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Procedia Computer Science 221 (2023) 657–663

Procedia Computer Science

www.elsevier.com/locate/procedia

Tenth International Conference on Information Technology and Quantitative Management (ITQM 2023)

# Graph classification based fault detection in nuclear power plants with graph formulation

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## Abstract

In the routine production and operation of nuclear power plants (NPPs), safety management is extremely important, and consequently, a fault detection system yielding high accuracy could provide effective decision support and prevent the accidents to the maximum extent. Most of existing studies are based on the analysis of time-series data, while researches oriented to the implementation of graph data mining are barely seen. In this paper, we propose an improved fault detection method to address this task from the perspective of graph representation learning. By calculating the similarity between indicators, the multivariate temporal sequences of the running characteristics of NPPs have been formulated as a group of graphs with corresponding labels, on which the graph convolutional network (GCN) has been introduced to detect fault samples in the way of graph classification. Compared to conventional supervised learning classifiers, our proposed methodology performs more superior identification of major faults, and the sensitivity regarding significant parameter or settings in the model design has been analyzed to investigate their optimal arrangements. The findings in this article not only present the promising prospects of introducing graph learning techniques into safety management, also indicate that various kinds of digital signals could be reformulated into graph dataset based on which the original task could be executed more effectively in the way of graph representation learning.


Peer-review under responsibility of the scientific committee of the Tenth International Conference on Information Technology and Quantitative Management

*Keywords:* Fault detection, Graph classification, Graph convolutional network (GCN), Graph formulation, Nuclear power plants (NPPs)

## 1. Introduction

Currently, the nuclear power has become an important source in national energy supply and security of many countries, while its safety is always the first priority in daily production and management of nuclear power plants (NPPs). According to its developing route and evolving trends, data-driven fault diagnosis and detection in NPPs

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Peer-review under responsibility of the scientific committee of the Tenth International Conference on Information Technology and Quantitative Management
10.1016/j.procs.2023.08.035

are of emerging interests [1], leading to quantities of researches introducing advanced machine learning and deep learning techniques to solve real problems in related fields of management science, computer science, artificial intelligence, and decision sciences. Along with the frequent implementations of new models, diversification of data or information also contribute to the promotion of forecasting performances [2], which indicates the great value of various kinds of unstructured dataset like images, texts, and relations. In summary, if attempting to realize improved prediction, both better analytical tools and more beneficial information are significant as this is also consistent in the safety management of NPPs including fault detection.

As one type of non-Euclidean data, graph is prevalent but sophisticated, and traditional machine learning cannot directly process or model it. In a recent decade, the discipline of graph representation learning has accomplished great achievements with many productive models emerged, among which the graph convolutional network (GCN) invented by [3], shows strong discriminative ability in node or graph classification. Following this direction, a group of graph neural network (GNN) models have been gradually developed, e.g., the GraphSAGE for inductive learning [4], the graph attention network (GAT) with attention mechanism introduced [5], leading to revolutionary progresses in graph data mining and graph learning. Besides graph representation learning, many other domains have also been infiltrated by GNN methods by their increasing popularity and outstanding performance in dealing with graph related tasks.

Speaking of graph learning based studies in fault diagnosis and detection, specific cases for NPPs are rarely seen, however, there are existed pioneering works utilizing GNN in related areas, like fault detection in rotating machinery [6], adaptive fault diagnosis in tunnel ventilation systems [7], and distribution fault location in power systems [8]. No matter how advanced the implemented GNN models are, it's always essential to formulate appropriate graph structures so that the requirements in original task could be efficiently satisfied. For instance, based on the horizontal visibility graph (HVG) algorithm, [9] maps the time-series into graphs presented as horizontal relations between data points. [6] applies and calculates Laplacian Matrix for graphs generation. [10] uses the clustering with adaptive neighbor (CAN) method to construct graphs, and introduces a Conditional Random Field based Graph Attention Network (CRF-GAT) to detect faults in rotating machinery by means of semi-supervision, which is similar with the research on very limited labelled data [11]. [12] proposes a GCN model incorporating weighted horizontal visibility graph (WHVG) for bearing faults diagnosis, transforming the time-series into graph data from a geometric perspective. Also by the geometric distances formulation, [13] builds graphs based on acoustic signals and presents the edge weights as the similarity between connected vertices, with a deep GCN (DGCN) carried out to detect different kinds and severities of faults in roller bearings. [14] invents a novel interaction-aware graph neural networks (IAGNNs) for fault diagnosis in complex industrial processes, by exploring the complex interactions and converting the sensor signals into a heterogeneous graph with multiple edge types that are defined by the attention mechanism. In study [15], the finite graphs of signal and different scales are generated by the autoencoder layer in the proposed multi-scale cluster GCN with multi-channel residual network (MR-MCGCN) for machine fault diagnosis, which achieves intelligent fault diagnosis. From the above brief review, it can be seen that graph formulation plays a crucial role as it directly affects the prediction or forecasting results, so that the generated graphs have to be adapted with the realistic scenarios of the task.

Given the popularity and extendibility of GNN, also considering the aim of achieving fault detection from the perspective of graph representation learning, here we have proposed a graph classification based fault detection method in NPPs with GCN implemented and graph formulation. The rest of this article is arranged as follows: Section 2 is the general architecture of our proposed method, with comprehensive illustration of graph formulation and classification. Section 3 specifically presents the experimental setup for comparison and verification, and detailed analysis of experimental results. Section 4 summarizes the main contributions, conclusions, and discusses limitations with future prospects for further developing directions.

## 2. Methodology

The improved fault detection methodology proposed in this study contains two major parts: (i) First, formulate the original multivariate time-series data into a group of graphs with labels; (ii) Second, introduce the GCN to detect fault samples by graph classification.

### 2.1. Graph formulation for time-series data

Given the motivation of precisely detecting faults in NPPs by graph classification, the first essential thing is to build graphs which is to define nodes, edges (adjacency matrix $A$), node attributes, and graph labels. Now supposing a multivariate temporal sequence of running characteristics to describe the entire course of a fault in NPPs, we have a tabular data sized $T \times M$ with $T$ seconds of periods and $M$ indicators from sensors, e.g., the former $0.75 * T$ periods are normal state and the latter $0.25 * T$ are fault labelled because the fault occurs at $t = 0.75 * T$. We take the $M$ indicators as nodes and use the corresponding temporal sequences as node attributes. After that, the coefficient $a_{ij}$ is established to compute the similarity of node attributes, and compare it with the pre-set threshold $s$ in range [0, 1], as shown in formula 1, in which the $s_{ij}$ is the Pearson correlation coefficient of the attribute vectors of node $i$ and node $j$. In this way, the adjacency matrix $A = [a_{ij}]$ has been constructed, and the values of $s$ have become a significant parameter as it affects the sparsity of the graphs formulated, and then directly influences the performance of graph classification in the next stage.

$$a_{ij} = \begin{cases} 1, & \text{if } s_{ij} > s \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The node attributes are formulated by the sequences of $M$ indicators, however, to achieve precise detection and more importantly, the early warning of the faults, it's necessary to slice and dice the original sequences. For instance, considering a multivariate temporal sequence with 1000 periods ($T = 1000$) and the fault happens at $T = 750$, we partition the original sequences by 100 seconds and it gives us 10 continuous temporal sequences, of which the first 7 are normal and the latter 3 are fault. In addition, this slicing periods of 100 could also be adjusted according to the requirements of forecasting. Thus, with each sequence, 10 consecutive graphs are acquired and labels are also clearly defined by the slicing periods. Moreover, given $N$ sequences indicating different kinds of faults, the formulated graph dataset contains $10 * N$ graphs eventually.

### 2.2. Fault detection by graph classification

Based on the graphs obtained above, here we introduce the GCN and make necessary adaptations to enable it to perform graph classification. The general updating process of GCN is illustrated in formula 2, as the $\hat{A} = A + I$ (adjacency matrix added with self-loops), the $H^l$ and $H^{l-1}$ represents layer-wise message passing and information prorogation mechanism with $H^0 = X$. The $W^l$ is the weight in the $lth$ layer of GCN that is determined by training. The $\tilde{D}$ is the degree matrix computed by $\tilde{D} = \text{diag}\left(\sum_j \hat{A}_{ij}\right)$, while the $\sigma(\cdot)$ is the activation function normally utilizing $ReLU$.

In our proposed graph classification based method, the modifications of conventional GCN are as follows: (i) Incorporate multiple convolutional layers; (ii) Introduce various pooling operations; (iii) Add a linear transformation layer. The node attributes and adjacency matrixes are firstly fed into two/three convolutional layers with activation functions, and then get through Pooling functions, such as max pooling, mean pooling, or add pooling. The GCN utilized here is actually to extract embeddings for each graph, while the pooling operation here is for computation reduction and prevention of over-fitting. Finally the prediction could be realized by the graph classification through the linear layer based on the optimization between predicted labels and true labels of graphs. As shown in formula 3 and formula 4, the two/three layered GCN models are presented, while the number of layers and the pooling function implemented here have indeed influenced the results, as they produce different patterns in the graph embeddings, and thus greatly affect the model's identification capability of fault samples.

$$H^l = \sigma\left(\tilde{D}^{-\frac{1}{2}} \hat{A} \tilde{D}^{-\frac{1}{2}} H^{l-1} W^l\right) \tag{2}$$

$$Prediction = \text{Linear}\left(\text{Pooling}\left(\hat{A}\,\text{ReLU}\left(\hat{A} X W^0\right) W^1\right)\right) \tag{3}$$

$$Prediction = \mathrm{Linear}\left(\mathrm{Pooling}\left(\hat{A}\,\mathrm{ReLU}\left(\hat{A}\,\mathrm{ReLU}\left(\hat{A}XW^{0}\right)W^{1}\right)W^{2}\right)\right) \quad (4)$$

## 3. Experiment & Analysis

For fair and transparent verification, here we have arranged comparative experiments to comprehensively investigate the performance of our proposed method, including the comparison with baselines, and the sensitivity analysis of major parameters in the model.

### *3.1. Data, models and evaluation*

Given the difficulty of collecting real data in NPPs, its running characteristics are actually generated by the Personal Computer Transient Analyzer (PCTRAN), an universally applicable software package that simulates accidents and transient conditions for NPPs, which is also widely used in NPPs' operation training and accident analysis. With this professional simulation software, 30 multivariate temporal sequences have been acquired as the benchmark dataset in experiments, while each sequence lasts for 1000 seconds ($T = 1000$) and has 70 indicators ($M = 70$) with the fault starting at $T = 750$. According to the instructions in Section 2.1, we take 100 seconds to partition all sequences, and thus, the formulated graph dataset of 300 graphs can be obtained, of which the general characteristics are reported in Table 1. Moreover, there're five kinds of major faults in the dataset, which are main types of faults that might occur in the daily operation of NPPs, and may have huge impacts to its safety management, including Loss of Coolant Accidents (LOCA), Loss of Feedwater Accidents (LOFA), Steam Generator Tube Rupture (SGTR), Steam Line Break (SLB).

Table 1. General description of graph dataset formulated

| Type of Labels | # Graphs Formulated | Proportion of Labels |
|---|---|---|
| LOCA | 24 | 8.0% |
| LOFA | 18 | 6.0% |
| SGTR | 24 | 8.0% |
| SLB | 24 | 8.0% |
| Normal State | 210 | 70.0% |
| Total Instances | 300 | |

Furthermore, considering that the nature of our fault detection task is graph classification, here we have introduced conventional machine learning classifiers as baselines in experiments, such as the Bayesian approach (Naive Bayes, NB), the Logistic Regression (LR), the Decision Tree (Classification and Regression Tree, CART), the Multi-Layer Perceptron (MLP), the Support Vector Machines (SVM), and Tree-based Ensemble Learning methods like Random Forest (RF), AdaBoost and Gradient Boosting Decision Tree (GBDT). All experiments are executed by 5-fold cross validation and for clear presentation and comparison, we utilize the Accuracy as the only assessment metric for the classification performances of all techniques.

### *3.2. Performances comparison*

Detailed comparison of all models' performances in fault detection is presented in Table 2. For the graph classification based GCN, we have arranged two/three layers with three kinds of pooling functions, including max pooling (Max), mean pooling (Mean), add pooling (Add), and consequently, 6 versions of GCN could be obtained and implemented into experiments. Similarly, for the baselines of classifiers, four processing measures have been used as the max filtering (Max), mean filtering (Mean), add filtering (Add), concatenation (Concat). Based on the original temporal sequences, the major difference between the GCN and the baselines is that the former formulates each sliced sequence as a graph, while the latter process the sliced sequence into a flattened vector, with each sliced sequence sized $100 \times 70$. The results of GCN in Table 2 are actually the best performances among the 6 versions of models on 7 various values of $s$ (-0.7, -0.5, -0.3, 0, 0.3, 0.5, 0.7), and their sensitivity will be analyzed in the next subsection.

The bolded highlights in Table 2 are the top three fault detection results among different processing measures, while each grid has reported the average Accuracy (Acc.) and Standard Deviation (St.D.) under the experimental setup of 5-fold cross validation. It can be obviously observed that our proposed GCN model outperforms all baselines under the four kinds of processing, with the marginal promotions realized approximately 3 to 6 percentages to varying extents. Among the three pooling functions, the mean pooling achieves the best discrimination of fault detection with minimum standard deviation, yielding the optimal accuracy of 95.33%. Moreover, the GCN using mean pooling or max pooling is much better than the version of add pooling, indicating the effectiveness of the first two pooling functions.

Table 2. Performances comparison of baselines and our proposed GCN model

| Models/Processing | Max | Mean | Add | Concat |
|---|---|---|---|---|
| NB | 78.25±3.33 | 78.00±3.64 | 83.00±6.74 | 82.08±2.40 |
| CART | 85.17±3.33 | **89.92±4.08** | 88.50±1.84 | 81.17±7.69 |
| RF | 85.75±3.59 | 88.75±4.82 | 88.25±4.53 | 89.75±4.93 |
| AdaBoost | 56.08±32.59 | 73.50±23.98 | 73.50±23.98 | 64.92±22.1 |
| GBDT | 88.92±2.87 | 89.17±1.75 | 89.00±1.70 | 87.58±5.50 |
| MLP | **89.42±3.05** | **90.08±3.16** | 88.58±3.67 | **91.33±2.79** |
| SVM | **89.67±3.49** | 87.17±2.90 | **93.08±2.87** | **92.17±4.00** |
| LR | 85.75±3.37 | 86.00±1.62 | **93.42±0.76** | **92.33±3.93** |
| GCN | **95.33±3.40** | **95.33±1.25** | **89.67±4.40** | - |

### 3.3. Sensitivity analysis

The sensitivity analysis in our study are conducted from three aspects: the significant parameter $s$, the major settings in model design of GCN, including the number of convolutional layers, and the various pooling operations. Elaborately, the intertwined effects of $s$ values (-0.7, -0.5, -0.3, 0, 0.3, 0.5, 0.7), convolutional layers (2-layered, 3-layered), and pooling operations (max pooling, mean pooling, add pooling) are explored and discussed. Figure 1 and Figure 2 present the detailed results of sensitivity analysis, while the former shows the performance changes of GCN using different pooling functions under various $s$ values, and the latter is the gap of accuracy and standard deviation under various $s$ selections, which is computed by subtracting the results of 2-layered GCN from the results of 3-layered GCN, to more clearly display the performances differences.

Observing from Figure 1, there clearly remains an ascending trend for GCNs of all three poolings along with the rise of $s$ values, indicating that the model works better when the $s$ takes a larger value. This is due to that large values of $s$ lead to more sparse graphs generated, based on which the graph embeddings extracted by GCN are more easily to be distinguished than the embeddings from dense graphs of lower $s$ values. Comparing the three pooling functions in depth, the max pooling and mean pooling are much better than the add pooling, while when analyzing different convolutional layers, the 2-layered GCN performs more steady than the 3-layered one. Moreover, valid promotions by the 2-layers of convolutions could be observed in Figure 2, compared with 3-layered GCN, as positive gaps of accuracy indeed appear in most scenarios while there's no significant difference in the positive and negative gaps of variance. Thus, in our experimental settings, 2-layered GCN implemented with mean or max pooling functions and $s$ value set as larger than 0.5 enable to achieve optimal fault detection performances to a maximum extent.

## 4. Conclusion

In this article, we propose a graph classification based fault detection methodology for NPPs with more superior fault identification realized on the dataset simulated by a professional software. It has been experimentally verified that the GCN of 2 convolutional layers implemented with mean or max pooling functions and the large $s$ values set (e.g., $s \geq 0.5$) could promote the capability to its maximum performances. Our research successfully addresses this task from the perspective of graph representation learning, and more importantly, provides effective decision support in the safety management of NPPs. The main contribution of this study is that evolving patterns in the operating characteristics of NPPs are transformed into graphs, and then extracted as embeddings which

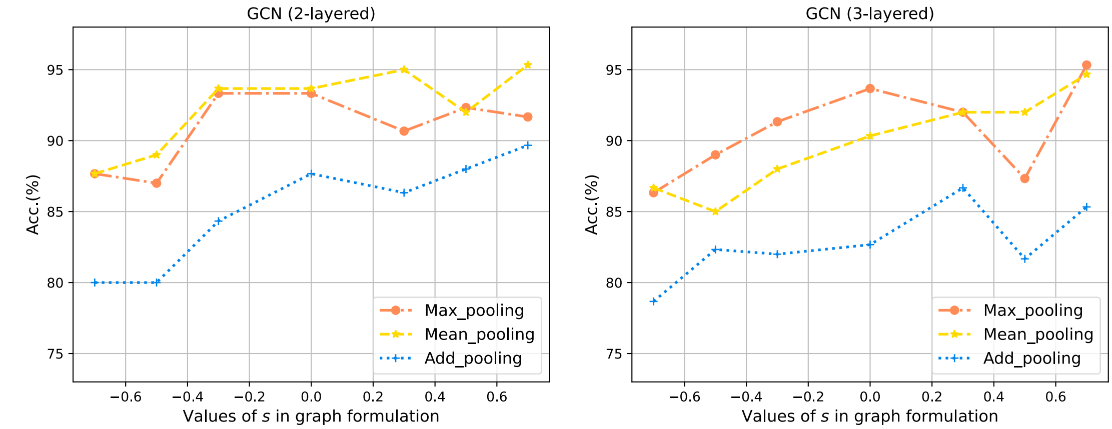


Fig. 1. Sensitivity of different pooling functions in GCN under various *s* values

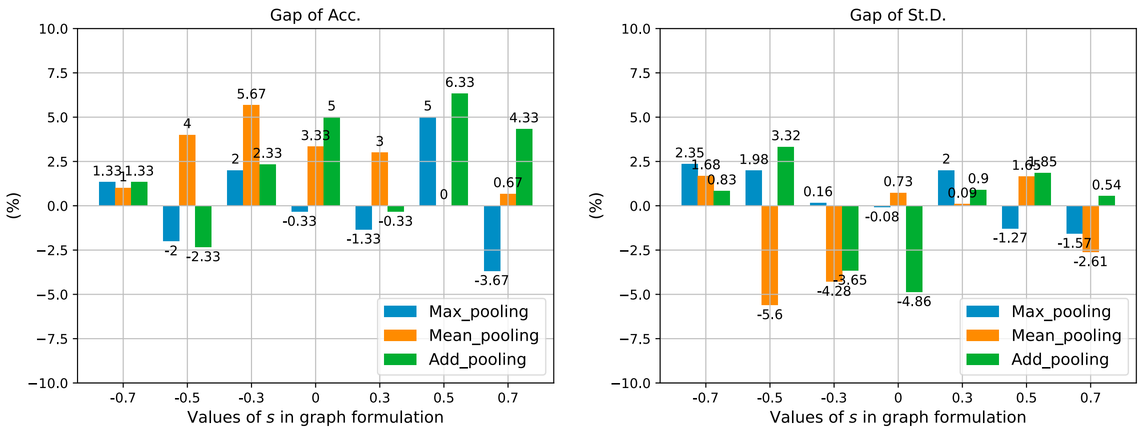


Fig. 2. Sensitivity of different convolutional layers in GCN under various *s* values

are easier to discriminate. From the above experimentations and analysis, it can also be seen that graph learning methods like GCN can be implemented to deal with real problems in NPPs' safety management, as long as the experimental dataset is appropriate. Advancing further, various types of digital signals could be reformulated into graph dataset, based on which the original task could be performed more efficiently in the way of graph representation learning. Although our proposal has yielded satisfactory results, there still remains limitations that could get improved in future developments. The first one is to test the performances of different GNN models with different information propagation rules, for example, GraphSAGE and GAT. Another possible promoting direction is to consider the time-varying trends in the running characteristics of NPPs, like designing spatial–temporal graph-driven methodology for prediction [16], as our study only focuses on simple classification, rather than predicting the labels based on temporal sequence modelling.

## Acknowledgements

This work has been supported by Key Projects (#71932008, #72231010) and Youth Project (#71901155) of National Natural Science Foundation of China. All authors hereby express gratitude to anonymous reviewers and organizing committee of the conference for their valuable comments and careful work.

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