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Compound Fault Diagnosis for Industrial Machinery: Data-Driven Methods, Challenges, and LLM-Enhanced Perspectives

Zihan Weng

Shandong University of Science and Technology, Qingdao, China
202413001230@sdust.edu.cn

Abstract. Compound faults occur when several local faults exist at the same time in industrial machinery and affect condition-monitoring signals together. Their signatures become mixed through modulation, structural transmission, operating-condition variation, and sensor response, which makes feature separation and state recognition more difficult. This paper reviews data-driven compound fault diagnosis from a scenario-oriented perspective. It first summarizes the task formulation and three main difficulties: coupled fault signatures, combinatorial growth of fault states, and distribution shifts across operating conditions and machines. The review then groups representative methods into three areas: signal representation, multi-label and fault-semantic modeling, and generalization under changing domains and unseen fault combinations. The paper also examines the emerging role of large language models, focusing on retrieval-augmented knowledge integration, evidence-grounded reasoning, tool-using diagnostic agents, and deployment reliability. It then points to several directions for future work, including compositional generalization, cross-machine transfer, multimodal sensing, industrial foundation models, and autonomous maintenance. Overall, the review argues that practical compound fault diagnosis depends on combining signal-level intelligence with reusable fault semantics and verifiable knowledge-based reasoning.

Keywords: industrial machinery, compound fault diagnosis, deep learning, multi-label learning, domain generalization, large language models

1. Introduction

Industrial machinery, including rotating machines, motors, gearboxes, and machine tools, now often works under more complex loads and operating conditions. Because of this, intelligent fault diagnosis has become a key part of condition monitoring and predictive maintenance. In data-driven diagnosis, the focus has gradually shifted from handcrafted feature engineering to deep representation learning. This allows fault-related information to be extracted directly from vibration, current, acoustic, and other monitoring signals [1-5].

Most diagnostic studies still treat each sample as if it contains one main fault. In actual equipment, bearing defects can appear together with misalignment, imbalance, gear damage, or

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looseness. These excitations travel through the same structural paths and often overlap in the time, frequency, and time-frequency domains. Classical signal processing is still useful for separating impulsive, modulated, and non-stationary components [6-9]. At the same time, deep models are increasingly used to learn fault-sensitive representations directly from measured data [1-5].

Compound fault diagnosis increasingly uses structured learning. In multi-label settings, a compound state is represented by reusable basic-fault labels and the correlations between them [10-14]. For combinations that do not appear in training, existing methods include joint generalization, fault-semantic learning, and zero-shot attribute modeling [15-18]. To handle distribution shifts across operating conditions and machines, researchers have also used domain adaptation, domain generalization, cross-machine transfer, and target-free self-contrastive learning [19-25]. This matters in practice. As the number of possible compound states increases quickly, complete industrial training data are usually not available.

Large language models (LLMs) and foundation models bring knowledge organization and interactive reasoning into industrial maintenance. Recent PHM studies have looked at large-scale foundation models [26], direct LLM-based fault diagnosis [27-29], data-analytics agents [30], multimodal predictive-maintenance applications [31], autonomous maintenance agents [32], and industrial time-series foundation models [33]. In this paper, compound fault diagnosis is reviewed through three questions: how compound states are represented, how diagnostic models generalize beyond the conditions and combinations already observed, and how LLM-based reasoning links diagnostic evidence with maintenance knowledge and analytical tools.

2. Compound fault diagnosis: problem formulation and key challenges

2.1. Task definition and diagnostic framework

A compound fault is an operating state where two or more basic faults affect the observed monitoring signals at the same time. For a machine with K potential basic fault types, the diagnostic state can be written as a multi-label vector:

$$y = [y_1, y_2, \ldots, y_k], y_k \in \{0, 1\}$$

Here, K denotes the number of basic fault categories, and $y_k = 1$ means that the k-th fault is present. More than one element can be equal to one at the same time, so this representation keeps the internal composition of a compound state. Multi-label formulations have been used for simultaneous and compound fault diagnosis, and they scale naturally as the number of basic fault components increases [10-14].

Fig. 1 shows the general diagnostic chain. Multiple local fault sources produce mechanical excitations, which are then shaped by structural transmission paths, operating conditions, and sensor responses. The monitoring channels record vibration, current, acoustic, temperature, or other signals. From these signals, signal processing and learned representations extract fault evidence. Diagnostic models then identify one or more basic fault components, and the output is used to support maintenance decisions. In compound diagnosis, this means performance depends on two linked parts: source-level fault semantics and the interactions that appear during propagation and measurement.

Single-fault classification usually assigns each sample to one mutually exclusive category. In a compound state, several fault components can be present at the same time, so the diagnostic result needs to keep information for each component. For a small and fully observed state set,

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independent-class modeling is still practical. Multi-label decomposition makes the connection between the identified state and its underlying basic faults explicit, and it allows fault-level information to be reused across different combinations [10-13].

At the signal level, concurrent faults rarely appear as a simple arithmetic sum. Structural transfer paths filter excitations, and the resulting responses can interact through modulation, resonance, and changes tied to operating conditions. Methods such as wavelet analysis, time-frequency feature extraction, spectral kurtosis, and variational decomposition are still useful when fault components differ in scale, impulsiveness, or spectral structure [6-9]. Data-driven models build on this by learning fault-sensitive representations from example data. Even so, physical coupling still sets the limits of what can actually be observed in the measurements.

A further practical problem is incomplete industrial data. Rare compound states are often underrepresented, and destructive or unsafe combinations may never be intentionally collected. Methods such as active learning, joint generalization, fault-semantic learning, and zero-shot attribute modeling can reduce the need for exhaustive compound-fault samples [14-18]. Even so, diagnostic models still need calibrated confidence when the available evidence is not enough to support a reliable component decomposition.

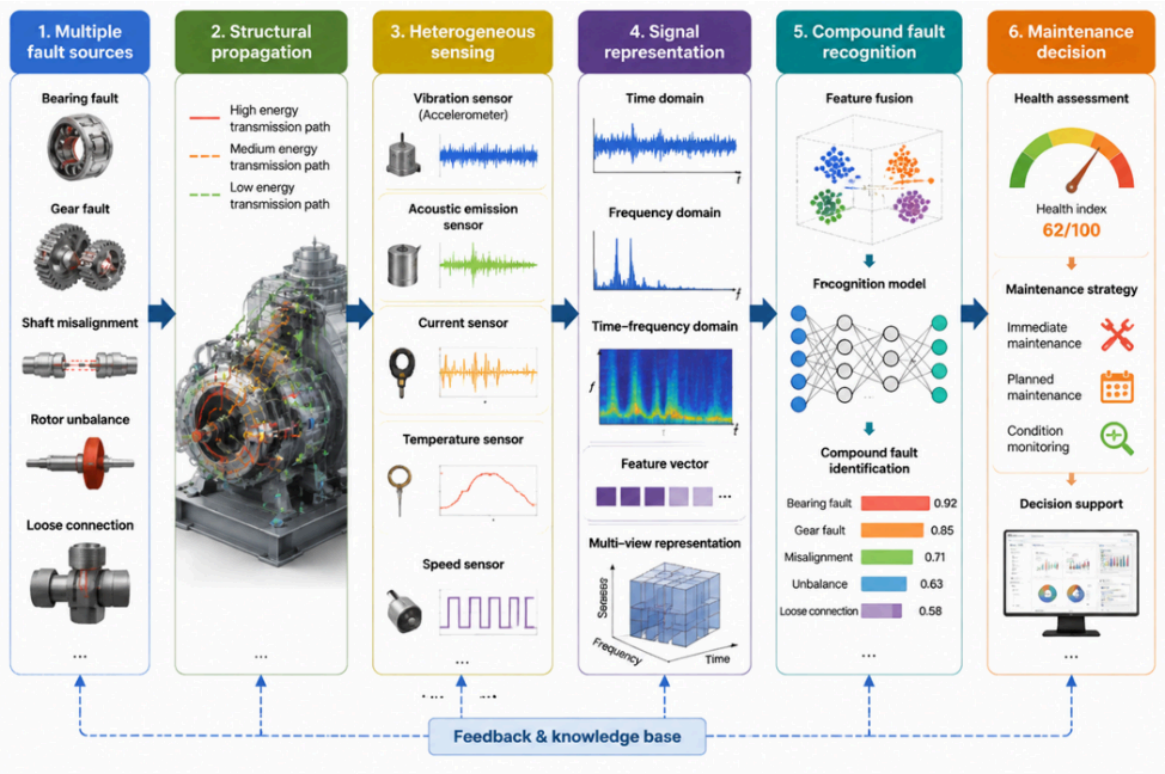


Figure 1. General framework of compound fault diagnosis for industrial machinery

2.2. Coupled characteristics and combinatorial complexity

Feature coupling is one of the main difficulties in compound fault diagnosis. Harmonics, transient impacts, modulation structures, resonance responses, and broadband components generated by different faults can overlap, and a weak fault signal may be hidden by a stronger excitation. For this reason, signal-processing studies have focused on decomposition, demodulation, spectral analysis, and non-stationary feature extraction to separate coupled fault signatures [6-9].

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Combinatorial growth creates another problem. With K basic faults, up to 2^K - 1 non-empty combinations are theoretically possible. In practice, many of these combinations are rare, destructive, unsafe to reproduce, or simply not included in laboratory test plans. That leaves gaps. As a result, a model trained on only part of the combination space may face unseen compound states during deployment. This is why recent work has focused on multi-label diagnosis, label-correlation modeling, active learning, joint generalization, and zero-shot fault-semantic learning [10-18].

2.3. Distribution variations and generalization challenges

Distribution variation is the third major challenge. Changes in rotation speed, load, machine structure, sensor installation, and acquisition systems can shift amplitudes, spectral locations, modulation patterns, and noise characteristics. In compound faults, these changes interact with fault coupling and can influence each fault component in different ways. The problem is practical. A diagnosis method needs to capture fault-discriminative information that stays relatively stable across operating conditions and across machines. This need has led researchers to study domain adaptation, domain generalization, multisource adaptation, cross-machine transfer, and self-contrastive learning [19-25].

3. Data-driven methods for compound fault diagnosis

3.1. Signal representation and feature learning

The way a signal is represented decides what kind of compound-fault information a learning model can use. Time-domain networks work directly on raw sequences, so they can capture impacts, periodicity, and temporal dependence without much preprocessing [34, 35]. Frequency-domain representations make harmonics, characteristic frequencies, and sidebands easier to observe [35]. For non-stationary signals, time-frequency and wavelet representations retain local changes over time and support multiscale feature learning [36, 37]. The difference matters. Some lightweight cross-machine models also combine multiscale tokenization with selective feature processing [38]. Multi-sensor models bring together complementary vibration, current, and related channels [39]. Table 1 summarizes the main trade-offs among these representations.

Table 1. Comparison of representative signal representations

Representation	Typical Methods	Advantages	Main Limitations
Time domain	CNN, TCN, RNN	Simple processing pipeline	Sensitive to condition variation
Frequency domain	FFT, envelope spectrum	Explicit harmonic information	Limited temporal information
Time-frequency	STFT, WT, CWT	Rich transient information	Increased computational cost
Multi-view	Time-frequency fusion	Complementary information	More complex architecture
Multi-modal	Vibration, current, acoustic	Improved robustness	Sensor dependency

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Different signal representations bring out different diagnostic cues. Raw time sequences keep short-lived waveform details, spectra show periodic components and sidebands, and time-frequency maps keep track of how non-stationary content changes over time. For compound faults, the evidence is often spread across multiple scales and sensing domains, so multiscale and multi-sensor fusion can be useful when sensing and computational resources allow it [16, 25, 37-39]. The choice of representation needs to keep weak component signatures visible without becoming too sensitive to changes in operating conditions.

3.2. Compound fault modeling and multi-label diagnosis

Representation alone does not solve the compound-state problem. When all states are known, one simple option is to treat each observed combination as its own class. That works at small scale. As the number of basic faults increases, however, this approach becomes much harder to scale. Multi-label learning instead uses one binary output for each basic fault, so several components can be predicted at the same time [10-14]. In this setup, the internal makeup of a compound state is kept explicit, and fault-level outputs can still be reused across combinations that contain the same components.

Recent compound-fault models improve component separation by using multiscale feature extraction, attention mechanisms, label-correlation modeling, decoupled representations, and data-efficient training [13-16, 38]. Deep multi-label learning also offers a unified output space for recognizing multiple faults at the same time [12]. As a result, compound diagnosis has moved away from closed-set state indexing and toward structured representations that preserve information about individual fault factors.

Fig. 2 traces the shift from independent state classification to multi-label decomposition, fault-specific representation, and compositional generalization. When state coverage is incomplete, diagnosis needs to identify which basic faults are present and keep fault-level representations that can be reused across compound states.

The learning objective matters just as much. In a multi-label network, each output corresponds to a basic fault, and several outputs can be active at the same time. Shared feature extraction reduces the need for a separate classifier for every fault combination, but label imbalance and feature dominance may let strong faults mask weaker ones. Under noise and overlapping signatures, multiscale attention, label-correlation learning, and decoupled feature extraction can improve component-sensitive information [13, 14, 16].

Fault-semantic and self-supervised learning add more structure to the representation space. Semantic embeddings link diagnostic features to reusable fault attributes, which can help with zero-shot recognition of compound states [17, 18]. Self-supervised objectives use unlabeled machine data to learn representations that transfer before task-specific training [40]. When useful mechanical relationships are available, physics-informed constraints can also regularize feature learning [41]. These approaches are most useful when labeled combinations cover only a small part of the deployment state space.

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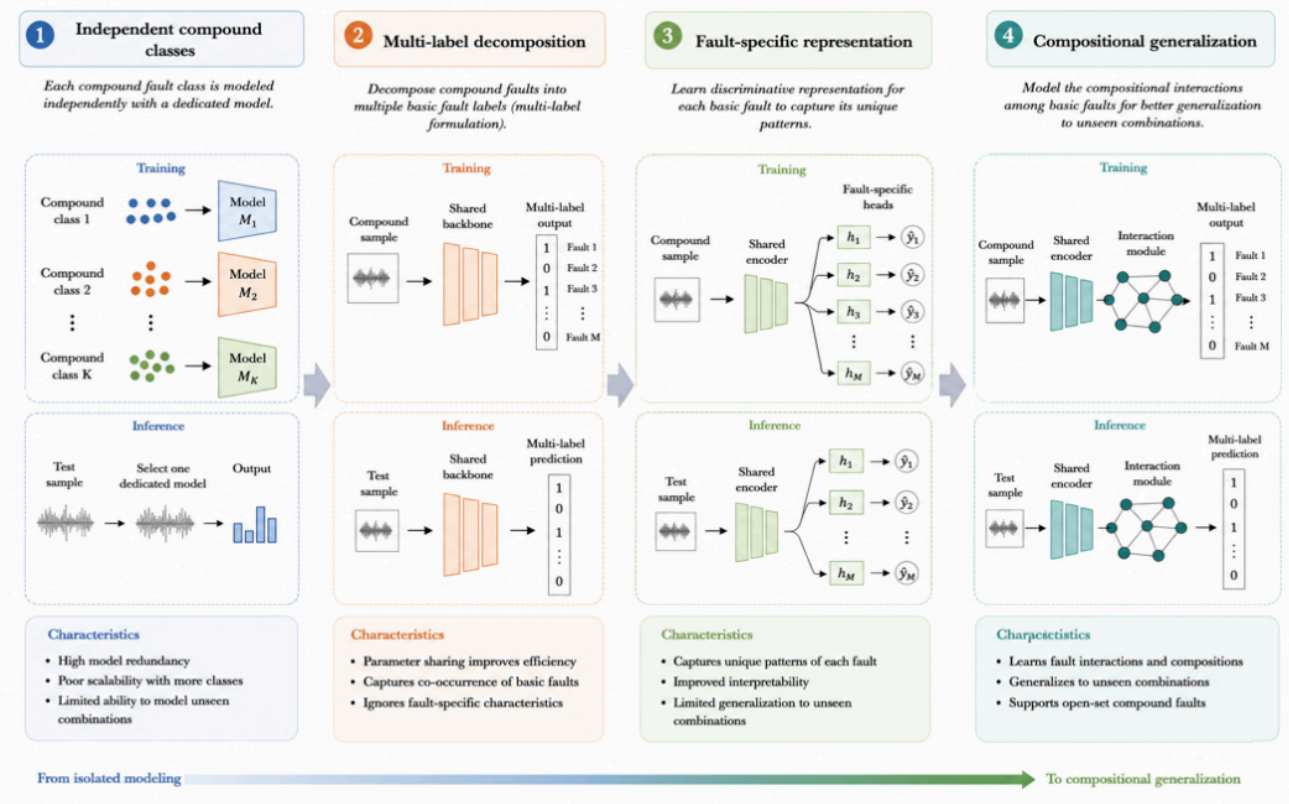


Figure 2. Evolution of compound fault modeling strategies

3.3. Generalization across conditions, machines, and fault combinations

Generalization is needed when the operating environment at deployment is different from the training data. Domain adaptation uses target-domain samples during training and reduces differences between source and target domains through representation alignment or similar transfer methods [20, 23, 24]. By contrast, domain generalization learns information from source domains that can transfer to an unseen target without access to target data in advance [21, 25]. Cross-machine diagnosis adds further differences in machine structure and sensing conditions across equipment [19, 38].

In compound faults, changes in operating conditions do not affect every fault component equally, and strong distribution alignment can blur weak component-level signatures. For this reason, cross-domain diagnosis needs features that still separate faults clearly while reducing variation tied to the domain itself. This is the key issue. Multisource and multi-target adaptation are used to handle heterogeneous domain shifts [22, 23], while transfer learning and target-free self-contrastive learning offer practical ways to improve machine-to-machine and cross-condition generalization [24, 25].

A second kind of generalization involves fault combinations the model did not see during training. For example, the training set may include A, B, C, A+B, and B+C, but in deployment the system encounters A+C or A+B+C. The model therefore needs to carry over what it learned about each fault and use that knowledge to make sense of new combinations.

Several approaches address this problem from different angles. Multi-label and label-correlation modeling produce structured outputs [10-13]. Joint generalization and zero-shot semantics link

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information about individual components to unseen states [15, 17, 18]. Collaborative decision models add evidence from different diagnostic sources [42].

Zero-shot fault-semantic learning gives a direct way to recognize unseen compound states [17, 18]. The main difficulty is keeping the information linked to each fault factor while also dealing with the interaction effects caused by simultaneous occurrence and mechanical transmission. For evaluation, complete fault combinations should be excluded during training so the test can separate generalization to unseen combinations from interpolation among observed states.

4. Large language models for intelligent compound fault diagnosis

4.1. Knowledge-enhanced fault diagnosis

Industrial diagnosis involves more than matching a signal to a label. Maintenance manuals, failure-mode descriptions, historical work orders, expert rules, and machine-specific records add context that can support what the signal data suggests. In this setting, retrieval-augmented generation offers a practical way to ground LLM responses in external documents [43]. Work on foundation models in PHM has focused on reusable representations across tasks and data sources [26]. More recent CNC diagnosis systems pair LLMs with domain knowledge graphs and retrieval methods [28]. This matters for compound faults. It allows several predicted fault components to be linked back to machine-specific maintenance information.

Knowledge integration can be set up as a retrieval-and-reasoning pipeline. A query may include predicted fault components, operating conditions, confidence scores, and extracted spectral evidence. The retrieval step selects relevant manuals, historical cases, or structured fault relations, then combines the returned evidence with the current diagnostic result. This helps with traceability. When several interacting fault hypotheses need to be assessed, keeping a record of retrieval sources alongside the diagnostic evidence makes it easier to track how each conclusion was reached.

4.2. LLM-assisted diagnostic reasoning

An LLM can work as a reasoning layer on top of specialized diagnostic models. Recent studies have combined vibration, time-frequency, statistical, and structured equipment information in LLM-based fault-diagnosis frameworks [27-29]. Multimodal predictive-maintenance studies also show that sensor observations can be integrated with textual maintenance information [31]. In these systems, predicted fault components, operating context, and analytical evidence are brought together within one diagnostic interaction.

In engineering applications, diagnostic evidence is easier to use when it is organized in a clear structure. Useful fields include sensing channel, operating condition, detected characteristic frequencies, model outputs, confidence values, retrieved knowledge, and tool provenance. This makes the reasoning easier to audit and keeps the link between measured evidence, retrieved information, and the diagnostic interpretation that was generated.

4.3. Tool-using diagnostic agents and reliability

The agent paradigm extends LLM-based diagnosis by letting the model call external tools. General frameworks such as TaskWeaver show that an LLM can plan data-analysis steps and then execute those tools [30]. In predictive maintenance, studies and reviews apply similar agent workflows to monitoring, diagnosis, maintenance planning, and iterative decision support [31, 32].

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This creates new demands. Once tool use is part of the workflow, generated reasoning has to be reliable and the use of those tools has to stay controlled [44]. Recent compound-fault architectures move further in this direction by combining LLM orchestration with distributed diagnostic models and collaborative cloud-edge-terminal execution [45].

Fig. 3 shows how the model and tools work together. The LLM handles task understanding, reasoning, and interaction, while specialized algorithms are still used for numerical signal analysis. In this workflow, diagnostic models, signal-processing tools, retrieved knowledge, and maintenance records each add a different kind of evidence within the same process.

With tool use, the LLM works more like an interactive diagnostic controller. It can ask for additional FFT or envelope analysis, call a trained classifier, compare alternative models, retrieve similar historical cases, or check structured maintenance knowledge before reaching a conclusion. This makes the process more grounded. If the inputs and outputs of each tool call are kept, the final recommendation can be traced back to verifiable evidence.

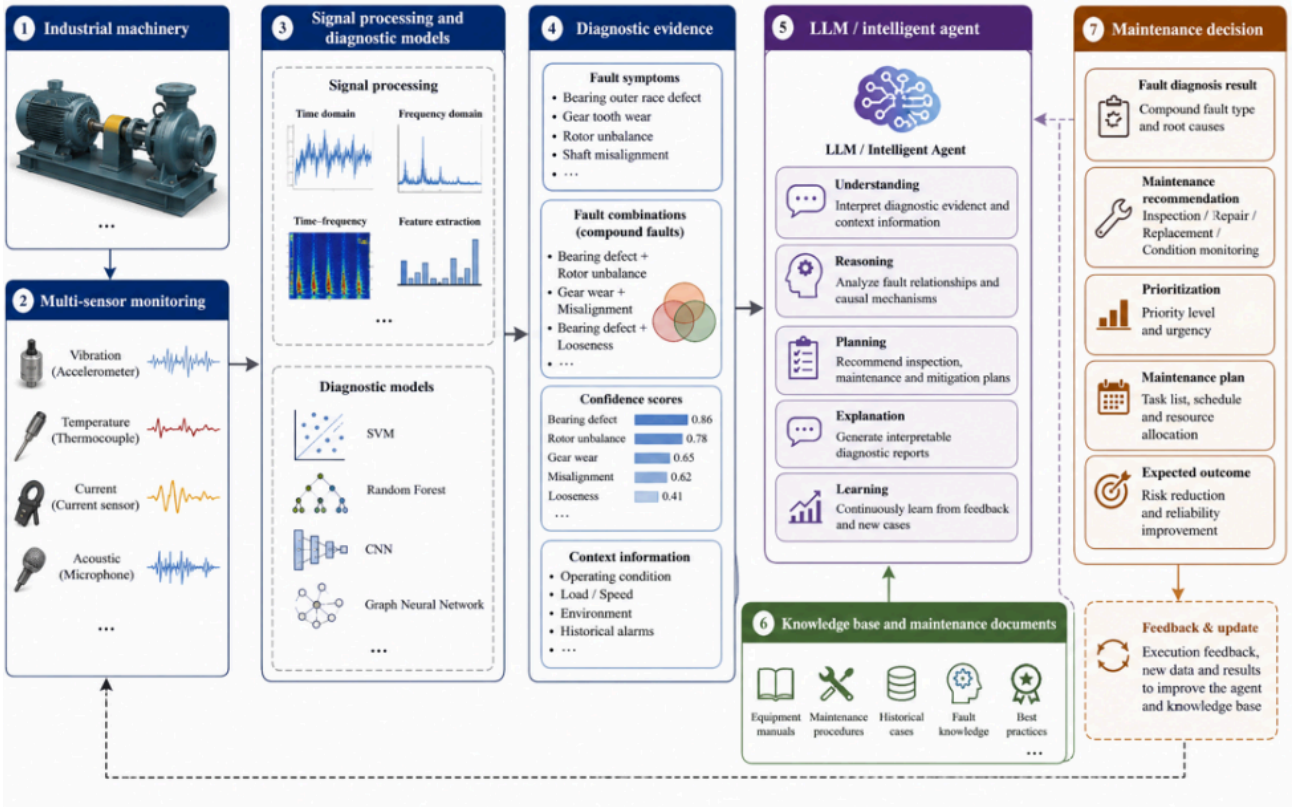


Figure 3. LLM-enhanced compound fault diagnosis and maintenance framework

Reliability is still a major constraint. LLMs can produce unsupported explanations, may not have enough machine-specific industrial knowledge, and raise privacy, latency, and computation concerns. Hallucination has been widely documented in natural-language generation [44]. In autonomous maintenance agents, the bar is higher because tool validity, evidence provenance, and controlled decision making also matter [32, 45]. For safety-critical maintenance decisions, grounded retrieval, confidence handling, tool-call records, and expert validation appear necessary.

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5. Challenges and future directions

5.1. Compositional generalization to unseen compound faults

Future work should test more directly whether these methods generalize to unseen compound faults. Studies on joint generalization, fault-semantic learning, and zero-shot attribute modeling suggest that reusable component information can help identify faults even when full compound combinations are missing from the training set [15, 17, 18]. Self-supervised pretraining may also make better use of unlabeled machine data and improve how well representations transfer across settings [40]. For that reason, later benchmarks should hold out entire fault combinations on purpose and report component-level precision, recall, and confidence alongside overall state accuracy.

5.2. Cross-machine and multimodal generalization

A second direction concerns generalization across machines, along with multimodal and heterogeneous sensing. Changes in machine structure, transfer paths, and sensor configuration can alter the observed signatures even when the underlying fault semantics remain similar. This makes transfer harder.

Several approaches address this from different angles. Cross-machine transfer, self-supervised learning, physics-informed learning, and lightweight cross-machine modeling may improve transferability [19, 24, 38, 40, 41]. At the same time, vibration, current, acoustic, and other sensing channels can contribute different kinds of fault evidence [39]. Even so, some problems remain unresolved: missing sensors, asynchronous sampling rates or timestamps that do not align well in practice (depending on the setup), inconsistent signal quality across operating conditions or devices (which can affect feature stability), and dynamic sensing configurations where available channels change over time.

5.3. Knowledge-enhanced foundation models and autonomous diagnostic agents

The third direction concerns knowledge-enhanced foundation models and autonomous diagnostic agents. In PHM, work on foundation models is shifting toward reusable representations that can transfer across equipment, tasks, and data modalities [26]. A recent example is frequency-aware industrial time-series foundation models, which use domain-specific pretraining [33]. On the diagnostic side, LLM-based models can bring together structured evidence, domain knowledge, analytical tools, and maintenance history in an interactive reasoning process [27-32, 43, 45].

Progress also needs evaluation at the system level. Closed-set accuracy on its own does not show whether a model still captures weak fault factors, transfers to a new machine, identifies unseen combinations, or gives an agent reliable evidence. Benchmarks should therefore include explicit unseen-combination and cross-machine splits, component-level precision and recall, confidence calibration, retrieval correctness, tool-selection validity, evidence-conclusion consistency, and maintenance-action quality.

6. Conclusion

Compound fault diagnosis moves intelligent machinery diagnosis beyond identifying a single operating state and toward inferring several fault factors at the same time. The main problems come from overlapping signatures, the rapid growth of possible state combinations, and distribution shifts between working conditions and across different machines. To deal with this, researchers have used

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deep representation learning, multi-label modeling, cross-domain generalization, and fault-semantic learning. These methods address different parts of the problem and help extract reusable component information from data that is incomplete or changes over time.

LLM-enhanced systems can link signal evidence more directly to maintenance knowledge and analysis tools. In practice, this only works when the reasoning stays tied to the data, tool use is reliable, machine-specific context is included, and each step is checked clearly. A useful next step is to combine reusable fault semantics, cross-machine generalization, multimodal sensing, industrial foundation models, and auditable agent workflows so that industrial maintenance can become more autonomous and dependable.

References

[1] Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing, 138*, 106587.

[2] Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing, 115*, 213-237.

[3] Fink, O., Wang, Q., Svensén, M., Dersin, P., Lee, W. J., & Ducoffe, M. (2020). Potential, challenges and future directions for deep learning in prognostics and health management applications. *Engineering Applications of Artificial Intelligence, 92*, 103678.

[4] Liu, R., Yang, B., Zio, E., & Chen, X. (2018). Artificial intelligence for fault diagnosis of rotating machinery: A review. *Mechanical Systems and Signal Processing, 108*, 33-47.

[5] Wen, L., Li, X., Gao, L., & Zhang, Y. (2018). A new convolutional neural network-based data-driven fault diagnosis method. *IEEE Transactions on Industrial Electronics, 65*(7), 5990-5998.

[6] Chen, J., Li, Z., Pan, J., Chen, G., Zi, Y., Yuan, J., Chen, B., & He, Z. (2016). Wavelet transform based on inner product in fault diagnosis of rotating machinery: A review. *Mechanical Systems and Signal Processing, 70-71*, 1-35.

[7] Dhamande, L. S., & Chaudhari, M. B. (2018). Compound gear-bearing fault feature extraction using statistical features based on time-frequency method. *Measurement, 125*, 63-77.

[8] Antoni, J. (2006). The spectral kurtosis: A useful tool for characterising non-stationary signals. *Mechanical Systems and Signal Processing, 20*(2), 282-307.

[9] Yan, X., Jia, M., & Xiang, L. (2016). Compound fault diagnosis of rotating machinery based on OVMD and a 1.5-dimension envelope spectrum. *Measurement Science and Technology, 27*(7), 075002.

[10] Liang, P., Deng, C., Wu, J., Yang, Z., Zhu, J., & Zhang, Z. (2019). Compound fault diagnosis of gearboxes via multi-label convolutional neural network and wavelet transform. *Computers in Industry, 113*, 103132.

[11] Yu, C., Ning, Y., Qin, Y., Su, W., & Zhao, X. (2021). Multi-label fault diagnosis of rolling bearing based on meta-learning. *Neural Computing and Applications, 33*(10), 5393-5407.

[12] Shen, J., Li, S., Jia, F., Zuo, H., & Ma, J. (2020). A deep multi-label learning framework for the intelligent fault diagnosis of machines. *IEEE Access, 8*, 113557-113566.

[13] Pu, H., Teng, S., Xiao, D., Xu, L., Qin, Y., & Luo, J. (2024). Compound fault diagnosis of rotating machine through label correlation modeling via graph convolutional neural network. *IEEE Transactions on Instrumentation and Measurement, 73*, 3503110, 1-10.

[14] Jin, Y., Qin, C., Huang, Y., & Liu, C. (2021). Actual bearing compound fault diagnosis based on active learning and decoupling attentional residual network. *Measurement, 173*, 108500.

[15] He, Y., Zhao, C., Zhou, X., & Shen, W. (2024). MJAR: A novel joint generalization-based diagnosis method for industrial robots with compound faults. *Robotics and Computer-Integrated Manufacturing, 86*, 102668.

[16] Jin, Y., Qin, C., Zhang, Z., Tao, J., & Liu, C. (2022). A multi-scale convolutional neural network for bearing compound fault diagnosis under various noise conditions. *Science China Technological Sciences, 65*, 2551-2563.

[17] Xu, J., Liang, S., Ding, X., & Yan, R. (2023). A zero-shot fault semantics learning model for compound fault diagnosis. *Expert Systems with Applications, 221*, 119642.

[18] Wang, L., Chen, D., Mao, Y., & Qin, Y. (2025). A zero-shot attribute-embedded model with a feature difference mapping sigmoid function for compound fault diagnosis of rotating machinery. *ISA Transactions, 157*, 451-465.

[19] He, Y., & Shen, W. (2023). MSRCN: A cross-machine diagnosis method for the CNC spindle motors with compound faults. *Expert Systems with Applications, 233*, 120957.

DOI: 10.54254/2755-2721/2026.GF37867

[20] Lu, W., Liang, B., Cheng, Y., Meng, D., Yang, J., & Zhang, T. (2017). Deep model based domain adaptation for fault diagnosis. *IEEE Transactions on Industrial Electronics, 64*(3), 2296-2305.
[21] Liao, Y., Huang, R., Li, J., Chen, Z., & Li, W. (2020). Deep semisupervised domain generalization network for rotary machinery fault diagnosis under variable speed. *IEEE Transactions on Instrumentation and Measurement, 69*(10), 8064-8075.
[22] Feng, Y., Chen, J., He, S., Pan, T., & Zhou, Z. (2023). Globally localized multisource domain adaptation for cross-domain fault diagnosis with category shift. *IEEE Transactions on Neural Networks and Learning Systems, 34*(6), 3082-3096.
[23] Ragab, M., Chen, Z., Wu, M., Li, H., Kwoh, C.-K., Yan, R., & Li, X. (2021). Adversarial multiple-target domain adaptation for fault classification. *IEEE Transactions on Instrumentation and Measurement, 70*, 3500211, 1-11.
[24] Guo, L., Lei, Y., Xing, S., Yan, T., & Li, N. (2019). Deep convolutional transfer learning network: A new method for intelligent fault diagnosis of machines with unlabeled data. *IEEE Transactions on Industrial Electronics, 66*(9), 7316-7325.
[25] He, Y., Zhao, C., & Shen, W. (2024). Cross-domain compound fault diagnosis of machine-level motors via time-frequency self-contrastive learning. *IEEE Transactions on Industrial Informatics, 20*(7), 9692-9701.
[26] Li, Y.-F., Wang, H., & Sun, M. (2024). ChatGPT-like large-scale foundation models for prognostics and health management: A survey and roadmaps. *Reliability Engineering & System Safety, 243*, 109850.
[27] Tao, L., Liu, H., Ning, G., Cao, W., Huang, B., & Lu, C. (2025). LLM-based framework for bearing fault diagnosis. *Mechanical Systems and Signal Processing, 224*, 112127.
[28] Liu, Y., Zhou, Y., Liu, Y., Xu, Z., & He, Y. (2025). Intelligent fault diagnosis for CNC through the integration of large language models and domain knowledge graphs. *Engineering, 53*, 311-322.
[29] Lin, L., Zhang, S., Fu, S., & Liu, Y. (2025). FD-LLM: Large language model for fault diagnosis of complex equipment. *Advanced Engineering Informatics, 65*, 103208.
[30] Qiao, B., et al. (2023). TaskWeaver: A code-first agent framework. *arXiv preprint arXiv:2311.17541*.
[31] Palma, G., Cecchi, G., & Rizzo, A. (2025). Large language models for predictive maintenance in the leather tanning industry: Multimodal anomaly detection in compressors. *Electronics, 14*(10), 2061.
[32] Di Maggio, L. G. (2025). Toward autonomous LLM-based AI agents for predictive maintenance: State of the art, challenges, and future perspectives. *Applied Sciences, 15*(21), 11515.
[33] Wang, H., Ren, L., Li, Y., & Wang, Y. (2025). MetaIndux-TS: Frequency-aware AIGC foundation model for industrial time series. *IEEE Transactions on Neural Networks and Learning Systems, 36*(10), 18062-18074.
[34] Zhang, W., Peng, G., Li, C., Chen, Y., & Zhang, Z. (2017). A new deep learning model for fault diagnosis with good anti-noise and domain adaptation ability on raw vibration signals. *Sensors, 17*(2), 425.
[35] Jia, F., Lei, Y., Lin, J., Zhou, X., & Lu, N. (2016). Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. *Mechanical Systems and Signal Processing, 72-73*, 303-315.
[36] Jiao, J., Zhao, M., Lin, J., & Zhao, J. (2018). A multivariate encoder information based convolutional neural network for intelligent fault diagnosis of planetary gearboxes. *Knowledge-Based Systems, 160*, 237-250.
[37] Zhao, M., Kang, M., Tang, B., & Pecht, M. (2018). Deep residual networks with dynamically weighted wavelet coefficients for fault diagnosis of planetary gearboxes. *IEEE Transactions on Industrial Electronics, 65*(5), 4290-4300.
[38] He, Y., & Shen, W. (2024). CFSPT: A lightweight cross-machine model for compound fault diagnosis of machine-level motors. *Information Fusion, 111*, 102490.
[39] Azamfar, M., Singh, J., Bravo-Imaz, I., & Lee, J. (2020). Multisensor data fusion for gearbox fault diagnosis using 2-D convolutional neural network and motor current signature analysis. *Mechanical Systems and Signal Processing, 144*, 106861.
[40] Li, G., Wu, J., Deng, C., Wei, M., & Xu, X. (2022). Self-supervised learning for intelligent fault diagnosis of rotating machinery with limited labeled data. *Applied Acoustics, 191*, 108663.
[41] Shen, S., Lu, H., Sadoughi, M., Hu, C., Nemani, V., Thelen, A., Webster, K., Darr, M., Sidon, J., & Kenny, S. (2021). A physics-informed deep learning approach for bearing fault detection. *Engineering Applications of Artificial Intelligence, 103*, 104295.
[42] He, Y., Yang, X., & Shen, W. (2025). A multi-model collaborative decision-making approach for compound fault diagnosis. In *2025 28th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, 485-489.
[43] Lewis, P., et al. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems, 33*, 9459-9474.

DOI: 10.54254/2755-2721/2026.GF37867

[44] Ji, Z., et al. (2023). Survey of hallucination in natural language generation. *ACM Computing Surveys, 55*(12), Article 248, 1-38.
[45] He, Y., Hu, X., & Shen, W. (2026). Cloud-edge-terminal collaborative AI agent for compound fault detection and diagnosis. *Engineering*. https://doi.org/10.1016/j.eng.2026.02.029.