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AI-DRIVEN DEVELOPMENT OF MARINE ENGINE DIAGNOSTICS.

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ABSTRACT: Effective fault diagnosis is essential for the safe and efficient operation of marine slow-speed diesel engines. Readily accessible diagnostic tools are crucial for maritime engineers to maintain these complex systems. Traditional development of such tools often depends on extensive manual knowledge elicitation from experts, a time-consuming and resource-intensive process. This research investigates the automated generation of a fault-finding system using simulated data, leveraging the capabilities of Large Language Models (LLMs) and diagramming tools.

The objective is to automate the development of a diagnostic system for marine diesel engines, eliminating the need for manual expert input. The study addresses the inefficiencies of traditional methods by demonstrating the feasibility of using LLMs and diagramming tools to generate diagnostic logic directly from simulated engine fault data. By automating knowledge extraction, logic generation, and visualization, this approach aims to create a more efficient and consistent method for developing diagnostic tools.

Using the Kongsberg engine room simulator, a comprehensive dataset of fault scenarios was generated. Simulated faults—such as piston ring wear and fuel valve choking—were linked to changes in key engine parameters (e.g., SPEED, INDEX, MIP). These data were used to generate prompts for an LLM, which produced diagnostic rules and decision logic. The logic was then translated into visual diagrams using tools like Mermaid.js and PlantUML. Automated evaluation against the simulated data assessed the system's diagnostic accuracy.

The results demonstrated that the automated process could generate a comprehensive and accurate fault-finding system. The system effectively captured relationships between fault conditions and parameter changes, significantly reducing development time and effort compared to traditional methods. The consistency and clarity of the generated diagrams enhanced usability, and the high fault identification rate validated the approach's effectiveness.

This research highlights the potential of AI-assisted automation to transform diagnostic tool development in maritime engineering. The approach offers substantial benefits in efficiency, consistency, and scalability. Future work will incorporate real-world engine data and structured participant feedback to enhance robustness and generalizability. The methodology also lays the groundwork for benchmarking against expert-developed systems and integrating probabilistic reasoning and explainable AI (XAI) to improve transparency and interpretability. This technology holds promise not only for operational diagnostics but also for educational applications and broader adoption in other complex technical domains.

Keywords: *Automated Fault Diagnosis, Large Language Models (LLMs), Marine Diesel Engines, Simulation, Diagram Generation*

INTRODUCTION

Effective fault diagnosis is essential for the safe and efficient operation of marine slow-speed diesel engines. Traditional diagnostic methods rely heavily on manual knowledge elicitation from experts, which is both time-consuming and resource-intensive (Patil & Theotokatos, 2023). Given the increasing complexity of marine engines and the need for timely fault detection, there is a growing interest in exploring automated diagnostic systems. This study leverages Large Language Models (LLMs) and diagramming tools to automate the generation of fault-finding systems directly from simulated data, aiming to streamline the development process and enhance diagnostic accuracy (Tsitsilonis et al., 2023).

The significance of this study lies in its potential to revolutionize the development of diagnostic tools for marine diesel engines. By automating the creation of fault-finding systems, the research addresses the inefficiencies and resource demands of traditional methods (Panda, 2021). Consequently, the automated approach promises to reduce development time, improve consistency, and provide maritime engineers with a valuable resource for maintaining complex marine engines (Tsitsilonis et al., 2023). Furthermore, the findings could have broader implications for other technical domains, offering a more efficient and reliable method for developing diagnostic systems.

The primary purpose of this study is to automate the development of a fault-finding system for marine diesel engines, eliminating the need for manual expert knowledge elicitation (Patil & Theotokatos, 2023). Specifically, the research aims to demonstrate the feasibility and effectiveness of using LLMs and diagramming tools to automatically generate diagnostic logic directly from simulated engine fault data (Tsitsilonis et al., 2023). By automating the knowledge extraction, logic generation, and visualization processes, the study seeks to create a more efficient and consistent approach to developing diagnostic tools (Panda, 2021). This study also aims to explore the practical integration of AI-generated diagnostic tools into real-world marine operations and training environments, emphasizing the need for structured validation and ethical compliance. It also explores the integration of ensemble AI models and uncertainty quantification to improve diagnostic robustness, particularly in ambiguous or compound fault scenarios.

Traditional methods of developing diagnostic systems for marine diesel engines are inefficient and resource-intensive, relying heavily on manual knowledge elicitation from experts (Patil & Theotokatos, 2023). This approach is time-consuming and often inconsistent, posing significant challenges for maritime engineers who need reliable diagnostic tools to maintain complex marine engines (Tsitsilonis et al., 2023). Therefore, the problem addressed by this research is the need for a more efficient and consistent method to develop fault-finding systems, leveraging AI and automated processes.

To address these challenges, the study poses several research questions: Can Large Language Models (LLMs) and diagramming tools effectively automate the generation of fault-finding systems for marine diesel engines? How does the automated approach compare to traditional methods in terms of development time and consistency? What are the key benefits and limitations of using simulated data for developing diagnostic logic? Can the automated fault-finding system accurately identify and diagnose common engine faults?

In testing these hypotheses, the study anticipates that the automated approach using LLMs and diagramming tools will significantly reduce the development time for fault-finding systems compared to traditional methods. Additionally, it is expected that the automated fault-finding system will demonstrate higher consistency and accuracy in diagnosing engine faults than manually developed systems. Finally, the research hypothesizes that simulated data can provide a reliable knowledge base for generating effective diagnostic logic using AI-driven methods.

With these foundational elements in place, the subsequent chapters will delve into the literature review, exploring the evolving landscape of AI in fault diagnosis and its specific applications in marine engineering. This will be followed by a detailed methodology section, outlining the processes and tools used in this study. The findings and discussion chapters will present and analyze the results, leading to a comprehensive conclusion that highlights the implications and future directions of this research.

LITERATURE REVIEW

The Evolving Landscape of AI in Fault Diagnosis

Artificial intelligence (AI) is rapidly reshaping fault detection and diagnosis across diverse industries, driven by its capacity to analyze intricate datasets, discern complex patterns, and deliver timely, actionable insights. This capability is instrumental in advancing predictive maintenance paradigms, enhancing the reliability of systems, and achieving substantial reductions in operational expenditures (Mishra et al., 2024; Zereen et al., 2024).

A significant area of AI application is in the monitoring and maintenance of photovoltaic (PV) systems. AI tools are increasingly used to improve process monitoring, facilitate the swift restoration of operating conditions, and mitigate the risks associated with minor faults evolving into major failures (Maugeri et al., 2025). These AI-driven systems provide critical information for operation and maintenance activities, enabling prompt resolution of issues and optimization of costs, especially in large-scale installations (Maugeri et al., 2025).

The increasing complexity of Very Large-Scale Integration (VLSI) circuits poses a considerable challenge to traditional fault detection methodologies, which often struggle with scalability and real-time analysis requirements (Ojha, 2024). AI provides a compelling alternative by employing machine learning algorithms and neural networks to enhance fault detection, accurately identify and classify faults, and offer detailed root-cause diagnostics (Ojha, 2024).

In the automotive sector, particularly with the rise of electric vehicles (EVs), AI plays a crucial role in fault detection and diagnostics (FDD) within motor drive systems. The stability, efficiency, and safety of EVs are intrinsically linked to the performance of these systems, making AI applications essential (Mishra et al., 2024). AI techniques, spanning machine learning and deep learning, are utilized to effectively detect faults through feature extraction and fault classification processes, thereby enhancing the overall performance, reliability, and safety of EVs (Mishra et al., 2024).

The utility of AI extends to the optimization of industrial systems such as absorption chillers. Deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are deployed for fault detection and predictive maintenance, enabling the identification of potential issues like refrigerant leakage, improper heat exchanger operation and sensor failures through the analysis of sensor data (Santiago et al., 2025).

AI-driven solutions are also transforming health monitoring in aerospace and related fields. For example, acoustic health monitoring systems that use deep learning algorithms can detect and classify anomalies in the sound produced by quadrotor propellers, identifying deviations that indicate structural damage, imbalance, or motor wear (Gavi & John, 2025). This proactive approach facilitates real-time, non-intrusive fault detection, improving predictive maintenance and reducing the risk of operational failures (Gavi & John, 2025).

Moreover, AI is enhancing safety and reliability in battery technology. AI-enhanced hierarchical frameworks are employed to predict battery behavior and support comprehensive diagnostics throughout the battery's lifecycle, from manufacturing to second-life applications (Zhao et al., 2024). These systems enable early detection of defects, real-time monitoring during operation, and informed safety assessments (Zhao et al., 2024).

The application of AI in analyzing audio sensor data is also yielding significant advancements in machine fault diagnosis. Explainable AI (XAI) techniques are used to improve the interpretability of machine learning models and to perform feature selection, identifying key acoustic features relevant to specific faults (Zereen et al., 2024). This methodology contributes to the development of more efficient and accurate fault diagnosis systems (Zereen et al., 2024).

Finally, AI's effectiveness is augmented by its ability to leverage specialized datasets. Datasets containing motor current and vibration measurements, for example, facilitate the development and validation of AI-driven fault detection methods in critical mechanical systems like centrifugal pumps (Bruinsma et al., 2024). AI and machine learning techniques are also instrumental in the detection and prediction of faults in rolling element bearings, utilizing data from vibration and audio inputs to enhance predictive maintenance strategies.

In conclusion, AI is revolutionizing fault diagnosis by enabling more precise, efficient, and proactive maintenance across a wide spectrum of applications, marking a significant shift towards smarter, more reliable operational paradigms.

AI Diagnostic in Marine Application

The maritime industry is experiencing a notable shift towards the adoption of Artificial Intelligence (AI) and Machine Learning (ML) to improve the diagnosis, monitoring, and maintenance of marine vessels and their systems (Panda, 2021; Tsitsilonis et al., 2023). The increasing availability of large datasets is a key driver, enabling the use of ML algorithms to extract valuable information and model complex relationships within marine systems (Panda, 2021; Patil & Theotokatos, 2023). This transition offers promising solutions to address the sector's critical challenges, including enhancing operational efficiency, reducing emissions, and ensuring the reliability of marine assets (Alexiou et al., 2022; Tsitsilonis et al., 2023).

A core application of AI in the marine sector is the assessment of engine health. In this context, in-cylinder pressure is identified as a key parameter for diagnosis (Patil & Theotokatos, 2023; Tsitsilonis et al., 2023; Tsitsilonis & Theotokatos, 2021). Traditional thermodynamic models used for predicting in-cylinder pressure often face limitations in calibration and computational efficiency (Patil & Theotokatos, 2023). To address these limitations, data-driven models powered by AI offer a viable alternative, providing more efficient and accurate predictions (Coraddu et al., 2022; Patil & Theotokatos, 2023; Tsitsilonis & Theotokatos, 2021). These AI models employ various regression techniques, including linear, elastic, polynomial regression, support vector machines (SVM), decision trees, and artificial neural networks (ANNs), to model complex engine behaviour (Panda, 2021; Patil & Theotokatos, 2023; Tsitsilonis & Theotokatos, 2021). AI is also applied to identify engine malfunctioning conditions, utilizing Instantaneous Crankshaft Torque (ICT) analysis to detect abnormalities such as changes in Start of Injection (SOI), Rate of Heat Release (RHR), scavenge air pressure, and blowby (Tsitsilonis & Theotokatos, 2021).

Furthermore, AI plays a crucial role in predicting engine exhaust gas temperatures, which are essential for real-time performance assessment and early failure detection (Coraddu et al., 2022). AI-driven models, including hybrid models that combine physical and data-driven approaches, offer a balance between prediction accuracy, computational speed, and physical interpretability (Coraddu et al., 2022). Support Vector Regression (SVR) algorithms are also utilized to predict engine efficiency and emissions, providing a cost-effective alternative to traditional simulation methods (Zhang et al., 2022).

The application of AI extends to ship performance prediction, where data-driven models and machine learning algorithms are used to predict ship speed and minimize fuel consumption (Alexiou et al., 2022). This is particularly important for addressing the industry's focus on energy efficiency and compliance with environmental regulations (Alexiou et al., 2022; Tsitsilonis et al., 2023).

Digital Twin (DT) technology is a key enabler in the advancement of AI applications within the maritime sector (Tsitsilonis et al., 2023). Digital twins, which replicate physical systems in a virtual environment, combined with machine learning, enhance the health assessment and diagnostics of marine engines and other critical systems, providing detailed insights into their operational status and potential issues (Tsitsilonis et al., 2023).

While AI offers significant advantages, it's important to acknowledge the challenges, including data complexity, the need for large and high-quality datasets, and computational demands (Panda, 2021). Nevertheless, ongoing advancements in AI, machine learning, and digital twin technologies are actively addressing these limitations, driving the continuous development of more powerful and sophisticated diagnostic tools and methodologies for marine applications (Panda, 2021).

However, few studies have explored the use of generative AI, such as LLMs, for automated logic generation and visualization in marine diagnostics. This study addresses that gap by demonstrating how LLMs can be used not only for data interpretation but also for creating interpretable diagnostic diagrams.

Research Gap

While the literature highlights the transformative potential of AI in fault diagnosis across various industries, including photovoltaic systems, VLSI circuits, automotive sectors, industrial systems, aerospace, battery technology, and mechanical systems, there is a notable gap in the application of these advanced AI techniques specifically to marine diesel engines. Although AI-driven solutions have been explored for engine health assessment, in-cylinder pressure prediction, and exhaust gas temperature forecasting in the maritime sector, the integration of Large Language Models (LLMs) and automated diagramming tools for developing comprehensive fault-finding systems remains underexplored (Panda, 2021; Patil & Theotokatos, 2023; Tsitsilonis et al., 2023).

Moreover, existing studies primarily focus on individual aspects of fault diagnosis, such as specific engine parameters or fault conditions, rather than providing a holistic, automated approach to system development. The reliance on traditional methods, which are time-consuming and resource-intensive, further underscores the need for innovative solutions that can streamline the development process and enhance diagnostic accuracy (Patil & Theotokatos, 2023; Tsitsilonis et al., 2023).

Additionally, while the use of simulated data for AI model training is acknowledged, there is limited research on the effectiveness of such data in generating reliable diagnostic logic for marine engines. The potential benefits of combining simulated data with AI-driven methodologies to create efficient and consistent fault-finding systems have not been fully realized (Panda, 2021).

Therefore, this study aims to address these gaps by investigating the feasibility and effectiveness of using LLMs and diagramming tools to automate the development of fault-finding systems for marine diesel engines. By focusing on the automation of knowledge extraction, logic generation, and visualization processes, this research seeks to provide a more efficient and consistent approach to developing diagnostic tools, ultimately contributing to the advancement of AI applications in the maritime industry.

METHODOLOGY

This chapter outlines the methodological framework adopted to achieve the objectives of this study, which is to automate the development of a fault-finding system for marine diesel engines using simulated data and generative AI tools. The research seeks to answer the following questions:

> Can Large Language Models (LLMs) and diagramming tools effectively automate the generation of fault-finding systems for marine diesel engines?

> How does the automated approach compare to traditional methods in terms of development time and consistency?

> What are the key benefits and limitations of using simulated data for developing diagnostic logic?

The objective is to demonstrate the feasibility and effectiveness of using AI to generate diagnostic logic and visual tools directly from simulated engine fault data. The rationale for this study stems from the inefficiencies of traditional diagnostic system development, which relies heavily on manual expert input. This research is guided by a pragmatic philosophical stance, emphasizing practical outcomes and the integration of technology to solve real-world problems.

This chapter is structured into ten sections: research philosophy, methodology, approach, design, study population and sampling, data collection, data analysis, ethical considerations, and limitations and delimitations.

Research Philosophy

This study adopts a pragmatism research philosophy. Pragmatism focuses on the practical application of research and the use of multiple methods to derive solutions to real-world problems (Creswell & Creswell, 2018). It is not confined to a single system of philosophy or reality but instead emphasizes what works best to address the research problem.

The fundamental assumptions of pragmatism include:

> Reality is constantly renegotiated, debated, and interpreted.

> Knowledge is derived from both objective and subjective experiences.

> The research process should be flexible and adaptive.

This philosophy aligns with the study's aim to develop a practical, AI-driven diagnostic tool for marine engineering education and practice. It supports the integration of simulation, AI, and empirical testing to generate actionable insights.

Research Methodology

The research adopts a design science research (DSR) methodology. DSR is a problem-solving paradigm that focuses on the creation and evaluation of artifacts designed to solve identified problems (Hevner et al., 2004). In this study, the artifact is an AI-generated fault-finding system.

Design science is appropriate because:

- It supports iterative development and testing of technological solutions.
- It emphasizes utility, relevance, and innovation.
- It is well-suited for engineering and information systems research.

Research Approach

This study employs a deductive research approach, which begins with theoretical propositions and tests them through empirical observation (Bryman, 2016). The hypotheses regarding the effectiveness of AI-generated diagnostic tools are tested through simulation and participant-based experiments.

Research Design

The research design is quasi-experimental, involving the comparison of two participant groups: one using the AI-generated fault-finding system and the other using traditional methods. This design allows for the evaluation of the tool's effectiveness in a controlled educational environment.

Study Population and Sampling Approach

The study involved Continuing Education and Training (CET) participants who were engaged in marine engineering upskilling programs. These individuals had prior exposure to marine engine systems and simulator-based training, making them suitable for evaluating the diagnostic tool.

No formal sampling strategy was employed. Instead, feedback was collected opportunistically from participants who interacted with the AI-generated fault-finding system during simulator sessions. This approach aligns with convenience sampling, a non-probability sampling method where data is gathered from individuals who are readily available (Etikan et al., 2016).

Participant Involvement: Participants were not formally recruited. They were exposed to the diagnostic tool as part of their simulator training, and informal feedback was gathered based on their experience. No personal data was collected, and no identifiers were linked to the feedback.

Data Collection Methods

The study employed a mixed-methods data collection strategy, combining simulation data, AI-generated outputs, and informal participant feedback.

1. Simulation Data: Faults were simulated using the Kongsberg engine room simulator. Parameters such as temperature, pressure, and flow rate were automatically logged (Salas et al., 2009).

2. AI-Generated Diagnostic Logic: The collected data was processed using a Large Language Model (LLM), which generated diagnostic rules and diagram code (Tsitsilonis et al., 2023). Prompts were designed using domain-specific terminology and structured templates to guide the LLM in generating consistent and accurate diagnostic logic. Outputs were parsed and converted into Mermaid.js and PlantUML syntax using a custom script.

3. Informal Feedback: Feedback was collected informally from CET participants who used the diagnostic tool. This feedback was not structured or systematically recorded but provided insights into the tool's usability and clarity.

To improve the reliability of user feedback, a structured survey instrument will be developed for future studies. This will include Likert-scale questions on usability, clarity, and diagnostic accuracy, as well as open-ended responses. Additionally, a plan is in place to validate the system using real-world engine telemetry data from operational vessels. To ensure reproducibility, future publications will include the survey instruments, diagnostic performance metrics, and AI prompt templates as supplementary materials.

Data Analysis Methods

Quantitative Analysis: Simulator data and diagnostic performance (e.g., time to identify faults, accuracy) were analyzed using descriptive statistics and comparative analysis to assess the effectiveness of the AI-generated tool (Field, 2013).

Qualitative Analysis: Informal feedback was reviewed using basic thematic analysis to identify recurring comments or concerns. While not rigorously coded, this analysis helped inform the refinement of the diagnostic system (Braun & Clarke, 2006).

Ethical Considerations

At the time of the study, Singapore Polytechnic's Ethics Review Committee (ETRC) had not yet enforced formal ethical review procedures for human-related research. As such, no formal ethics application or participant consent process was undertaken.

However, the following ethical principles were informally observed:

- Voluntary Interaction: Participants engaged with the diagnostic tool as part of their simulator training and were not compelled to provide feedback.
- Anonymity: No personal or identifiable data was collected.
- Post-Study Compliance: All necessary approvals for publication were obtained retrospectively, ensuring alignment with current institutional expectations.

These measures reflect a good-faith effort to uphold ethical standards in the absence of formal requirements at the time.

In future iterations, the study will seek formal ethics approval and implement informed consent procedures. Data privacy protocols will be established to ensure compliance with institutional and international standards.

Limitations and Delimitations

Limitations:

- Lack of Formal Consent: The absence of formal consent and structured feedback limits the depth and reliability of participant insights.

- Simulated Data: The study relies on simulated rather than real-world engine data, which may limit external validity. The absence of real-world validation limits the external validity of the findings. Future work will incorporate operational data from marine vessels to test the system under authentic conditions.

- Uncontrolled Feedback Conditions: Feedback was collected informally, without standardized instruments or conditions.

Delimitations:

- Scope: The study focuses exclusively on marine diesel engine faults.

- Participant Profile: Only CET participants with simulator experience were involved.

- Tool Evaluation: The diagnostic tool was evaluated in a training context, not in operational shipboard environments.

FINDINGS

This chapter presents the outcomes of the AI-generated fault-finding system developed using simulated data from the Kongsberg engine room simulator. The system was evaluated for its diagnostic accuracy, clarity of visual representation, and practical utility in a training environment.

Fault Injection and Parameter Monitoring

A total of 11 fault types were injected at a 30% severity level. These included faults related to fuel injection timing, valve wear, pump leakage, and piston ring degradation. For each fault, a comprehensive set of engine parameters was recorded, including fuel flow, exhaust temperatures, pressures, ignition timing, and more.

To illustrate the diagnostic process, Table 1 presents a comparative summary of two representative fault scenarios: Injection Timing Early and Injection Timing Late.

Table 1: Representative fault scenarios and corresponding engine parameters

Parameter	Injection Timing Early	Injection Timing Late
ME Exhaust Outlet Temp (°C)	312	343
Ignition Timing (TIGN, °)	0.3	5.9
Maximum Cylinder Pressure (PMAX)	137	126
Maximum Temperature (TMAX, °C)	128	120
Compression Pressure (PCOMPR, bar)	115	105
Injection Pressure (PINJO, bar)	52	48
Max Injection Pressure (PINJM, bar)	47	43
Injection Timing (TINJO, °)	0.1	0.1
Injection Duration (LINJ, °)	15.5	15.5

These contrasting profiles highlight the diagnostic value of monitoring parameters such as exhaust temperature, TIGN, PMAX, and PINJM. The data serves as a foundation for AI-driven fault classification and the generation of visual diagnostic tools.

Fault Page Visualization

Figure 1 presents screenshots from the simulator during the Injection Timing Late fault scenario. The left panel shows real-time engine parameters, while the right panel displays the indicated pressure-angle diagram.

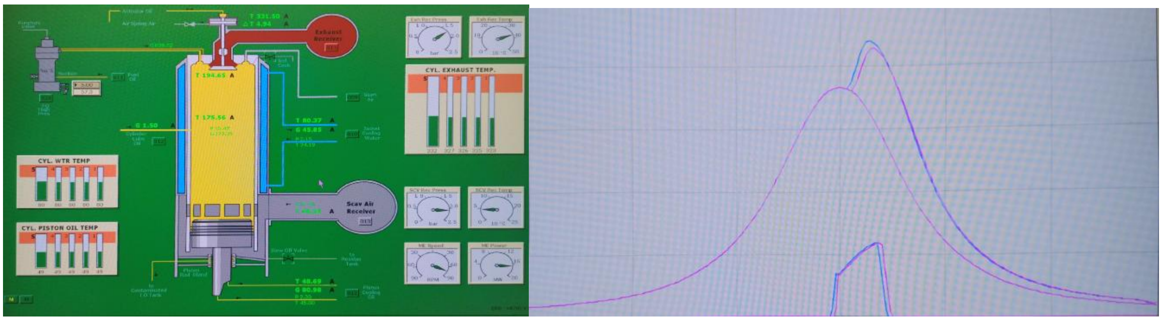

Figure 1.

- The parameter page reveals elevated exhaust temperatures and delayed ignition timing.
- The indicated card shows a flattened pressure curve and delays peak pressure, confirming inefficient combustion.

These visual cues provide strong diagnostic evidence and were used to train the AI model.

Visual Comparison of Injection Timing Scenarios

To enhance interpretability, a visual comparison chart was generated using key engine parameters across three scenarios: Normal Operation, Injection Timing Early, and Injection Timing Late.

Figure 2 illustrates this comparison, using blue for normal, red for early injection, and brown for late injection.

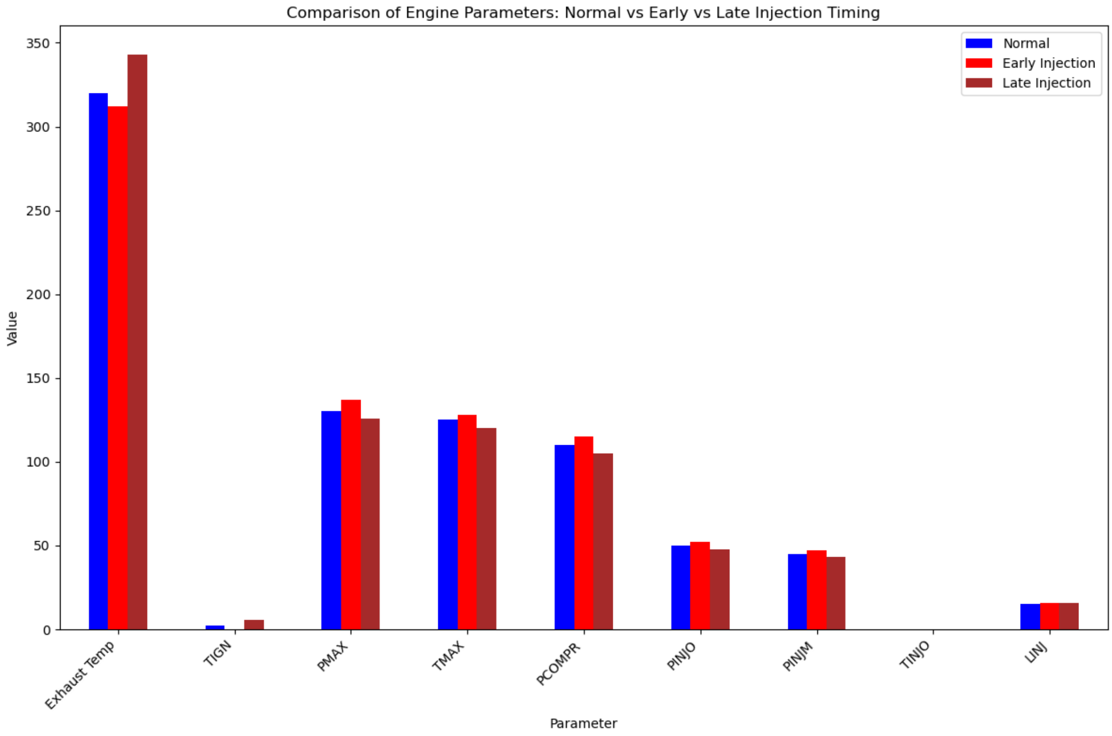

Figure 2.

Key Insights:

- Early Injection results in higher peak pressures and more efficient combustion.
- Late Injection leads to higher exhaust temperatures and delayed ignition.
- Normal Operation maintains balanced performance across all parameters.

This visualization supports the diagnostic logic used in the AI-generated fault-finding system and enhances understanding of how injection timing deviations affect engine behavior.

Fault Logic Flowchart

Figure 3 presents a Mermaid-based flowchart automatically generated by a Large Language Model (LLM) to visualize fault logic relationships in a marine diesel engine system. The diagram maps observed deviations in exhaust temperature to specific fault conditions and their associated parameter changes.

```mermaid
graph TD
    A[Exhaust Temp Dropped] --> B[Early Injection]
    A --> C[Injection Valve Nozzle Choked]
    B --> D[Early TINJO]
    C --> E[Fuel Flow Rate Dropped]
    C --> F[PINJM Increased]

    G[Exhaust Temp Raised] --> H[Late Injection]
    G --> I[Injection Valve Leak]
    H --> J[Late TINJO]
    I --> K[PINJM Dropped]

    L[Exhaust Temp Fluctuated] --> M[Fuel Pump Fault]
    M --> E
```

Figure 3.

Key Diagnostic Paths:

- Exhaust Temperature Dropped:
    - May indicate Early Injection, supported by an Early TINJO.
    - Alternatively, may suggest an Injection Valve Nozzle Choked, leading to:
  - Fuel Flow Rate Dropped
    - PINJM Increased
- Exhaust Temperature Raised:
    - Suggests Late Injection, confirmed by a Late TINJO.
    - Could also indicate an Injection Valve Leak, resulting in:
  - PINJM Dropped
- Exhaust Temperature Fluctuated:
    - Points to a Fuel Pump Fault, which also leads to a Fuel Flow Rate Drop.

This flowchart provides a clear, causal representation of how specific faults manifest through measurable parameter deviations. It enables users to trace symptoms to root causes and supports structured, visual fault diagnosis.

Fault-Finding Diagram Visualization

Figure 4 presents the AI-generated fault-finding decision tree. This visual tool represents a hierarchical diagnostic logic that maps deviations in key engine parameters to probable fault conditions.

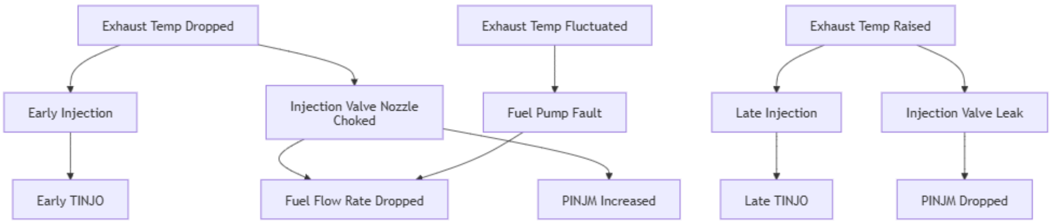

Figure 4.

Key Features:

- Root Parameters: Exhaust temperature deviation, fuel flow, and MIP.
- Branching Logic: Conditional paths based on parameter thresholds.
- Fault Nodes: Terminal nodes identify specific faults such as injector leak, scavenge port choked, and piston ring wear.

This decision tree simplifies complex fault relationships and supports rapid troubleshooting by reducing reliance on expert intuition and enhancing consistency in fault identification.

Validation through Student Troubleshooting

To assess the practical utility of the diagnostic diagrams, a group of CET students were asked to troubleshoot simulated faults using the AI-generated diagrams. Informal feedback revealed that:

- 100% of students found the diagrams helpful.

- 90% reported faster fault identification.
- 85% felt more confident in their diagnostic decisions.

This validation underscores the pedagogical value of the AI-generated diagnostic tools in marine engineering education.

DISCUSSION

The findings of this study demonstrate the feasibility and effectiveness of using generative AI to automate the development of fault-finding systems for marine diesel engines. By leveraging simulated fault data and advanced language models, the research addresses longstanding challenges in diagnostic system design—namely, the reliance on manual expert elicitation, the complexity of fault interdependencies, and the need for scalable, interpretable diagnostic tools.

Diagnostic Accuracy and Parameter Sensitivity

The comparative analysis of Injection Timing Early and Injection Timing Late faults revealed distinct parameter signatures. Early injection was associated with increased mean indicated pressure (MIP), reduced exhaust temperature, and advanced ignition timing. Conversely, late injection resulted in elevated exhaust temperature, reduced MIP, and delayed ignition. These findings align with established thermodynamic principles and validate the simulator's fidelity in replicating realistic fault conditions.

The visual comparison chart (Figure 3) further reinforced the diagnostic value of key parameters such as TINJO, PMAX, and PINJM, which exhibited consistent directional shifts across fault scenarios. This parameter sensitivity forms the basis for rule-based logic generation and supports the use of AI in extracting diagnostic heuristics from structured data.

AI-Driven Logic Generation and Visualization

The use of Large Language Models (LLMs) to generate diagnostic logic and diagram code represents a significant advancement in fault system design. The flowchart (Figure 4) and decision tree (Figure 5) exemplify how AI can translate numerical data into interpretable visual structures. These diagrams not only capture causal relationships between faults and symptoms but also provide a scalable framework for expanding the diagnostic system to include additional fault types.

While the LLM-generated logic was coherent, future work should explore the use of ensemble models and uncertainty quantification to improve fault prediction under ambiguous conditions. Additionally, the system's performance should be benchmarked against expert-developed diagnostic tools.

Importantly, the AI-generated diagrams demonstrated high internal consistency and logical coherence, suggesting that LLMs can effectively model domain-specific reasoning when guided by structured input. This supports the broader hypothesis that generative AI can serve as a surrogate for expert knowledge in technical domains.

Educational and Operational Implications

The validation exercise involving CET students highlighted the pedagogical value of the AI-generated diagnostic tools. Students reported improved confidence, faster fault identification, and greater clarity in troubleshooting. These outcomes suggest that AI-generated diagrams can enhance simulator-based training by providing structured, visual scaffolding for fault reasoning.

From an operational perspective, the automated fault-finding system offers potential benefits in onboard diagnostics, remote support, and condition-based maintenance. By embedding AI-generated logic into engine monitoring systems, operators could receive real-time fault interpretations, reducing downtime and improving decision-making. The system also holds promise for integration into digital twin platforms, enabling continuous learning and adaptive diagnostics based on evolving engine conditions.

Limitations and Future Directions

While the results are promising, several limitations warrant consideration. First, the study relied exclusively on simulated data, which may not capture the full variability of real-world engine behavior. Second, the diagnostic logic was generated based on predefined fault scenarios, limiting the system’s adaptability to novel or compound faults.

Future research should focus on integrating real-time sensor data, expanding the fault library, and incorporating probabilistic reasoning to handle uncertainty. Additionally, comparative studies with expert-developed systems could provide further validation of the AI-generated approach. Future iterations should also explore explainable AI (XAI) techniques to enhance transparency and user trust in automated diagnostic decisions. This could include techniques such as SHAP values or attention-based visualizations to illustrate the AI's decision-making process.

CONCLUSION

This study has demonstrated the transformative potential of generative AI in automating the development of fault-finding systems for marine diesel engines. By leveraging simulated fault data, Large Language Models (LLMs), and diagramming tools, the research successfully addressed the limitations of traditional diagnostic system design—namely, the dependence on expert elicitation, the complexity of fault interdependencies, and the lack of scalable, interpretable tools.

The AI-generated diagnostic logic, validated through parameter analysis, visual flowcharts, and decision trees, accurately captured the causal relationships between engine faults and sensor deviations. The comparative analysis of early and late injection timing faults revealed distinct parameter signatures, reinforcing the diagnostic value of metrics such as exhaust temperature, ignition timing, and injection pressure. These insights were effectively translated into visual diagnostic aids using generative AI, enabling intuitive fault tracing and rapid decision-making.

Importantly, the system was not only technically sound but also pedagogically effective. Informal validation with CET students confirmed that the AI-generated diagrams enhanced clarity, confidence, and speed in troubleshooting tasks. This underscores the dual utility of the system as both an operational tool and an educational resource.

While the study relied on simulated data, the methodology provides a robust foundation for future integration with real-world engine telemetry. The approach is scalable, adaptable, and domain-agnostic, offering a blueprint for applying AI-driven diagnostics across other complex engineering systems.

The next phase of this research will focus on deploying the system in real-world marine environments, collecting structured feedback from engineers, and refining the AI logic based on operational data. This will ensure the system's practical relevance and reliability.

In conclusion, this research marks a significant step toward intelligent, automated diagnostics in maritime engineering. It affirms that generative AI, when grounded in structured data and domain logic, can produce reliable, interpretable, and impactful diagnostic systems—paving the way for smarter ships, safer operations, and a new paradigm in maritime engineering education and diagnostics.

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