ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) | 978-1-7281-6327-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICASSP49357.2023.10095701

A HYBRID DEEP NEURAL NETWORK FOR NONLINEAR CAUSALITY ANALYSIS IN COMPLEX INDUSTRIAL CONTROL SYSTEM

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ABSTRACT

It is important to efficiently and accurately locate the fault root cause to maintain the control performance, when the industrial control system fails. However, this task is very challenging because the industrial control system is large in scale and complex in connection. This paper proposes a novel neural causality analysis network with directed acyclic graph to locate the root cause for complex industrial systems. This network fits the temporal nonlinearity and intervariable nonlinearity to mine the causal graph. The proposed method is data-driven, which acts without process knowledge. Compared with the state-of-the-art, this method can effectively output accurate root cause from nonlinear and highly coupled data. The effectiveness and advantages are demonstrated by industrial cases.

***Index Terms*—** root cause analysis, neural network, industrial control system

1. INTRODUCTION

Many safety-critical industrial systems' requirements for the accuracy and efficiency of system's fault troubleshooting are increasing with the modern industry [1]. People are becoming less tolerant of performance degradation, productivity loss and security concerns. However, it is a challenging task to locate the root cause, because the industrial systems are with large scale and complex structure. Model-based approaches for root cause diagnosis require accruate process knowledges to analysis the process dynamics. Nevertheness, the more complex the mechanism model, the more uncertain assumptions it contains. Therefore, it is difficult to analyze the fault root cause by utilizing model-based methods in complex industrial systems.

With the large amount of data collected by industrial control systems, the application of data-driven techniques to locating root cause in modern industry is becoming more and more popular [2, 3, 4, 5, 6, 7]. Causal analysis methods based on data-driven have gradually flourished [8, 9, 10], such as Granger Causality (GC) [11], transfer entropy [12], Bayesian network [13], neural network [14], etc. Based on the above methods, the root cause can be located in some case efficiently.

GC method can analysis the causal relationships of time series variables. It has strong interpretability. However, there are two key issues, when using traditional GC method in industrial troubleshooting. On the one hand, the method use vector autoregression model to fit time series data, which is unable to handle nonlinear data. On the other hand, no appropriate mechanism is able to reduce redundant causality in the method.

Similarly, transfer entropy method is limited to detect pairwise causality. The effect of Bayesian network depends on two kinds of algorithms. The scoring-search-based algorithm is easy to fall into local optimum, and the dependency analysis-based algorithm needs to deal with complex independence test problems.

Recently, Alex Tank et al. [15] proposed the Neural Granger Causality (NGC), which is able to fit nonlinear variables because of neural network. Xu et al. [16], proposed a new causal network called scalable causal graph learning (SCGL). It can decompose the nonlinearity of variables into two parts, which include temporal nonlinearity and intervariable nonlinearity. It is better to clarify the nonlinearity of variables for deconstructing the coupling relationships between variables. However, NGC method is still limited to detecting pairwise causality. In addition, the causal graph learned from SCGL is based on traditional singular value decomposition, which is limited to processing linear data. Therefore, this means is not applicable to strongly nonlinear data.

To tackle these issues, a novel causal analysis framework is proposed for locating the fault root cause of industrial control systems. This method constructs the casual graph by fitting temporal nonlinearity and intervariable nonlinearity of multivariable time series data. It consist of three modules. The first module is composed of multilayer perceptron (MLP) and activation function. The input temporal nonlinearity can be fitted by this module. Then, the second part is a varia-

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Supported by National Natural Science Foundation of P. R. China (NO. 62003298, NSFC: 62073286), Yunnan Fundamental Research Projects (NO. 202201AT070577)

tional autoencoder (VAE) [17] combined with directly acyclic graph (DAG). This part introduces the structural equation to combine the input of VAE with the latent variables. DAG as an adjacent matrix is also a component of the structural equation. DAG is able to represent causal relationships between variables. The last model is a regression network for further constraining the front network parameters. The entire network will output a causal matrix. The redundant causality relationships can be pruned by imposing threshold to the causal matrix. The specific implementation is shown in the experimental part.

The main contributions of this work are as follows:

(i) A novel data-driven causality analysis network is proposed. This network can not only reveal the causality related to a single targeted variable, but also provide the causal graph with relationships between each pair of variables.

(ii) The nonlinear relationships discussed in this work are classified into two types, namely, the temporal nonlinearity defined on a single variable and the intervariable nonlinearity among multi-variates. The proposed network presents two modules, i.e., the MLP layer and the modified VAE layer, to handle these two types of nonlinearity problems, thus improving the ability to analyze the nonlinear causality relationships.

(iii) A sparse mechanism is embedded into the last module to reduce the redundancy in the resulting causal graph. This procedure can improve the root cause location accuracy.

(iv) Compared with the exiting methods, the proposed method shows better performance in fault root cause location accuracy for industrial control systems.

2. PRELIMINARIES

2.1. Nerual Granger Causality

Given N stationary time series $x = x_1, ...x_N$ across timesteps $t = 1, ..., T$ and a nonlinear autoregressive function g_j, such that

$$x_j^{t+1} = g_j(x_1^{\leq t}, ..., x_N^{\leq t}) + \epsilon_j^{t+1}, \tag{1}$$

where $x_j^{\leq t} = (..., x_j^{\leq t-1}, x_j^{\leq t})$ denotes the present and past of series j. ϵ_j^{t+1} represents independent noise. Time series i Granger cause j, if g_j depends on $x_i^{\leq t}$. *i.e.*, $\exists x_i'^{\leq t} \neq x_i^{\leq t}$:

$$g_j(x_1^{\leq t}, ..., x_i'^{\leq t}, ..., x_N^{\leq t}) \neq g_j(x_1^{\leq t}, ..., x_i^{\leq t}, ...x_N^{\leq t}).$$

2.2. Isolate Variable Nonlinearity

For the time series data sampled from industrial control systems, they are usually coupled and nonlinear. For single time series data, there is nonlinearity based on time. For different variables, there is nonlinearity exists between variables. The usual methods of fitting nonlinearity is finished in one time. The interpretability of the model is poor. Based on the two nonlinearity proposed above, this method uses two-step network to fit them. The temporal nonlinearity is firstly fitting

$$X(3,t_3) = \boxed{X(1,t_1)^2} + \boxed{\log(X(2,t_1))} + \boxed{X(1,t_2)^{X(3,t_1)}} + \boxed{\boxed{X(1,t_1)^3}\,\boxed{\cos(X(3,t_2))}}$$

Fig. 1. The equation is an example to illustrate temporal nonlinearity and intervariable nonlinearity in multivariable time series data, while $X(i, t_j)$ denotes the value of the i-th variable at time t_j. The expressions with red frame represent temporal nonlinearity defined on the univariate level, while the expressions with black frame represent intervariable nonlinearity defined on the multivariable level.

for time series data. The output is fitted with the intervariable nonlinearity.

2.3. Causal Discovery

In Graph Theory, DAG can express the relationships between variables. Actually, it can also be casual graph by constructing appropriate deep learning model and loss. However, traditional DAG learning methods usually deal with discrete variables due to the Non-deterministic Polynomial problem [18]. A new continuous optimization approach is proposed. It can transform the discrete search procedure into an equality constraint [19, 20].

3. THE PROPOSED MODULES

Based on the above work, a causal analysis framework is suitable for nonlinear time series variables. The framework is composed of three modules, which are presented as follows. The framework is shown in Fig. 2.

3.1. Temporal nonlinear layer

Similar to the GC method, time series variables as the input of the network need pass the stationarity test. Then select a appropriate time lag by AIC or BIC. The lag can be uesd to affirm the input dimension of the first layer. This modules is mainly used to fit the nonlinear relationships of a single variable based on its own time lag.

For multivariable time series data $X^1, X^2, ..., X^i, ..., X^N$, where $X = x_1, x_2, ..., x_t$, Module 1 is:

$$x_t = g_j(x_{t-k}, x_{t-k+1}, ..., x_{t-1}) + \epsilon. \tag{2}$$

In order to capture more information from original data, this framework constructs multilayer network with residual block.

3.2. Intervariable nonlinear layer

DAG can not only express the relationships between variables, but also be a causal graph by constructing reasonable learning structure. The output in the Module 1 has learned

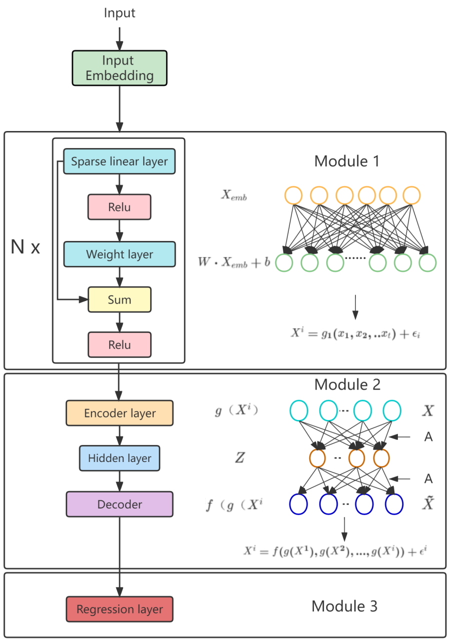

Fig. 2. The causal network of the proposed method

temporal variable nonlinearity. It can be an input of the second modules in order to further learn intervariable nonlinearity (causal graph). As an excellent generative model, VAE has a satisfied performance in computer vision field. It is used for DAG learning in this module.

To combine DAG with time series data, $A \in \mathbb{R}^{i\times i}$ is constructed to be the weighted adjacency matrix with i nodes. $X \in \mathbb{R}^{i\times t}$ is the time series having been learned temporal nonlinearity. Through linear structural equation model, the equation is :

$$X = A^T X + Z. \tag{3}$$

After equation transformation, it can be:

$$X = (I - A^T)^{-1} Z. \tag{4}$$

From above equation, the function $X = f_A(Z)$ is clear, where $Z \in \mathbb{R}^{i\times d}$. Through the Module 2, the probability distributions of one original input is $P(x) = \int_Z P(x)P(x \mid z)dz$. For all X with log, the following formula is established:

$$\frac{1}{n}\sum_{k=1}^{i} logp(X^k) = \frac{1}{n}\sum_{k=1}^{i} log \int p(X^k \mid Z)p(Z)dZ \tag{5}$$

To simplify the formula above, this module use a variational posterior $q(Z \mid X)$ to approximate the actual posterior $p(Z \mid X)$. The Module 2 result is the evidence lower bound (ELBO).

$$L_{ELBO} = \frac{1}{n}\sum_{k=1}^{i} L_{ELBO}^k \tag{6}$$

From the work of Yue Yu et al. [19], the formula is as following: Let $A \in R^{i\times i}$ be the weighted adjacency matrix of a directed graph. For any $a > 0$, the graph is acyclic if and only if:

$$tr[(I + \alpha A \circ A)^m] - m = 0. \tag{7}$$

This module use above formula as the equality constraint when maximizing the ELBO, where $\circ$ denotes the element-wise multiplication.

Another theorem in their work [19] is as following: Let $\alpha = c/m > 0$ for some c. Then for any complex λ, $(1 + \alpha|\lambda|^m \leq e^{c|\lambda|})$ satisfies.

3.3. Temporal regression layer

Through the fitting of the first two modules, $f(g(x))$ has been learned for each time series variable input. The task in this modules is regression based on $f(g(x))$. Thus the parameters of the first two modules are further constrained and optimized by calculating the loss.

3.4. Model training

For training the network, the Module 2 optimization problem is:

$$min_{A,\theta} \;\; f(A, \theta) \equiv -L_{ELBO} \tag{8}$$

$$s.t. \;\; h(A) \equiv tr[(I + \alpha A \circ A)^m] - m = 0. \tag{9}$$

The corresponding augmented Lagrangian is:

$$L_c(A, \theta, \lambda) = f(A, \theta) + \lambda h(A) + \frac{c}{2}|h(A)|^2, \tag{10}$$

where λ and c denote the Lagrange multiplier and the penalty parameter, respectively. The general idea of the method is to gradually increase the penalty parameter for ensuring that the constraint is eventually satisfied. The update rule at the kth iteration is as following:

$$A^k, \theta^k = argmin_{A,\theta} L_{c^k}(A, \theta, \lambda^k) \tag{11}$$

$$\lambda^{k+1} = \lambda^k + c^k h(A^k) \tag{12}$$

$$c^{k+1} = \begin{cases} \eta c^k, & if|h(A^k)| > \gamma|h(A^{k-1})| \\ c^k, & otherwise. \end{cases} \tag{13}$$

where $\eta > 1$ and $\gamma < 1$ are tuning parameters, respectively. Usually $\eta = 10$ and $\gamma = \frac{1}{4}$ work well in the model.

Module 3 optimization problem is:

$$MSE = \sum_{i=1}^{n}(x_i - x_i^p)^2 \tag{14}$$

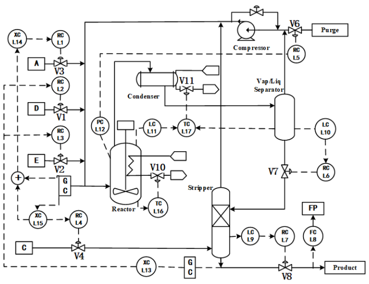

Fig. 3. TE process

4. EXPERIMENTS

4.1. Tennessee Eastman (TE) data introduce

TE process is a digital equation test platform built on the basis of the chemical process actually generated and operated. Fig. 3 shows the TE process structure diagram. It is a benchmark dataset for evaluating the effectiveness of various performance indicators of industrial process. The data in TE process have nonlinear and time-varying characteristics. It is used to be a data source to conduct research on control, optimization, process monitoring, fault diagnosis, etc. [21, 22].

In this paper, the root cause analysis is performed based on the data of fault condition 1. According to the analysis of the flow chart of the TE process, the measured variable x_1 (A feed) can be identified as the root cause of the fault, while x_4 (A and C feed) and x_{44} (A feed flow) will change accordingly. Then the fault propagates further down and variables such as x_{19} (Stripper stream flow), x_{18} (Stripper temperature), x_{50} (Stripper steam valve) are all affected.

4.2. Data preprocessing

In a single fault, some variables will not be affected. It is easy to generate redundant casual relationships without data preprocessing. Therefore, in order to enhance the accuracy of the network, this method use principal component analysis (PCA) method [23] to select variables. According two working conditions (normal and abnormal), two key statistic T^2 and SPE are obtained by PCA. The contribution of each variable to the out-of-control state is calculated after determining the out-of-contorl node.

4.3. The causal relationships of main variables

In this part, through analysising the contribution graph producted by PCA method, the first six variables are selected as the input, which are $x_1, x_4, x_{18}, x_{19}, x_{44}, x_{50}$. The causal adjacent matrix of input through causal network is shown in Fig. 4. Three thresholds are set to constrain the causal adjacent matrix in order to reduce redundant causal relationships. When the value in causal adjacent matrix is below the threshold, its value is adjusted to 0. The row variables is the cause of the column ones in causal matirx.

Based on the causal adjacent matrix with three threshold, the fault propagate path is shown in Fig. 6. x_1, x_4, x_{44} are the upstream variables. The fault is propagated down to x_{18}, x_{19}, x_{50}. x_1 as the root node of the causal graph, and only has arrows for the output, it is reasonable to infer x_1 is the root cause of the fault in TE process. The causal matrix via SCGL mehtod is shown in Fig. 5. GC method is also used for this dataset. The corresponding causal graph is displayed in Fig. 6. Compared with these methods, the proposed method in this paper shows better performance.

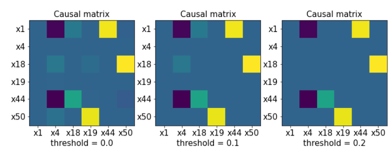

Fig. 4. The causal matrix obtained from the proposed method.

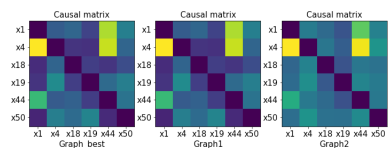

Fig. 5. The causal matrix obtained from SCGL. The causal relationships in them are obscure.

5. CONCLUSIONS

In this paper, a novel data-driven causality analysis network is proposed. This method constructs the MLP layer and the modified VAE layer to fit temporal nonlinearity and intervariable nonlinearity. Then, the DAG is embedded into the network to learn the causal graph. In order to improve the root cause location accuracy, a sparse mechanism is introduced to prune the redundant causality relationships in the causal graph. In the end, the effectiveness and advantages of the proposed method are demonstrated with an industrial case. In the future, we would like to apply this method to more fields.

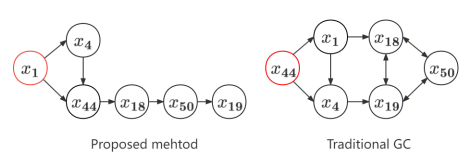

Fig. 6. The fault propagate path obtained from two methods. It is observed that x_1 is fault root cause in proposed method. The causal graph with GC method found wrong root cause.

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