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Editorial

Advances in Machine Condition Monitoring and Fault Diagnosis

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1. Introduction

In the past few decades, with the great progress made in the field of computer technology, non-destructive testing, signal and image processing, and artificial intelligence, machine condition monitoring and fault diagnosis technology have also achieved great technological progress and played an active and important role in various industries to ensure the efficient and reliable operation of machines, lower the operation and maintenance costs, and improve the reliability and availability of large critical equipment. However, with the continual advance of intelligent production and the emergence and flourishing of new production fields, such as renewable energy, medical care, and remote sensing, today's research into machine condition monitoring and fault diagnosis technology has become even richer than ever before. The object being dealt with is no longer restricted to a specific machine or component but extends to more complex systems or even the whole industrial production lines (e.g., industrial assembly lines). The purpose of condition monitoring is no longer just to determine whether the machine is operating properly or whether certain predictable or unpredictable faults have occurred in the machine but extends to providing more reliable and valid information for fault ride-through and optimizing machine operation and industrial production, or even to directly guiding the operation of the machine. This special issue has been organised specifically to reflect on these new changes and the latest research results achieved in these areas.

2. The Present Issue

This Special Issue consists of ten papers covering important progress in the relevant areas. Among the ten papers, three papers are for improving wafer production, three for increasing the safety of power generation and power transmissions, two for guaranteeing satellite control, one for improving medical care, and one for controlling industrial assembly lines with the aid of non-destructive testing, condition monitoring, and fault diagnosis techniques. They are summarized in Table 1, and more details of these papers are given below.

Table 1. Summary of the work reported in the ten papers.

Paper Reference No.	Field of Application	Type of Data or Information Used	Data Processing Methods or Work Delivered
1	Wafer production	Vibration	K-means algorithm and neural network
2	Wafer production	Temperature	Sensing system for measuring temperature distribution
3	Wafer production	Optical emission spectroscopy data	Extended isolation forest
4	Power transmission	Infrared images	Convolutional neural network
5	Power transmission	Infrared images	Multiple convolutional neural networks
6	Power generation	Vibration	Long short-term memory neural network and Bayesian hypothesis
7	Satellite control	System parameters	Long short-term memory recurrent neural network
8	Satellite control	Gyro assembly data	Multi-step classification
9	Medical care	Infrared temperature	Data monitoring
10	Industrial assembly lines	Assembly line data	Parallel deep reinforcement learning

In Reference [1], a new predictive maintenance system has been developed that uses the K-means algorithm to identify features of sensor data from wafer transfer robots and to diagnose abnormal robot states using a neural network model. As a result of training the designed model and evaluating the classification results, the classification accuracy of over 97% was obtained. In addition, it was confirmed that normal data and first-order error data that started to appear abnormal could be classified with high accuracy. By using the system to accurately predict equipment conditions and to maintain equipment before failures occur, unnecessary equipment inspection costs in semiconductor processes can be significantly reduced. Moreover, it shows that the system works well in predicting the likelihood of errors and notifying maintenance times. It is worth noting that the function of detecting and notifying equipment errors is performed by the system itself, rather than by humans, which is an important difference from previous studies. Besides semiconductor manufacturing, this system can be applied to a variety of areas that use sensor data. Considering that temperature variation of the electrostatic chuck (ESC) has a direct impact on the characteristics of the etching process, a wireless on-wafer temperature monitoring (OTMS) system consisting of 65 temperature measurement units was developed in Reference [2] to monitor the operating condition of the ESC. In this study, by comparing the data collected before and after the repair of the ESC, it has been confirmed that the abnormal state of the ESC can be correctly detected using the temperature distribution diagram. The most important thing is that compared with those currently available sensors that should be manufactured using semiconductor processes (e.g., etching, sputtering, deposition, etc.), the proposed OTMS is manufactured based on a PCB board. Therefore, its fabrication is much easier and simpler. It is well known that faster and more accurate fault detection during the plasma process is quite important to minimize wafer production loss by misprocessing during semiconductor manufacturing. In Reference [3], the authors proposed a new method for achieving more accurate process fault detection from optical emission spectroscopy (OES) data. In the study, under a controlled experimental setup of arbitrarily induced fault scenarios, the extended isolation forest was applied to detect the anomalies in the OES data. The OES data were also used to generate features related to electron temperature. It was found that with the aid of OES data, the generated electron temperature features, and equipment status variable identification data, the prediction accuracy of process or equipment fault detection can be improved by 0.84%.

To guarantee the safety of the equipment in a substation, an efficient thermal defect detection technique was developed in Reference [4] based on infrared image processing using a convolutional neural network (CNN). To improve the quality of the images, the authors applied an improved pre-processing method to reduce the background information in the images. Then, the temperature values in the images were segmented to build the dataset. Finally, a CNN model was constructed to extract features of the images and a support vector machine (SVM) was trained for classification. The results have shown that the image classification accuracy of the proposed method can reach 99.50%. It is well known that a metal oxide arrester (MOA) is an important piece of protection equipment for ensuring the safe operation of a power transmission system. To monitor the health condition of the MOA, a novel MOA fault detection technology based on a small sample infrared image was proposed in Reference [5]. In the study, a lightweight MOA identification and location algorithm was developed, which can not only reduce the amount of data uploaded but also reduce the search space of the cloud algorithm. In order to improve the accuracy and generalization ability of the defect detection model under the condition of small samples, a multi-model fusion detection algorithm was also proposed. The features of the images were extracted by multiple convolutional neural networks, and then multiple classifiers are trained. Finally, the weighted voting strategy is used for classification. The experimental results have shown that the proposed method can realize the accurate location of the arrester under the condition of small samples, and after the data expansion, the recognition rate of arrester anomalies can be improved from 83% to 85%, showing high effectiveness and reliability. Reference [6] proposed a Bayesian dynamic thresholding method, which combined Bayesian inference with neural network signal prediction to aid decision-making during condition monitoring. The method makes full use of prior historical data to build an anomaly identification and warning model applicable under single variable or multidimensional variables. A long short-term memory signal prediction model is established, and then a Bayesian hypothesis testing-based anomaly identification strategy is presented to quantify the probability of anomaly occurrence and issue early warnings for anomalies beyond a certain probability. The model developed was applied to the open data sets of a pumping station and actual operating data of a nuclear power turbine. The results have shown that the model can successfully predict the failure probability and failure time.

In Reference [7], a three-step prognosis technique was proposed for predicting the remaining useful life (RUL) of the reaction wheels (RWs) that are widely used in the attitude control of small satellites. In the study, a version of long short-term memory recurrent neural network was used to predict future system measurements, i.e., state reconstruction. A multivariate long short-term memory recurrent neural network was used to predict the health index parameter of the RWs. From the failure threshold for the health index and its intersection with the health index predicted trend, the RUL of the RW was predicted. The proposed method has been tested for robustness under noise, missing data, and different input frequencies. The results show promising performance for the proposed scheme with accuracy in predicting the health index parameter around 0.01–0.02 normalized root mean squared error, the accuracy in prediction of RUL of 1–2.5%, and robustness to various uncertainty factors. In Reference [8], a data-driven fault diagnosis method was developed for detecting faults occurring in the satellite control moment gyroscope assembly. The proposed method is based on an optimized SVM, and the results yield fault predictions with up to 95.6% accuracy. In addition, a sensitivity analysis with regard to noise, missing values, and missing sensors was done. The results show that the proposed model is robust enough to be used in real applications.

In Reference [9], medical equipment for turning over by pneumatic or mechanical drive was developed to aid pressure ulcer prevention. This is an important research topic in the field of medical care especially in the light of the fact that the number of long-term bedridden disabled and semi-disabled elderly people is increasing with the continuous increase of ageing today and in the meantime, there is a serious shortage of professional pressure ulcer nursing staff. To improve the safety of the turning mattress during automatic turning, a temperature sensor based on the principle of infrared reflection was added to monitor the status of bedridden patients. With the aid of such a temperature monitoring system, one can readily realize real-time temperature measurement, monitoring of getting out of bed, and monitoring of the whole turning process.

Finally, the optimal control of industrial assembly lines was studied in Reference [10]. In this work, a complex instance of industrial assembly line control is formalized and a parallel deep reinforcement learning approach is presented. In an assembly line control problem, a set of tasks (e.g., vehicle assembly tasks) needs to be planned and controlled during their execution. The aim of the optimal control is to properly plan each task and thereby minimize the total time taken to execute all the tasks run on workstations in the assembly lines. The authors used deep reinforcement learning to learn a tasks/resources mapping policy that is effective in minimizing the resulting cycle time. Such a method allows us to explicitly take into account all the constraints. So, the trained deep reinforcement learning network can be used in real-time to dynamically control the execution of all tasks. Simulations have shown that the proposed method can provide effective real-time decision support to industrial operators for scheduling and rescheduling activities.

3. Future

From Table 1 and the work summary depicted above, it is noticed that the recent study of machine condition monitoring and fault diagnosis technology has shown the following three new trends:

Firstly, various types of machine learning technologies are being increasingly used in the practice of data or image processing, feature extraction, classification, and decision-making. This will, to a certain extent, reduce the reliance on the operator's knowledge, thereby greatly reducing the costs of personnel training and the labour of staff while increasing the efficiency and accuracy of machine condition monitoring and fault diagnosis. However, these technologies are highly dependent on the quantity and quality of historical data. Once it is difficult for the historical data to meet the requirements of machine learning algorithms in terms of quantity and quality, they may lead to condition monitoring and fault diagnosis errors. Although some efforts (e.g., [5,11]) have been made in the development of machine learning algorithms based on small sample data, the machine learning using small samples is still an unsolved problem that requires further efforts to overcome in the future.

Secondly, to further improve the reliability of machine condition assessment and fault diagnosis, the benefits of using information integration and information fusion techniques [12,13] have been further explored with the help of machine learning techniques. The introduction of multivariate analysis and image processing techniques allows condition monitoring and fault diagnosis techniques to be no longer dependent on the analysis of a single type of signal, but to rely on the more reliable assessment of the health status of more objectives in a system (e.g., machines in industrial assembly lines) from a more macroscopic perspective. The only problem with this is that such complex information evaluation and data processing calculations will place higher demands and challenges on the parallel processing capabilities of condition monitoring and fault diagnosis systems. This will inevitably increase the cost of machine condition monitoring and fault diagnosis. How to achieve complex information and data processing at a lower cost will also be a challenging issue to be addressed in the future.

Finally, the functions of condition monitoring and fault diagnosis are further expanded in recent years. It is no longer limited to assisting in the operation and maintenance of equipment, but extends to the optimization of complex workflows, and even directly participates in the operation of machines, providing real-time and effective guidance for their control operations [9,10], thus greatly improving the intelligence and efficiency of machine operations. However, the premise of this is that the results of condition monitoring and fault diagnosis must be correct and reliable. Otherwise, it will be counterproductive. Therefore, how to further improve the reliability and validity of machine condition monitoring and fault diagnosis results remains an important area for further efforts in the future.

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References

1. Yoo, J.-H.; Park, Y.-K.; Han, S.-S. Predictive Maintenance System for Wafer Transport Robot Using K-Means Algorithm and Neural Network Model. *Electronics* **2022**, *11*, 1324. [CrossRef]
2. Kim, J.-H.; Koo, Y.; Song, W.; Hong, S.J. On-Wafer Temperature Monitoring Sensor for Condition Monitoring of Repaired Electrostatic Chuck. *Electronics* **2022**, *11*, 880. [CrossRef]
3. Kwon, H.; Hong, S.J. Use of Optical Emission Spectroscopy Data for Fault Detection of Mass Flow Controller in Plasma Etch Equipment. *Electronics* **2022**, *11*, 253. [CrossRef]
4. Wang, K.; Zhang, J.; Ni, H.; Ren, F. Thermal Defect Detection for Substation Equipment Based on Infrared Image Using Convolutional Neural Network. *Electronics* **2021**, *10*, 1986. [CrossRef]
5. Wei, B.; Zuo, Y.; Liu, Y.; Luo, W.; Wen, K.; Deng, F. Novel MOA Fault Detection Technology Based on Small Sample Infrared Image. *Electronics* **2021**, *10*, 1748. [CrossRef]
6. Liu, G.; Yang, S.; Wang, G.; Li, F.; You, D. A Decision-Making Method for Machinery Abnormalities Based on Neural Network Prediction and Bayesian Hypothesis Testing. *Electronics* **2021**, *10*, 1610. [CrossRef]
7. Islam, M.S.; Rahimi, A. A Three-Stage Data-Driven Approach for Determining Reaction Wheels' Remaining Useful Life Using Long Short-Term Memory. *Electronics* **2021**, *10*, 2432. [CrossRef]
8. Varvani Farahani, H.; Rahimi, A. Data-Driven Fault Diagnosis for Satellite Control Moment Gyro Assembly with Multiple In-Phase Faults. *Electronics* **2021**, *10*, 1537. [CrossRef]
9. Zhang, Y.; Zou, X.; Zhang, B.; Han, Y.; Wang, S.; Liu, T.; Zhang, X. A Flexible Turning and Sensing System for Pressure Ulcers Prevention. *Electronics* **2021**, *10*, 2971. [CrossRef]
10. Tortorelli, A.; Imran, M.; Delli Priscoli, F.; Liberati, F. A Parallel Deep Reinforcement Learning Framework for Controlling Industrial Assembly Lines. *Electronics* **2022**, *11*, 539. [CrossRef]
11. Wang, X.; Yang, W.; Qin, B.; Wei, K.; Ma, Y.; Zhang, D. Intelligent Monitoring of Photovoltaic Panels based on Infrared Detection. *Energy Rep.* **2022**, *8*, 5005–5015. [CrossRef]
12. Yang, W.; Court, R.; Tavner, P.; Crabtree, C. Bivariate Empirical Mode Decomposition and Its Contribution to Wind Turbine Condition Monitoring. *J. Sound Vib.* **2011**, *330*, 3766–3782. [CrossRef]
13. Luo, S.; Yang, W.; Luo, Y. A Novel Fault Detection Scheme Using Improved Inherent Multiscale Fuzzy Entropy with Partly Ensemble Local Characteristic-Scale Decomposition. *IEEE Access* **2020**, *8*, 6650–6661. [CrossRef]