

The effect of graph complexity in an energy-based FDI approach

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Abstract:

This paper introduces a structured approach for creating node signature graphs in energy graph-based visualization for industrial systems, focusing on anomaly detection. It examines the relationship between graph cardinality and the singular value decomposition analysis applied in the energy graph-based visualization method. The results reveal a trade-off between graph complexity and singular value resolution. The study highlights how graph structure affects energy flow monitoring and anomaly detection. It notably enables fault detection in components not represented as nodes, enhancing the methodology in energy-based system monitoring.

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Keywords: Fault detection and isolation, Graph reduction, Graph matching, Hybrid FDI, Industrial process, Thermal flow process, Graph-based anomaly detection.

1 INTRODUCTION

The continual advancement in monitoring methodologies is crucial for the operational integrity of large-scale industrial systems. According to Ouyang et al. (2022), the integration of energy and graph-based anomaly detection methods is gaining traction, especially in these complex systems. This emergence is motivated by Greyling et al. (2020) based on the imperative to enhance safety and operational efficiency within these complex industrial environments while reducing the dimensionality of the process data. This is especially relevant to this study where energy exchange and interactions can be visualised as a structural configuration using a graph. The problem with large complex industrial systems lies in the dimensionality of the input space and, if graphs are used, the cardinality of the graph complicates the analysis (Greyling et al., 2020). Simplifying the graph of the system to reduce graph cardinality is therefore imperative. This problem is currently addressed using approaches like, machine learning (Zhou et al., 2017), statistical process control (He and Wang, 2018), high-performance computing (Lee et al., 2011), distributed computing, edge computing and various other methods (Coimbra et al., 2021). One such method is the energy graph-based visualisation (EGBV) method (Van Schoor and Uren, 2018). This method is considered a hybrid method between model-based and data-driven techniques combining the structural information within a plant with the process variability encapsulated within the unifying parameter that is energy (Wolmarans et al., 2023). However, the current methodology for graph composition in the energy graph-based visualization (EGBV)

method warrants refinement to standardise the construction of the graphs, necessitating analysis of variations to the graph structure and form (Smith et al., 2023). This paper addresses this need by introducing a structured process for composing graphs. The focus is predominantly on fault detection and isolation in complex thermal flow industrial systems where energy constitutes the principal feature attribute. The approach followed to develop this process, consists of composing a list of reason-based guidelines regarding what must be considered when constructing a node signature graph. An analysis, aimed at identifying the effects of employing varied graph structures or graph cardinality, is executed. This analysis consists of a singular value decomposition of the residual matrix obtained from an adjacency matrix (called node signature matrices) of the node signature graph. Secondly, an analysis is conducted utilising the results from the singular value decomposition to capture the inherent causal process information. The contribution of the paper lies in analysing the relationship between the cardinality of the graph and singular value decomposition (SVD) resolution. The insights derived from this study aim to substantively contribute to the further refinement and evolution of the EGBV method, thereby elevating the paradigms of safety and reliability in large-scale industrial systems and providing a nuanced perspective on energy-based process monitoring and anomaly detection. The paper is structured as follows: Section 2 introduces the EGBV method using a simple example. Section 3 discusses the proposed methodology for composition of the node signature graph through node and link selection. Section 4 elaborates on the system information used for the case study and illustrates the

application of the EGBV method to a complex industrial system. In section 5 a detailed discussion of the result is portrayed and finally, section 6 concludes the paper.

2 EGBV METHOD

The EGBV method can be considered as a five-step process starting with the system analysis which might include the modelling of the system, node and link selection, attributed node signature graph composition, node signature matrix composition, and residual generation. The residual generation forms a transitional part from the EGBV to the fault detection and isolation (FDI) process and might depend on the type of FDI analysis that will be executed. Within the context of the EGBV method, a node signature graph is considered as a collection of edges and vertices mathematically represented as a node signature matrix defined as follows Smith et al. (2023). Consider a directed attributed graph $G = (N, L, \dot{\mathbf{E}}, \Delta\dot{\mathbf{B}})$ where $N = \{n_1, n_2, \dots, n_n\}$ is a set of n nodes. $L \subseteq N \times N$ is defined as a set of links, where the cartesian product of N with itself is a set of all ordered pairs (n_i, n_j) such that $n_i \in N$ and $n_j \in N$. $\dot{\mathbf{E}} \in \mathbb{R}^{n \times n}$ is a link attribute matrix where $\dot{E}_{ij}$ represents the power flow attribute of link $(n_i, n_j) = l_{ij}$. $\Delta\dot{\mathbf{B}} \in \mathbb{R}^{n \times 1}$ is a node attribute vector where $\Delta\dot{B}_i$ represents the rate of exergy change attribute of node n_i . An attributed node signature matrix may then be defined as,

$$\mathbf{N}_s = [\Delta\dot{\mathbf{B}} | \dot{\mathbf{E}}]. \quad (1)$$

To explain the EGBV method, consider the simple plant diagram in Fig. 1 illustrating a pump driving a turbine.

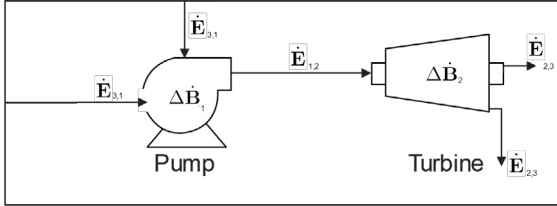


Fig. 1. Illustrative simple system

The energy input from other components is considered to be supplied from the environment. Similarly, the energy output is supplied back to the environment. An attributed graph can be composed for this system using the attributes $\dot{E}$ (rate of energy transfer) and $\Delta\dot{B}$ (rate of exergy destruction) as node and link attributes respectively. In this simple example, the components (pump and turbine) and environment form the minimum set of possible nodes. Since each of these components can be divided into sub-components, it would be possible to consider each of these as possible nodes. The links between these components automatically form the links in the graph. In complex systems, the identification of components to be represented as nodes and links becomes more challenging. In section 3 this process is discussed in more detail, constituting the contribution of this paper. The attributed graph can then be composed as shown in Fig. 2. The nodes n_1 , n_2 , and n_3 represent the pump, turbine, and environment respectively. Using this graph, a node signature matrix from (1) can be composed as a mathematical representation of the actual system as shown in (2). The link

and node attributes encapsulate the casual information in the system while the graph structure retains the system's structural information. Considering k instances in the system's operation being measured in real-time at specific intervals, the node signature matrix can be populated with the attribute values characteristic to the specific system operation. Through analysis of each k^{th} time instance node signature matrix, FDI is possible.

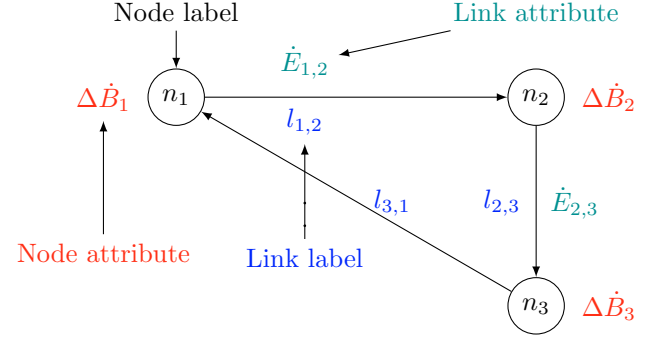


Fig. 2. Attributed graph example.

$$\mathbf{N}_s = \begin{bmatrix} \Delta\dot{B}_1 & \dot{E}_{11} & \dot{E}_{12} & \dot{E}_{13} \\ \Delta\dot{B}_2 & \dot{E}_{21} & \dot{E}_{22} & \dot{E}_{23} \\ \Delta\dot{B}_3 & \dot{E}_{31} & \dot{E}_{32} & \dot{E}_{33} \end{bmatrix}. \quad (2)$$

3 GRAPH COMPOSITION APPROACH

Referring to the example, it is clear that the graph composition for complex systems can become challenging. Besides complexity in terms of system scale, the system control and operation can also complicate the graph construction. Components like controlled valves can change the link-to-node composition simply due to the normal process control during the plant operation. The identification of components and sub-components to be considered for nodes can easily result in an extensive graph. The approach that considers all components as nodes, would of course result in an extensive graph with many zeros in the node signature matrix, depending on the particular system mode. The approach of only including active components as nodes, would reduce the size of the graph and the number of zeros in the node signature matrix but may require different graphs for different system modes. To direct this process of graph composition, a list of guidelines is proposed that allows for systematic reason-based node selection:

- 1) Select components at which faults should be detected.
- 2) Select components that are energy-converting or -manipulating components e.g. turbines and valves and not nuts or bolts.
- 3) Select components for which the data required for the attributes are available.
- 4) Select components with many inflows or outflows in terms of energy e.g. a multistage turbine instead of a valve with only one inflow and one outflow.
- 5) Select components that will affect the system if a relatively small change in the energy occurs at/in these components.
- 6) Select components at which large amounts of energy flow in/out.

- 7) Neglect nodes that do not influence the system operation and are not required by guideline 1.

The process of reason-based node selection is illustrated in Figure 3.

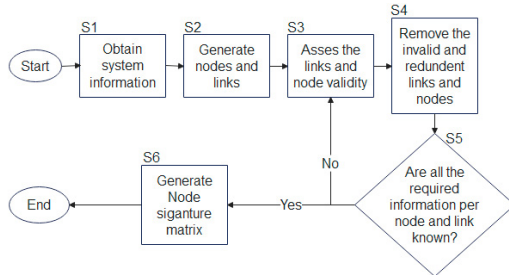


Fig. 3. Process for obtaining the attributed node signature graph.

The adequate fault detection capabilities of the EGBV method rely on the availability of energy attributes and structural information of the system (Wolmarans et al., 2023). It is therefore required that the interconnection of components and their interaction with each other is known. To this extent, expert knowledge is typically required as a once-off input that will allow the accurate composition of the attributed graph. It is important to know:

- which components are connected to which,
- what type of energy exchange or conversion happens within and between these components,
- how the process variables are measured,
- to what extent do the various components contribute to the control of the system,
- and most importantly, is it required to detect a fault in these components since faults can only be detected at components which are included as a node?

Considering all these aspects a component list can be composed which will constitute the nodes of the graph. Secondly, an interaction list can be composed indicating the link interactions from one node to another. Typically the component list will be extensive and can then be reduced. Considering Fig. 3 and the list of guidelines, guidelines 1 and 2 fall within the scope of S1 to S3 of Fig. 3. Once the components are identified the reduction and elimination process starts from S4 to S6 during which guidelines 3 to 7 guide the process. The discussion in this paper constitutes the node signature graph before and after this reduction took place, elaborating on the effects that these changes have on the sensitivity of the node signature matrix to fault-related changes in the system.

4 THERESA CASE STUDY

For illustration purposes, a graph composition exercise was executed on a complex industrial thermal storage system (THERESA). The system shown in Fig. 4) is from the University of Applied Sciences Zittau/Görlitz in Germany and is used as an experimental facility that facilitates research on various aspects of a thermal power plant (the, 2023).

4.1 System overview

THERESA is a thermal energy storage system that consists of four distinct operating modes referred to as, warm up, charging, holding, and discharging. The system can be considered as a thermal battery where steam or hot water is used as the energy-carrying source (Schneider et al., 2016). The steam is generated and superheated via an electrical boiler and superheater unit. Additionally, steam for preheating of feed water can be provided by a neighbouring facility where steam is generated for residential heating. Due to the research functionality of the facility, the system consists of a universal interface to which various testing apparatus can be connected.

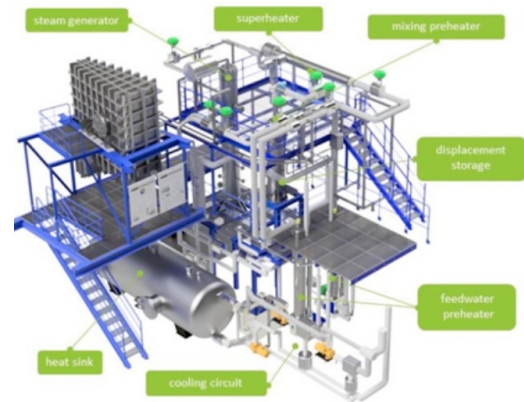


Fig. 4. CAD rendering of the THERESA test facility Klette et al. (2019).

Depending on the experiment and system operation, the displacement storage will act as a battery cycling between being charged and discharged. Various sensors ranging from temperature, pressure, and mass flow sensors to level and humidity sensors are installed throughout the system to capture process variables during system operation. These process variables are used to calculate the required attributes for the EGBV method. However, some components e.g. the storage tank lacks the required sensors to obtain the necessary energy attributes. To address this, technical system information on the component configuration was used to model required parameters. All process variables are then stored in a central database for further analysis.

4.2 EGBV application

Considering the valve and flow path changes when one mode changes into another there are 4 distinct node signature graphs that can be obtained. Following the rules as defined previously, a fifth node signature graph as an all-inclusive graph is also composed, encapsulating all the interactions of each possible system mode. As an example Figs. 5, 6, and 7 depict the comprehensive, charging mode and discharging mode graphs. Considering the node and link count, the node signature matrix for the comprehensive graph has dimensions 21×22 . This is reduced to only 14×15 for the discharging graph. Note that certain nodes in Figs. 6 and 7 are simply not present since these nodes are representative of components that are inactive in these modes.

Table 1. List of nodes and the corresponding component names

Node No	Component name
1	Feedpump
2	Pre-heater1, Primary side
3	Pre-heater1, Secondary side
4	Boiler
5	Superheater
6	Universal interface
7	Storage tank 1
8	HX1 pump
9	Heat exchanger 1, primary side
10	Heat exchanger 1, secondary side
11	Storage tank 2
12	HX2 pump
13	Heat exchanger 2, primary side
14	Heat exchanger 2, secondary side
15	Outlet pump
16	Pre-heater 2, Primary side
17	Pre-heater 2, Secondary side
18	Displacement storage
19	Mixing pre-heater
20	T joint
21	Environment

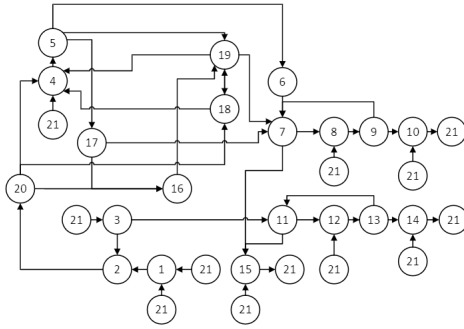


Fig. 5. Comprehensive all-in-one graph.

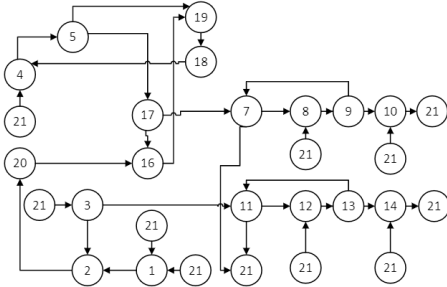


Fig. 6. Graph of the system in charging mode

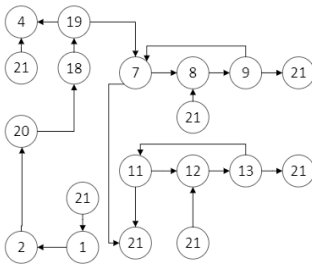


Fig. 7. Graph of the system in discharging mode

Following the EGBV process, the subsequent steps for FDI entail the comparison of the node signature matrices

while the system process variables are measured in pre-determined intervals. In this study, the heterogeneous Euclidean overlap metric (HEOM) is used as a distance metric for composing cost matrices ($c_{ij,k}$). The function compares the node signature matrices and composes a square normalised cost matrix (Wilson and Martinez, 1997). The HEOM metric is given as

$$c_{ij,k} = \sqrt{\sum_{a=1}^{n+1} \left[\frac{|\mathbf{N}_{sref}(i,a) - \mathbf{N}_{s,k}(j,a)|}{\{range\}_a} \right]^2}, \quad (3)$$

where $\mathbf{N}_{s,k}(j,a)$ refers to the (j,a) entry in the operational signature matrix, $\mathbf{N}_{sref}(i,a)$ to the (i,a) entry in the reference signature matrix, and a , the entry in a row's a^{th} column. The *range* normalises the attribute and is given by

$$range_a = \max(a) - \min(a), \quad (4)$$

with $\max(a)$ and $\min(a)$ the respective maximum and minimum values in the a^{th} column of $\mathbf{N}_{sref}$. The input matrices to this function can either consist of a reference node signature matrix compared to each k^{th} sample or a sample-to-sample comparison can be executed. The approach encompasses two distinct methodologies: comparing a reference node signature matrix against each k^{th} sample or conducting a sample-to-sample comparison. In this paper, the second approach is followed consisting of normal operational data from the THERESA system with the process changing modes from warm-up to charging, holding and discharging consecutively. Evaluation of the singular values or vectors of the resulting cost matrices is used for fault detection or isolation. In the context of this paper, only the singular values are evaluated to show the effects of changes in the node signature graphs over $k = 27800$ samples. From the practical experiment, 5 separate sets of data were obtained. These data sets are referred to as data sets 89, 90, 91, 92, and, 95. Table 2 summarise the data and testing conditions.

The data from 92 and 95 consisted of various anomalies. It should be noted that a fault was emulated and the responding change in process variable was used as an indication of the fault. For example, dataset 92 has data from a pressure sensor in the displacement storage that logged pressure values higher than 62 bar at around $k = 7000$. This can be seen as a system-level faulty condition even though no component faults are present. Similarly, at approximately $k = 10000$ one of the controlled valves in the system saturated resulting in a controller oscillation that caused oscillations in the mass flow. Considering dataset 95, the data was obtained during a safety procedure where the safety systems of the facilities were tested against certain standards. During these tests, some equipment was disabled to force the system to run under faulty conditions that would activate the safety equipment of the facilities. Due to the nature of the tests, they were only executed in the warmup mode. Four faults were recorded of which two resulted in over-pressure and the other two caused over and under-level errors in the storage tanks respectively.

5 RESULTS AND DISCUSSION

Cost matrices were composed for the datasets using a sample-by-sample approach, analyzing changes in the node

Table 2. Data information

Dataset	Data Description	Parameters
89	Turbulent charging conditions	140°C, 1.5 m ³ /h
90	Turbulent charging conditions	140°C, 1 m ³ /h
91	Laminar charging conditions	140°C, 0.4 m ³ /h
92	High pressure and stuck control valve	140°C, 1.5 m ³ /h
95	Safety test, under/over level and pressure	Warmup mode at 26°C

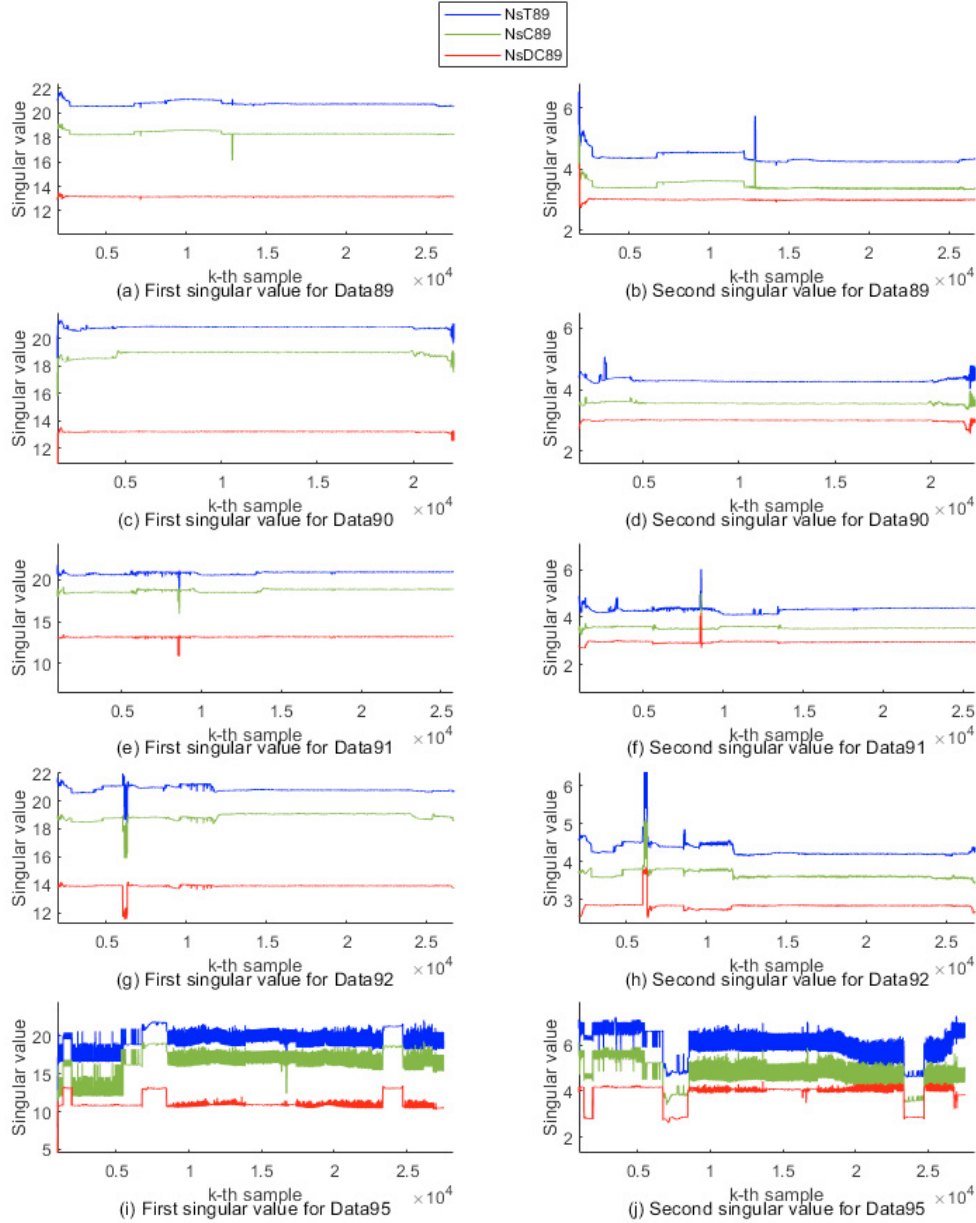


Fig. 8. Graphs of the first and second singular values for the 5 datasets in descending order.

signature graphs. Each node signature matrix comparison is indicated using $C_{ij,k} = N_{sl,k} \Psi_{N_{sl,k}}$, where l indicates the graph composition $l \in \{T, C, DC\}$ with T for the comprehensive node signature graph, C for the graph under charging mode conditions, and DC for the graph under discharging mode conditions. Three key observations emerged: 1) The pattern between plots remained roughly consistent as graph cardinality decreased, though

resolution diminished. 2) Plot amplitudes roughly aligned with the number of nodes in the node signature graph, e.g., $N_s T$ fluctuated around 21 nodes. 3) Expected variations in datasets 92 and 95 were observed at the relative k 'th sample ($k = 6000$, $k = 10000$ in dataset 92, $k = \pm 7500$, $k = \pm 17000$, and $k = \pm 23000$ in dataset 95) where the flow, temperature, and pressure changes occurred, correlating with simulated faults. However, some level changes

in dataset 95 were not evident, and minor changes were seen in dataset 92 for the valve oscillations fault. A time delay was noted between the occurrence of process variable anomalies and their detection through SVD. The second singular value largely mirrored these findings, with the major effects of comprehensive system control masking faults and complicating fault detection and isolation (FDI). The goal of the analysis was to evaluate how the singular values are affected by changes in the node signature graph's cardinality. To this extent, the 5 datasets were used as a well-representative data sample that will allow for the evaluation of the singular values at various workpoint under normal and faulty conditions. The effects of changes in the graph structure are illustrated by a comparison of the singular values for k samples from the comprehensive, charge, and, discharging mode graphs shown in Figs. 5 to 7. For both the first and second SVD the data from set 95 appears to be extremely noisy. This is misleading since the data are simply representative of the warmup mode and therefore zoomed in. If the results from datasets 89 to 92 were to be examined by zooming into the range $0 < k < 5000$ (the warmup range) similar noise is seen. However, besides this fact, the data from 95 still seems to have undesirable large amplitudes of relative noise and might require some filtering. Due to length limitations, this paper does not include results of the remaining singular values. From inspection it was however observed that the smaller singular values showed similar patterns as the first two but with increased noise. Overall the responsiveness of the singular values to changes in the system even with lower cardinality node signature graphs seems promising and warrants further investigation.

6 CONCLUSION

This study analyzed the impact of graph cardinality on fault detection in complex industrial systems using the THERESA system. Results showed that higher graph connectivity leads to better anomaly detection, while lower connectivity graphs might miss subtle yet critical changes. The study suggests an optimal balance between detailed monitoring and computational efficiency. Examination of specific datasets that incorporated faults validated the applicability of the energy graph-based visualisation method to practical scenarios. The key takeaway is the strategic optimization of graph-based visualization methodologies to enhance fault detection without imposing excessive computational demands. Ultimately, the insights serve to refine the tools and techniques for fault detection, steering towards more efficient, safe and resilient industrial operations. The main findings include identifying faults in components not represented as nodes and understanding the relationship between graph structure and detection sensitivity. Future research should focus on scalability, integrating machine learning hybrid models, advanced graph theoretical metrics, time delay in energy-based attributes, and fault propagation analysis.

7 ACKNOWLEDGEMENT

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