# Integration of Symptom Notions on Failure Causes for Diagnostic Process Enhancement

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*Abstract*— **This paper presents a probabilistic approach to enhance failure cause diagnosis, with a focus on the integration of symptom-based analysis to improve isolation accuracy. The proposed method utilizes a Bayesian Network (BN) model, whose structure is derived from the transformation of a deterministic tree provided by a system expert. The BN approach enables continuous probability updates based on dataset inputs, allowing the model to adapt over time. Through the integration of expert knowledge, experience feedback, and symptom-based reason, this method enhances the precision and efficiency of failure isolation. The methodology is demonstrated through a case study, presented in a simplified format for clarity. The results highlight the potential to support informed maintenance decisions, with a contribution to improvement in the availability of the monitored system.**

## I. Introduction

Industrial sectors are increasingly focused on how to meet the demand for superior performance while ensuring the reliability of monitored systems, which lead to the implementation of advanced operational strategies [1]. Meet these requirements often involve implementation of reliability-centered solutions, predictive maintenance, and real-time supervision [2],[3]. Failure diagnostics, integrated into maintenance processes, can improve uptime by reduction of downtime and maintenance costs through quick identification of failure causes [4].

As defined by ISO 13372 [5], diagnostic involve assessment of the current condition of a component or system by symptoms analysis. Fault Detection and Isolation (FDI) or Fault Detection and Diagnostic (FDD) specifically address three main objectives [6]: (1) fault detection, which signals the presence of an issue within the system; (2) fault isolation, which identifies the precise type and location of the fault; and (3) fault identification, which assesses the fault's influence on system behavior [7]. Isolation follows detection, while identification builds on isolation to enable fault-tolerant control. A variety of FDI methods have been developed, and continuous literature reviews explore progress in this field [8], [9].

Related with these industrial needs, this paper is aims to integrate quantitative feedback dataset within a causal digraph framework to improve failure isolation [10], [11]. In this context, Bayesian networks (BNs) appear particularly well-suited, as they capture causal relationships and integrate quantitative dataset. BNs also allow for the representation of uncertain associations between symptoms and root causes. Additionally, maintenance-related knowledge over time can be integrated within the BN, where it can generate new insights through Bayesian inference mechanisms [12], [13].

The BN approach offers a robust framework to represent probabilistic events, causal relationships, and correlations between symptoms and causes. Within this framework, several BN-based methodologies have been proposed for failure diagnostic; for instance, the dynamic BN model in [14] is applied to fault detection. However, this model does not include experience-based feedback, which is crucial for improvement of the isolation process in industrial applications. [15] introduces a static BN that integrates experience feedback (EF) through conditional probabilities, to emphasize causal relationships while exclusion of symptom signatures and expert-provided causal chains, which could further enhance the isolation process.

To address symptom-based diagnostic, a BN model presented in [16] was developed from a parity matrix that connects symptoms to failures, but it introduces significant ambiguities. These uncertainties are partly resolved the integration of component reliability into the analysis. Additionally, [17] offers a comprehensive methodology to construct BNs for diagnostic, with a modification of component failure probabilities based on observed symptoms via inference. However, neither [16] nor [17] integrates feedback to adjust all probabilities across their networks. [18] presents an approach which allows to combine data-driven and model-based methods through a continuous BN, yet without leveraging EF dataset to enhance isolation.

To make use of the advantages of various FDI methods, hybrid approaches with a combination of different techniques have been proposed [19]. To our knowledge, no exists research combines causal graphs and fault signatures with EF-based updates. Our goal is to enhance isolation efficiency by the consideration of expert knowledge through causal graphs, link them to imperfect symptom-cause relationships, and integrate the EF dataset on both causes and symptoms through BNs. This dataset allows for the adjustment of probability distributions within the network, which supports maintenance personal in their decision make.

This paper is structured as follows: Section II offers an overview of the key contributions of this work. Section II-A revisits the fundamental principles of BNs, highlight their application in fault diagnostic and their effectiveness in the modelisation of causal relationships. Section II-B explores

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the integration of symptom signatures within the causal graph framework. Section II-C presents a method to update the diagnostic model through the EF dataset, with detail on how this data is used to compute posterior probabilities. Then, the complete practical implementation procedure for the proposed approach is described in section II-D. Section III highlights a case study to demonstrate the approach effectiveness and practical applicability. Finally, Section IV presents the conclusion and future perspectives.

## II. BN MODEL FOR CAUSE ISOLATION

To construct the BN for cause isolation and failure diagnostic, system experts provide a causal directed graph (digraph) structured as a deterministic tree. Maintenance teams use this digraph as a reference to identify failure causes. The objective is to transform this causal digraph into an equivalent Bayesian Network (BN) [9].

### A. Bayesian Networks

A BN functions as both a framework for knowledge representation and a tool for probabilistic inference. It models probabilistic dependencies and independencies among variables through a directed acyclic graph [13]. The network comprises nodes that represent random variables and directed arcs that depict the connections between them [9]. Root nodes are associated with prior probabilities, while child nodes include conditional probabilities that quantify the degree of probabilistic relationships between variables [2].

A BN can be formally represented as a directed acyclic graph $\mathbf{G} = \langle (N, A), (\mathbb{P}_r, \mathbb{P}_c) \rangle$, as described in [2] :

- $N$ represents the set of nodes in $\mathbf{G}$, where each node corresponds to a random variable from the set $\{x_1, x_2, \ldots, x_n\}$.
- $A$ represents the set of directed edges (arcs) that depict causal or probabilistic dependencies between these variables.
- $\mathbb{P}_c$ is the set of conditional probabilities and $\mathbb{P}_r$ is the set of root probabilities.

The joint probability of the set of variables $\{x_1, x_2, \ldots, x_n\}$ can be determined by using the following equation:

$$p(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} p(x_i | pa(x_i)) \quad (1)$$

where $pa(x_i)$ represents the set of parents of nodes $x_i$ in $\mathbf{G}$ and $p(x_i|pa(x_i))$ comes from the set $\mathbb{P}_c$ or $\mathbb{P}_r$. The objective of the proposed equation is to concretely explain $\mathbb{P}_r$, the set of prior probabilities of the root nodes. This set of probabilities is estimated based on the EF provided by maintenance staff.

### B. Integration of symptoms on the causes

A symptom is the observed physical effect of a failure on the monitored system and reveals malfunction. A set of symptoms can be observed and their values can be a characteristic signature to help the identification of the cause. The relationship between symptom values and the state of root causes can be defined from expert knowledge and also from EF.

The relationship between a symptom (set of variables values) and a cause is considered as stochastic and can be defined as a Conditional Probability Table (CPT) in the BN dedicated to root cause isolation. If a symptom is independent to a cause, there is no new arc defined which reduced the graph complexity and also the computation. If an arc is defined then the realated conditional distribution is equiprobable. Only root causes are considered because a root cause implies its chain of consequences until the system failure node. So, it is not necessary to include the child variables in the relation with symptoms.

The symptom range values are discretized into several classes. These classes are exhaustive and exclusive. They can be defined automatically by a classification technique but usually by the system experts through a FMEA (failure modes and effects analysis) for instance. Figure 1 shows a BN example for cause isolation extended with three symptom nodes. To compute the probability distribution of a symptom $S_j$, a CPT is defined according to its parents $C_{ij}$. An

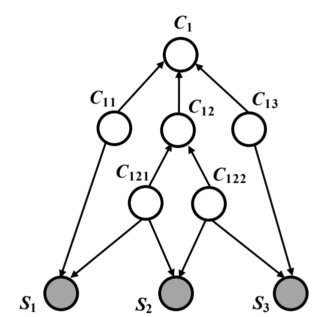


Fig. 1: Example of relationships between symptoms and causes

example of CPT is given in table I which allows to represent the relation between causes $C_{121}$, $C_{122}$ and symptom $\mathbf{S_2}$ (cf.figure 1). In table I, the symptom $S_2$ is described by three classes, respectively $\{S_2^1, S_2^2, S_2^3\}$. The CPT is defined by cartesian product of each input and output states *i.e* $|C_{121}|.|C_{122}|.|S_2|$ where $|x|$ is the cardinality of the set $x$. $\gamma_{ij}$ represents the probability distribution of the classes of the symptom $S_2^i$ given its causes $C_{ij}$.

TABLE I: Conditional Probability Table for node $S_2$

| *Causes* | | *Symptom* $S_2$ | | |
|---|---|---|---|---|
| $\mathbf{C_{121}}$ | $\mathbf{C_{122}}$ | $S_2^1$ | $S_2^2$ | $S_2^3$ |
| $\neg C_{121}$ | $\neg C_{122}$ | $\gamma_{11}$ | $\gamma_{12}$ | $\gamma_{13}$ |
| $\neg C_{121}$ | $C_{122}$ | $\gamma_{21}$ | $\gamma_{22}$ | $\gamma_{23}$ |
| $C_{121}$ | $\neg C_{122}$ | $\gamma_{31}$ | $\gamma_{32}$ | $\gamma_{33}$ |
| $C_{121}$ | $C_{122}$ | $\gamma_{41}$ | $\gamma_{42}$ | $\gamma_{43}$ |

If the causes are incompatible then only $\gamma_{21}$, $\gamma_{22}$, $\gamma_{23}$, $\gamma_{31}$, $\gamma_{32}$ and $\gamma_{33}$ are of interest.

### C. Estimation of posterior probabilities

As discussed in earlier sections, the use of EF plays a crucial role in the adjustment of the set of BN probabilities to improve the isolation process. Maintenance personnel continuously monitor various variables and systematically record the identified causes of failures.

The purpose of integration the EF data set is to refine the posterior probabilities, denoted as $\theta_{ij}$, based on the available information, whether it pertains to the root cause or observed symptoms.

$$\theta_{ij} = \frac{N_{ij}}{C_{ij}} \tag{2}$$

In this equation, $|N_{ij}|$ represents the number of instances (or lines) in which $C_{ij}$ is present, while $N_i$ corresponds to the total number of instances where the child of $C_{ij}$ is observed. It is important to note that this computation implicitly includes the entire causal chain that lead up to the top event. Equation 2 is applied at every level of the BN.

However, when the use of EF, equation 3 becomes less practical since it assumes the retention of the entire dataset, which can be computationally expensive.

$$\begin{cases} \theta_{ij}(k) = \frac{N_{ij}(k-1)+1}{N_i(k-1)+1} & \text{if } C_{ij} \text{ occurs} \\ \theta_{ij}(k) = \frac{N_{ij}(k-1)}{N_i(k-1)+1} & \text{if } C_{ik} \text{ occurs} \end{cases} \tag{3}$$

Here, $k$ represents the number of top events. The term $N_{ij}(k)$ tracks the number of occurrences where the top event implies $C_{ij}$, while $N_i(k)$ tracks the number of instances where $C_i$ is present.

At the same time, the CPT of symptoms given their causes is estimated. The off-line equation is given by eq. 4 whereas the on-line is given by eq.5.

$$\gamma_{ij} = \frac{M_{ij}}{\sum M_{ij}} \tag{4}$$

where $M_{ij}$ is the number of events in the dataset where symptom $S_x$ is in class $S_x^j$ and the set of its parent causes are in the related states (cf. line $i$ in table I).

If the whole dataset is not stored, a recursive computation can be made following eq. 5.

$$\begin{cases} \gamma_{ij}(k) = \frac{M_{ij}(k-1)+1}{\sum M_{ij}(k-1)+1} & \text{if } S_x = S_x^i \\ \gamma_{ij}(k) = \frac{M_{ij}(k-1)}{\sum M_{ij}(k-1)+1} & \text{if } S_x = S_x^k \end{cases} \tag{5}$$

where $M_{ij}(k)$ is the number of events in the dataset at system failure $k$ where symptom $\mathbf{S_x}$ is in class $S_x^j$ and the set of its parent causes are in the related state (cf. line $j$ in table I).

### D. Proposed methodology for failure cause isolation

Previous contribution aim to enhance the isolation process and provide valuable information for decision make. However, these contributions should be integrated into a usage scenario. This scenario outlines a methodology for the isolation failure causes based on system observations and update probability distributions through EF from cause isolation. The methodology is detailed in the algorithm 1. The proposed algorithm aims to identify the component (or combination of components) most likely responsible for the system failure. Beginning with an initial BN structure $\mathbf{G_0}$, maintenance personal input observed symptom signatures and the system failure state (represented by the top node) into the model. The Use of the BN's inference mechanism, the probabilities of root causes at the base level are then iteratively updated.

**Algorithm 1** Scenario of use

1. Configure the initial BN $\mathbf{G_0} = \langle N, A, (\mathbb{P}_c, \mathbb{P}_r^0)\rangle$ *i.e.* its structure and its initial probability set.
2. At the occurrence of a new failure,
   - 2.1. $k = k + 1$
   - 2.2. Introduce the signature of symptoms in $\mathbf{G_{k-1}}$ (set of their classes).
   - 2.3. Isolate the root or intermediate cause by the introduction of evidence following inspections in $\mathbf{G_k}$.
   - 2.4. Define the set of implied causes following the chain rule $C_{ij} \to C_i$.
3. Integrate the identified cause and the related symptom classes into the EF.
4. Definition of $\mathbf{G_k} = \langle N, A, (\mathbb{P}_c, \mathbb{P}_r^{k-1})\rangle$ allow to adjust the set of probabilities based on the identified cause:
   - 4.1. Estimation of the posterior probabilities $\theta_{ij}^{k-1}$ (cf. eq. 2 for off-line EF, eq. 3 for on-line feedback).
   - 4.2. Estimation of new $\mathbb{P}_r^{k-1} = p(C_{ij})$ by the optimization process.
   - 4.3. Estimation of the conditional probabilities $p(S_x|C_i)$ (cf. eq. 4 for off-line EF, eq. 5 for on-line EF)
5. Wait for a new system failure, go to step 2

## III. Application Case

In this section, the proposed methodology is implemented and validated through a specific application case. This case involves a deterministic causal graph derived from expert knowledge and a dataset consist of 363 recorded symptoms and related causes of failure events for the system under investigation. Figure 2 presents a simplified segment of the deterministic causal graph used in this application case.

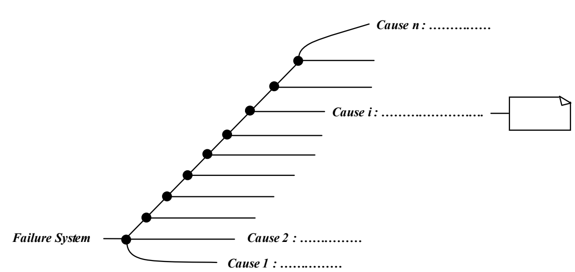


Fig. 2: Example of diagnostic causal graph

Figure 3 illustrates the BN equivalent to the deterministic graph used for demonstration purposes. In this example, ten primary causes are direct causes (nodes at level 1). $C_1$, $C_5$,

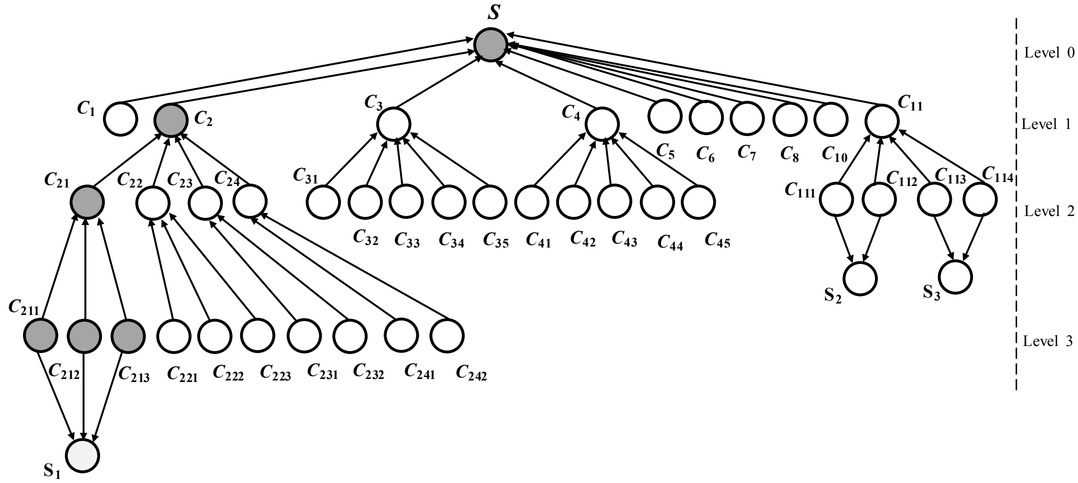


Fig. 3: Representation of equivalent BN

$C_6$, $C_7$, $C_8$, and $C_{10}$ are designated as root nodes and $C_2$, $C_3$, $C_4$, and $C_{11}$ are intermediate causes. The tree contains 30 root causes and four hierarchical levels. Some causes are not precisely described whereas 4 causes at level 1 are only intermediate causes. Cause $C_2$ is the best described. Three symptoms are considered. Symptom $S_1$ has 3 classes of values $\{Low, Medium, High\}$ and can help the isolation the cause among $C_{211}$, $C_{212}$ and $C_{213}$. Symptom $S_2$ (resp. $S_3$) is the consequence of $C_{111}$ and $C_{112}$ (resp. $C_{113}$ and $C_{114}$). The chain rule contains $C_2$ is exhibited in gray.

The algorithm 1 described in section II-D is utilized to identify the root cause of system failure and ensure the system's continued operation. When multiple causes are identified, they are isolated one at a time, with each cause being added to the dataset for further examination. Figure

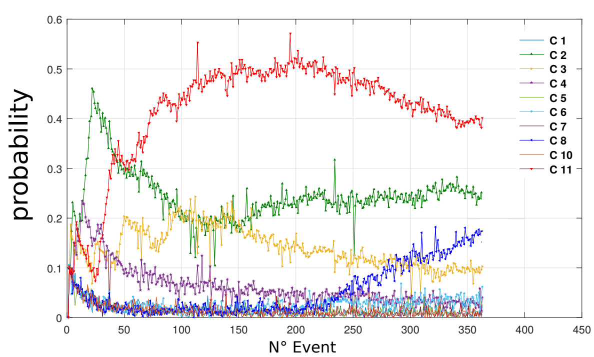


Fig. 4: $P(C_i|S)$ distributions for first level

4 presents the posterior estimated probability distribution $\hat{\theta}_i$ starts from equiprobability and evolves based on the EF. Because the causes are positioned at first level, the identification of any cause, be it intermediate or root, requires all causes that consider its chain rule. This explains why the curves show significant progression toward a final value, representation the asymptotic distribution. Nevertheless, after 363 events the asymptotic values seem not obtained. New failure causes isolated are needed for the convergence toward the real probability distribution. As depicted in figure 4 highlights that $C_{11}$ is the most probable reason for the system failure, with a likelihood of 0.398. In contrast, the probabilities for causes $C_1$, $C_7$ et $C_{10}$ are zero. This is attributed to the fact that these causes have never triggered the occurrence of the Undesirable Event (system failure) and are absent from the feedback dataset provided by the maintenance agent.

Similar to previous cases, figure 5, present the sequence of causes remains mostly consistent, with only slight fluctuations noted among $C_{22}$, $C_{23}$ and $C_{24}$. Despite these variations, the system ultimately converges to the same final distribution. At the second level (cf. Fig. 5), when cause $C_2$ is

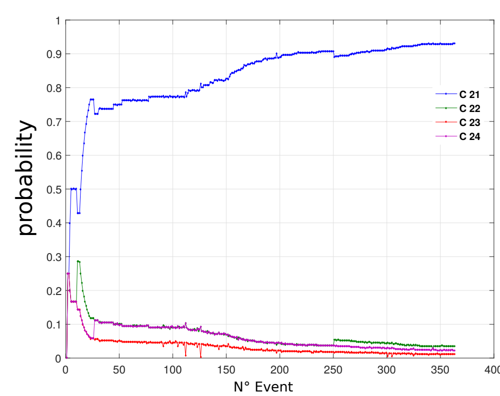


Fig. 5: $P(C_{2x}|C_2)$ distributions for second level

active, the estimated probability of $C_{21}$ is 0.964,establishing it as the most probable cause associated with $C_2$.

Figure 6 shows the propagation of the root cause within the chain rule of $C_{21x}$. Given the limited data set at this level, the probability pattern evolves slowly, displaying a staircase like progression. While it is less certain whether feedback contributes significantly to reaching the final distribution, the distinct differences in probabilities highlight the relative importance of each root cause. This information supports

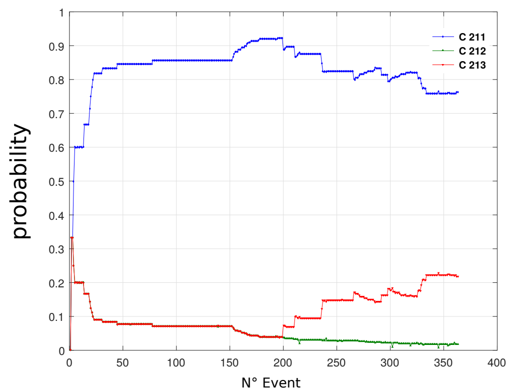


Fig. 6: $P(C_{21x}|C_{21})$ distributions for level 3

the determination of the optimal inspection order. Start with equal probabilities, the posterior distributions evolve to align with the actual likelihoods of individual causes. As depicted in Figure 6, the probability of the cause is 0.785, marking it as the most probable contributor to the appearance of $C_{211}$ .

The EF dataset is also used to estimate the CPTs for symptoms based on the causes. The result of BN allows us to determine, for each inspection, the main factor contribution of to system failure. Shortly before system failure occurs, a set of physical variables is monitored. The integration of symptom data, the isolation process of root causes becomes more effective, ambiguity reduction and the identification improvement of the most probable causes.

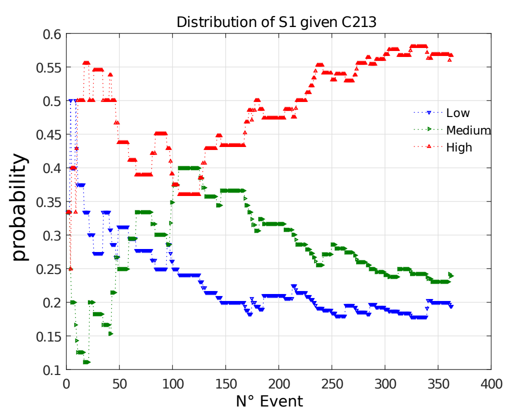


Fig. 7: Evolution of $\hat{\gamma}_{3.} = p(S_1|C_{213})$

The coefficients $\gamma_{ij}$ which model the relationship between causes and symptoms, are estimated by the analysis of the dataset. Estimators are employed to determine the probability distributions of the symptom classes $S_{ij}$ based on their related causes $C_{ij}$. Within this framework, eqs 4 and 5 are applied. Figure 7 displays the estimated values of the conditional distribution of $S_1$ given $C_{213}$ computed from the dataset each time an event occurs. The distribution displays a staircase form, which arises due to the discrete nature of the occurrences of $C_{213}$. This behavior reflects how the dataset captures the evolve of relationship between the cause $C_{213}$ the symptom $S_1$, highlight the dependency of the symptom's probability distribution on the frequency and time of the cause's occurrence.

Around the $125^{th}$ event, the order of classes is stable and it means that $C_{213}$ usually induces the medium class of $S_1$. Figure 8 shows the estimated values of the conditional distribution of $C_{21x}$ given $S_1 = High$ at each event occurrence. It is interesting to see that the order of values changes during the EF. Starting with $C_{211}$ as the maximum likelihood, $C_{213}$ becomes the main cause if the symptom $S_1$ remains high.

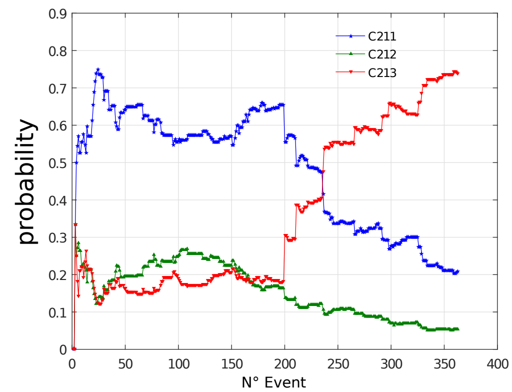


Fig. 8: Evolution of $\hat{\theta}_{21.} = p(C_{21x}|C_{21}, S_1)$

Figure 9 shows the evolution of cause probabilities $p(C_{211}|C_{21})$, $p(C_{212}|C_{21})$ and $p(C_{213}|C_{21})$ compared to the evolution of cause probabilities $p(C_{211}|C_{21}, S_1)$, $p(C_{212}|C_{21}, S_1)$ and $p(C_{213}|C_{21}, S_1)$. As clearly shown after the $240^{th}$ event, the knowledge of the symptom state $S_1$ changes the most implicant cause in the system state. The symptom helps to discriminate of the root cause $C_{21x}$.

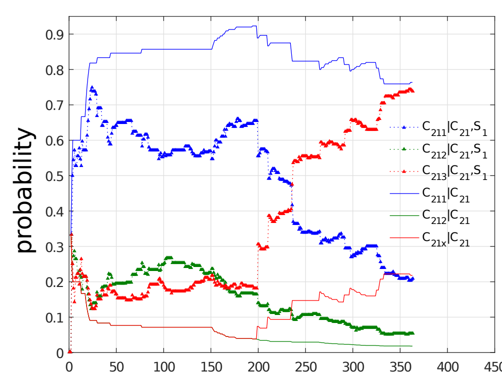


Fig. 9: Comparison of $p(C_{21x}|C_{21})$ and $p(C_{21x}|C_{21}, S_1)$ distributions

As illustrated in the previous figures (cf. Figs 4-9), real time estimation of the relationships between causes and their associated symptoms enables the identification of a unique signature (a specific set of symptom values) that enhances the precision and effectiveness of determination of the probable cause of system failures. The comprehension of these symptom values not only clarifies the cause but also impacts the entire probability distribution within the BN, which allow to improve the isolation process. This approach enables maintenance staff to accurately identify the cause of the failure more efficiently, thereby reduction of downtime and improvement of the availability and reliability of the monitored system.

## IV. Conclusion

This article presents a probabilistic approach designed to support diagnostic processes. The proposed method is based on a Bayesian network (BN) model, whose structure is derived from the transformation of a deterministic (not-probabilistic) tree provided by a system expert. Over time, experience feedback dataset are used to regularly update the model's probabilities using Bayesian theory.

Several features make this approach an effective and preferable solution for the case study compared to other models:

- The proposed BN model integrates and merges various types of knowledge within a single framework, including feedback (historical or empirical data), expert knowledge, and observations (symptoms).
- The algorithm is explicit and easy to understand, even for non-specialists, which makes the model more accessible and practical.
- Knowledge utilization is versatile: the same BN model can be used to evaluate, isolate, and diagnose probable causes of failure, as well as to optimize maintenance decisions.

A fundamental aspect of the proposed methodology is the integration of symptom data linked to failure causes. This integration aims to refine the isolation process by the reduction of ambiguity in the determination of the root causes of observed system behaviors. By the acceleration of diagnostic and the increase of accuracy in fault isolation, the approach ultimately enhances the monitored system's availability and reliability

The dataset from the monitored system demonstrated the performance of the proposed methodology. However, certain assumptions, such as the occurrence of only one cause at a time, could be reconsidered to better reflect real-world scenarios, even though maintenance teams currently operate under this assumption. Similarly, the condition of exhaustive causes, which assumes all potential causes are accounted for, is debatable and could be refined to improve the isolation process further.

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