Intelligent Fault Diagnosis

Subjects: Computer Science, Artificial Intelligence
Contributor: Hongtian Chen

For ensuring the safety and reliability of high-speed trains, fault diagnosis (FD) technique plays an important role. Benefiting from the rapid developments of artificial intelligence, intelligent FD (IFD) strategies have obtained much attention in the field of academics and applications, where the qualitative approach is an important branch.

Keywords: Intelligent Fault Diagnosis,High-Speed Trains ; Artificial Intelligence

1. Introduction

Since the Japanese Shinkansen was born in 1964, high-speed trains had made rapid progress all over the world [1][2][3]. Due to their various advantages, such as large capacity and low energy consumption, high-speed trains have become one of the efficient tools in the transportation field, which are responsible for carrying goods and passengers [4][5][6]. Thanks to these superiorities, the most representative high-speed train techniques, like Shinkansen-N700 and E5 in Japan, China Railway Highspeed (CRH) in China, InterCityExpress (ICE) in Germany, and Train à Grande Vitesse (TGV) in France, play an essential role in the transportation of various countries [7][8][9].

A major topic of high-speed trains is its safety. In order to protect passengers to the greatest extent, a common manner is to establish reasonable maintenance strategies [10]. Therefore, issues, like fault diagnosis (FD), attract enhanced attention from academia and application aspects in the transportation field [11][12][13]. In the FD tasks of high-speed trains, there are three basic requirements [14]: judging there is a fault in high-speed trains or not, finding the original cause of faults, and forecasting fault-evolution trends. Furthermore, these achievements also provide engineers valuable references in formulating maintenance strategies [15].

However, traditional FD techniques make it difficult to diagnose some faults in high-speed trains [16][17]. One of the reasons behind this challenge is that the inherent characteristics of faults in high-speed trains could be often confused. There are many kinds of faults among high-speed trains, differing in both fault symptoms and fault causes. A few faults can be directly determined by simple logic judgements [8]. Unfortunately, the features of other faults are complicated, especially for the large-scale system composed of many subsystems [18]. Moreover, when a one-one mapping relationship between fault types and their symptoms is not achieved, it will pose difficulties in successfully diagnosing faults. In fact, there are several aspects resulting in difficulties of successful detection and diagnosis of faults, which should be taken into account [19]. To sum up, these factors are listed as follows.

- Gradation. The structure of high-speed trains has several levels, including train level, system level, subsystem level, and component level. Thus, referring to gradational structure of trains, their faults and symptoms have similar features [21].
- Confusion. Aiming at complex system with the high structure coupling, the relationship among different fault characteristics is complicated. When fault occurs, factors, like redundancy and relevance, reflecting on these characteristics should be considered [22].
- Propagation. When a fault appears in systems, it is a high probability with the phenomenon of causing other systems or subsystems to fail at the same time [23].
- Uncertainty. The occurrence of faults in high-speed trains is often random. Moreover, there are still several uncertainties under the following situations, such as monitoring process of measurement data, transformation in external operation environment, and so on [24].

Apart from the above characteristics, the real-time ability of FD schemes should be taken into account. Because of these demanding requirements, traditional FD techniques make it difficult to achieve our desired results [20][21]. Until the 1980s, benefiting from developments of artificial intelligence (AI), especially for the utilization of expert system (ES), intelligent FD (IFD) techniques, regarded as a new research topic, could perform the FD tasks accurately, autonomously, and quickly [27][28][29][30][31]. Following the trend, IFD techniques have also been introduced into the transportation domain. The beginning of implementing IFD techniques needs to extract a large amount of diagnostic knowledge [32]. Fortunately, the primary requirement can be met in the FD tasks of high-speed trains due to rich knowledge that has been formed in the train maintenance and monitoring process. In comparison with the principle of traditional FD techniques (i.e., signal detection and feature extraction), IFD techniques can make use of knowledge acquisition and reasoning to obtain the FD results [33].

Many researchers have summarized the IFD approaches applied in high-speed trains on the basis of different perspectives for nearly half a century. In the early research, Frank [34] divided IFD techniques into analytical model-based, signal processing-based, and knowledge-based approaches. On this basis, Reference [35] summarized IFD approaches again according to recently emerging techniques, i.e., qualitative and quantitative approaches. Under the new classified way, both model-based and data-driven approaches are the branches of the quantitative approach. In addition, graph theory, expert system, and qualitative simulation are the branch of the qualitative approach. In particular, it is a remarkable work that IFD techniques are firstly comprehensively summarized.

2. Challenges and Future Trends

Over the past three decades, qualitative IFD approaches have been successfully applied in transportation areas of FD. Currently, qualitative techniques have gotten onto the intelligent stage. However, some challenges need to be addressed, especially in FD of high-speed trains, are given as follows:

- Qualitative IFD techniques are useful for a specific system.
- In qualitative IFD techniques, it is difficult to ensure that all rules are applicable.
- The lower quality of knowledge results in worse FD performance in qualitative IFD techniques.
- With the complexity of system mechanism, knowledge becomes difficult to be extracted and stored.
- Qualitative IFD techniques are difficult to diagnose and detect incipient faults in high-speed trains.
- The diagnostic KB with complete fault knowledge, viewed as a prerequisite for using qualitative IFD techniques, is difficult to be constructed.

In addition to summarizing their limitations and challenges, future research trends centered on qualitative IFD techniques are exposed. One of the recent trends is that qualitative IFD techniques combine other approaches to improve the FD performance. The core of the research is still fault identification, location, and prediction. For another, remote and real-time requirements should be considered in FD procedures of high-speed trains. Here, several advanced trends are listed below.

(1)Management and maintenance of explicit diagnostic knowledge. It is well known that the construction of diagnostic KB about high-speed trains is a huge task. One of the difficulties lies in the need to expose invisible knowledge because most researchers or engineers only use existing technologies and explicit diagnostic knowledge to build a KB containing enough rich information. But, it is not even close to sufficient. But, invisible knowledge, especially in the human brain of train maintenance engineers, is also an indispensable knowledge resource. At the moment, there have been many studies aiming at explicit knowledge extraction, but few reports consider invisible knowledge extraction. To overcome this difficulty, it is helpful to construct a complete diagnostic KB from the perspective of knowledge extraction.

(2)Improvements in the quality of known quantitative information in high-speed trains. A large amount of historical data is recorded during the operation of high-speed trains and then can be converted into fault knowledge through data mining methods. However, these data collected from the onboard information system in high-speed trains often suffer from missing data points. When extracting knowledge from missing data and building a diagnostic KB, it is easy to lose important knowledge. Thus, the selection of appropriate preprocessing techniques can improve the quality of knowledge discovery and monitoring data (will be used in data mining methods to extract fault knowledge), thereby improving the quality of the diagnostic KB and the result provided via qualitative IFD techniques.

(3)Deep knowledge mining, extraction, and application. Shallow knowledge could be summarized from the massive historical data collected from high-speed trains. On the contrary, deep knowledge is helpful to explore relationships among subsystems in high-speed trains, providing the new solution for system level faults. It is expected that qualitative IFD techniques combining deep and shallow knowledge will be further developed in the future, so as to break the constraints of traditional qualitative methods for special applications in system level or component level FD.

(4)The fusion of qualitative IFD and health management approaches. Under some special conditions (e.g., complete diagnostic KB, the transparent and interpretable FD procedure), qualitative IFD approaches can show accuracy results. These conditions are also necessary for health management techniques. One emerging solution for qualitative IFD approaches is to integrate into health management techniques, and the whole framework can be regarded as an autonomous and accurate comprehensive evaluation system for high-speed trains. With the critical advantages of health management, engineers can easily report the dynamic degradation of high-speed trains, providing effective suggestions for train maintenance. However, there are some challenges with the above technology, like system integration, sensor selection and optimal layout, and measurement data fusion. Fortunately, solutions to these challenges can improve the reliability of high-speed trains and reduce the operation cost of systems.

The research and application of integrated qualitative IFD techniques. Some critical systems in high-speed trains usually have complex nonlinear features, such as strong coupling and time-varying parameters. In addition, process uncertainties and external interferences also have negative effects on FD procedures. Therefore, different qualitative IFD approaches need to be integrated to improve the FD effect. However, there are still many problems to be further studied, such as combination principles of different methods, the fuzzy knowledge expression after fusion, etc.

(6)The research and application of distributed qualitative IFD techniques. With the development of materials and technologies, high-speed trains are becoming systematic, continuous, and automated, many distributed frameworks, like distributed open-scale FD systems, are applied in FD procedures of trains. Distributed techniques provide a potential way for large-scale IFD. Through the description, decomposition and allocation of FD tasks, distributed qualitative IFD techniques can be designed for the decentralized and problem-oriented subsystems to overcome challenges in a parallel collaboration. Furthermore, FD schemes based on the fusion of multi-agent techniques and qualitative IFD techniques are also the advanced research topics in FD domains.

(7)The research and application of remote cooperative qualitative IFD techniques. The premise is to integrate computer networks into qualitative IFD techniques, in which multicenter computers as servers work together. With the aid of computer remote monitoring, information transmission, remote IFD techniques are easy to realize the processing, transmission, storage, query, and display of monitoring information in high-speed trains. The successful implementation of remote cooperative qualitative IFD techniques will be helpful for online IFD in high-speed trains, providing real-time results for engineers in the operation center. Based on these results, engineers and experts can adjust maintenance plans of trains. The key to this technique includes remote signal analysis, remote transmission of real-time data, and open ES design.

References

1. Chen, H.T.; Jiang, B. A review of fault detection and diagnosis for the traction system in high-Speed trains. IEEE Trans. Intell.Transp. Syst. 2020, 21, 450–465.
2. Yang, C.H.; Yang, C.; Peng, T.; Yang, X.Y.; Gui, W.H. A fault-injection strategy for traction drive control systems. IEEE Trans.Ind. Electron. 2017, 64, 5719–5727.
3. Tu, D.Y.; Zheng, J.D.; Jiang, Z.W.; Pan, H.Y. Multiscale distribution entropy and t-distributed stochastic neighbor embedding-based fault diagnosis of rolling bearings. Entropy 2018, 20, 360.
4. Chen, Z.W.; Ding, S.X.; Peng, T.; Yang, C.H.; Gui, W.H. Fault detection for non-gaussian processes using generalized canonical correlation analysis and randomized algorithms. IEEE Trans. Ind. Electron. 2018, 65, 1559–1567.
5. Chen, H.T.; Jiang, B.; Lu, N.Y. A newly robust fault detection and diagnosis method for high-speed trains. IEEE Trans. Intell. Transp. Syst. 2019, 20, 2198–2208.
6. Guo, L.; Lei, Y.G.; Xing, S.B.; Yan, T.; Li, N.P. Deep convolutional transfer learning network: A new method for intelligent fault diagnosis of machines with unlabeled data. IEEE Trans. Ind. Electron. 2019, 50, 92–111.
7. Cheng, C.; Wang, W.J.; Luo, H.; Zhang, B.C.; Cheng, G.L.; Teng, W.X. State-degradation-oriented fault diagnosis for high-speed train running gears system. Sensors 2020, 4, 1017.
8. Chen, H.T.; Jiang, B.; Zhang, T.Y.; Lu, N.Y. Data-driven and deep learning-based detection and diagnosis of incipient faults with application to electrical traction systems. Neurocomputing 2020, 396, 429–437.
9. Chen, H.T.; Jiang, B.; Ding, S.X.; Lu, N.Y.; Chen, W. Probability-relevant incipient fault detection and diagnosis methodology with applications to electric drive systems. IEEE Trans. Control Syst. Technol. 2019, 27, 2766–2773.
10. Cheng, C.; Wang, J.H.; Fu, C.X.; Zhang, B.C. A status assessment model for dynamic system based on cloud evidence reasoning. In Proceedings of the IECON 2019, Lisbon, Portugal, 14–17 October 2019.
11. Chen, H.T.; Jiang, B.; Lu, N.Y.; Chen, W. Real-time incipient fault detection for electrical traction systems of CRH2. Neurocomputing 2018, 306, 119–129.

12. Chen, H.T.; Jiang, B.; Chen, W.; Li, Z.H. Edge computing-aided framework of fault detection for traction control systems in high-speed trains. IEEE Trans. Veh. Technol. 2020, 69, 1309–1318.

13. Lei, Y.G.; Lin, J.; He, Z.J.; Zuo, M.J. A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mech. Syst. Signal Process 2013, 35, 108–126.

14. Liu, R.; Yang, B.; Zio, E.; Chen, X.F. Artifificial intelligence for fault diagnosis of rotating machinery: A review. Mech. Sys t. Signal Process 2018, 108, 33–47.

15. Liu, Z.G.; Liu, K.; Zhong, J.P.; Han, Z.W.; Zhang, W.X. A high-precision positioning approach for catenary support comp onents with multi-scale difference. IEEE Trans. Instrum. Meas. 2020, 69, 700–711.

16. Wang, X.F.; Yang, G.H. Event-triggered fault detection observer design for T-S fuzzy systems. IEEE Trans. Fuzzy Syst. in press.

17. Chen, H.; Chai, Z.; Jiang, B.; Huang, B. Data-driven fault detection for dynamic systems with performance degradation: A unified transfer learning framework. IEEE Trans. Instrum. Meas. in press.

18. Shang, C.; Yang, F.; Gao, X.; Huang, X.; Suykens, J.A.K.; Huang, D. Concurrent monitoring of operating condition devi ations and process dynamics anomalies with slow feature analysis. AIChE J. 2015, 61, 3666–3682.

19. Chen, H.T.; Jiang, B.; Lu, N.Y.; Mao, Z.H. Deep PCA based real-time incipient fault detection and diagnosis methodolog y for electrical drive in high-speed trains. IEEE Trans. Veh. Technol. 2018, 67, 4819–4830.

20. Lu, J.G.; Zhang, H.; Tang, X.H. A novel method for intelligent single fault detection of bearings using SAE and improved D-S evidence theory. Entropy 2019, 21, 687.

21. Chen, H.T.; Jiang, B.; Chen, W.; Yi, H. Data-driven detection and diagnosis of incipient faults in electrical drives of high-speed trains. IEEE Trans. Ind. Electron. 2019, 66, 4716–4725.

22. Cheng, C.; Wang, J.H.; Zhou, Z.J.; Teng, W.X.; Sun, Z.B.; Zhang, B.C. A BRB-based effective fault diagnosis model for high-speed trains running gear systems. IEEE Trans. Intell. Transp. Syst. in press.

23. Zhou, D.H.; Zhao, Y.H.; Wang, Z.D.; He, X.; Gao, M. Review on diagnosis techniques for intermittent faults in dynamic systems. IEEE Trans. Ind. Electron. 2020, 67, 2337–2347.

24. Song, L.L. Synthetically intelligent diagnosis approach of high-speed trains based on the non-canonical knowledge pro cessing. Ph.D. Thesis, Beijing Jiaotong University, Beijing, China, 2016.

25. Cheng, C.; Qiao, X.Y.; Luo, H.; Teng, W.X.; Gao, M.L.; Zhang, B.C.; Yin, X.J. A semi-quantitative information based faul t diagnosis method for the running gears system of high-speed trains. IEEE Access 2019, 7, 38168–38178.

26. Glowacz, A.; Glowacz, W.; Kozik, J.; Piech, K.; Gutten, M.; Caesarendra, W.; Liu, H.; Brumercik, F.; Irfan, K.; Khan, Z. Detection ofdeterioration of three-phase induction motor using vibration signals, measurement science review. Meas. S ci. Rev. 2019, 19,241–249.

27. Delpha, C.; Diallo, D.; Samrout, A.H.; Moubayed, N. Multiple incipient fault diagnosis in three-phase electrical systems using multivariate statistical signal processing. Eng. Appl. Artif. Intell. 2018, 73, 68–79.

28. Yuan, X.F.; Li, L.; Shardt, Y.; Wang, Y.L.; Yang, C.H. Deep learning with spatiotemporal attention-based LSTM for indust rial soft sensor model development. IEEE Trans. Ind. Electron. in press.

29. Tian, E.G.; Wang, X.M.; Peng, C. Probabilistic-constrained distributed filtering for a class of nonlinear stochastic system s subject to periodic DOS attacks. IEEE Trans. Circuit. Syst.–I in press.

30. Yu, W.K.; Zhao, C.H.; Huang, B. Stationary subspace analysis based hierarchical model for batch processes monitorin g. IEEE Trans. Control Syst. Technol. in press.

31. Tian, E.G.; Peng, C. Memory-based event-triggering H-infinity load frequency control for power systems under deceptio n attacks. IEEE Trans. Cybernetics in press.

32. Delpha, C.; Chen, H.; Diallo, D. SVM based diagnosis of inverter fed induction machine drive: A new challenge. In Proc eedings of the 38th Annual Conference on IEEE Industrial Electronics Society, Montreal, QC, Canada, 25–28 October 2012.

33. Wan, S.T.; Peng, B. An integrated approach based on swarm decomposition, morphology envelope dispersion entropy, and random forest for multi-fault recognition of rolling bearing. Entropy 2019, 21, 354.

34. Frank, P.M. Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results. Automatica 1990, 26, 459–474.

35. Zhou, D.H.; Hu, Y.Y. Fault diagnosis techniques for dynamic systems. Acta Autom. Sinica 2009, 35, 748–758.