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# Root Cause Diagnosis with Error Correction Model Based Granger Causality

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**Abstract:**With the rise of data science, data-based fault root diagnosis methods have attracted widespread attention. Among these methods, the Granger causalitytest is one of the most common methods which can infer causal associations between signals based on temporal precedence. However, there are some strong constraints when using this method. First, the time series analyzed should be stationary. Besides, the GC is based on the linear model. In the actual process, the system is often nonlinear, and the time series caused by the fault are mostly nonstationary. In this paper, error correction model is introduced into the root cause diagnosis to solve the problem that Granger causality can't be applied to non-stationary time series analysis directly.The effectiveness of the proposed method is illustrated by two cases of TE process.

**Key Words:**Co-integration, Error Correction Model,TE Process, Granger Causality, Nonstationary Time Series Process

## 1 Introduction

In the chemical process, for a single reaction unit, the cause of the fault can be quickly located. But for a system with multiple reaction modules, when a fault happens, its signal will affect the entire system along the reaction process, which requires us to troubleshoot the entire system rather than a single unit that issues a fault alarm. The propagation of faults in the system makes the diagnosis of the root cause of the fault a hard problem. Besides, the current industrial processes, especially the chemical industry processes, have become very large and complex in scale. Each unit consists of many control loops, and the number of variables that need to be controlled and detected is very large. For such a complex system, how to conduct effective root cause diagnosis and fault propagation path inference has attracted the interest of many researchers.

In the recent decades, the research on fault root cause diagnosis is mainly divided into two aspects: research based on process knowledge and research based on process data. The first aspect contains adjacency matrix [2], signed directed graph [3,4], etc. These methods require complete and accurate process knowledge, which may hardly to obtain. In addition, these methods need to be customized for the system, so the portability is very poor. For the above reasons, using these methods is costly and the effect may not be good. On the contrary, the methods based on process data, such as the Bayesian networks [5,6], transfer entropy [7,8], and Granger causality [9]. These methods attempt to find a statistically causal relationship of fault propagation by analyzing the fault data thought statistical method. These method do not require prior knowledge of the system and are very portable, so they have received widespread attention in recent years, especially the Granger causality.

Causality generally refers to the relationship between a series of factors and a phenomenon. When analyzing a system, the first step is often to explore the causal link between the variables in the system. Through this known causal inference, the root cause of the fault can be quickly found based on the mechanism after the fault occurs. [10,11]. Granger causality and transfer entropy are both effective methods for analyzing causal relationships between variables. Transfer entropy is a frequency method that measures the amount of information passed between variables to obtain the causal relationship between variables, and works well when dealing with turbulent type failures. Shu Xu [12] and Ping Duan [13] both use transfer entropy to achieve good results in root cause diagnosis. However, this method has the following disadvantages [14]. First, it costs a lot of computing resources. Second, the time delay cannot be estimated. Third, the precondition for use transfer entropy is that the time series is stable. The initial granger causality id obtained by fitting autoregressive (AR) models and is easy to calculate and explain.But the result is statistically causal, only suitable for analysis, and does not represent the true causal relationship between variables [15]. Granger causality need less computing resources, and the time delay can be calculated by Akaike information criterion (AIC) and Bayesian information criterion (BIC). However, this method of causal calculation still has some limitations, requiring data to satisfy linearity and stationarity.Many researchers have attempted to modify the Granger causal analysis method to enable it to analyze data that does not meet the above criteria and to obtain correct results [16]. Nevertheless, those approach still can't make the method handle the all kinds of data.

Mostof the data collected during the fault process is non-stationary, and the appearing of smooth time series is rarely. However, the most common methods introduced above don't have the ability to process non-stationary time series. Therefore, it is important to improve existing methods to make these methods able to the process the

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non-stationary time series. The common method for processing non-stationary time series is differentiate, but it will lose trend information after doing difference on time serious. The trend change is also an important feature of the fault, so differential processing is not suitable for fault diagnosis. Cointegration analysis is an important method for analyzing non-stationary time series [17]. Through cointegration test, an error correction model can be built to analysis the non-stationary time serious. With this approach, the information loss caused by difference can be compensated. This is a common method used to deal with non-stationary sequences in economics [18]. In this study, the cointegration and error correction models are introduced into the framework of Granger causality test to conduct the root cause diagnosis for the fault with non-stationary time series.

The rest of this paper is organized as follows. Section 2 is the method introduction. First, the conventional granger causality and the multivariate version is introduced in 2.1 and 2.2. Then, the co-integration and error correction model is introduced in 2.3 and 2.4. 2.5 introduced how to apply the method mentioned above into root cause diagnosis. In Section 3, the effectiveness of root cause diagnosis method is verified through two typical fault of Tennessee Eastman (TE) process. Both of these faults will cause non-stationarity time serious. Section 4 summarizes the article and discusses some phenomena that appear in the simulation process.

## 2 Methods Introduction

### 2.1 Granger Causality Test

Granger causality was first proposed in 19679. This is a method based on statistically relevant theory. The basic idea is to judge the interaction between variables through the historical data by build the autoregressive model.That is, when try to discuss whether there is a causal effect from the variable x to y, then we need to consider whether x in a lag period will affect the prediction of y. In the framework of Granger causal analysis, measuring the causal relationship between the two variables of $x_1$ and $x_2$ requires the creation of two different models, one of which is called full model, which is shown as below:

$$x_1(t)=\sum_{l=1}^{p}a_{11,l}x_1(t-l)+\sum_{l=1}^{p}a_{12,l}x_2(t-l)+\varepsilon_1(t) \quad (1)$$

$$x_2(t)=\sum_{l=1}^{p}a_{21,l}x_1(t-l)+\sum_{l=1}^{p}a_{22,l}x_2(t-l)+\varepsilon_2(t) \quad (2)$$

and the other one is called reduced model:

$$x_1(t)=\sum_{l=1}^{p}b_{1,l}x_1(t-l)+\varepsilon_{1(2)}(t) \quad (3)$$

$$x_2(t)=\sum_{l=1}^{p}b_{2,l}x_2(t-l)+\varepsilon_{2(1)}(t) \quad (4)$$

In the above two kinds of models, $\alpha_{ij,l}$ and $b_{i,l}$ are the coefficients of the $x_1$ to estimate $x_i$ . $\varepsilon_i$ and $\varepsilon_{i(j)}$ represents the residuals of the full model and the reduced model, respectively. $p$ is the time delay coefficient.

If the residual of the full model is significantly less than that of the reduced model, which means that the addition of new variables in the regression model leads to an improvement in the performance of the prediction, which also means a causal relationship between the variables. This influence can be quantified as follows:

$$F_{X_j\to X_i}=\ln\frac{\operatorname{var}\left(\varepsilon_{i(j)}\right)}{\operatorname{var}\left(\varepsilon_i\right)} \quad (5)$$

$F_{X_j\to X_i}$ is a positive value. When $F_{X_j\to X_i}=0$ , it means there is no causal influence from $X_j$ to $X_i$ ; otherwise, $F_{X_j\to X_i}>0$ .The statistical significance of the above causality can be test by constructing the following statistics and performing an F test:

$$F_{\text{statistic}}=\frac{\left(\mathrm{RSS}_0-\mathrm{RSS}_1\right)/p}{\mathrm{RSS}_1/(N-2p-1)} \sim F(p,N-2p-1) \quad (6)$$

The $\mathrm{RSS}_0$ and $\mathrm{RSS}_1$ in the above function is the residual sum of squares in the reduced model and full model and $N$ represents the number of samples used for modeling.

### 2.2 Multivariate Conditional Granger Causality Test

Conditional Granger Causal Analysis is an extension of Granger causal analysis, where the variables used for modeling contain all process variables. The full model ofconditional granger causal analysis is as follows:

$$\begin{aligned}x_1(t)&=\sum_{l=1}^{p}a_{11,l}x_1(t-l)+\sum_{l=1}^{p}a_{12,l}x_2(t-l)\\&+\sum_{j=3}^{J}\sum_{l=1}^{p}a_{1j,l}x_j(t-l)+\varepsilon_1(t)\end{aligned} \quad (7)$$

and the reduced model of conditional granger causal is defined as follows:

$$\begin{aligned}x_1(t)&=\sum_{l=1}^{p}b_{11,l}x_1(t-l)\\&+\sum_{j=3}^{J}\sum_{l=1}^{p}b_{1j,l}x_j(t-l)+\varepsilon_{1(2)}(t)\end{aligned} \quad (8)$$

In the above equations, $J$ represents the number of the process variables used for modeling, and $x_j(j=3,\ldots,J)$ include the time series of the chosen variablesexcept $x_1$ and $x_2$ .

By introducing other variables, the analysis of granger causality becomes an indirect way so that the cause and effect of other variables on the predictor does not affect the actual causality test [19]. Besides, in the root cause detection, this can reduce the number of models that need to be built, making the causality test more simplified.

### 2.3 Cointegration and Error Correction Model (ECM)

When autoregressive is performed on a non-stationary time series, various regression metrics are good, but the residual sequence is a non-stationary sequence. It means the regression cannot truly reflect the relationship between the dependent variable and the explanatory variable, so the non-stationary time series cannot be analyzed by autoregressive. This situation is called pseudo-regression. In 1987, Granger proposed the concept of cointegration for analyzing non-stationary time series.

a process is integrated to order d if taking repeated differences d times yields a stationary process. If two or more series are individually integrated but there is a vector α makes the following equation true, then these variables are considered to be cointegrated.

$$Z_t = \alpha X_t \tag{9}$$

Where $X_t$ is the matrix of time series, $\alpha$ is the co-integration vector. $Z_t$ is a stationary time series.

After several time series have been confirmed to be cointegrated, then the error correction model can be built to regression analysis of non-stationary time series. Error correction model is a category of multiple time series models most commonly used for data where the underlying variables have a long-run stochastic trend, ECMs are a theoretically-driven approach useful for estimating both short-term and long-term effects of one time series on another. The term error-correction relates to the fact thatthe change of the independent variable at a certain time depends not only on the change of the dependent variable, but also on the state of the dependent and independent variable at the previous moment. Thus ECMs directly estimate the speed at which a dependent variable returns to equilibrium after a change in other variables. The basic error correction model has the form of equation 10.

$$\Delta Y_t = \beta \Delta X_t - \lambda ecm + \varepsilon_t \tag{10}$$

Wherethe $\Delta Y_t$ and $\Delta X_t$ is the difference of the dependent and independent variable. $\beta$ is the coefficient of independent variable matrix. $\varepsilon_t$ is the errors. $\lambda$ is the coefficient error correction part and the error correction part is obtained by the equation 11, which is derived from the cointegration model.

$$ecm = Y_{t-1} - \alpha_0 - \alpha_1 X_{t-1} \tag{11}$$

## 3 Case Study

### 3.1 Data Description

The simulation data used in this paper is the Tennessee-Eastman Process (TE process) data. This process is a benchmark in the field of fault diagnosis and is widely used to test process control strategies and multi-statistics process monitoring. The flowchart of TE process is shown in the figure. The chemical plant simulator is based on an industrial process where the components, kinetics, and operating conditions were modified for proprietary reasons.This system mainly includes five parts: reactor, condenser, separation tower, stripper and compressor.There are four kinds of reactants, which are represented by the letters A, C, D, and E respectively. Through the reaction, there are two kinds of products and one by-product, which are expressed as G, H, and E. In addition, there is aninert component B that does not participate in the reaction.The whole system consists of 52 variables, including 11 operational variables and 41 measured variables. The normal data and fault data are recorded separately in the normal operation and abnormal situations with 3 min as the sampling frequency. The simulation system is designed with 21 different fault types.More details about this chemical simulation are included in [20].

### 3.2 IDV7

The IDV7 of TE is caused by the pressure loss of C header. When this fault occurs, the flow in stream 4 (x4) will decrease instantaneously. Subsequently, when the controller detects this change, it attempts to counteract the flow drop by increasing the valve opening (x45) in flow 4. After a period of oscillation, the flow in stream 4 (x4) will return to the initial stable value. While the valve opening of the control flow 4 (x45) will undergo a step change and stabilize to a new value. Therefore, both variable x4 and x45 can be considered as the root cause of IDV7. During the oscillating period, the fault propagates between the variables, causing a smear effect and make many other variables to oscillate and be detected as fault variables.

First, the fault variables are selected through the PCA-based contribution graphs. This work has already been done in the relevant literature, and their results are directly used here.Variable x4, x7, x13, x16, x20, x21, x22, x45, x51 were chosen as the candidate. It can be seen that the selected variables are basically consistent with the above analysis. Then, the data segment is selected. In this paper, multiple data segments are selected. These data segments start from the time when the fault occurs, and the length ranges from 300 to 400 sampling points. The experimental results show that the results of causal analysis of these data segments with different lengths are consistent. Therefore, only the results of some data segment are shown below. Before performing a causality test, a stationary test should be done to test if series are stationary. In this paper, the ADF test method is used to test the stationarity of the variables. The test results show that the time series of these variables are non-stationary. The analysis result will be less feasible if using the conventional granger causality test. The result is shown in Fig.1.

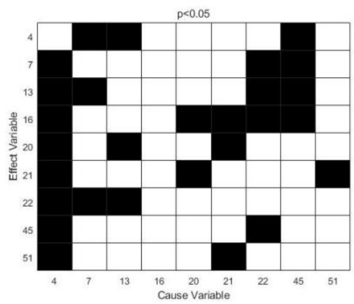
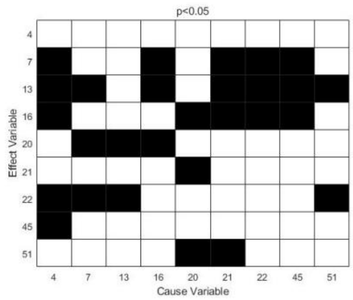


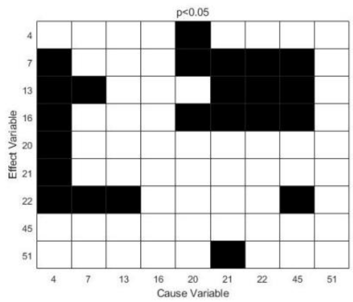

Fig.2:Result of IDV7 with conditional GC test

In the figure, the X axis represents the cause variable, and the Y axis represents the affected variable. Each black block in the figure indicates that the variable corresponding to x axis has a Granger causal effect on the variable corresponding to the y axis. The first column is all black except the first row, which means that variable x4 has an effect on all other variables and should be considered as an important candidate variable. However, as can be seen from the first line of the figure, variable 4 is also affected by variables x7, x13, x45. This result indicates that X4 is an intermediate variable andcannot be considered a root. For another major fault variable x45, it is similar to the case of variable x4. Therefore, such a result cannot detect the root cause.

The results of the VEC based Granger causal analysis are shown in Fig. 3.




(a)




(b)

Fig. 4:Result of IDV7 with VEC based GC test

These two figures are the result with different data segments. It can be seen that variable x4 and variable x45 affect many other variables, but in the first picture, variable x4 is not affected by any variable, and variable x45 is only affected by variable x4. Similarly, in the second picture, variable x45 is not affected by any variables, and variable x4 is only affected by one variable. These two results are consistent, which indicates that variables x4 and x45 are the source of fault IDV7.

### 3.3 IDV1

The cause of fault IDV1 is that the ratio of raw materials A to C is changed in stream 4. This fault is also a step fault. When the fault occurs, the component change sensor in stream 6 is detected first, and the corresponding detection result is that component C of stream 6 (x25) suddenly rises, component A in stream 6 (X23) suddenly drops. Through the control loop, the feed valve opening in stream 4 (x45) reduced, and the feed valve opening of A (x44) is Increased; this causes the flow rate in the flow 4 (x4) to decrease, and the feed amount of the A (x1) increase. This process is repeatedly adjusted by the controller, which will generate a period of oscillation and eventually return to a new balance. During this time, some variables will be affected, oscillated and detected as fault variables. However, after the oscillated period, they will return to the initial stable value.The flow rates of feed A and stream 4 (x1 and x4) and the valve opening controlling these two flows (x45 and x44) will stabilize to a new value. Also, since the feed in stream 4 is not only C, but also other raw materials. Therefore, the variable that associated with the amount of A feed (x1 and x44) should be set as the root cause of fault IDV1.

As with the fault IDV7 processing method, the candidate fault variable is first selected, then the appropriate data segment is selected, and then the selected data segment is checked for stationarity. TE data is a widely used data, and a lot of work has been done in the previous literatures.Here, variable x1, x4, x7, x13, x16, x18, x19, x44, x50 were chosen as the fault variable candidate of fault IDV1 based on the research of literature [15]. The data segments start from the time when the fault occurs, and the length ranges is 350 sampling points. The ADF test results shows that the time series of these variables are non-stationary.The result of the conventional granger causality test is shown in Fig. 3.

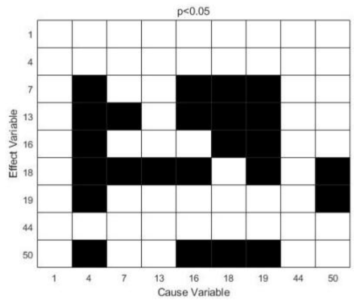



Fig. 3:Result of IDV1 with conditional Grangercausality test

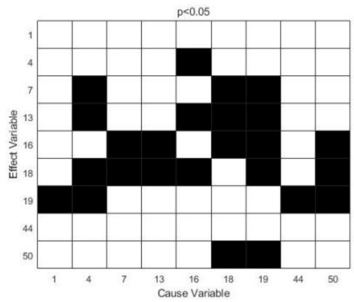



Fig. 4:Result of IDV1 with VEC based GC test

The figure shows that the x1 and x44 are not affected by any variables and does not affect any other variables. In addition, variable x4 is not affected by any variable, but affects many variables. Therefore, the above figure shows that variable 4 is the root variable of fault IDV1. This result is contrary to the analysis above, so the result is wrong.

The results of the VEC based Granger causal analysis are shown in Fig. 4.

As can be seen from the above figure, variables x1 and x44 are no longer independent of other variables, and they all have an effect on variable x19. Besides, they are not affected by any variables. In addition, the variable x4 is affected by the variable x16. The results of the figure show that variable 1 and variable 44 are the root variables of fault 1, and the results are consistent with analysis above. Therefore, the results of the Granger causality test based on the error correction model are correct.

## 4 Conclusions

From the above two examples, it can be seen that for a fault that with non-stationary time series, VEC based granger causality test can obtain the correct root cause. But, there still some issues exist.

In the result of causal detection of fault IDV1, both variable x1 and x44 only effect variable x19. However, through the above analysis of fault IDV1, variable x1 and x44 are the root variables, and their influence on other variables should be more significant. That is, it should influence more variables. the following experiments were conducted to find out why this happens.

First, variable x1 is removed from the candidate variables, replaced with x2, and then causality test is performed. The results are shown in the Fig. 5.

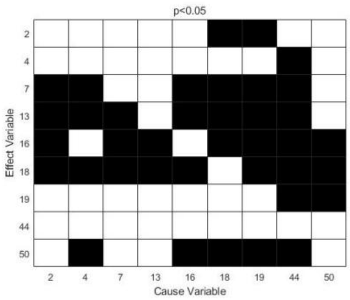



Fig. 5:Result of IDV1 with x1 out of the candidate

As can be seen from the figure, the variable x44 is not affected by any variables, but its influence is greatly improved compared to the result in 3.3. Such a test result clearly shows that the variable x44 is the root variable.

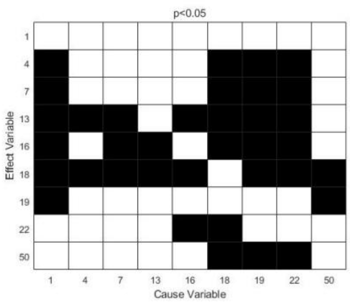



Fig. 6:Result of IDV1 with x44 out of the candidate

Similarly, while the variable x44 is removed from the range of candidate variables, replaced with one of the other variable x22, and then causality detection is performed. The results obtained are shown in the Fig. 6.

As can be seen from the figure, variable 1 is not affected by any variable, but its influence is greatly improved compared to the presence of variable x44. This test result clearly shows that variable x1 is the root variable.

Through the above two experiments, it can be concluded that when variable x1 and variable x44 exist at the same time, the two variables will interference with each other, and such interference is not conducive to causal information to obtain correct information.

The understanding of this kind of interference is that, whether the causal relationship between variables is determined through the F test of the error obtained by full model and reduce model. But variable 1 and variable 44 are homologous, that means they have the same effect on other variables and the prediction error is almost the same. So, when one of these two variables exist as an unrelated item in the model, the significant test will fail when detect the causality from the other one to the dependent variable.

This exposes the high dependence of the Granger causality test on the selection of candidate variables. When the variables are selected properly, the Granger causality test can draw the correct conclusions, and the conclusions are more consistent in practice; while the selected variables are correlated or not realistic, it will be difficult to get the correct conclusions. Therefore, when selecting a fault variable in fault isolation, it is necessary consider the mechanism of the system.

In addition, the methods based on the Granger causal analysis framework are pure data analysis methods. Although such methods are very portable, but it can only be used as a reference. Whether it is possible to introduce some mechanism knowledge, so that the results have a stronger credibility, which deserves further study. Besides, there is no suitable method for selecting the data length and the fault data segment of Granger causal analysis, which also needs further discussion.

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