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Using SVM based method for equipment fault detection in a thermal power plant

Kai-Ying Chen [a], Long-Sheng Chen [b,*], Mu-Chen Chen [c], Chia-Lung Lee [d]

[a] Department of Industrial Engineering and Management, National Taipei University of Technology, Taipei, Taiwan, ROC
[b] Department of Information Management, Chaoyang University of Technology, Taichung, Taiwan, ROC
[c] Institute of Traffic and Transportation, National Chiao Tung University, Taipei, Taiwan, ROC
[d] Shanghai FirstTech Company Limited, China

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ABSTRACT

Due to the growing demand on electricity, how to improve the efficiency of equipment in a thermal power plant has become one of the critical issues. Reports indicate that efficiency and availability are heavily dependant upon high reliability and maintainability. Recently, the concept of e-maintenance has been introduced to reduce the cost of maintenance. In e-maintenance systems, the intelligent fault detection system plays a crucial role for identifying failures. Data mining techniques are at the core of such intelligent systems and can greatly influence their performance. Applying these techniques to fault detection makes it possible to shorten shutdown maintenance and thus increase the capacity utilization rates of equipment. Therefore, this work proposes a support vector machines (SVM) based model which integrates a dimension reduction scheme to analyze the failures of turbines in thermal power facilities. Finally, a real case from a thermal power plant is provided to evaluate the effectiveness of the proposed SVM based model. Experimental results show that SVM outperforms linear discriminant analysis (LDA) and back-propagation neural networks (BPN) in classification performance.

1. Introduction

Thermal power plants fired by fossil fuels are one of the primary sources of noxious greenhouse gas emissions, producing, carbon dioxide. Even so, they are still the major source of supplying electricity in Taiwan. According to the annual report of the Taiwan Power Company (TPC), the total power generation of their eight thermal power plants exceeds 70% of the total energy generated nowadays [3] in Taiwan. Consequently, due to growing demands on electricity, how to improve the efficiency of equipment in a thermal power plant has become a critical issue.

Huang et al. [6] indicated that the efficiency and availability depend heavily on high reliability and maintainability. In order to raise efficiency, the equipment of thermal power plants is becoming larger and more complex. However, due to lack of manpower and information resources, the diagnosis and repair of failed equipment cannot usually be performed immediately. From lots of published articles [58–62], we can find that to identify the failure types of steam turbines and their root causes is time consuming. It needs professional knowledge regarding materials and mechanical engineering. Generally speaking, thermal power plant engineers can merely handle routine or uncomplicated maintenance tasks. Additional tests and expert advice are additionally required from the technical support of original equipment manufacturers for complex fault diagnosis and maintenance, although these additional tests are often costly and involve some risk to equipment [8]. Hence it leads to long downtimes for equipment and causes significant production losses [11]. In order to reduce the cost of maintenance and risky experiments, the concept of e-maintenance has been introduced to identify the root cause of component failure, to reduce the failures of production systems, to eliminate costly unscheduled shutdown maintenances, and to improve productivity [12].

In an e-maintenance system, the intelligent fault detection system plays a crucial role for identifying failures. Data mining techniques are the core of such intelligent systems and can greatly enhance their performance [6,8,9]. Applying these techniques to fault detection makes it possible to eliminate additional tests or experiments which usually involve high expense and highly risk [8]. Recently, several data mining techniques such as artificial neural networks, fuzzy logic systems, genetic algorithms, and rough set theory have all been employed to assist the detection and condition monitoring tasks [4,10]. For example, Yang and Liu [8] presented a hybrid-intelligence data mining framework which involves an attribute reduction technique and rough set theory to diagnose the faults of boilers. Shu [45] established an interactive data mining approach based inference system to solve the basic technical challenge and speed up the discovery of knowledge in nuclear power plant. Besides, some related works designed data

* Corresponding author.
E-mail addresses: kychen@ntut.edu.tw (K.-Y. Chen), lschen@cyut.edu.tw (L.-S. Chen), ittchen@mail.nctu.edu.tw (M.-C. Chen).

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mining based models for failure inspections, but not for fault predictions, such as the work of Yang and Liu [8]. Vast amounts of data describing process variables for boilers and turbines have been used for monitoring, control and over-limit alarms. Huang et al. [6] used principle component analysis (PCA) and T^2 statistics to inspect different types of faults in a thermal power plant. Prasad et al. [9] proposed a histogram based method to monitor and maximize the performance of thermal power plants. Therefore, building an intelligent system for the fault prediction of any thermal power plants most valuable equipment, namely turbines, has become necessary.

Since artificial intelligence techniques can improve prediction accuracy and decrease people involvement, it is very important to select an appropriate learning algorithm. In recent years, support vector machines (SVM) [15], has been considered as one of the most effective supervised learning algorithm in many pattern recognition problems [16–18]. It has been reported that SVM provides a better classification result than other methods such as neural networks or decision trees [1,14,19–21,23,35]. Moreover, SVM has been widely applied to fault detection and diagnosis in production environment. For examples, Hsu et al. [47] integrated a feature extraction technique, independent component analysis (ICA), into SVM to develop an intelligent fault detector for non-Gaussian in multivariate processes. Li et al. [48] combined another dimension reduction method, partial least squares (PLS), with SVM to increase the performance of on-line fault detection in batch processes. In the work of Zhang [49], both kernel independent component analysis (KICA, for non-Gaussian distribution) and kernel principal component analysis (KPCA, for Gaussian distribution) are used for fault detection in, named Tennessee Eastman process, which is a complex non-linear process created by Eastman Chemical Company. Mahadevan and Shah [50] utilized one-class SVM for fault detection and diagnosis and claimed that their approach outperformed principal components analysis (PCA) and dynamic principal components analysis (DPCA). From these works, we can know that SVM is one of effective fault detection approach in realistic industrial processes. In addition, SVM has been usually combined with feature extraction techniques including ICA, PLS, PCA, KPCA, KICA, and DPCA. But, by using feature extraction techniques, the transformed smaller feature space cannot be explainable and this is not good for searching root causes further.

Therefore, this work proposes a SVM based model which integrates a dimension reduction scheme and the SVM classifier is used to predict the failures of turbines. In this proposed model, in order to handle the huge amounts of collected data, correlation analysis (CA) and decision tree (DT) feature reduction methods have been introduced. Moreover, back-propagation neural network (BPN) and linear discriminant analysis (LDA) are utilized as the benchmarks for comparison purposes. Finally, a real case from a thermal power plant in Taiwan is provided to evaluate the effectiveness of the proposed SVM based model.

2. Thermal power plant

This section provides a brief introduction of a thermal power plant. In a power plant, the prime mover is steam driven. By heating, water is transformed into steam, and it is then condensed to push a turbine of power generators to produce electricity. Fig. 1 illustrates the basic steps in converting fossil fuels to electricity.

2.1. Equipment in a thermal power plant

The equipment of a thermal power plant is schematically shown in Fig. 2. The equipment can be classified into four major groups. As described below, they are the steam generator, the steam turbine generator, the electrical driven generator, and the monitoring and alarm system.

1. Steam generator: The steam generating boiler produces steam with high purity, pressure and temperature required for the steam turbine that drives the electrical generator. The generator includes boiler, water feeding system, fuel system, SCR, air heater, EP, FGD, etc.
2. Steam turbine generator: The steam turbine generator is used to transform the thermal energy to mechanical energy. The generator includes the turbine and the condensed system. It is the major piece of equipment of a thermal power plant.
3. Electrical driven generator: The electrical driven generator transforms the mechanical energy to the electrical energy. The generator includes electrical generator, exciter, transformer, etc.
4. Monitoring and alarm system: The system is used to monitor the above generators, and sounds the alarm if any abnormal event occurs.

Among them, the steam turbine generator is one of the most valuable pieces of equipment in a thermal power plant. Therefore, we focus on analyzing the failures of turbines in this work.

2.2. The important monitoring parameters and failure analysis of the steam turbine generator

The steam turbine generator is the most crucial piece of equipment in a thermal power plant. The turbine is a complex multi-axle system involving high-pressure generators, low-pressure generators, and exciter rotors [51]. The steam turbine blade is extremely complex since it must be flexible enough to change shape during operation in response to cold temperatures and the dynamic coupling effect [58]. Researchers have paid lots of attention on analyzing failures including failure types and causes [52,53,59,60]. Besides, Marco et al. [62] indicated that turbine startup is one of the critical problems in the operation of electrical power plants. Parka et al. [61] indicated that reducing environmental damage and increasing turbine efficiency are essential issues. Chen [51] indicated that reliable power generation and low maintenance costs are the major goals of power plant administration. He considered turbines are one of major parts for maintenance to enhance the efficiency of power plant equipment. Therefore, he presented an operational maintenance model by employing radio frequency identification technology. Moreover, in the work of Akturk and Gurel [52], the operational importance of turbines was heightened and realized. Therefore, to keep this generator operating smoothly without interruption by any faults, inspecting the data of parameters reported by the monitoring and alarm system is an important task.

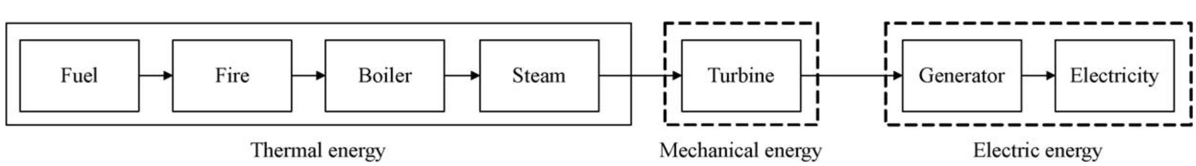

Fig. 1. Energy transformation of thermal power plant [31].