SDG (Signed Directed Graph) Based Process Description and Fault Propagation Analysis for a Tailings Pumping Process

Fan Yang***. Sirish L. Shah**. Deyun Xiao*

*Department of Automation, Tsinghua University, Beijing 100084 China (e-mail: {yangfan, xiaody}@tsinghua.edu.cn).
**Department of Chemical & Materials Engineering, University of Alberta, Edmonton, AB T6G2G6 Canada (Tel: 780-492-5162; e-mail: {fyang.cme, Sirish.Shah}@ualberta.ca)

Abstract: Variables in a process are interacting, thus they can be described as an SDG in which arcs show causal relations between variables. Based on the SDG, the fault propagation can be tracked along consistent paths. Hence the SDG modeling can form the basis of fault propagation analysis. Regarding the modeling issue, this paper suggests a knowledge-based method to capture connectivity information between and within units from piping and instrumentation diagrams and other process knowledge. On the other hand, process data can be employed to construct SDGs by correlation analysis. An SDG generation procedure is proposed in this paper. The individual disadvantages of these two methods are summarized. However it is shown that they complement each other when combined. The SDG modeling and fault propagation analysis are applied to a tailings pumping process to illustrate and validate the methods proposed in this paper.

Keywords: signed directed graph, P&ID, fault propagation, cross-correlation, correlation color map.

1. INTRODUCTION

In modern industries, the scale and complexity of process systems increase continuously. These systems are subject to low productivity, system failures or even hazardous operation because of abnormal conditions such as faulty operation, equipment quality change, external disturbances, and control system failure. In these systems, many elements are interacting, so a local fault can propagate and spread to other interconnected units. Therefore, in the design stage, cause-effect relationships between variables should be captured correctly so that the operation procedures, HAZOP (hazard and operability) analysis and alarm settings can be well designed. After the design stage and during on-line applications, it is important to monitor and rationalize multiple alarms to find the real root causes promptly and predict possible consequences according to the current symptoms to estimate the severity level of all hazards. All the above requires a method that can capture connectivity or topological description of the process and combine this with reasoning methods to analyze process faults.

To describe variables and their cause-effect relations in process systems, typically continuous systems, a signed directed graph (SDG) model is employed. The SDG is a qualitative graphical model, with variables denoted by nodes and their causal relations by directed arcs. Due to controls in the process systems, the variables include not only process variables, but also manipulated variables, set points and known disturbances. Based on the graph search, fault propagation paths can be obtained, which can be useful for the analysis of root causes and the sequences it may result in (Yang et al., 2009). With the development of the computer-aided technology, graph theory has been implemented successfully by some graph editors, some of whom such as Graphviz (http://www.graphviz.org/), can transform text description into graphs easily. Hence the SDG technique can be potentially automated and combined with the other design, analysis and management tools.

The definition and its application of SDGs in fault propagation analysis was firstly presented by Iri et al. (1979). Ever since then, many researchers have contributed to this area, including modeling, reasoning, software development and industrial applications. Many efforts have been particularly made to implement the methods and to overcome the disadvantages, such as spurious solutions because of the inaccurate information and qualitative simplification. Oyeleye and Kramer (1988) took into account the qualitative simulation for the SDG inference. Maurya et al. (2003) described the modeling method based on differential and algebraic equations (DAEs), analyzed the initial and final responses based on SDGs, and studied the description and analysis of control loops. Practical modeling methods to capture process connectivity information (Thambirajah et al., 2009; Jiang et al., 2009) from process data (Bauer and Thornhill, 2008) have also been presented. However, these two methods have their own disadvantages. Thus the combination of them is needed. What is needed is a synergistic combination of both these methods.

This paper is organized as follows. Sections 2 and 3 propose SDG modeling methods from process knowledge and its validation via correlation analysis respectively. Their disadvantages are also summarized at the end of each section. An industrial case study is given for a tailings pumping
process in Section 4 to illustrate the application of SDG modeling and fault propagation methods, followed by concluding remarks in Section 5.

2. SDG MODELING BY PROCESS KNOWLEDGE

SDGs are established by representing the process variables as graph nodes and representing causal relations as directed arcs. An arc from node $A$ to node $B$ implies that the deviation or perturbation in $A$ may cause the deviation in $B$. For convenience, “+” or “−” or “0” is assigned to the nodes in comparison with normal operating value thresholds to denote higher than, lower than or within the normal region respectively. Positive or negative influence between nodes is distinguished by the sign “+” (promotion) or “−” (suppression), shown as solid and dotted arcs respectively (Iri et al., 1979). Based on an SDG, fault propagation can be explained by searching for consistent paths.

If we have the DAEs, then we can derive the structure and signs of the graph by specific methods (Maurya, 2003). However, accurate DAEs are difficult to obtain, and usually they are not necessary for fault propagation analysis because only qualitative information is needed. On the other hand, practical process knowledge and experience is available and it is suggested that one should capture process topology from this information.

2.1 SDG Modeling Within a Unit

For a single unit, such as a tank, several physical quantities reflect the characteristics of the process. The relationships between these process variables can be described as DAEs which include three types:

Type I: DEs which reflect dynamic causal relationships. Arcs can be established towards accumulation variables from other cause variables.

Type II: AEs with causal meanings which include driving force equations, functional relationships, and other algebraic equalities. Since they reflect clear causalities, arc directions can be easily determined.

Type III: AEs with no causal relationships. They are mostly balances such as mass, energy, and species conservations used as constraints.

For the first two types, Maurya et al. (2003) have summarized the modeling methods and discussed the analysis methods of system dynamic responses. The last type can be used as redundant constraints to reduce illusive solutions (Oyeleye and Kramer, 1988).

Based on these concepts, an SDG within a unit can be obtained from qualitative knowledge instead of DAEs. For example, a tank process is shown as Fig. 1, where $L$ is the level in the tank, $K$ is the valve position in the outlet pipe, $F_1$ and $F_2$ are inlet and outlet flowrates respectively. The DAEs of this process appear below:

$$A(\frac{dL}{dr}) = F_1 - F_2$$  \hspace{1cm} (1)

$$F_2 = K\sqrt{L}$$  \hspace{1cm} (2)

$$K = \alpha L$$  \hspace{1cm} (3)

where $A$ is the cross sectional area of the tank and $\alpha$ is the proportional coefficient of the control law. By these DAEs, the SDG is set up as shown in Fig. 2 in which Fig. 2(a) is obtained from (1) (type I), Fig. 2(b) is obtained from (2) and (3) (type II), and Fig. 2(c) is the combination of them. This SDG can also be obtained from process knowledge that the level is determined by the input and output and the outlet flowrate is affected by the level and the valve position. Irrespective of the type of control: P, PI, or PID, it is shown as an arc from $L$ to $K$, and it is unnecessary to write their DAEs. The accurate parameters and functions are not important.

![Fig. 1. Tank process schematic.](image)

![Fig. 2. SDG of the tank process. (a) SDG obtained from (1); (b) SDG obtained from (2); (c) combination of (a) and (b).](image)

In the process industry, standard units such as tanks, towers, exchangers, etc. can be modelled and saved as templates or modules for reuse. We can build SDGs for special units by using the qualitative information obtained from knowledge and first-principles or mathematical models. After all the units are modelled, they should be connected according to the linkage information.

2.2 SDG Modeling Concerning Transportations

Units are connected because of material and signal transportation. The directions of arcs are consistent with the transportation paths. The variables upstream influence the variables downstream, but there are arcs with reverse directions when recycles exist. The arcs should be connected to corresponding variables in different units.

The efficient way of showing these transportations is via P&IDs (piping and instrumentation diagrams) in which both material flow and information flow (control signal) are shown. SDGs can be set up by unfolding the units in P&IDs as unit SDGs and connecting them according to flow directions. Thus the SDGs bring out not only the connectivity.
and topology between the units but also the causality between variables. Connectivity matrices (Thambirajah et al., 2009) and adjacency matrices (Jiang et al., 2009) are two matrix forms to express topology with directionality. The former shows the connectivity between units, and the latter shows relationships between variables. The former is the basis of the latter. In addition to connectivity, SDGs add signs to all the links to show dynamic trends (reinforcement or suppression) or causality properties (positive or negative correlation).

For a standard extraction of connectivity information, XML (eXtensible Markup Language) provides a possibility (Thambirajah et al., 2009). Some software tools such as SmartPlant P&ID from Intergraph and Comos P&ID can export XML text, and some techniques such as Regular Expression in computing science can be employed to capture the connectivity from the text. Then the above information can be expressed as matrices and furthermore SDGs by using some tools such as Graphviz.

2.3 Disadvantages of Knowledge-Based Modeling

Knowledge-based modeling is practical and may be even more convenient if some software tools are available, which can be based on computer aided engineering exchange (CAEX). However, it has some essential disadvantages. First, it provides necessary but not sufficient condition for causality, i.e. a fault should be propagated along one of the paths but the propagation may stop at some point because of signal attenuation which is not uncommon. An arc will be set up even if the relationship is weak, thus some arcs can be hardly validated. The SDGs built this way include all the possibilities without filtering.

Secondly, if we do not have enough knowledge about some parts of the process, the SDG cannot be built. In addition, relationships between multiple inputs of the process cannot be described because they are not included in the scope of research.

Thirdly, there are some differences between transient responses and steady-state responses. Using the same SDG for the analysis with different purposes can lead to wrong conclusions. Although Oyeleye and Kramer (1988) and Maurya et al. (2003) have presented some rules to modify the SDGs, the problems still exist because SDGs do not include quantitative information and thus cannot identify the major factors.

These disadvantages lead us to another modeling viewpoint – data driven methods.

3. SDG MODELING BY PROCESS DATA

In a process, variables are interacting. By analyzing the correlation between them, we can somehow capture the causality. Although correlation does not imply causality, it can be used as a validation. Moreover, when computing Pearson’s correlation, cause and effect can be recognized by introducing lags in a time series to find the maximum correlation. This offers another viewpoint of causality by checking the correlation between lagged time series of different variables.

3.1 Correlation Analysis Based on Process Data

Assume that $x$ and $y$ are time series of $n$ observations (normalized by subtracting the means and then dividing the standard deviations), then the cross-correlation function (CCF) is defined as

$$\phi_n(k) = \frac{E[x_{n+k}, y]}{\sigma_x \sigma_y}, \quad k = -n+1, \ldots, n-1.$$  \hspace{1cm} (4)

By computing the positive and negative maximum values

$$\phi^{\text{max}} = \max_k \{\phi_n(k), 0\} \geq 0, \quad \phi^{\text{min}} = \min_k \{\phi_n(k), 0\} \leq 0,$$  \hspace{1cm} (5)

the arguments to reach the two extremums are $k^{\text{max}}$ and $k^{\text{min}}$ respectively. Thus the estimated time delay from $x$ to $y$ is:

$$\lambda = \begin{cases} k^{\text{max}}, & \phi^{\text{max}} > -\phi^{\text{min}}, \\ k^{\text{min}}, & \phi^{\text{max}} < -\phi^{\text{min}}. \end{cases}$$  \hspace{1cm} (6)

Note that $\lambda < 0$ means that the delay is from $y$ to $x$. Therefore the time delayed cross-correlation coefficient is estimated as $\rho = \phi_n(\lambda)$ (between -1 and 1) whose sign indicates whether the correlation is positive or negative. These time delays between every two variables are arranged in a causality matrix $A$ in a specifically ranked order (Bauer et al., 2007). The correlation values are arranged in the same order of variables as a correlation matrix $P$.

However, the reliability of correlation information for each linkage is different, and there are inaccuracy and errors in these estimates, which requires significance tests to delete the improper ones. Bauer and Thornhill (2008) have presented some significance testing methods for the correlation analysis, i.e. correlation test, directionality test, and consistency test. Based on them, the propagation paths can be constructed.

3.2 SDG Modeling from Process Data

Based on the above three tests, when some entries in the causality matrix are replaced by empty cells, one can transform it into an SDG. According to Bauer and Thornhill (2008), one of the two typical topologies is generated according to the number of nonzero entries in the first row and above the main diagonal. Topology I is a serial arrangement of variables, while Topology II includes one root cause connected to all other variables. However, this method cannot give satisfactory results in some cases. Here we propose a method based on correlation, which introduces the resulted quantitative information obtained by CCF computations.

Step 1: In matrix $P$, select the maximum value in the elements that has not been used and tested.

Step 2: Check the results of correlation test and directionality test. If the correlation value fails to pass the tests, then stop, otherwise go on.

Step 3: Check the result of consistency test for all the variables in the existing arcs. If it fails, then go to Step 5.
Step 4: Add an arc corresponding to this element with estimated time delay. The sign of the arc is determined by the sign of the element.

Step 5: Go to Step 1.

3.3 Disadvantages of Data-Based Modeling

Data-based modeling methods can provide not only the causality but also the time delay. It is based on measurements, thus the variables involved are measured variables, whereas the SDG built by knowledge-based method includes all the variables of concern. Thus data-based methods overcome the three disadvantages mentioned in Section 2.3 to some extent. This method, however, has its own disadvantages. There are no perfect ways for the topology generation from filtered correlations and time delays. And for the significance tests, threshold selection is also a problem.

In addition, the data-based method can lead to some confusion. For example, in Fig. 3(a), each pair of variables has causality, but from data analysis, whether there is direct influence from \( x \) to \( z \) is a question. If the causality is propagated via \( y \), then the figure in the left panel of Fig. 3(a) should be chosen. However, if there are two mechanisms for this influence, then the SDG on the right panel of Fig. 3(a) should be chosen. Also, in the case of Fig. 3(b), \( y \) and \( z \) are correlated, but the real cause is \( x \). If \( x \) is unmeasured, then the SDG on the right side will be generated, which is wrong; the correct figure is in the left panel of Fig. 3(b).

![Fig. 3. Some examples of inconsistency of data-based modeling. (a) Direct influence from \( x \) to \( y \) is illusive on the right; (b) unmeasured \( x \) is the common cause of \( y \) and \( z \), but the right one indicates the inexistent arc from \( y \) to \( z \).](image)

Therefore, the knowledge-based method and data-based method should be combined for SDG modeling. Since the knowledge-based method is more complete in variable selections, it is usually used as the main method and the data-based method can be used for validation.

4. CASE STUDY

Suncor Energy uses the Hot Water Process to extract bitumen from oil sands. The tailings from this process are a slurry of water, fines, sand, residual bitumen and chemicals. This slurry is disposed into the tailings ponds. Suncor Energy uses Consolidated Tailings technology to eliminate the need for large tailings ponds. The plant consists of 5 Lines running in parallel. Line A was selected to illustrate the application of the proposed methods. Fig. 4 shows the core part, known as the final tailings pump house (FTPH) process. From this figure, we find that there are 3 units for tailings consolidation and discharge – distributor, cyclo-pack, and pump box. Because the recycling is via a large pond, the process is regarded as an open-loop.

Using Fig. 4 and other knowledge including control, we build the SDG as shown in Fig. 5 in which several logic nodes are added because there are prioritization and select control that are not typical continuous structures. The black arcs are material flow while the red ones are information flow.

Based on the data (1 week, 1 minute interval), the correlation color map (Tangirala et al., 2005) is shown in Fig. 6. We use these data and corresponding time delays for SDG validation.

Take the level control of the pump box for example. The paired level controller and density controller use a single variable (CPW addition) to achieve both the control objectives of maintaining level and density at their respective set points. This is achieved by sending the higher one of the two values \( y_{25} \) and \( y_{29} \) to the CPW valve output \( y_{24} \). This selection control can be described as two loops connected by a logic node as shown in Fig. 7. Compared with the corresponding values in Fig. 6, most of the arcs can be validated and the estimated time delays are also labelled by green letters in Fig. 7. The path \((y_{30}, y_{31}, y_{24}, y_{28})\) is confirmed as a fault propagation path. In the alarm data for this process, there is similarity in \( y_{30} \) and \( y_{28} \), which again validates the path. The arc from \( y_{24} \) to \( y_{30} \) cannot be validated because the level \( y_{30} \) is affected by many inlet flows besides CPW. The correlation within the density loop is weak because the selector selects the output of the level controller most of the time in the data set.

![Fig. 6. Correlation color map of variables involved in FTPH – Line A.](image)

![Fig. 7. Example of a fault propagation path for the FTPH case study.](image)
There are 6 important variables to be monitored, as shown in Table 1. The corresponding correlation matrix and causality matrix are computed as:

\[
P = \begin{bmatrix}
1 & 0.28 & -0.28 & -0.18 & 0.39 & 0.41 \\
0.28 & 1 & 0.36 & -0.31 & 0.74 & 0.50 \\
-0.28 & 0.36 & 1 & 0.14 & 0.10 & -0.11 \\
-0.18 & -0.31 & 0.14 & 1 & -0.25 & -0.24 \\
0.39 & 0.74 & 0.10 & -0.25 & 1 & 0.75 \\
0.41 & 0.50 & -0.11 & -0.24 & 0.75 & 1
\end{bmatrix}
\]  

(7)

Table 1. Process variables in FTPH process – Line A

<table>
<thead>
<tr>
<th>Notation</th>
<th>Tag name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>x₁</td>
<td>y₁₀</td>
<td>distributor pressure</td>
</tr>
<tr>
<td>x₂</td>
<td>y₁₆</td>
<td>gypsum addition flow rate</td>
</tr>
<tr>
<td>x₃</td>
<td>y₁₈</td>
<td>gypsum density</td>
</tr>
<tr>
<td>x₄</td>
<td>y₂₁</td>
<td>sludge header pressure</td>
</tr>
<tr>
<td>x₅</td>
<td>y₂₈</td>
<td>sump density</td>
</tr>
<tr>
<td>x₆</td>
<td>y₃₀</td>
<td>sump level</td>
</tr>
</tbody>
</table>

Fig. 4. Flowsheet of FTPH process.

Fig. 5. SDG of FTPH process and the fault propagation paths. Relationships between variables are shown by black lines, feedback in control loops is shown by red lines, and the fault propagation path is shown by green lines.
Based on an SDG, a fault is propagated along a consistent path, which can be validated from process data. The data used for modeling are process operational data in all situations. Alarm data can also be analyzed and compared with the SDG for explanation of parent-child alarms and multiple simultaneous alarms during alarm rationalization.

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5. CONCLUSIONS
SDGs can be obtained in three different ways: via mathematical models, process knowledge, and process operational data. This paper takes the knowledge-based method as the major modeling method and uses data-based method for validation. These two methods complement each other, resulting in the SDG to reflect the topological nature of the process. This procedure improves the completeness of the model description and meanwhile reduces the redundancy by information fusion. The semi-automation of knowledge-based SDG modeling is necessary for applications in large-scale processes.

\[
\Lambda = \begin{bmatrix}
-271 & 220 & 32 & 49 & 5 \\
-360 & 2 & 1 & 1 \\
357 & 359 & -360 \\
20 & 60 & -1 \\
-1 & -1 & -1 & -1 & -1
\end{bmatrix}
\]

The directionallities are recorded in the following matrix, thus all the elements pass the directionality test.

\[
\Psi = \begin{bmatrix}
1 & 1 & -1 & -0.90 & 1 & 1 \\
1 & 1 & -1 & 1 & 1 & 1 \\
1 & -1 & 0.53 & -1 & 1 & 1 \\
0.96 & -1 & -1 & 1 & 1 & 1
\end{bmatrix}
\]

According to the procedure in Section 3.2, 0.74 is selected, so there is an arc between \(x_3\) and \(x_6\), and the sign is “+”. The corresponding element in \(\Lambda\) is -1, so the direction is from \(x_6\) to \(x_3\). The second arc is from \(x_2\) to \(x_5\), and third one is from \(x_2\) to \(x_6\). For the latter, because the two associated nodes have been used, the consistency test should be undertaken. The time delays associated with the three arcs are 1’s that are reliable. Other arcs are set up by the same procedure. Note that the arc from \(x_1\) to \(x_5\) is ignored because the time delay is 49, which fails to pass the consistency test.

The SDG of the 6 variables is shown in Fig. 8 which is a simplified version of Fig. 5. For example, the path (\(x_1, x_6, x_2\)) in Fig. 8 is marked in Fig. 5. There are two paths from \(x_2\) to \(x_5\) in Fig. 8 because there are different influence paths within the process which are shown in Fig. 5. The arc from \(x_2\) to \(x_4\) cannot be explained in Fig. 5 because they are in different inlets. Their correlation is due to some external reasons.

\[\text{Fig. 8. SDG of some process variables in the FTPH process.}\]