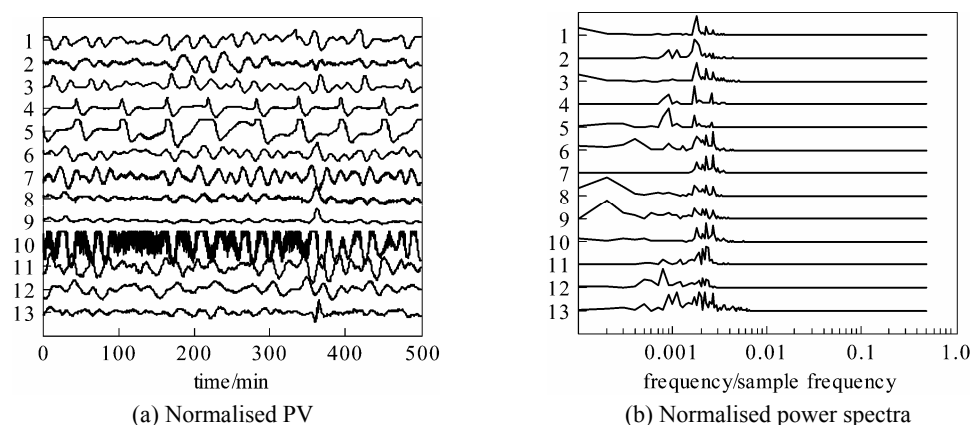


Figure 10 Time trends and power spectral of 13 time series

Table 6 Quantitative indexes of Granger causality (Case 2)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.0	0.0	146.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	7.52	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	108.6
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	16.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	84.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	5.28	0.0	0.0	8.57	0.0	0.0	0.0
7	0.0	0.0	10.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	9.2	0.0	7.4	0.0	0.0	0.0	5.21
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.5	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0	39.4	50.9	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	5.24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	63.4	0.0
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	450.5	0.0	0.0
13	0.0	155.1	0.0	0.0	0.0	0.0	0.0	0.0	8.3	0.0	0.0	0.0	0.0

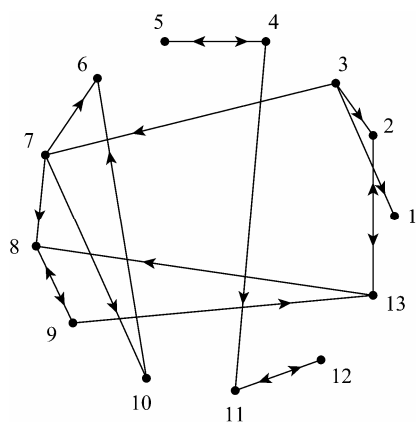


Figure 11 Granger causality diagram (Case 2)

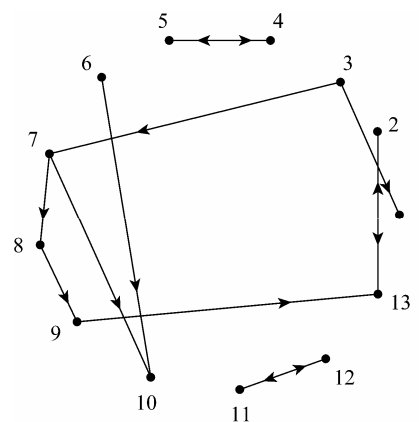


Figure 12 Simplified Granger causality diagram (Case 2)

loops need to be simplified. DFS-based cutting-off threshold search procedure is performed and the final cutting-off threshold is set at 5.24. The simplified Granger causality diagram is shown in Fig. 12. According to Fig. 8, point 4 (LIC342) and point 5 (FI343)

are flow value and liquid level value in the same pipe. Point 11 (LIC332) and point 12 (FI334) also have apparent relevancies. These two separate causal pairs refer to loop LIC342 and LIC332, which is apart from the main casual link, where point 3 (TIC521) and

point 6 (TI001-305) are the most likely root-cause process variables. It is known from Fig. 11 that point 7 is a Granger cause of point 6 and point 3 is a Granger cause of point 7. Thus the resulting candidate source of oscillation disturbances is point 3 (TIC521). Since valve problem is one of the most common causes for plant oscillations, alert of valve maintenance for this loop is given to the field engineers with high priority.

The on-site field investigation was done according to the maintenance alerts. The field engineer successfully found a malfunction positioner in the coarse adjustment valve HC521, which parallels the tuning valve TIC521.

4 CONCLUSIONS

An integrated approach to oscillation propagation identification and source locating in process multi-loop systems is proposed in this paper. Spectral ICA is used to extract the dominant oscillation components and select the relevant process variables for further analysis. Granger causality test is performed to reveal the complicated causalities quantitatively among process variables and a depth-first search (DFS) based cutting-off threshold search procedure is used to simplified the signed causality diagram, according to which the oscillation source is located by finding the source node of the diagram. Both simulated and real plant data are tested to show the feasibility of the proposed method. A comparison between the proposed method and the spectral ICA method shows the accuracy and the advantage of this method.

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