A Weighted Network Graph Approach for Trend Analysis of Nuclear Power Plant Events

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1. Introduction

Trends analysis of human error events in nuclear power plants serves as an important indicator for understanding operation performance. Traditional tools such as Pareto charts and control charts are useful for identifying major weak points by focusing on the frequency of recurring causes. However, these methods fail to capture the relationships among different contributing factors. To overcome this limitation, we introduce a network analysis approach that structurally represents events. When modeled as a graph, events consist of nodes and edges, where nodes represent causes or components and edges denote the relationships between these factors. By assigning weights to this network, the analysis goes beyond simple frequency counts to identify critical factors and their interconnections.

This study therefore propose a weighted network graph approach for trend analysis of human error events in nuclear power plants.

2. Methods and Results

2.1 Network Graph of Nuclear Power Plants Events

Events in nuclear power plants rarely result from a sing factor; rather, multiple causes, systems, and components are typically intertwined. Traditional tools such as Pareto charts and frequency analysis can enumerate such factor independently but are limited in capturing the multi-dimensional interaction structure of events.

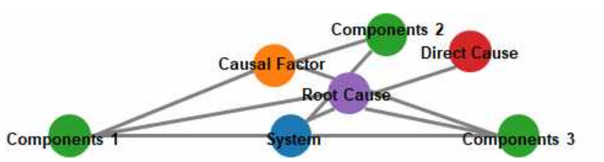

Fig. 1. Conceptual Network Graph of Nuclear Power plant Events

To reflect these complex characteristics, we employ the network graph (fig. 1) as an analytical tool. A network graph is mathematically defined as

$$G=(V,E)$$

Where V denotes the set of nodes representing the essential components of events, and E denotes the set of edges indicating the co-occurrence of two nodes within the same event. In other words, a single event generates multiple nodes simultaneously, and the entire dataset can be represented as a collection of such co-occurrence relationships.

However, constructing the network solely on the existence of nodes and edges tends to disproportionately highlight only the most frequently occurring factors. This neglects the importance level and the severity of outcomes, leading to potential distortion in analysis. Therefore, it is necessary to assign weights to both nodes and edges that reflect the event importance and outcome severity.

2.2 Node Weight

To assign node weights, the initial approach was to simply aggregate the importance scores of events associated with each node. Let I_i denote the set of events linked to node iii. The initial node weight was defined as:

$$wi = \sum k \in I_i S(k)$$

where $S(k)$ represents the importance score of event k. However, this formulation does not sufficiently account for the multifaceted outcomes of events. For example, two Level 1 events may differ significantly: one might cause an unplanned shutdown, while another may only result in a power derate or regulatory reporting requirement. Thus, a simple summation of importance scores fails to capture the true impact of each event.

To address this limitation, an event weight was introduced, incorporating both importance and outcome effects:

$$W_{event} = S \times F_{outcom\ e}$$

Here, SSS denotes the importance score of the event, while $F_{outcome}$ is a correction factor reflecting the consequences of the event. In cases where multiple outcomes occur simultaneously, normalization or a maximum-value adjustment is applied to prevent excessive inflation of weights.

Accordingly, the final node weight is defined as:

$$w^{node}{}_i = \sum k \in I_i W_{event}\ (k)$$

This formulation ensures that a node's weight reflects not only the frequency of its occurrence but also the severity and significance of the events it is involved in. Therefore, nodes representing root causes, systems, or equipment are evaluated in terms of both event frequency and consequence severity, providing a more accurate representation in network-based trend analysis.

2.3 Edge Weight

While node weights reflect the importance of individual events, edges represent the relationships between nodes within an event. A straightforward approach would be to assign a binary value: if two nodes co-occur in the same event, the edge weight is 1; otherwise, it is 0. However, such a binary representation fails to capture the relative importance of the edge.

To address this limitation, this study incorporates the event weight (W_{event}) into edge construction. Let I_{ij} denote the set of events in which both node i and node j appear simultaneously. The edge weight is then defined as:

$$w^{edge}{}_j = \sum k \in I_{ij}\ W_{event}\ (k)$$

This formulation not only reflects how frequently two nodes co-occur but also accounts for the importance and severity of the events they share. As a result, edges connecting nodes that co-occur in high-risk events are assigned greater weights compared to those appearing only in minor events. This allows the network analysis to highlight high-risk associations, moving beyond simple co-occurrence frequency to reveal more meaningful structural insights.

2.4 Characteristics of Weighted Networks

The application of node and edge weights differentiates the proposed method from traditional frequency-based analyses. Node weights represent the extent to which specific causes, systems, or equipment are involved in high-impact events, while edge weights capture the strength of co-occurrence relationships in severe events.

As a result, weighted networks exhibit structural properties that simple co-occurrence graphs cannot reveal. For example, two causes may appear with the same frequency, but if one is repeatedly associated with unplanned shutdowns or regulatory reportable events, it will attain higher centrality. This distinction highlights not just how often factors occur, but how critical their interactions are in shaping event outcomes.

Key characteristics of weighted networks include:

①Integration of both event frequency and severity of consequences.

②Emphasis on high-risk associations among causes, systems, and equipment.

③Enhanced applicability of advanced metrics (e.g., centrality, clustering) to identify hidden vulnerabilities.

Thus, weighted networks provide a more risk-sensitive and structurally informed framework for trend analysis of human error events in nuclear power plants.

3. Conclusions

The network model proposed in this study assigns weights to both nodes and edges, allowing the analysis to consider not only how frequently factors occur, but also how strongly they are involved in severe events and how intensively they are interconnected in high-risk cases. Node weights reflect the severity and importance of event outcomes, highlighting the criticality of specific causes, systems, or equipment. Edge weights represent the degree to which factors co-occur within events, combined with the event weight. This approach enables the identification of high-risk associations, going beyond simple co-occurrence frequency.

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