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# Improving fault diagnosis efficiency by integrating FMEA and FTA in a compact fault signature matrix

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Complex systems have an integrated architecture that leads to non-trivial interdependencies between components. Any fault in such a system can impact other components, reducing system performance. While most existing methods can detect process abnormalities and component faults, they often fail to identify root causes. In response, this study presents a fault diagnosis framework based on domain-specific knowledge. The framework enhances root cause identification by leveraging expert insights, maintenance logs, and/or other documented knowledge. The proposed method integrates this knowledge through a structured approach. First, a Failure Mode and Effects Analysis (FMEA) is conducted to determine the most critical failure modes and associated fault symptoms for each component. Second, a Fault Tree Analysis (FTA) is used to reveal dependencies between components. The resulting information is used to construct an improved Fault Signature Matrix (FSM) that captures individual failures and their system-level dependencies. In this way, people with and without knowledge can use this tool to investigate failure causes after detecting malfunctions. The proposed methodology is applied to a ship propulsion technology, providing information on the parameters required to diagnose the state of the system.

*Keywords*: Root cause analysis, diagnosis, fault signature matrix, fault detection and identification, knowledge-based, ship propulsion, internal combustion engine

## 1. Introduction

The demand for greater functionality in today's world drives the increasing complexity of engineered systems. Modern systems feature a greater number of components along with intricate interdependencies (Krishnan and Bhada, 2020; Jia et al., 2020). While these complex architectures are designed to address real-world problems, they also introduce significant challenges in ensuring system reliability. Achieving high availability and reliability requires an optimal fault diagnosis process (Soleimani et al., 2021). Consequently, this is a critical area of study; understanding fault characteristics is essential to ensure consistent performance without failure over a specified period.

The fault diagnosis process consists of three tasks: fault detection, isolation, and identification (Marra et al., 2016). These tasks determine whether a fault has occurred, where it has occurred, and identify its root cause, respectively. An effective fault diagnosis process is vital for preventing catastrophic consequences, especially in high-risk applications such as transportation, energy, and manufacturing.

Over the past years, various approaches have been explored. These include model-based, data-driven, and knowledge-based methods (Tinga, 2013; Peng et al., 2021). Although they have contributed to fault diagnosis, their application in modern systems is hindered by some limitations.

Model-based approaches struggle to represent complex systems accurately due to intricate physical interactions. Data-driven methods, reliant on extensive high-quality datasets, are limited by data scarcity in new systems and their inability to diagnose faults not represented in training datasets (Silveira et al., 2023; Keizers et al., 2024). Knowledge-based methods, though promising, remain underutilized despite their foundation in physical principles, documented knowledge, and operator experience. These methods excel at identifying critical monitoring parameters and their optimal locations, offering a potential advantage in systems closely monitored by human operators (Tinga and Loendersloot, 2014).

One method often used in reliability and safety analysis is the Fault Signature Matrix (FSM); its rows represent specific faults, while its columns indicate the observed symptoms (Arsie et al., 2010; Polverino et al., 2015). When a fault occurs, the entries in the associated symptom vector are assigned a value of one; otherwise, they remain zero. The FSM is valuable in ensuring system reliability in complex systems, as it streamlines the fault detection and isolation process. However, there is another crucial aspect of fault diagnosis: fault identification. That is why current research efforts are focused on addressing this aspect. Integrating root cause identification into the FSM framework offers a promising solution. This enhancement would extend the FSM capabilities beyond fault detection and isolation, enabling it to identify the underlying causes of system failures – a critical need in fault diagnosis practices.

Bond Graphs (BG) are robust tools for modeling physical systems in model-based approaches. BGs represent system structure and causal properties through bonds (half arrows) connected to elements, enabling the derivation of Analytical Redundancy Relations (ARRs). These ARRs, in turn, support FSM construction. Although the literature extensively explores BG development, recent research focuses on enhancing its practical use. For instance, Termeche et al. (2018) addressed non-unique fault signatures in FSMs by combining BG model outputs with actual system measurements, generating additional ARRs for unique signatures. Similarly, Rijsdijk et al. (2024) employed BGs to derive ARRs encapsulating system causality, which were subsequently used to construct FSMs. Their study noted the challenges of representing system causality and the resource-intensive nature of modeling complex systems.

In knowledge-based methods, the approach typically taken is failure analysis, which focuses on identifying failure modes and their symptoms. For example, Arsie et al. (2010) applied Fault Tree Analysis (FTA) to a Solid Oxide Fuel Cell (SOFC) system, identifying critical failures and organizing findings into an FSM. While effective for fault detection and isolation, this method cannot identify root causes. Building on this work, Yousfi Steiner et al. (2012) extended the analysis by including additional failure modes, but root cause identification remains a challenge.

Consequently, the present study emphasizes the importance of knowledge-based methods in addressing gaps in root cause identification, a critical step often overlooked in fault diagnosis. The above-mentioned approaches mainly focus on individual diagnosis, with consideration for fault detection and isolation. However, the diagnostic process does not end there. This process also involves identifying the actual cause of the failure, for which collective aspects and not just individual diagnosis must be considered. This gap motivates the current research, which extends the traditional FSM to improve root cause identification and enhance the overall diagnosis process.

The remainder of this paper is organized as follows. Section 2 presents the proposed FSM framework. Section 3 illustrates the approach using a marine combustion engine system. Section 4 discusses the practical impact and future work. Section 5 is reserved for concluding remarks.

## 2. Method

The technical framework of this paper builds upon the traditional approach to constructing the signature matrix. The present approach includes two phases: failure analysis and interaction analysis. The latter is the novel contribution to studying the interdependencies among system components before constructing the FSM. This study defines system dependencies to understand how individual failures can impact the overall system rather than just performing a failure analysis as in the traditional approach. An overview of the methodology is depicted in Figure 1.

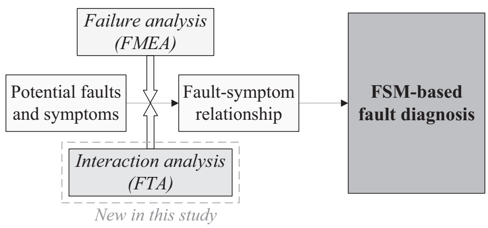


Fig. 1. Overview of the stages of the framework.

The resulting framework uses already-known methods to leverage and integrate available experience and knowledge. Accordingly, a Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA) are used for failure and interaction analysis, respectively. The proposed steps for such analyses are detailed in Figure 2.

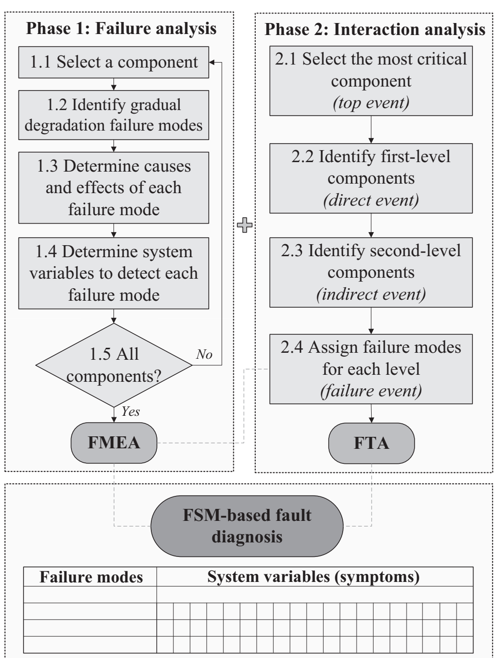


Fig. 2. Overview of phases and steps in the proposed FSM framework.

## 2.1. *Failure analysis*

Failure analysis is performed using FMEA. It is a bottom-up approach employed to identify potential failure modes. The analysis starts at the component level, systematically tracing the potential consequences of failures to higher system levels (Tinga, 2013). FMEA leverages expertise from different backgrounds to estimate potential failures accurately.

The steps of this analysis are outlined in Figure 2. It is worth noting that the proposed methodology introduces a column dedicated to detecting observed failure modes (step 1.4). This addition, uncommon in conventional FMEA, aims to generate a unique signature for each observed failure mode. Specifically, if each identified failure mode can be uniquely detected, the corresponding detection signature will be distinct.

## 2.2. *Interaction analysis*

While the above analysis identifies relevant failure modes, it remains limited by one fact: system interactions. FMEA assumes independent failure modes, which overlooks dependencies between system components. Component dependencies are critical in fault diagnosis in complex systems, as they describe how one component relies on another to work properly. These interactions often introduce cascading effects that are not captured by traditional failure analysis methods such as FMEA. Hence, incorporating dependencies into failure analysis not only improves fault diagnosis accuracy but also enhances system reliability.

This study addresses this challenge by incorporating system dependencies into failure analysis. Specifically, FMEA is integrated with FTA to capture dependency relationships between system components. This integration enables the construction of an improved FSM capable of evaluating the different ways a component of interest may fail. FTA displays hierarchical failure relationships and identifies component dependencies.

The proposed steps are detailed in Figure 2. The procedure categorizes components hierarchically. The critical component represents the core unit of the system. First-level components directly influence the critical component. Second-level components indirectly affect the critical component by first influencing the first-level components.

## 3. Case study

### 3.1. *Motivation*

The proposed methodology is illustrated using a marine internal combustion engine (ICE). This system is considered complex due to the following reasons: (1) the ICE is a large-scale system with multiple components; (2) the operation of the ICE relies on intricate mechanical and thermodynamic processes; and (3) the complex architecture of the system increases the chances of cascading failures, meaning that a failure in one component can be the result of multiple interacting factors. Considering these factors, the marine ICE aligns well with the purpose of the present study.

### 3.2. *Layout*

The system layout used is shown in Figure 3.

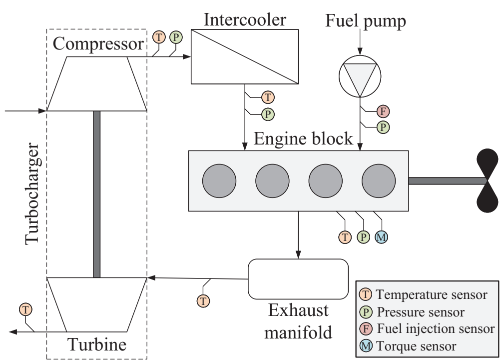


Fig. 3. A marine ICE system scheme. Adapted from Kougiatsos and Reppa (2022).

It is seen that other components surround the engine (block); the most important are the turbocharger (comprising the turbine and air compressor), intercooler, fuel pump, and exhaust manifold. On the air side, the compressor draws ambient air and delivers it to the intercooler. The latter cools the compressed air before supplying it to the engine. On the fuel side, the fuel pump supplies fuel to the engine injectors; fuel delivery timing and quantity are critical for optimal performance and efficiency. Within the engine, the air from the intercooler and the fuel from the injectors are combined in the combustion chamber. This mixture is ignited (via compression or spark, depending on the engine type), generating power to drive the crankshaft. Finally, the exhaust manifold collects the exhaust gases from the engine cylinders; these gases are used to drive the turbine, which ultimately powers the compressor.

### 3.3. *Phase 1: Failure analysis*

The most relevant failure modes within the ICE system are analyzed below and summarized in Figure 4. It should be noted that this analysis aims to identify the various factors that can lead to engine block failure. Failures in the engine block may result from issues such as valve failures, cylinder leakage, or blockage; however, this study refers to as "engine failure," as this simplification is sufficient to illustrate the concept. The reason why this approach is followed is because the engine is the critical component of the system. In fact, when a decrease in system performance is detected, the first component to be evaluated is the engine block. Consequently, this analysis examines the typical failures that may occur in the components of this system with high frequency and significant influence so that the diagnosis of these is of engineering importance to prevent damage to the engine sub-unit.

**Turbocharger** Air leaks are a common issue in the turbocharger subsystem. Insufficient air supply to the cylinders could significantly affect the operation of the engine block due to improper combustion process. Furthermore, fouling of compressor surfaces is another critical gradual process. After some hours of operation, fouling may occur, leading to excessive resistance to airflow. Environmental conditions can also exacerbate deposit accumulation, reducing compressor efficiency. Finally, fouled turbine blades are also a concern. High-temperature exhaust gases are the primary cause of this problem. Inadequate preventive maintenance allows deposits from combustion to accumulate on the turbine. This reduces turbine efficiency, which impairs the conversion of exhaust gas energy into mechanical energy. As a result, the turbine cannot adequately power the air

| Component | Ref. No. | Failure mode | Failure cause | Failure effect | Detection |
|---|---|---|---|---|---|
| 1. Turbocharger | 1.1 | Air leaks in compressor system | Loose fittings, seal problems<br>Worn/damaged hoses, joins or connectors | Reduced compressor efficiency | Decrease in compressor pressure |
| | 1.2 | Fouled surfaces in compressor | Build-up of unwanted materials which leave the surface of the compressor blades rough<br>Pollutants entering the compressor system and a range of environmental conditions (fog, humidity) | Excessive airflow resistance, reducing compressor efficiency | High temperature at compressor outlet |
| | 1.3 | Fouled turbine blades | Blades contaminated with layer deposits from an incomplete combustion process | Excessive exhaust gas flow resistance, reducing turbine efficiency and increasing fuel consumption | Decrease in pressure of exhaust gases |
| 2. Intercooler | 2.1 | Leaking hoses | Worn-out or damaged hoses | Rise in temperature entering the engine cylinders | Decrease in intercooler pressure |
| | 2.2 | Blocked intercooler | Fouling at the air side<br>Intercooler clogged with debris on the outside | Insufficient airflow and ineffective cooling | High temperature at intercooler outlet |
| 3. Fuel pump | 3.1 | Failure to adjust fuel supply | Failed pump, clogged filter, or blocked fuel line | Incomplete combustion process | Low fuel injection supply |
| | 3.2 | Failure to create pressure | Impeller get corrosion and erosion | Decreased fuel efficiency due to more power consumption | Decrease in pump pressure |

Fig. 4. Failure Mode and Effects Analysis (FMEA) for a marine ICE system.

compressor, further affecting system performance.

**Intercooler** An efficient combustion process relies heavily on maintaining optimal system temperatures. Hence, an intercooler is used to prevent excessive temperatures in the ICE module. A reduction in cooling efficiency is often related to leaking hoses and blocked intercoolers. On the one hand, leaking houses, typically due to worn and damaged hoses, result in low air supply to the cylinders. On the other hand, a blocked intercooler can also significantly increase air and exhaust gas temperatures. Both issues lead to inefficient combustion process within the cylinders. Consequently, detecting fouling levels at an early stage is highly recommended.

**Fuel pump** Insufficient fuel delivery is a critical issue within the fuel delivery system. This is often caused by a faulty pump or a blocked fuel line, leading to several performance and efficiency issues. Inadequate fuel delivery disrupts the air-fuel ratio, resulting in incomplete combustion; this reduces power output and increases emissions. Similarly, an increase in fuel consumption is also caused by inadequate fuel delivery, as it forces the engine to consume more fuel to maintain the desired performance. Finally, insufficient fuel pressure due to corrosion and erosion in the impeller causes a decrease in fuel efficiency.

### 3.4. *Phase 2: Interaction analysis*

This phase identifies the most important dependencies among ICE components. The FTA for this case study is shown in Figure 5.

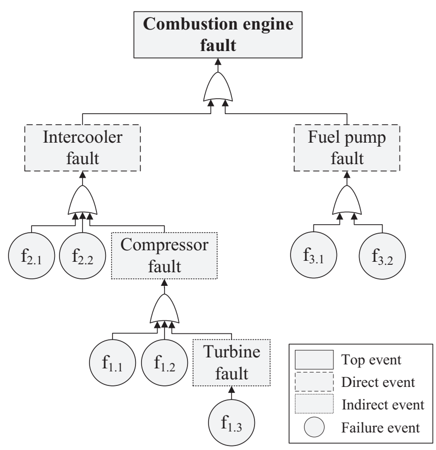


Fig. 5. A Fault Tree Analysis (FTA) to illustrate the direct and indirect dependencies that relate to a particular damage in the engine unit. The labels of the failure events refer to the fault numbers in Figure 4.

The first-level components identified are the intercooler and the fuel pump. The second-level components include the compressor and the turbine, forming the turbocharger subsystem. Note that the exhaust manifold does not appear in this categorization as it is supposed that it does not affect the engine but only the turbine side. This is because the high-velocity exhaust gases only go directly to the turbine blades. Once the components are categorized, the previously identified failure modes can be assigned to each component. The FTA shows that a functional failure in any component leads to either immediate or delayed degradation of the engine block. Therefore, the key takeaway from this analysis is that considering system interactions prior to constructing the FSM is essential for root cause identification.

### 3.5. *FSM construction*

The sensor variables to monitor the ICE system are presented in Table 1. The sensors provide direct measurements, except for the torque sensor, which enables indirect monitoring of engine power. Furthermore, the distinction between $s_3$ and $s_4$ is based on the severity of the observed deviation. Specifically, $s_3$ represents a gradual deviation from normal operating power, whereas $s_4$ indicates a sudden and significant drop in engine power. This distinction is essential, as failure modes affect engine power in different ways.

Table 1. Set of monitored symptoms.

| | Symptoms | Sensor |
|---|---|---|
| 1 | Increase in engine temperature | T |
| 2 | Increase in fuel consumption | F |
| 3 | Gradual reduction in engine power | M |
| 4 | Sudden and significant drop in engine power | M |
| 5 | High temperature at turbine outlet | T |
| 6 | Decrease in compressor pressure | P |
| 7 | High temperature at compressor outlet | T |
| 8 | High temperature at intercooler outlet | T |
| 9 | Decrease in intercooler pressure | P |
| 10 | Low fuel injection supply | F |
| 11 | Decrease in pump pressure | P |
| 12 | High temperature of exhaust gases | T |

The FSM matrix is presented in Figure 6, where $f$ stands for faults, and $s$ for symptoms. It considers seven system faults that impact engine performance: three related to the turbocharger, two to the intercooler, and two to the fuel pump. The sensors used for system monitoring are assumed to be free from damage.

Air leaks ($f_{1.1}$) are detected by a decrease in compressor pressure ($s_6$). Similarly, compressor fouling ($f_{1.2}$) and turbine fouling ($f_{1.3}$) are detected by monitoring the compressor outlet temperature ($s_7$) and turbine outlet temperature ($s_5$), respectively. These faults lead to high engine temperatures ($s_1$), increased fuel consumption ($s_2$), and gradual reduction in engine power ($s_3$). The latter manifests as a sudden drop in power ($s_4$) when dealing with reduced airflow in the system.

Intercooler faults, such as leaking hoses ($f_{2.1}$) or blocked intercoolers ($f_{2.2}$), can be detected by measuring the intercooler outlet pressure ($s_9$) and outlet temperature ($s_8$), respectively. The effects on the engine are similar to those caused by turbocharger faults. A reduced cooling efficiency leads to potential overheating, which is associated with increased engine and exhaust gas temperatures ($s_1$, $s_{12}$), indirectly affecting combustion quality and power output ($s_3$, $s_4$).

Fuel pump failures, including insufficient fuel supply ($f_{3.1}$) and inadequate pressure ($f_{3.2}$), are detected through reduced fuel injection supply ($s_{10}$) and decreased pump pressure ($s_{11}$), respectively. These faults lead to common consequences, including increased fuel consumption ($s_2$) and elevated engine temperatures ($s_1$). Additionally, insufficient fuel delivery causes a sudden drop in power output ($s_4$).

These insights lead to the FSM in Figure 6, revealing that a set of unique signatures is obtained.

## 4. Discussion

### 4.1. *Practical impact*

The approach presented follows the conventional procedure for constructing FSMs based on knowledge-based methodologies. The improved FSM retains its suitability for fault detection and isolation but integrates FTA to identify root causes of engine block damage. Instead of focusing solely on failure analysis, this study focuses on understanding how individual component faults impact overall system performance. It attributes engine problems to specific components and uncovers the root causes of typical failures. Hence, this improvement should not be seen as including more failure modes or symptoms but rather as

| | | Traditional FSM | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Increase in engine temperature | Increase in fuel consumption | Gradual reduction in engine power | Sudden drop in engine power | High temperature at turbine outlet | Decrease in compressor pressure | High temperature at compressor outlet | High temperature at intercooler outlet | Decrease in intercooler pressure | Low fuel injection supply | Decrease in pump pressure | High temperature of exhaust gases |
| **Failure modes** | | $s_1$ | $s_2$ | $s_3$ | $s_4$ | $s_5$ | $s_6$ | $s_7$ | $s_8$ | $s_9$ | $s_{10}$ | $s_{11}$ | $s_{12}$ |
| ***Turbocharger*** | | | | | | | | | | | | | |
| Air leaks in compressor system | $f_{1.1}$ | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Fouled surfaces in compressor | $f_{1.2}$ | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Fouled turbine blades | $f_{1.3}$ | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ***Intercooler*** | | | | | | | | | | | | | |
| Leaking hoses | $f_{2.1}$ | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| Blocked intercooler | $f_{2.2}$ | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| ***Fuel pump*** | | | | | | | | | | | | | |
| Failure to adjust fuel supply | $f_{3.1}$ | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| Failure to create pressure | $f_{3.2}$ | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |

Fig. 6. Fault Signature Matrix (FSM) for a marine ICE system.

associating root causes to specific components.

As highlighted in Figure 6, a traditional FSM approach would include only symptoms 1-4, as these are directly associated with engine block failure. In a more advanced approach, it may also include symptoms 8-11, which represent the subsystems directly connected to the engine (direct events in Fig. 5). The key addition of the improved FSM is the incorporation of indirect events (symptoms 5-7, 12). These enable the identification of root cause for events that otherwise could only be detected. For simplicity, this study assumes that arbitrarily chosen deviations from nominal values serve as fault symptoms. In real-world applications, the actual deviation threshold must be defined to classify a condition as a fault symptom.

Other subsystems, such as the lubrication loop, can also be implemented, and the methodology is still applicable. The authors acknowledge that complexity was not a significant factor in this case study. However, complexity may play a role in other cases. Therefore, the methodology should be applied to more complex systems. Still, this work is structured with specific steps to ensure broader applicability across diverse system architectures.

Future enhancements involve accounting for additional failure modes. While incorporating more failure modes increases the likelihood of repetitive fault signatures, the current work addresses this issue by including a detection column in the failure analysis (step 1.4 in Fig. 2). If a unique detection is guaranteed for each detected failure mode, the failure signature will be unique. In this example, the method has resulted in unique signature matrices, enhancing the robustness of the diagnosis process. However, for faults $f_{1,1}$ and $f_{1,3}$, robustness relies on retaining $s_5$ and $s_6$, as their omission may result in repetitive signatures. Increasing the number of sensors can also help generate unique failures, though this depends on the real-world constraint for sensor placement.

Finally, this work also offers valuable insights for optimizing sensor architecture. The proposed methodology implicitly evaluates which sensors should be integrated to improve system representation and diagnostic capabilities. While the process may seem straightforward, it encourages both experienced and inexperienced practitioners to critically assess and determine the most effective sensor architecture for diagnosing faults.

### 4.2. *Future work*

One key challenge in fault diagnosis is the representation of causality. Unfortunately, the current FSM framework cannot explicitly capture causal relationships within the system. These causalities, often embedded in the interactions between components, are essential to achieve a more robust and insightful diagnostic process.

Additionally, the FSM analyzed in this work is purely diagnostic in nature. That is why current research efforts increasingly emphasize the importance of integrating prognostics. Estimating fault propagation paths in complex systems is a particularly pressing issue, as it enables proactive maintenance strategies. The intricate cause-effect relationships in such systems pose challenges for tool construction and interpretation, especially for practitioners with limited system expertise.

As a result, the authors are actively exploring ways to enhance the presented FSM framework. Specifically, efforts are focused on integrating fault propagation insights while preserving root cause identification capabilities. This ongoing research builds on the present study's key findings, aiming to develop a more comprehensive and practical diagnostic and prognostic tool.

## 5. Conclusion

This study examines fault diagnosis with a focus on enhancing root cause identification. An improved FSM based on a knowledge-based approach is presented. The FSM is constructed using failure information while accounting for system interactions. Incorporating these interactions has proven beneficial for improving root cause identification. The developed method is applied to a marine ICE. The proposed approach identifies seven causes of engine subsystem failures without the need for additional sensors.

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## References

Arsie, I., A. Di Filippi, D. Marra, C. Pianese, and M. Sorrentino (2010). Fault Tree Analysis Aimed to Design and Implement On-Field Fault Detection and Isolation Schemes for SOFC Systems.

Jia, L., Q. Gao, Z. Liu, H. Tan, and L. Zhou (2020). Multidisciplinary fault diagnosis of complex engineering systems: A case study of nuclear power plants. *International Journal of Industrial Ergonomics 80*, 103060.

Keizers, L., R. Loendersloot, and T. Tinga (2024). Towards a Hybrid Framework for Prognostics with Limited Run-to-Failure Data. *PHM Society European Conference 8*(1), 12.

Kougiatsos, N. and V. Reppa (2022). A distributed virtual sensor scheme for marine fuel engines. *IFAC-PapersOnLine 55*(31), 333–338.

Krishnan, R. and S. Bhada (2020). An Integrated System Design and Safety Framework for Model-Based Safety Analysis. *IEEE Access PP*, 1–1.

Marra, D., C. Pianese, P. Polverino, and M. Sorrentino (2016). *Models for Solid Oxide Fuel Cell Systems*. Springer London.

Peng, J., J. Huang, X.-l. Wu, Y.-w. Xu, H. Chen, and X. Li (2021). Solid oxide fuel cell (SOFC) performance evaluation, fault diagnosis and health control: A review. *Journal of Power Sources 505*, 230058.

Polverino, P., C. Pianese, M. Sorrentino, and D. Marra (2015). Model-based development of a fault signature matrix to improve solid oxide fuel cell systems on-site diagnosis. *Journal of Power Sources 280*, 320–338.

Rijsdijk, C., M. Van De Wijnckel, and T. Tinga (2024). Maturity framework for data driven maintenance. *PHM Society European Conference 8*(1).

Silveira, N., A. Meghoe, and T. Tinga (2023). Integration of multiple failure mechanisms in a life assessment method for centrifugal pump impellers. *Advances in Mechanical Engineering 15*(6).

Soleimani, M., F. Campean, and D. Neagu (2021). Diagnostics and prognostics for complex systems: A review of methods and challenges. *Quality and Reliability Engineering International 37*(8), 3746–3778.

Termeche, A., D. Benazzouz, B. O. Bouamama, and I. Abdallah (2018). Augmented analytical redundancy relations to improve the fault isolation. *Mechatronics 55*, 129–140.

Tinga, T. (2013). Principles of loads and failure mechanisms. *Springer Series in Reliability Engineering*.

Tinga, T. and R. Loendersloot (2014). Aligning PHM, SHM and CBM by understanding the physical system failure behaviour. *PHM Society European Conference 2*(1).

Yousfi Steiner, N., D. Hissel, P. Moçotéguy, D. Candusso, D. Marra, C. Pianese, and M. Sorrentino (2012). Application of Fault Tree Analysis to Fuel Cell diagnosis. *Fuel Cells 12*(2), 302–309.