

Low-sample fault diagnosis method of high-voltage circuit breaker based on Deep Learning

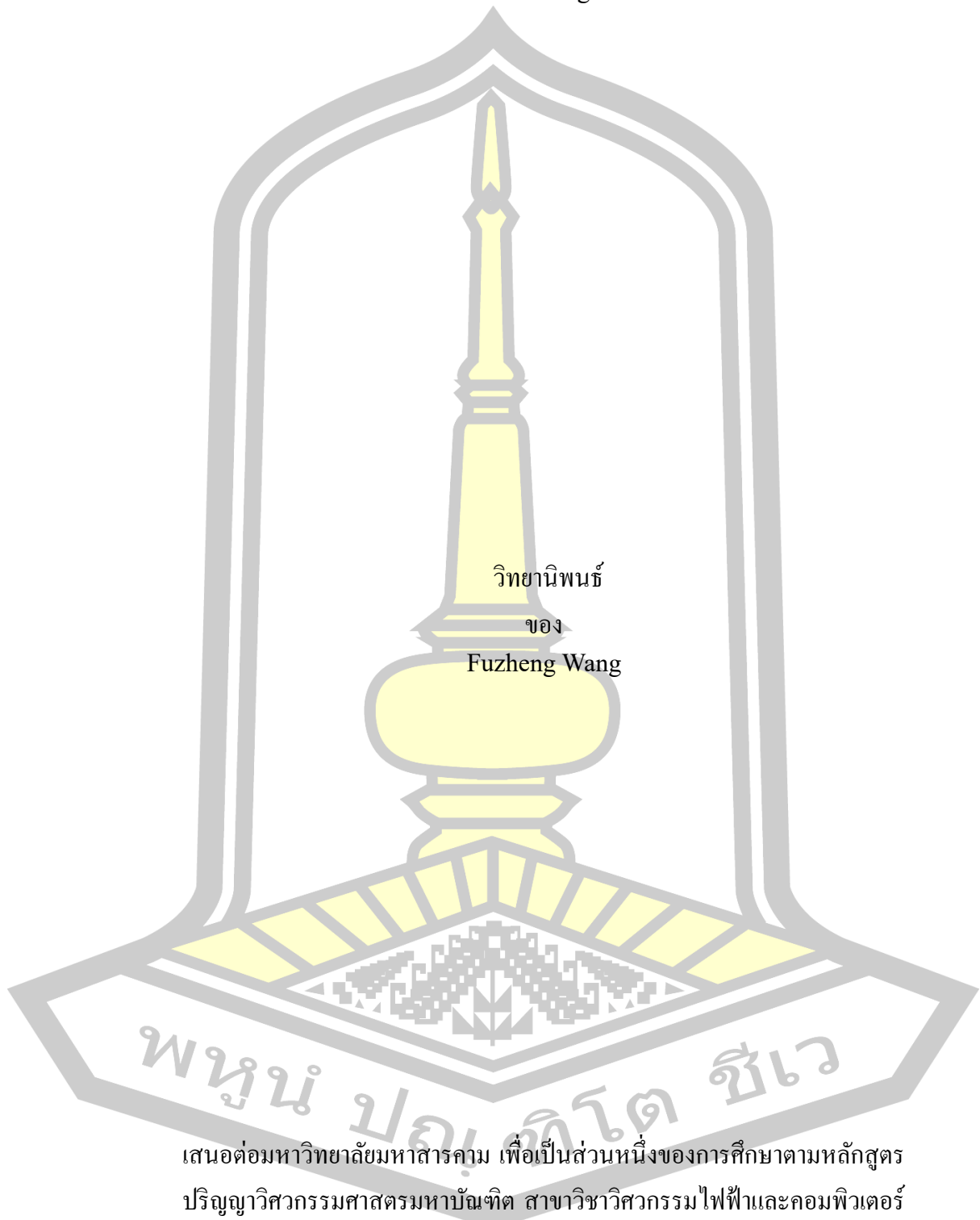
Fuzheng Wang

A Thesis Submitted in Partial Fulfillment of Requirements for
degree of Master of Engineering in Electrical and Computer Engineering

August 2025

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Low-sample fault diagnosis method of high-voltage circuit breaker based on Deep Learning



วิทยานิพนธ์
ของ
Fuzheng Wang

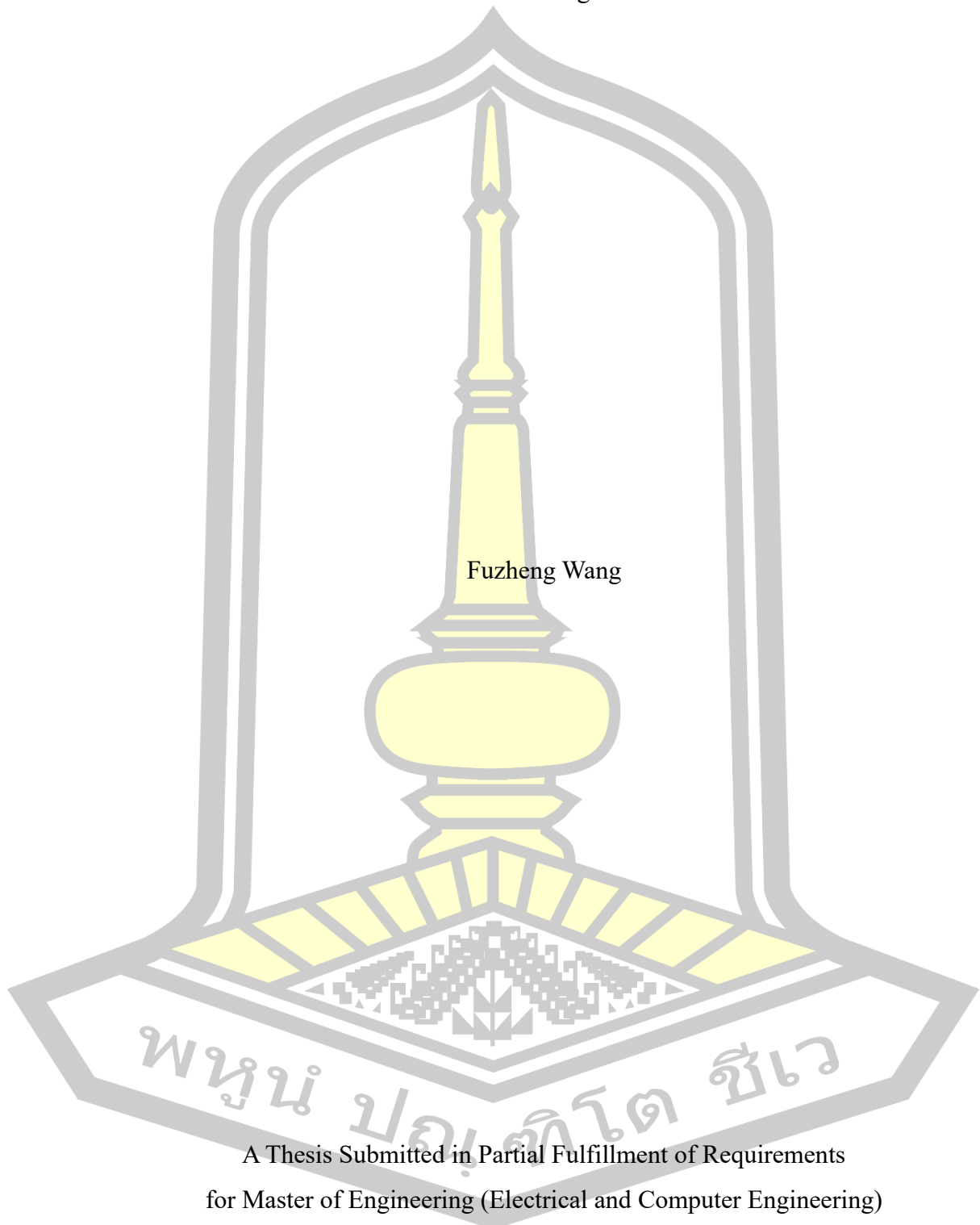
เสนอต่อมหาวิทยาลัยมหาสารคาม เพื่อเป็นส่วนหนึ่งของการศึกษาตามหลักสูตร
ปริญญาวิทยาศาสตรมหาบัณฑิต สาขาวิชาวิศวกรรมไฟฟ้าและคอมพิวเตอร์

สิงหาคม 2568

ลิขสิทธิ์เป็นของมหาวิทยาลัยมหาสารคาม

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A Thesis Submitted in Partial Fulfillment of Requirements
for Master of Engineering (Electrical and Computer Engineering)

August 2025

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TITLE Low-sample fault diagnosis method of high-voltage circuit breaker based on Deep Learning

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DEGREE Master of Engineering **MAJOR** Electrical and Computer Engineering

UNIVERSITY Mahasarakham University **YEAR** 2025

ABSTRACT

High-voltage vacuum circuit-breakers are essential for power systems. They ensure a stable power grid. Due to their complex nature, vacuum circuit breakers are susceptible to failure over time. Failure can occur due to operational, faulty, contact or actuator problems. This paper presents a fault diagnosis method for high voltage vacuum circuit breakers based on CGAN and CNN. It addresses the lack of fault data and limited diagnostic accuracy. The operating principles of high-voltage vacuum circuit breakers are first examined, followed by the construction of a platform to replicate fault scenarios. The data will be collected to create datasets on different types of faults. CGAN generates diverse fault data to improve model generalisation. A one-dimensional convolutional neural network is used for fault diagnosis. This model identifies and classifies a wide variety of fault types in high-voltage vacuum circuit breakers with an accuracy rate of over 98%. This ensures safe operation of power systems.

Keyword : High-voltage vacuum circuit breaker, Fault diagnosis, Conditional generative adversarial network, One-dimensional convolutional neural network

ACKNOWLEDGEMENTS

In the process of pursuing my master's degree, there are too many people and things that I am grateful for. I would like to thank my supervisor, Associate Professor Chonlatee Photong, for your valuable guidance and selfless help throughout the research process. When I encountered problems in my studies, it was your professional knowledge and experience that enabled me to keep moving forward on the road of research, and you patiently corrected my mistakes and pointed out the direction for me. I am really grateful for your guidance and encouragement. I would like to thank all the professors and staff of the School of Engineering. Your advice and help made me feel the beauty of research and study. I would like to thank my seniors, classmates and juniors who discussed and struggled together in the library every day, which made my study journey in a foreign country full of warmth. In study and life, your selfless guidance and help made me very moved and happy. I would like to thank the literature cited in the thesis and the people who provided the information. In my research, the information you provided made my research more comprehensive and detailed, and allowed me to better understand the knowledge and ideas of related disciplines. I would like to thank my family for their support and understanding of my study. Without their support and encouragement, none of this would have happened, and I would not have been able to persist and complete my research work. Thank you very much, and I would like to express my deep gratitude and blessings to you!

Fuzheng Wang

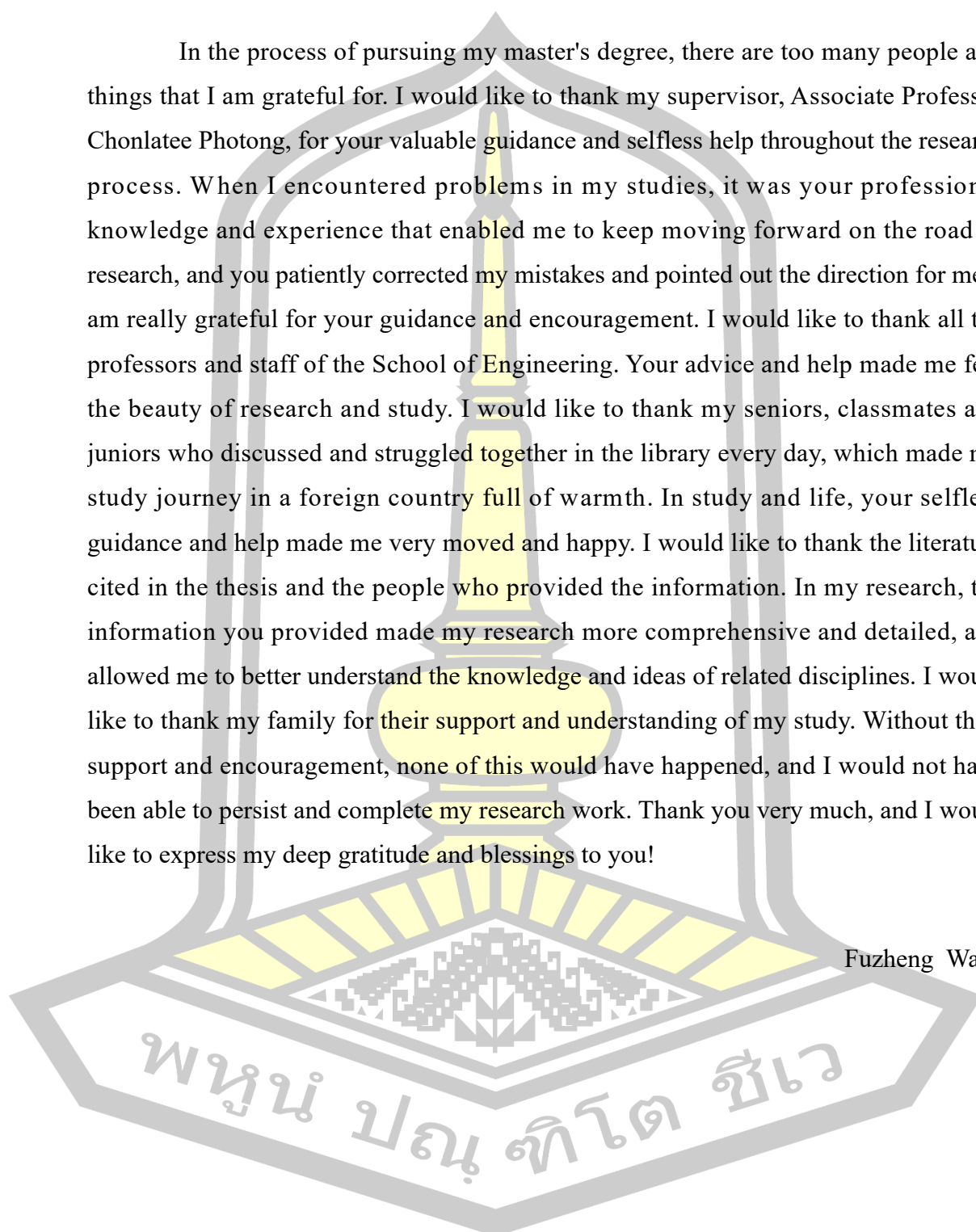
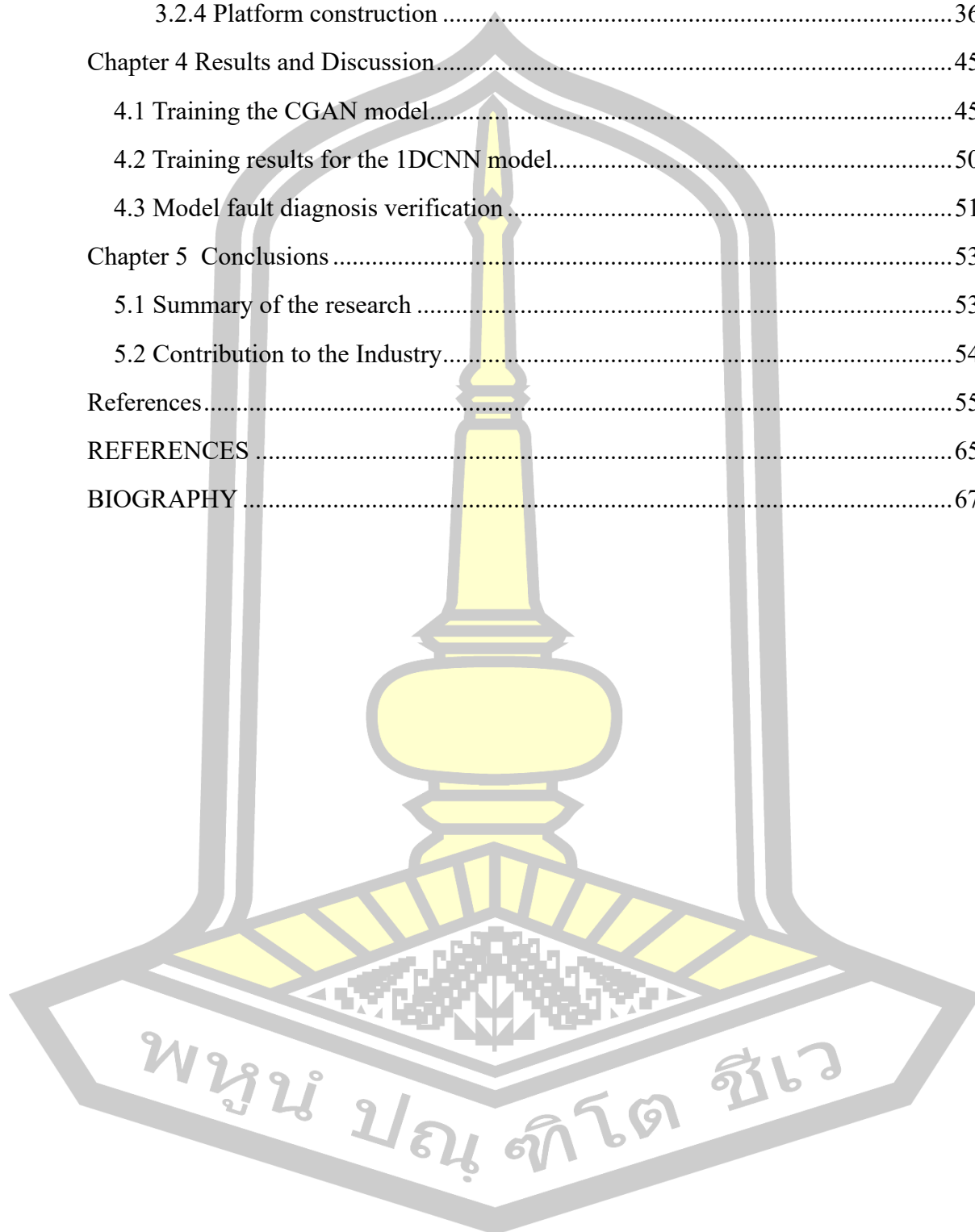


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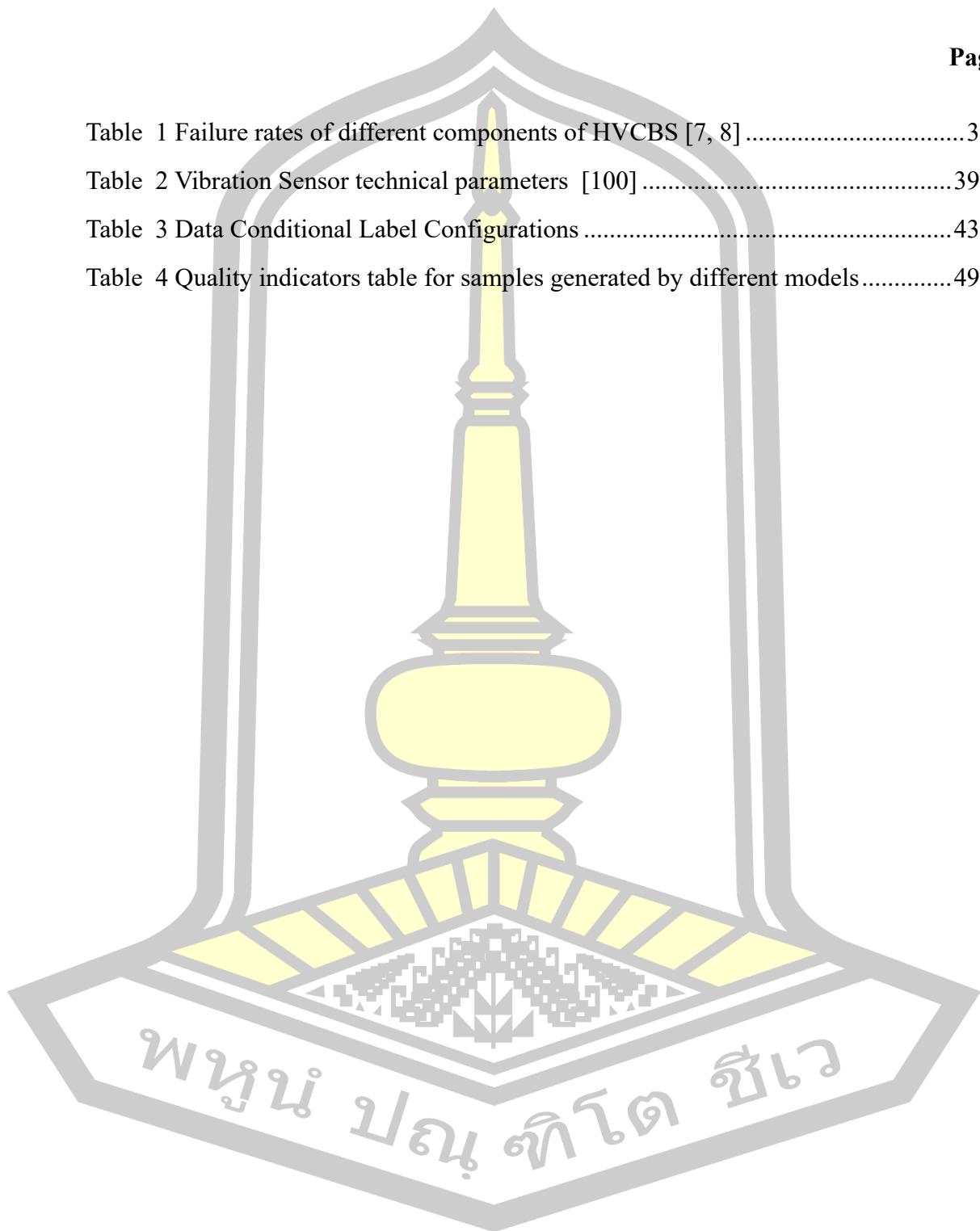
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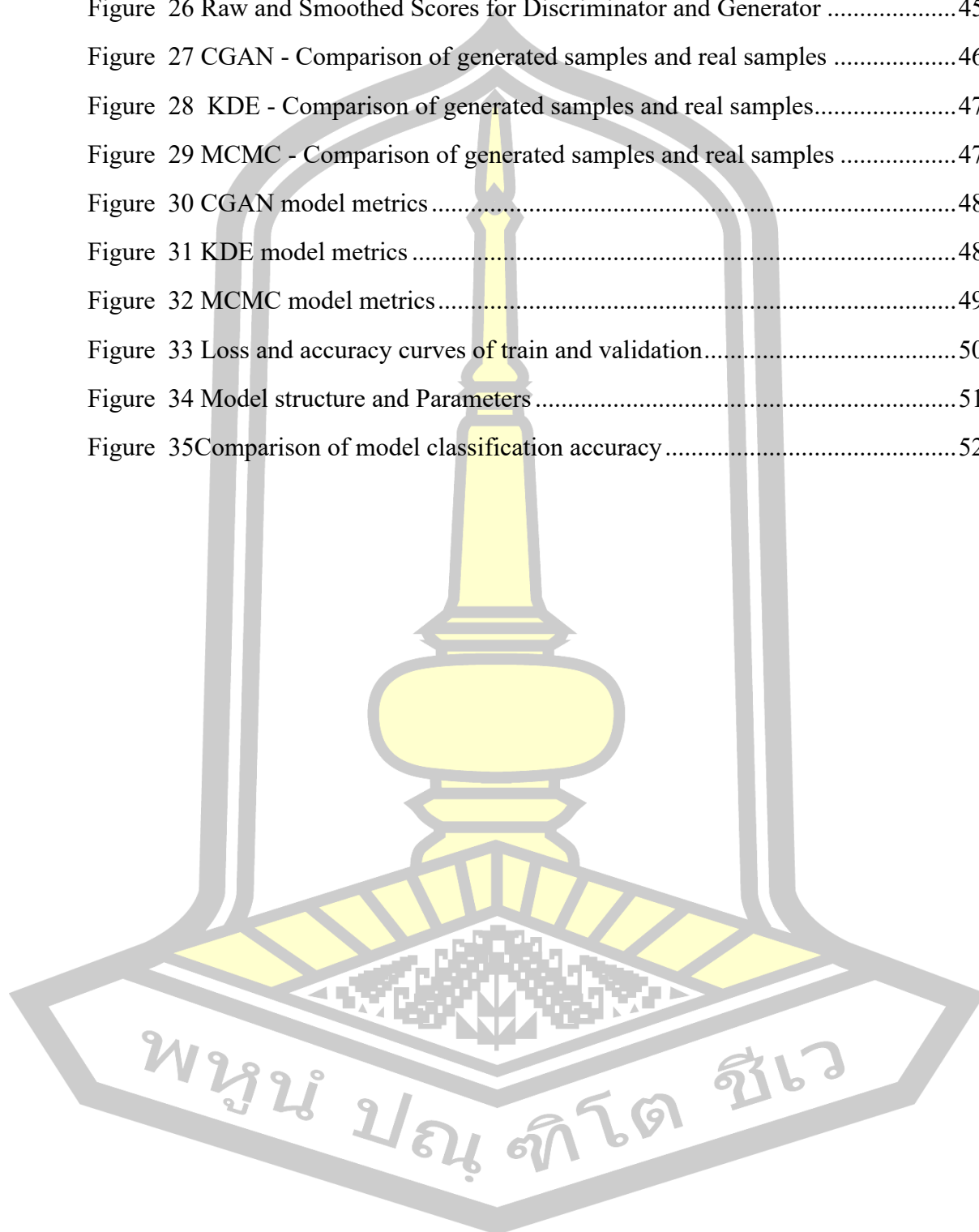
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Chapter 1 Introduction

1 Research Background

1.1.1 Research background and significance

High-voltage circuit breakers are indispensable in the power system, and they mainly bear the dual responsibilities of system control and fault protection. In terms of control, the circuit breaker switches the system equipment or lines in and out according to actual needs to adjust the operation mode; in terms of protection, the circuit breaker can quickly isolate the faulty equipment or lines to ensure the normal operation of the power grid. As the switch gear with the most tasks in the power system, high-voltage circuit breakers are in great demand in the power industry. Therefore, once they fail, the economic losses they bring are often huge [1].

As the power system develops towards higher voltage levels and larger scales, high-voltage circuit breakers, as important electrical switch gear to maintain the stability and safe operation of the power system, have been widely used in various fields of the power system, such as: protection of high-voltage transmission networks, protection of low-voltage distribution networks and protection of modern power plants, box-type substations and many high-voltage distribution projects. The expansion of the scope of application has brought about an increasing number of operational failures of high-voltage circuit breakers. The high-voltage circuit breaker consists of an operating mechanism, a transmission mechanism, an insulating part, a conductive part and an arc extinguishing chamber, etc. Its appearance and internal structure are shown in Figure 1 [2] below. Once a fault occurs or it operates under potential fault hazards, it will damage electrical components, cause damage to electrical equipment and chain failures, cause environmental pollution and waste of resources, and even cause serious safety accidents such as fires, thereby causing significant economic losses and threatening the lives of people [3].

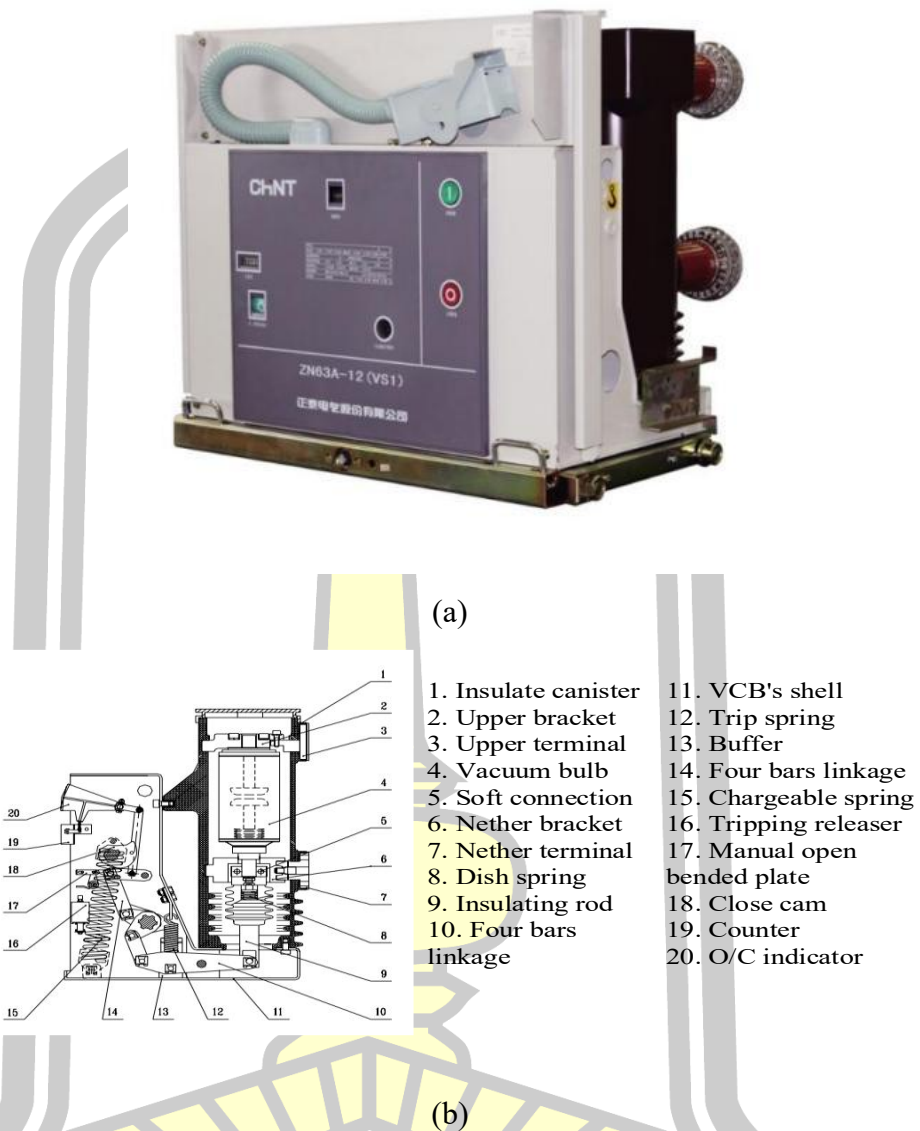


Figure 1 HVCB with (a) appearance picture and (b) internal components [2]

Therefore, it is particularly important to ensure the normal operation of high-voltage circuit breakers. Research on the diagnosis and prediction of high-voltage circuit breaker faults and defects can effectively ensure the stable operation of the power system, while reducing or avoiding the consequences of system failures and reducing maintenance costs. It is a key measure to ensure the safe, reliable and efficient operation of the power system.

The results of three global surveys on the reliability of high-voltage circuit breakers conducted by the International Council on Large Electric Power (CIGRE) since 1970 [4, 5, 6], the failure rates of different components of high-voltage circuit

breakers are shown in Table 1. As can be seen from Table 1-1, in the three survey results, mechanical failures of the operating mechanism accounted for 33%, 46% and 58% of the major failures, and 58%, 46% and 53% of the minor failures[7, 8]. This data shows that among the various failures that occur in circuit breakers, operating mechanism failure is the main type of failure, and mechanical failure is the most likely failure of spring operating mechanisms [9] .

Table 1 Failure rates of different components of HVCBS [7, 8]

where the fault occurred	Major Failure(%)			Secondary Failure(%)		
	First time	Second time	Third time	First time	Second time	Third time
Charge main circuit	48	23	7	26	33	19
Control circuit	19	31	28	16	21	23
Operating mechanism	33	46	58	58	46	53
other			7			5

It can be seen that the mechanical failure of the operating mechanism is the main failure of the circuit breaker. Studying the occurrence types of mechanical failures of high-voltage circuit breakers and their corresponding fault diagnosis technologies is of great significance for timely eliminating faults and enhancing the safety, reliability and economy of the power system [9].

By detecting the mechanical state of the circuit breaker, on the one hand, the mechanical fault of the circuit breaker's operating mechanism can be more accurately located, assisting the staff to find and repair the fault in time, thereby avoiding the expansion of the fault and improving the safety and reliability of the circuit breaker [10, 11]. On the other hand, it has high economic value. By mining the state data, the changing rules of parameters such as the mechanical vibration of the circuit breaker can be obtained, the possibility of fault occurrence can be analyzed, and early warning can be issued based on the data results, so that the operation and maintenance personnel can carry out maintenance in advance, thereby extending the life of the equipment and reducing unnecessary replacement.

1.1.2 Fault diagnosis development trend

In recent years, the development of signal processing technologies such as time domain analysis, amplitude domain analysis, Fourier transform, wavelet analysis, and

wavelet packet analysis has provided a technical basis for circuit breaker fault diagnosis. At present, fault diagnosis is the development trend of high-voltage circuit breaker maintenance. This method uses various sensors to collect signals with different physical properties (two major categories of electrical signals and mechanical signals commonly seen in high-voltage circuit breakers). After reprocessing and feature extraction, the sampled signals are obtained to obtain feature quantities that can characterize the state of the circuit breaker, thereby identifying the circuit breaker fault and determining its maintenance items and frequency [12, 13].

Improving the accuracy and speed of fault detection can not only ensure the safe and stable operation of the power system, but also greatly improve the overall operating efficiency and economic benefits of the power system. In addition, compared with traditional maintenance methods, high-voltage circuit breaker fault diagnosis can shorten downtime, extend equipment life, and reduce maintenance costs.

1.1.3 Problems to be solved by this thesis

At present, the main problems in the research process of mechanical fault diagnosis of high-voltage short-circuit breaker operating mechanism are as follows:

(1) Limited samples

High-voltage circuit breakers are relatively expensive, and more importantly, they are limited by the test platform. Due to the complex stress load of the circuit breaker or the large size of the circuit breaker, a set of test platforms can usually only test one sample. Therefore, limited by economic and time costs, small sample problems are usually encountered [14].

(2) Limited failure data

Since the working characteristics of high-voltage circuit breakers require high reliability and long life, it is difficult to obtain sufficient fault data (even zero fault) within a limited time [15].

(3) Due to the complexity of vibration signals, high-voltage circuit breaker fault diagnosis based on vibration signals places higher requirements on signal processing methods. Selecting appropriate feature extraction algorithms, optimizing algorithm performance, improving the accuracy and completeness of classification and recognition algorithms, and establishing a complete operating mechanism

operating status and characteristic parameter database are still urgent issues to be solved in circuit breaker operating mechanism fault detection [16].

1.2 Research Objectives

Study mainly focuses on the following objectives

- (1) To Study and research the working mechanism of high-voltage circuit breakers, understand the types of common faults and the causes of faults.
- (2) To design, develop an experimental platform for collecting raw data and diagram of HVCB fault diagnosis framework.
- (3) To test the accuracy of a deep learning algorithm for expanding fault data and identifying fault types in high-voltage circuit breakers.
- (4) To optimize the algorithm network structure and training strategy to enhance the adaptability of the model in complex power environments and ensure its stable performance under different fault modes.

The research process divides the fault diagnosis of high-voltage vacuum circuit breakers into three stages: studying the working mechanism of high-voltage vacuum circuit breakers based on target requirements; researching and analyzing fault diagnosis types and deep learning algorithms.

1.2.1 Working mechanism of high voltage circuit breaker

(1) Working mechanism of primary side of high voltage circuit breaker

High-voltage circuit breakers primarily consist of contact systems, arc-extinguishing systems, operating mechanisms, trip devices, and shell. Based on their arc-extinguishing mechanisms, high-voltage circuit breakers can be classified into oil circuit breakers, compressed air circuit breakers, SF₆ circuit breakers, and vacuum circuit breakers. Depending on their operating mechanisms, they can be categorized into electromagnetic, electric, hydraulic, permanent magnet, and spring-operated mechanisms. High-voltage circuit breakers serve to connect or disconnect circuits during normal operation; in the event of a fault, they quickly disconnect the circuit upon receiving protection instructions from relay protection devices; under special circumstances, they can temporarily connect short-circuit currents. When the secondary electrical circuit of the high-voltage circuit breaker issues an opening or closing command, the operating mechanism receives the electrical command, and the

high-voltage circuit breaker immediately actuates. Through the interlocking device, the transmission mechanism is driven, ultimately completing the opening or closing of the moving and stationary contacts of the high-voltage circuit breaker, thereby achieving the disconnection or connection of the circuit [17].

A high-voltage circuit breaker completes the tripping operation, thereby disconnecting the load circuit or opening the high-voltage circuit. The speed of the tripping process of a high-voltage circuit breaker is determined by the parameter switch time. The switch time refers to the total time from the receipt of the trip signal until the arc current is completely extinguished. The switch time includes the inherent opening time and the arcing time. The time from the receipt of the trip signal command until the contacts of the circuit breaker are about to separate is called the switch time. The time from when the contacts of the circuit breaker are just about to separate until the arc is completely extinguished is called the arcing time. Figure 2 [18] shows a schematic diagram of the tripping process of a high-voltage circuit breaker, with each time segment corresponding to a different state process.

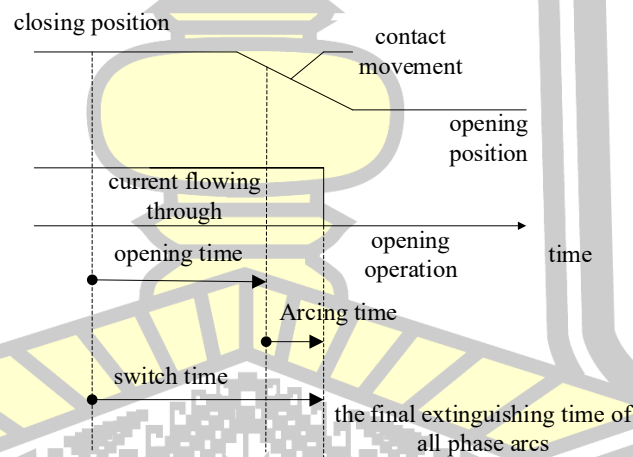


Figure 2 Circuit breaker opening process[18]

When the high-voltage circuit breaker completes the closing operation, the electrical device or line can be put into working condition. The speed of the high-voltage circuit breaker closing process is determined by the parameter closing time. The closing time refers to the total time from when the circuit breaker receives the closing command until the closing operation is completed. The closing time includes the switch time and the ore-breakdown time. The time from when the circuit breaker receives the closing signal command until the contacts are about to close is called the

closing time. The time from when the contacts of the circuit breaker begin to close until the arc is completely extinguished is called the ore-breakdown time. Figure 3 [18] shows a schematic diagram of the closing process of a high-voltage circuit breaker, with each time segment corresponding to a different state process.

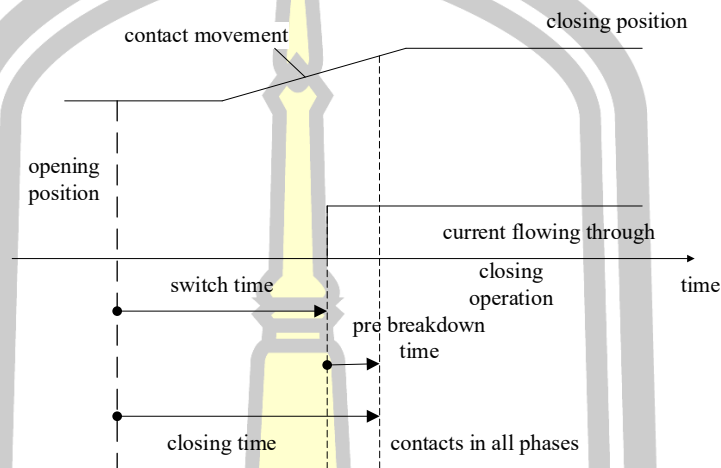


Figure 3 Closing process diagram[18]

(2) Working mechanism of spring operating mechanism on secondary side of high voltage circuit breaker

The structure of the spring operating mechanism of the high-voltage circuit breaker is shown in Figure 4.

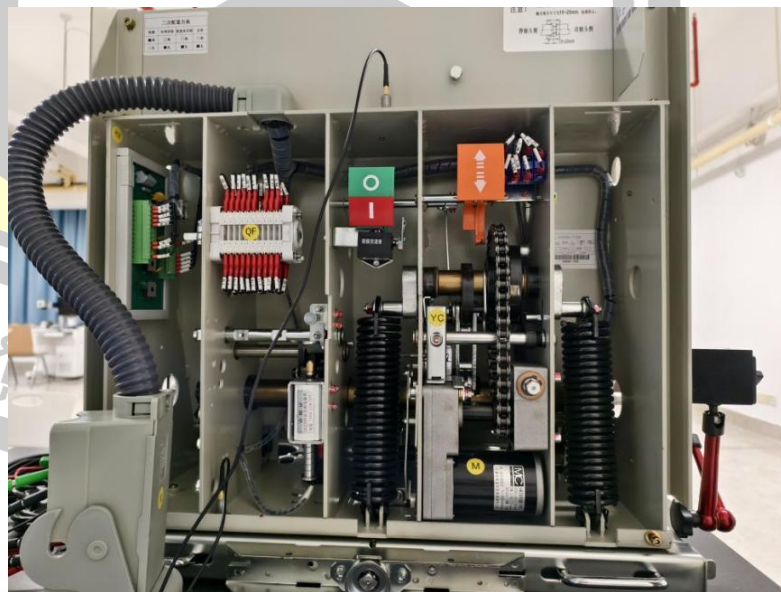


Figure 4 Structural diagram of the spring-operated mechanism of a high-voltage circuit breaker

A spring-operated mechanism is a type of mechanism that uses a spring as its energy storage element, primarily consisting of three major components: Energy storage, transmission and control. The energy storage mechanism provides energy for the opening and closing springs; the transmission mechanism is primarily used to transmit motion and power; the control mechanism is used to control the opening and closing actions and also serves as a buffer. The principle block diagram of the spring-operated mechanism is shown in Figure 5 [19].

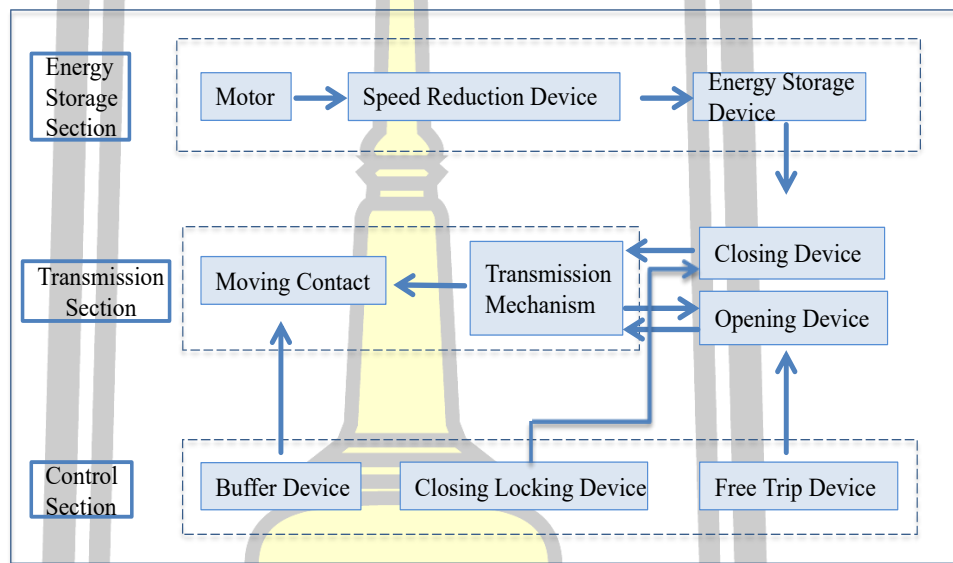


Figure 5 Schematic diagram of the composition principle of the spring operating mechanism[19]

This section focuses on circuit breakers with spring-operated mechanisms, analyzing the operational processes of the mechanism's tripping operation, closing operation, and energy storage operation.

(1) Opening operation

The process from Figure 6 to Figure 7 is a dynamic process. When the trip coil receives an energization signal, it drives the trip trigger to rotate clockwise and release the trip latch, causing it to also rotate clockwise and release the pin on the main lever arm. The force of the trip spring pushes the main lever arm to rotate counterclockwise, thereby completing the Opening operation.

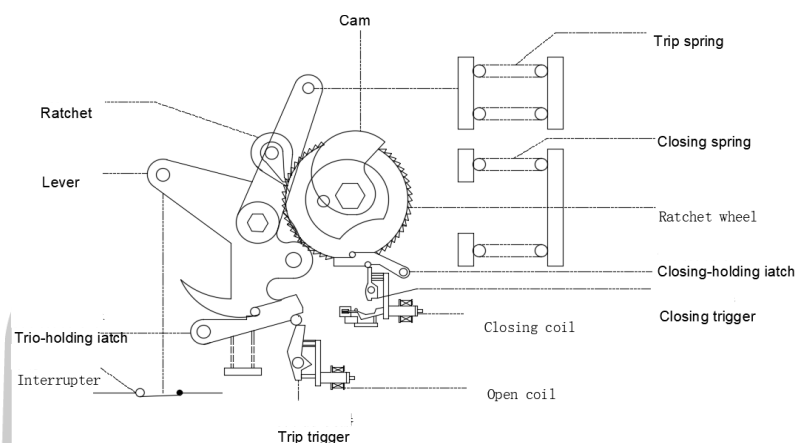


Figure 6 Closing position (closing spring energy storage) [20, 21, 22]

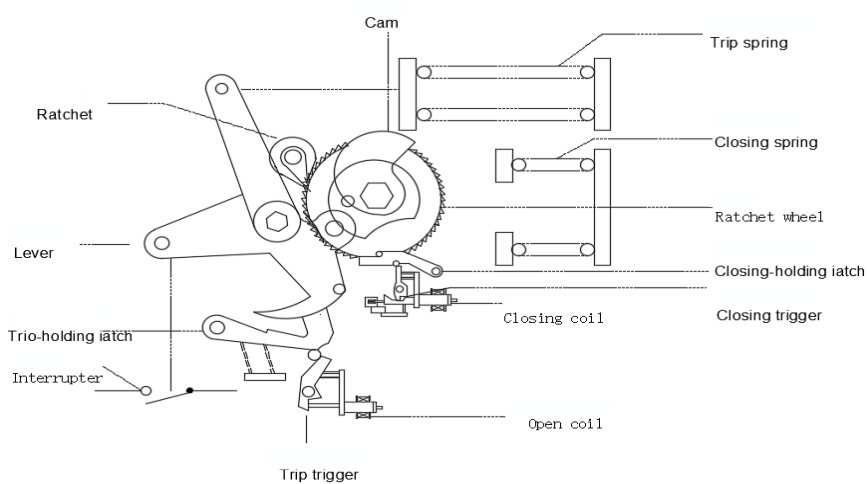


Figure 7 Opening position (closing spring stored energy)[20, 21, 22]

(2) Closing operation

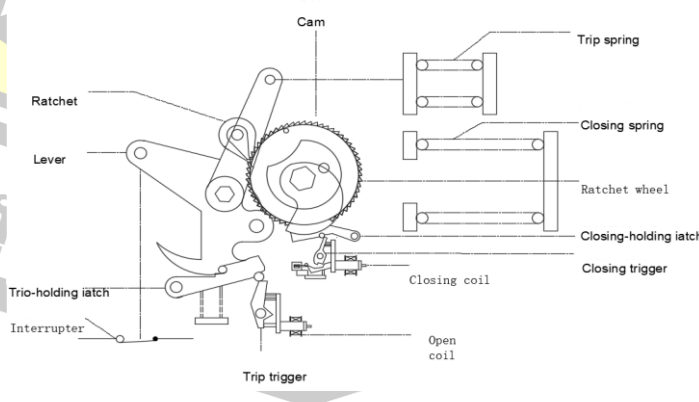


Figure 8 Closing position (closing spring released)[20, 21, 22]

Figures 7 to 8 illustrate a dynamic process. When the closing coil receives an energization signal, it drives the closing trigger to rotate clockwise, releasing the closing spring that holds the latch in place. This causes the latch to rotate counterclockwise and release the pin on the ratchet. The closing spring force pushes the ratchet, causing the camshaft to rotate counterclockwise, which in turn drives the main lever arm to rotate clockwise, thereby completing the closing operation. During the closing operation, the opening spring is simultaneously compressed to store energy. When the main lever arm rotates clockwise to the end of its travel, pin is locked by the trip release latch and the trip trigger, keeping the circuit breaker in the closed position.

(3) Closing spring energy storage operation

Figure 8 shows a schematic diagram of the circuit breaker in the closed state, at which point the closing spring is released. When the closing operation is complete, the cam plate triggers the limit switch to close, and the energy storage motor starts when energized. The energy storage motor drives the bevel gear and eccentric wheel, which in turn drive the ratchet to rotate counterclockwise, compressing the closing spring to store energy. Finally, the stored energy of the closing spring holds the latch in place. The cam plate triggers the limit switch again, the energy storage motor is DE-energized, the closing spring stops storing energy, and the system returns to the state shown in Figure 6.

In summary, the operations of tripping, closing, and energy storage all involve mechanical interlocking and impact processes. A normal tripping and closing cycle of the operating mechanism is accompanied by the generation of regular vibrations. Therefore, studying the vibration signals of the circuit breaker operating mechanism can indirectly provide information about the operating status of the mechanism.

1.2.2 Typical fault types of high voltage circuit breakers

The following Figure 9 lists the common fault types of high-voltage circuit breakers and their occurrence rates. As shown in Figure 9, among the common fault types of circuit breakers, failure to trip and incorrect tripping account for the highest proportion, at 46%. In cases of failure to trip and incorrect tripping, faults caused by the operating mechanism account for the highest proportion, at 89% [23, 24, 25, 26].

Faults in the operating mechanism are primarily caused by three types of faults: coil faults, mechanism jamming, and spring fatigue.

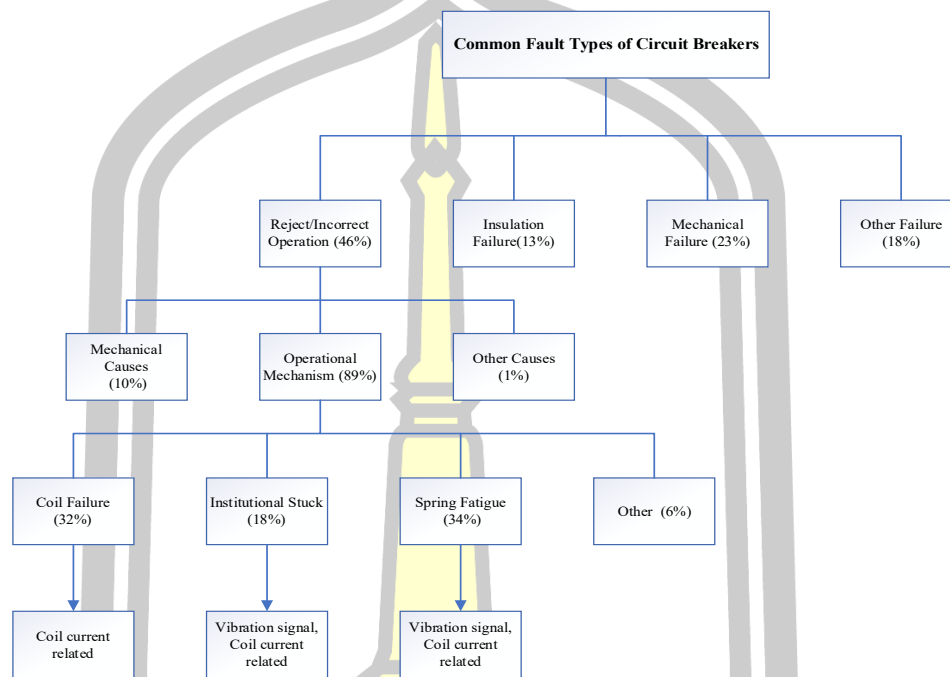


Figure 9 Common fault types of high-voltage circuit breakers[23, 24, 25, 26]

Coil faults can be classified as electrical secondary circuit faults. For electrical secondary circuit faults, the main types include poor closing contact faults, auxiliary switch faults, burning of the opening circuit resistance, burning of the closing/opening coils, sticking of the closing/opening coils, secondary wiring faults, and operating power supply faults.

Mechanical sticking and spring fatigue can be classified as secondary mechanical faults. Secondary mechanical faults in circuit breakers are caused by failures in the operating mechanism and transmission mechanism. The main faults including: core refusal to move, short core travel, failure of the closing or opening rods to disengage the trip mechanism, sticking of the closing or opening latches, mechanism jamming, damage or deformation, loose or fallen contacts, spring breakage, and broken flexible connections.

Failures caused by other factors account for a small proportion but still require attention. These include insulation faults, current-carrying faults, and leakage faults.

1.2.3 Deep learning algorithms

As an important branch of machine learning, deep learning has become a crucial tool in the research of high-voltage circuit breaker fault diagnosis. Its core role is to automatically learn and extract deep fault features directly from the original and complex multi modal monitoring signals (such as vibration wave forms, closing and opening coil currents, travel curves, acoustic emission signals, etc.) to achieve end-to-end intelligent diagnosis. It is different from the traditional machine learning signal processing method. (Including based on thresholds, mechanism models or artificially designed features). In the context of high-voltage circuit breaker fault diagnosis, the core research object attribute of deep learning is reflected in its use of the powerful ability of deep neural network structures (such as CNN, RNN, LSTM) to automatically mine the complex patterns and nonlinear relationships contained in high-dimensional time series data, so as to more accurately identify and classify a variety of potential faults such as mechanical jamming, contact wear, insulation degradation, refusal/malfunction, etc. This end-to-end feature learning and decision-making ability makes deep learning particularly good at handling complex scenarios where the circuit breaker state changes dynamically with the number of operations and environmental factors, and shows generalization performance that exceeds traditional “shallow” methods in handling complex and coupled faults.

Therefore, taking deep learning as the object of fault diagnosis research and utilizing its automated feature extraction, powerful complex pattern recognition capabilities, and potential for processing massive monitoring data provides a strong technical foundation for building a high-precision, adaptive intelligent diagnosis system for high-voltage circuit breakers, although it still faces challenges in actual research, such as obtaining high-quality fault samples, model interchangeability, and computing resource requirements.

1.3 Benefits of the research

This research overcomes the limitations of existing high-voltage circuit breaker fault diagnosis methods and proposes a method to solve the problems of insufficient data and limited samples, thereby improving the diagnostic performance of high-voltage circuit breakers. This is of great significance to ensure the safety of power equipment and optimize the efficiency of power grid operation.



Chapter 2 Literature Review

In the field of power equipment maintenance, the fault inspection and repair of high-voltage circuit breakers traditionally rely on two methods: regular inspection and post-fault repair [27]. Regular inspection is a preventive maintenance method. It formulates a fixed-cycle inspection and maintenance plan based on the equipment operation experience and aging law, and manages and maintains the equipment according to the plan. This method reduces the probability of equipment failure to a certain extent, so it has become the most common maintenance mode. However, regular inspection and maintenance consumes a lot of manpower, material and financial resources, and may cause unnecessary intervention and damage to equipment that is operating normally. In contrast, post-fault repair is a passive maintenance method. When the equipment fails, it is immediately handled and repaired. This method often causes irreversible damage to the operation of the power grid because the fault has already occurred, and the maintenance effect is limited. In order to effectively avoid the irreversible impact of equipment failure on the operation of the power grid, improve the reliability of equipment operation and the economy of maintenance, early diagnosis of faults is particularly important [28, 29].

At present, there are three main methods for high-voltage vacuum circuit breaker fault diagnosis: traditional methods (online monitoring and model state prediction, traditional machine learning and deep learning). Since the 1990s, researchers have successively studied the three methods with different research focuses and technical characteristics. The traditional method mainly relies on online monitoring technology and mechanical models to identify fault states by analyzing key signals (such as coil current, mechanical vibration, etc.) during the operation of the circuit breaker; the traditional machine learning method improves the accuracy of fault diagnosis by extracting features and constructing classifiers based on the traditional method; and the deep learning method relies on the automatic feature extraction capability of neural networks, and shows significant advantages in processing complex nonlinear data and improving model generalization performance [30]. The following will elaborate and analyze the research progress of these three methods in detail.

2.1 Research status of traditional HVCB mechanical fault diagnosis methods

Since the 1990s, the research on online monitoring of high-voltage circuit breakers has gradually developed, and scholars at home and abroad have invested a lot of research work in this regard [31, 32]. In 1992, Alston of France, Tokyo Electric Power Company of Japan, Toshiba, Hatchway of the United States and ABB successively launched a number of condition monitoring systems, mainly for vacuum circuit breakers, gas insulated switch gear (GIS) and SF₆ circuit breakers. The development of these systems has provided important theoretical and technical support for the online monitoring of circuit breakers [33, 34]. At the same time, Songhua University began to study the technical difficulties of the monitoring system in the 1990s and successfully developed an effective system for measuring circuit breaker status parameters [35], such as vibration signals, opening and closing coil currents and contact travel curves. The movement mechanism of the circuit breaker will change with factors such as wear and aging of mechanical parts during use, and these changes reflect the performance changes of the mechanical parts, and then reveal the possible fault state of the circuit breaker. Through online monitoring data, these mechanical changes can be captured and their characteristics can be displayed in various forms. At present, the online monitoring signals of circuit breakers usually include the following categories, among which coil current signals and mechanical vibration signals are the most commonly used:

(1) Vibration signal: The vibration signal is generated by the movement and energy transfer between the various components of the circuit breaker operating mechanism. It carries a large amount of circuit breaker status information and can effectively realize non-invasive monitoring of the circuit breaker [36]. The vibration signal has the characteristics of being non-destructive, easy to obtain and will not cause damage to the internal mechanical parts. The vibration signal can also be measured at the low voltage pole [37], avoiding the danger of high voltage measurement. In addition, the vibration signal has rich characteristics and can help diagnose circuit breaker abnormalities through time-frequency domain analysis and feature extraction. Vibration is usually accompanied by sound, and sound waves and vibration are of the same origin. Therefore, sound detection can also be used as an effective monitoring method [38].

(2) Opening and closing coil current signal: The waveform characteristics of the opening and closing coil current can reflect the working status of the operating mechanism and the electromagnetic core during the opening and closing process of the high-voltage circuit breaker [39, 40]. Generally, the double-peak current waveform is the most common feature. During long-term operation, high-voltage circuit breakers may become stuck, which is usually caused by a variety of factors, and auxiliary switch failures also occur frequently, which will cause the mechanical performance of the circuit breaker to deteriorate. These changes are usually reflected in the waveform characteristics of the opening and closing coil current. Many studies use the opening and closing coil current waveform to diagnose the state of the operating mechanism. For example, the expert system designed by H Xiaoguang et al. [41] of Harbin Institute of Technology can accurately analyze and diagnose circuit breaker faults by combining the contact state and the characteristic information in the coil current signal. Peng Zaixing et al. [42] of the Southern Power Grid also developed a test platform for testing and collecting opening and closing coil current signals. By simulating different fault conditions (such as voltage drop, poor contact, turn-to-turn short circuit, etc.), different coil current wave forms were obtained, which provided a theoretical basis for fault diagnosis based on current wave forms.

(3) Moving contact travel time characteristic curve: The moving contact travel characteristic curve can be obtained by installing a displacement sensor, thereby obtaining the moving contact time speed characteristic curve, opening and closing speed, contact opening distance and other important parameters related to the mechanical characteristics of the operating mechanism. The analysis of these characteristic parameters helps to detect potential faults in the circuit breaker early.

(4) Energy storage motor current signal: The energy storage process of the closing spring of the circuit breaker is driven by the motor. By collecting the motor stator current signal, the mechanical operating state of the motor and the spring can be determined [43]. For example, Bellini et al. [44] successfully discovered faults such as the asymmetry of the motor stator, rotor and air gap flux by analyzing the change of motor current. Zhao Lihua et al. [45] from Sichuan University studied the change law of the energy storage motor current signal and used the Pearson correlation coefficient method and support vector machine to diagnose three fault states of the

operating mechanism. Sun Shuguang et al. [46] from Hebei University of Technology used fuzzy clustering and optimized correlation vector machine to extract the characteristic quantity of the energy storage motor current envelope signal to diagnose the circuit breaker fault.

Online monitoring technology is of great significance in the fault detection and application of early high-voltage circuit breakers, but it also has some shortcomings. In actual applications, complex monitoring systems often require specialized technicians to operate and maintain, which increases the cost of maintaining the stability of the system, limits its effectiveness in actual applications, and reduces the popularity of the system. In addition, the amount of data collected by online monitoring is huge, and data processing and analysis require efficient algorithms and computing platforms. With limited equipment resources, the efficiency and accuracy of data processing is a huge challenge.

With the continuous updating of communication technology, computer technology and various model algorithms, the state prediction method of mechanical equipment has also attracted a lot of attention. The model-based prediction method is also called the mechanical state prediction method based on physical probability. This method uses professional basic theoretical knowledge of mechanical equipment to conduct in-depth analysis of the equipment and establish a mathematical model that can characterize the main characteristics of the mechanical equipment. This method has a good prediction effect and does not require a large amount of historical data [47]. Oppenheimer et al. [48] proposed a mechanical equipment state trend prediction method based on physical models. They analyzed the historical data of key components of mechanical equipment, mined the development trend of crack growth laws over time, and realized the prediction of the RUL of mechanical equipment. The modeling method proposed by Razi-Kazemi et al. [49] can use fuzzy probability methods to predict the mechanical state of the circuit breaker based on the measured travel curve, but the main disadvantage of such models is that they depend on the type of high-voltage circuit breaker. Xin Weifeng et al. [50] established a multi-body dynamics model of the spring mechanism of a high-voltage circuit breaker through experimental and theoretical models, and performed dynamic simulation, thereby realizing the mechanical state prediction of the high-voltage circuit breaker. Meng

Xiaocheng [51] combined the inexact Dirichlet model for dealing with inexact problems with the Bayesian network to predict the probability of mechanical failure of high-voltage circuit breakers in the absence of fault samples. Nicolau et al. [52] proposed a driving mechanism model based on the oil-gas mechanism based on the study of the oil-gas mechanism of high-voltage circuit breakers, and used the model to detect and predict mechanical failures of circuit breakers.

2.2 Research status of mechanical fault diagnosis methods for HVCB based on machine learning

With the development of science and technology, modern high-voltage circuit breaker fault diagnosis is increasingly dependent on advanced intelligent diagnostic technology. The essence of fault diagnosis is to analyze the monitoring signal and then determine the state of the equipment. Therefore, fault diagnosis can be regarded as a pattern recognition problem, which can be solved with the help of machine learning algorithms. The high-voltage circuit breaker fault diagnosis method based on machine learning algorithm includes feature extraction and feature learning. In layman's terms, feature extraction is to extract specific features from the monitoring signal to form a feature vector using some signal processing methods. Feature learning is that the machine learning algorithm learns (trains) the features extracted from the monitoring signal to establish the relationship between the features and the mechanical state of the circuit breaker. The established relationship is implicit in the final trained model. The accuracy of this relationship is related to the quality of feature extraction on the one hand, and the learning ability of the machine learning algorithm itself on the other hand. With the continuous development and improvement of machine learning algorithms, high-voltage circuit breaker fault diagnosis methods based on machine learning algorithms have received extensive research and attention in recent years. In particular, in the fields of mechanical vibration signals, multi-sensor fusion and acoustic signal processing, rich research results have been accumulated.

(1) Mechanical vibration signal

Mechanical vibration signals are an important research direction for high-voltage circuit breaker fault diagnosis, as they carry a large amount of information reflecting the mechanical state. In this field, J. Huang et al. [53] proposed a diagnostic

method based on improved empirical mode decomposition (EMD) energy entropy and multi-class support vector machine (MSVM). Compared with the traditional wavelet packet analysis method, the improved EMD energy entropy can process vibration signals more efficiently and accurately identify the mechanical fault type of the circuit breaker. This study provides strong support for the fine feature extraction of vibration signals.

On this basis, Wang Guodong et al. [54] further combined LMD marginal spectrum energy entropy and GPSO algorithm to propose a fault diagnosis method suitable for opening and closing vibration signals. Studies have shown that this method can not only accurately capture mechanical characteristics, but also optimize the performance of support vector machine (SVM) through GPSO, thereby significantly improving the accuracy and efficiency of diagnosis. At the same time, Xiao Pengbin et al. [55] focused on the fault diagnosis of electromagnetic repulsion mechanism and proposed a diagnosis method based on improved S transform and support vector machine. Experiments show that this method performs well in quickly identifying fault types and provides a new idea for efficient diagnosis of electromagnetic mechanisms.

In addition, Sun Yuchen et al. [56] innovative combined fully adaptive noise ensemble empirical mode decomposition (ICEEMDAN) and multi scale scatter entropy (RCMDE) for feature extraction and fault diagnosis of non-stationary and nonlinear vibration signals during the opening and closing process. This method effectively solves the diagnostic difficulties caused by signal complexity. Furthermore, Shao Yang et al. [57] studied the typical working conditions of LW30-252 SF6 high-voltage circuit breakers, simulated seven common fault conditions including spring fatigue and spindle jamming, and developed a fault signal acquisition system with vibration and sound signals as the core. This study provides an important experimental reference for data acquisition and processing under actual working conditions.

(2) Multi-sensor fusion signal

With the advancement of sensor technology, multi-sensor fusion signals have gradually become an important direction for high-voltage circuit breaker fault diagnosis. Ma S et al. [58] proposed an improved multi-sensor evidence fusion rule to

address the problem of sensor data conflict and invalidity. This method optimizes the information fusion effect between different sensors and has been successfully applied to circuit breaker fault diagnosis. Experimental results show that multi-sensor fusion can significantly improve diagnostic accuracy compared with a single sensor.

In addition, Zhang K et al. [59] proposed a diagnostic method that combines principal component analysis (PCA), particle swarm optimization (SSA) and learning vector quantization (LVQ) neural network. Through empirical mode decomposition (EMD) and information entropy extraction of vibration signals, combined with PCA dimensional reduction and LVQ model optimization, this method finally achieved high-precision fault diagnosis.

In order to improve the accuracy of fault diagnosis of high-voltage circuit breakers, Zehua Chen et al. [60] proposed an optimization method for noise reduction of acoustic vibration signals based on wavelet analysis and CS-VMD (composite signal variational mode decomposition). This method extracts the local minimum envelope entropy and fuses the local minimum envelope entropy of the acoustic vibration signal using the entropy weight method to form a composite feature vector. Finally, a neural network ANFIS (adaptive neural fuzzy inference system) model based on fuzzy theory is established. Studies have shown that compared with traditional diagnostic methods, this method can greatly improve the accuracy of fault diagnosis and significantly reduce diagnostic errors.

Wei Gao et al. [61] proposed a mechanical fault diagnosis method for high-voltage circuit breakers based on semi-supervised stacked auto-encoders (SSAE) and integrated extreme learning machines (IELM). Through effective feature learning and classification, the accuracy of this method reached 99.5%, providing an efficient and accurate solution for mechanical fault diagnosis of high-voltage circuit breakers.

In terms of the combination of multi-scale entropy (MSE) and support vector machine (SVM), Dou L et al. [62] proposed a fault diagnosis method based on variational mode decomposition (VMD) and multi scale entropy (MSE) calculation. This method processes the vibration signal of the high-voltage circuit breaker, calculates the multi scale entropy of the reconstructed signal and uses it as the feature vector, and finally uses SVM for fault identification and classification. The research

results show that this method has good applicability in the fault diagnosis of 35kV SF6 circuit breakers.

In term of the current and vibration signals of the electromagnetic coil of the opening and closing switch

Bao Weichuan et al. [63] proposed a fault diagnosis method for the joint analysis of the coil current and vibration signals. This method extracts the key time series features of the current signal and the features of the waveform distortion, and analyzes the vibration signal through the adaptive noise ensemble empirical mode decomposition (CEEMDAN), and further calculates the time-frequency distribution of each component. The high-dimensional features are reduced in dimension by factor analysis and then used as the input of the support vector machine (SVM), which successfully improves the accuracy of circuit breaker fault diagnosis.

Chen Zhigang et al. [64] proposed an operating mechanism state evaluation method based on the T-type grey correlation analysis method, combining the closing and opening coil current and time, and solving the limitation of setting multi-dimensional thresholds in the eigenvalue analysis method. This method significantly improves the reliability of fault diagnosis by calculating the correlation value between the standard reference sequence and the sequence to be evaluated, and verifies the effectiveness of the method through experiments.

(3) Sound signal

In the field of sound signal processing, researchers are committed to overcoming the bottleneck that traditional methods are difficult to effectively capture sound features. Chen Jiahao et al. [65] proposed a circuit breaker fault diagnosis method based on a probabilistic neural network (PNN) optimized by local mean decomposition (LMD) and differential evolution algorithm (DE). The experimental results show that the high-voltage circuit breaker mechanical fault diagnosis method based on LMD-DE-PNN can quickly and effectively identify circuit breaker mechanical faults compared with traditional circuit breaker fault diagnosis methods.

At the same time, Yi Lin et al. [66] proposed a feature recognition method based on non-parametric test to address the interference of pure noise and aftershocks in mechanical fault sound signals. By selecting Renyi entropy as the feature value, this method improved the diagnostic recognition rate by 10% compared with

traditional features, among which the Wilcoxon-on rank sum test method performed best.

Xia Xiaofei et al. [67] built an acoustic fingerprint fault simulation test platform, collected the sound signals of a 252 kV high-voltage circuit breaker opening and closing test, and proposed a high-voltage circuit breaker mechanical fault diagnosis method based on acoustic fingerprint. This method can realize the joint analysis of multiple feature quantities and effectively identify different working conditions of high-voltage circuit breakers.

High-voltage circuit breaker fault diagnosis technology based on machine learning has made significant progress. From mechanical vibration, multi-sensor fusion to acoustic signal processing, researchers in different fields have significantly improved the efficiency and accuracy of fault diagnosis through algorithm improvement, model optimization and multi-signal collaborative analysis. However, there are still some problems at this stage. For example, traditional feature extraction methods may not be sufficient to capture fine-grained features in complex signal processing; at the same time, in the face of large-scale data and real-time diagnosis needs, traditional machine learning methods (such as support vector machines, random forests, etc.) often face bottlenecks in computing efficiency and real-time performance when facing complex signals and large-scale data.

2.3 Research status of fault diagnosis methods based on CNN

With the rapid development of deep learning algorithms, its advantages in feature extraction accuracy and performance have gradually emerged, especially in the fields of image recognition, speech recognition and face recognition. In recent years, deep learning has gradually emerged in the fault diagnosis of high-voltage circuit breakers, especially the research based on convolution-neural network (CNN) has become a hot topic. These methods extract the features of complex signals and combine deep learning models for fault classification and diagnosis, showing certain advantages in accuracy, robustness and applicability. However, current research also has problems such as data imbalance, insufficient generalization performance of small samples and limited space for network structure optimization. The following is an analysis of the research results and characteristics of high-voltage circuit breaker fault diagnosis based on deep learning.

(1) Research on Fault Diagnosis Based on CNN

The introduction of deep learning has greatly improved the feature extraction and diagnosis capabilities of fault signals. Yang Qian et al. [68] proposes a condition evaluation method for opening damper of the spring operated HVCB based on vibration time-frequency image and convolution-neural network (CNN). The one-dimensional (1D) vibration signal of the HVCB is transformed into three-dimensional (3D) time-frequency image by utilizing Hilbert-Huang transform (HHT). The 3D time-frequency image directly served as a training sample for the CNN, achieves an accurate condition evaluation of the HVCB's opening damper. This method makes full use of the multi-dimensional information advantages of the time-frequency image and is suitable for circuit breaker scenarios with complex vibration signals, but it has high requirements for model training time and computing power.

Cao Yupeng et al. [69] proposed a diagnostic method that combines a convolution-neural network with a gated recurrent unit (GRU). The convolution-layer extracts the features of the original vibration signal and uses the GRU to capture local time domain features. Experiments show that this method performs well in terms of noise reduction and fault feature extraction accuracy. Compared with traditional methods, it has higher diagnostic accuracy and faster processing speed. However, this study relies heavily on the optimization of GRU parameters, and the robustness of the model in different scenarios needs to be further verified.

At the same time, Sun S et al. [70] proposed a traditional circuit breaker contact system fault diagnosis method that combines time-frequency analysis and improved AlexNet. The improved AlexNet model enhances the fault identification capability by extracting signal features through time-frequency analysis. Experimental results show that this method has significant advantages in characterizing and classifying complex signals. However, the reliance of this study on network depth and parameter optimization may limit its application in scenarios with high real-time requirements.

(2) Research on the improvement of introducing attention mechanism and transfer learning

In order to cope with the challenges of small sample scenarios of high-voltage circuit breakers, Wang Yong et al. [71] proposed a few-shot transfer learning method

combined with an attention mechanism. This method uses the attention mechanism to enhance the model's ability to extract key features, and uses transfer learning to improve the generalization performance under small sample conditions. Experiments show that this method can effectively improve the diagnostic accuracy and show strong adaptability to unknown fault modes. However, the introduction of the attention mechanism increases the complexity of the network and has relatively high requirements for hardware resources. Ye Xiaoming et al. [72] further proposed a 1-D attention mechanism (AM)-based convolution-capsule neural network. Using a wide convolution-kernel, the 1-DCNN captured temporal fine-grained information from the vibration signal. An AM in the pooling layer adjusted weight assignments for better feature extraction. A capsule layer between convolution and fully connected layers ensured comprehensive fault feature extraction through vectorization. The digital capsule, obtained via dynamic routing, achieved a 94.7% accuracy rate in experiments with a small-sample. However, the computational overhead of this method is large, and its real-time performance still needs to be improved .

In terms of optimizing the network structure, Ye Xiaoming et al. [73] also proposed a high-voltage circuit breaker fault diagnosis method that combines capsule network (CapsNet) and U-Net. By utilizing the high-resolution feature extraction capability of U-Net, capsule networks were introduced into its contraction and expansion paths to reduce feature loss in the pooling process, and the accuracy of diagnosis was improved through a dynamic routing algorithm. This method showed strong diagnostic capabilities under small sample conditions, but due to the complex network structure, its training time was relatively long.

The class imbalance of high-voltage circuit breaker monitoring data is an important challenge that affects the performance of fault diagnosis. In response to this, Chen Lei et al. [74] proposed a density-weighted minority oversampling (DWMO) method, which aims to improve the generalization ability of the model by balancing the data distribution. Experiments show that DWMO significantly improves the performance of AI-based diagnostic methods. The implementation of this method relies on accurate modeling of minority class sample features, which may place higher requirements on the monitoring system in actual scenarios. Jiang Nan et al. [75] proposed a method to optimize convolution-neural networks using genetic algorithms

to address the shortcomings of shallow vibration signal analysis models in feature extraction and fault diagnosis accuracy. Through the optimization operation of the genetic algorithm, the initial structure of the convolution-neural network can be effectively improved, and its performance in high-voltage circuit breaker fault diagnosis can be improved. Their research shows that the optimized convolution-neural network has a higher accuracy in fault diagnosis than the unoptimized model.

Finally, Qiuyu Yang et al. [76] designed a new convolution-neural network (RDSCNN) based on residual block and deep separable convolution for high-voltage circuit breaker fault diagnosis. The multi-scale analysis of mechanical vibration signals by wavelet transform, combined with RDSCNN and multi-label attribute learning network, can effectively identify invisible fault types. Experiments show that this method can provide accurate diagnosis results while identifying hidden faults, which promotes the further development of high-voltage circuit breaker fault diagnosis technology.

In summary, as a powerful deep learning tool, CNN can automatically extract features from raw signals, avoiding the tedious process of manually designing features, and exhibits strong learning ability when processing large-scale, high-dimensional data. It is also not difficult to see that the research on the application of deep learning models to high-voltage vacuum circuit breaker fault signals still lags behind other application fields, and is currently a direction worthy of research. For high-voltage circuit breaker mechanical fault diagnosis, the introduction of CNN provides a new idea for solving complex fault pattern recognition, data processing and real-time diagnosis.

However, although CNN has shown strong performance in many applications, its application in fault diagnosis still faces some challenges, such as the need for a large amount of training data, while the frequency of high-voltage vacuum circuit breakers in actual operation is low, and there are fewer fault sample data. This leads to a lack of sufficient fault samples when training machine learning models. It cannot accurately predict and diagnose new fault types.

2.4 Application of GAN in Solving Small Sample Problems

Methods based on deep convolution-neural networks (CNN) can effectively improve the model's adaptability to high noise and sparse samples by introducing

attention mechanisms, multi-module fusion, and transfer learning techniques. These methods make full use of the powerful feature extraction capabilities of deep learning and improve diagnostic accuracy by optimizing the network structure. However, deep learning models usually require a large number of labeled samples to achieve sufficient training. For situations where high-voltage circuit breaker data is scarce and unevenly distributed, this method may be limited by the sample size, resulting in a decrease in the model's generalization ability. Directly expanding the distribution diversity of the original samples still faces certain difficulties.

In contrast, the Generative Adversarial Network (GAN) provides a new solution to the small sample problem. GAN is a deep learning model first proposed by Ian Goodfellow et al. in 2014. The model consists of a generator and a discriminator, which generates sample data close to real samples in an adversarial learning manner. Generative adversarial network (GAN) provides a new research direction for the small sample fault diagnosis problem from the perspective of data generation. In small sample learning, GAN can be used to generate additional training samples, expand the data set, and improve the generalization ability of the model. By introducing generated samples, the model can better capture the data distribution and improve the generalization ability of the predicted samples. This feature is also applicable to problem scenarios such as high-voltage circuit breakers, where data collection is difficult, fault types are complex, and samples are unbalanced. Therefore, GAN provides a research direction for fault diagnosis tasks. At present, domestic and foreign scholars have done a lot of research on using GAN to solve the small sample problem.

In the fault diagnosis of rotating machinery, the small sample problem has long plagued researchers. To address this challenge, Liu Yaqian et al. [77] proposed a method based on deep convolution-generative adversarial networks (DCGAN) to expand the small sample library of rolling bearing faults. Experimental results show that using samples generated by GAN, the test set recognition rate of the diagnostic model is improved from 91.67% to 98.96%. This study not only demonstrates the advantages of GAN in expanding samples, but also verifies the authenticity and practicality of GAN-generated samples. However, in more complex working

conditions, how to balance the diversity and authenticity of generated samples remains a key direction for future research.

To further improve the sample augmentation effect, Zhang Zhaoguang et al. [78] combined the continuous wavelet transform (CWT) with the variation auto encoding generative adversarial network (VAE-GAN). By converting a one-dimensional signal into a two-dimensional image, using GAN to generate enhanced sample data, and then jointly training a CNN classifier with the original image, the experiment showed that this method significantly outperformed the traditional method in classification accuracy and robustness. This study demonstrated the applicability of GAN in multi modal feature extraction, and also showed that the generation ability of GAN provides more possibilities for processing high-dimensional data.

In addition, Huang Nantian et al. [79] proposed a new method for fan main bearing fault diagnosis using improved auxiliary classifier generative adversarial networks (AC-GAN) to address the problems of high noise and sample imbalance. Under the conditions of insufficient sample quantity and uneven sample type distribution, AC-GAN can still maintain a high diagnostic accuracy. Studies have shown that GAN can not only enhance samples of rare categories, but also effectively solve the bias problem caused by uneven sample distribution. This provides a reference for the application of GAN in other complex scenarios. In order to further expand the application of GAN, Yang Qing et al. [80] proposed a small sample fault diagnosis method for bearings based on information generation adversarial networks and convolution-neural networks. By extracting time-frequency image features through short-time Fourier transform (STFT) and combining information generation adversarial networks (InfoGAN) to generate more samples, they successfully improved the accuracy of fault diagnosis. This study not only improved the accuracy of small sample learning, but also expanded the application of GAN in time-frequency image data processing.

Further research also showed that GAN can not only improve the accuracy of small sample fault diagnosis, but also adapt to unbalanced data and high noise environments. For example, Shao Haidong et al. [81] proposed a dual-threshold attention generation adversarial network, which is used to generate high-quality infrared thermal imaging images and effectively solve the fault diagnosis problem of

rotor-bearing systems under time-varying speeds. Their research shows that GAN can still maintain good fault diagnosis performance under complex actual conditions, significantly better than traditional methods. Zhu Zhongkui et al. [82] successfully achieved efficient data enhancement in bearing, rotor and gearbox fault diagnosis by using GAN to reconstruct fault data. Their research has demonstrated the applicability and reliability of GAN in fault diagnosis of different types of mechanical equipment, especially its advantages in small sample data environments. In addition, Wang Rugen et al. [83] proposed a convolution-generative adversarial network (ConvGAN) method combined with K-means clustering to further improve the accuracy of small sample bearing fault diagnosis by optimizing clustering results. The research results show that this method has significant advantages over traditional diagnostic methods, especially when processing high-dimensional data. Liu Shaowei et al. [84] proposed a generative adversarial network (GAN) based on pull-away function for the generation of bearing imbalance data and its fault diagnosis. This method effectively solves the imbalance problem of small sample data in bearing fault diagnosis and improves the accuracy of fault diagnosis by generating more balanced sample data.

In the electrical field, the application of GAN has also performed well. He Yuhao et al. [85] proposed a method for generating power defect data based on an improved LoFGAN, which can effectively expand the power scenario defect data set with insufficient samples. The research results show that this method provides diversified data support for power equipment fault diagnosis and greatly improves the accuracy of the diagnosis model. Sun Ning et al. [86] designed an improved generative adversarial network (MGP-GAN) based on multi-module gradient penalty, which was applied to 27.5kV cable fault diagnosis, successfully solving the problem of scarce power defect data and providing reliable support for ensuring the reliable operation of EMUs.

Ye Lin et al. [87] proposed a small sample learning method for the problem of short-term wind power prediction under cold wave weather conditions, and showed excellent prediction performance under cold wave weather conditions. Lu Jixiang et al. [88] studied the generation of power equipment fault images and small sample learning, and significantly improved the fault diagnosis accuracy in transmission line inspection by combining GAN and transfer learning technology, with an accuracy

matching degree of nearly 95%, further proving the efficiency and feasibility of GAN in power equipment detection.

In other fields, the application of GAN has also received widespread attention. Liu Yufei et al. [89] proposed a method based on GAN and deep neural network (DNN) classifier for cancer staging identification in the biological field. The results show that this method has achieved higher recognition accuracy than traditional methods, demonstrating the great potential of GAN in the biomedical field. In order to solve the problem of insufficient fault sample data of high-pressure common rail diesel engines, Li Liangyu et al. [90] proposed a small sample learning method based on data enhancement and combined it with GA-BP neural network for fault diagnosis. Studies have shown that this method can significantly improve the fault diagnosis accuracy of high-pressure common rail systems.

Zhou Junyan et al. [91] proposed a data enhancement method based on generative adversarial networks to expand the corrosion loss rate data of small samples to improve the prediction accuracy of the subsequent analysis model. By generating more samples through GAN, the distribution of data was improved and the over-fitting phenomenon was effectively reduced. In order to cope with the challenges of cucumber leaf disease identification under complex field environments, Man Chao et al. [92] proposed an improved activation reconstruction generative adversarial network (IAR-GAN) and used the self-attention mechanism to improve the recognition accuracy of disease images. Their research shows that this method can effectively improve the generalization ability and recognition accuracy of the model.

Ding Kai et al. [93] studied the problem of small samples in vehicle damage image data-sets and solved the problem of insufficient sample size and diversity of vehicle damage images by using a conditional Style GAN generation method with high sample diversity. By analyzing and optimizing the parameters of the model training, the study showed that the application of this method in the vehicle damage image data-set achieved good results and greatly improved the convergence speed and accuracy of the training model.

GAN has shown significant advantages in dealing with data scarcity and imbalanced distribution. At the same time, GAN also has certain challenges, such as the authenticity of generated samples and the balanced training between the generator

and the discriminator. Future research should continue to optimize the network architecture of GAN, combine transfer learning, multi modal feature fusion and other technologies, and provide more powerful tool support for the practical application of high-voltage circuit breaker fault diagnosis.

In summary, the research on high-voltage vacuum circuit breaker fault diagnosis in the literature cited in this article has the following characteristics:

1. Traditional high-voltage circuit breaker fault diagnosis methods rely on manual experience and rules and cannot effectively handle complex fault types, especially when the equipment status changes greatly, misdiagnosis is prone to occur .
2. Although the fault diagnosis method based on machine learning and convolution-neural network (CNN) can effectively improve the accuracy and automation level, it faces the problems of insufficient data and difficulty in feature extraction in practical applications. Especially when processing high-dimensional and multi-noise signals, over fitting may occur, resulting in limited generalization and robustness of the model. At the same time, the computational complexity of convolution-neural networks is large, and the training process requires high computing resources. Especially under complex working conditions, the improvement of model performance is limited by data quality and feature selection.

The application of Generative Adversarial Network (GAN) in various fields is especially in solving the problem of small samples. It significantly improves the performance of the model by generating virtual data, especially in the fields of image generation, speech recognition , bearings , etc. However, in the field of high-voltage vacuum circuit breaker fault diagnosis, the application research of GAN is still insufficient.

Based on the above research, this paper proposes a method based on deep learning convolution-neural network (CNN) and conditional generative adversarial network (CGAN). By optimizing the algorithm network structure and training strategy, it seeks to achieve the expansion of high-voltage circuit breaker fault data and the identification of fault types .

Chapter 3 Research Methodology

3.1 Research plan

This study applies deep learning convolution-neural networks and adversarial generative training methods to the fault diagnosis of high-voltage vacuum circuit breakers. An experimental platform is built to obtain different types of fault data, and fault sample data close to the actual working conditions is generated through adversarial generative networks. The samples are expanded and combined with convolution-neural networks to diagnose the types of circuit breaker faults, and finally the effectiveness of the model is verified. This improves the accuracy of fault diagnosis. Figure 10 is a flowchart of the research plan for high-voltage vacuum circuit breaker fault diagnosis proposed in this paper.

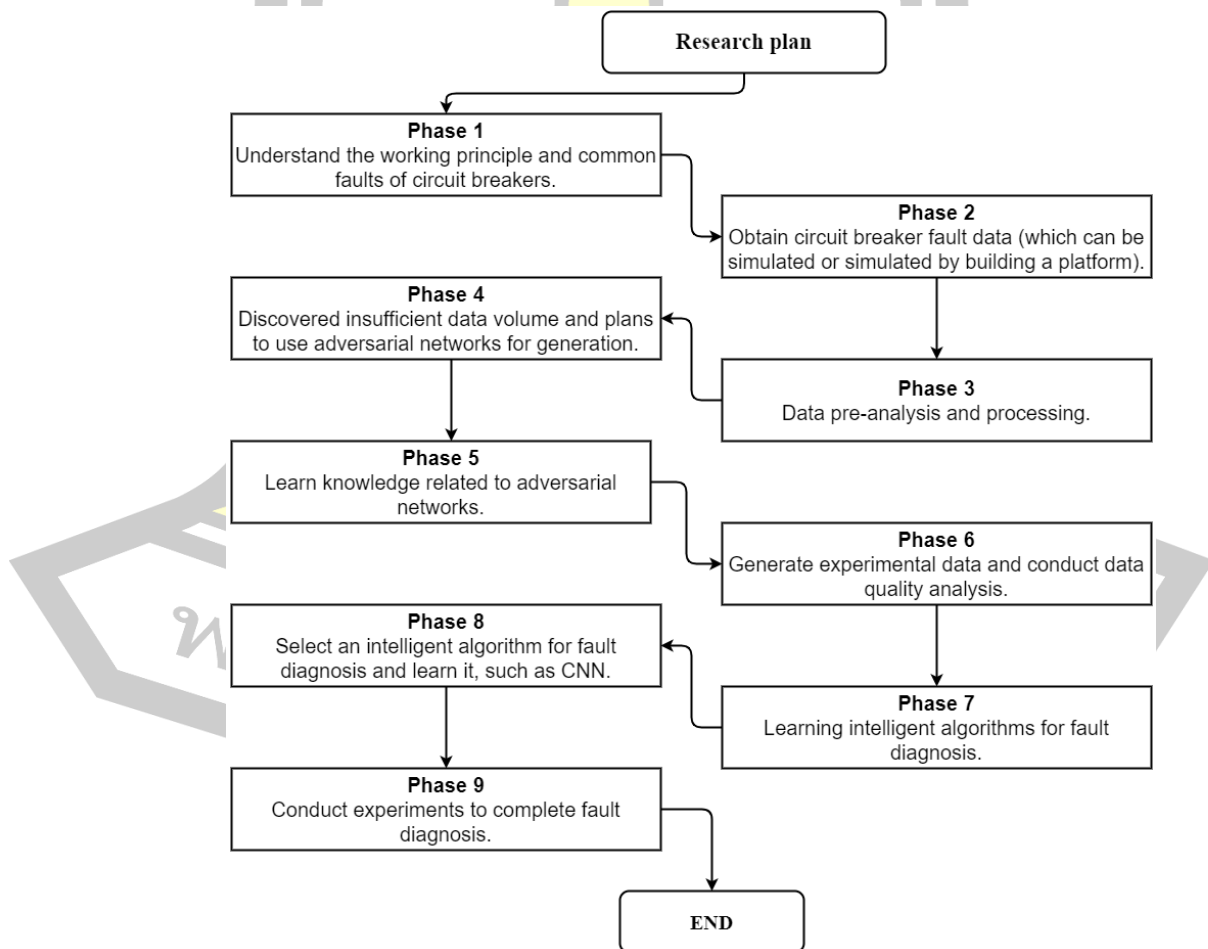


Figure 10 Research plan for HVCB

3.2 Relevant research theories, methods, and tools

Currently, there are various simulation and modelling tools available for diagnosing faults in high-voltage vacuum circuit breakers, such as MATLAB, Simulink, and Lab-view. This paper uses MATLAB and Simulink to construct a fault diagnosis system for circuit breakers, using 1DCNN and combining it with CGAN for optimization. MATLAB offers robust data analysis capabilities, user-friendly model building functions, and high computational performance, making it suitable for simulation under complex operating conditions. Additionally, this tool can be integrated with other software (such as Python) for joint simulation, further enhancing diagnostic accuracy and flexibility.

3.2.1 One-Dimensional Convolution Neural Network (1DCNN)

One-dimensional convolution-neural network (1DCNN), developed on the basis of 2D-CNN, is a variant of convolution-neural network, its model structure is shown in Figure11 [94]. The structure includes input layer, convolution layer, pooling layer, full connection layer and output layer.

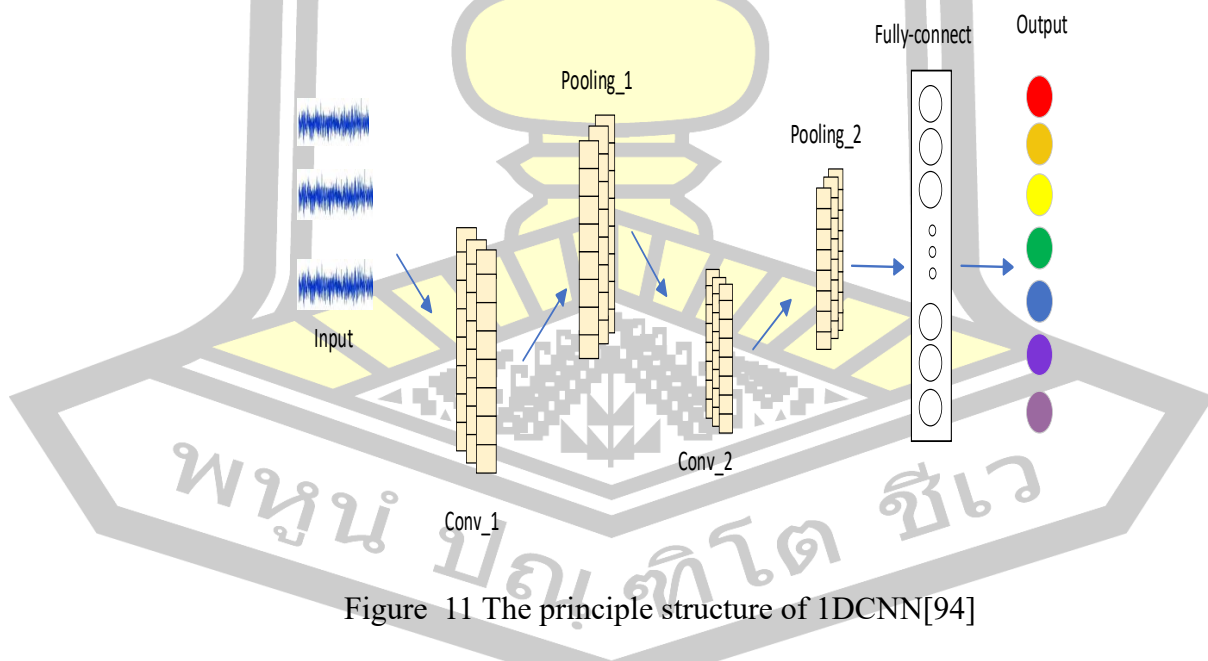


Figure 11 The principle structure of 1DCNN[94]

One-dimensional convolution neural network input data is fed directly in a one-dimensional format. Convolution and down-sampling layers are alternated to form a deep network. The size of the convolution kernel for the convolution and down-sampling layers is also in one-dimensional format, with the size denoted by

$c_l \times 1, s_l \times 1$ (the subscript l denotes the number of layers). A fully connected layer is one that connects all the features of the previous layer into a one-dimensional vector, finally utilizes a classifier to differentiate the state.

This paper uses a CNN convolution layer to extract features from HV vacuum circuit breaker faults. The generator uses convolution layers to expand the data set and generate high-dimensional features. This process creates realistic sequences. The discriminator uses a convolution layer to extract input sample features. The input is reduced through convolution and pooling operations, making it easier to distinguish between realistic and generated sequences. The pooling layer performs down-sampling, while the fully connected layer synthesizes features. The output is classified and generated by the soft max classifier.

In 1D CNN,

The convolution-layer is calculated as [95] :

$$y_i = f \left(\sum_{k=0}^{K-1} x_{i+k} \cdot \omega_k + b \right) \quad (1)$$

Where

x is the input sequence, representing one-dimensional data (e.g., time series or text)

ω is the convolution kernel (or filter), size K

b is the bias term.

f is the activation function (e.g. ReLU, Sigmoid, etc.).

y_i is the i th element of the output feature map.

i is the index of the output sequence

The pooling layer output function is called:

$$y_i = \frac{1}{k} \sum_{j=0}^{k-1} x_{i+j} \quad (2)$$

Where

y_i is the value of position i in the output sequence.

k is the size of the pooling window (2 in this paper), which indicates the number of consecutive input samples considered for each pooling operation.

x_{i+j} is the value of the input sequence corresponding to the pooling window

j is the position index of the current pooling window.

The fully connected layer's model structure function is:

$$y = f(W \cdot x + b) \quad (3)$$

where

y is output of the fully connected layer

f is activation function

W is weight matrix

x is input of the fully connected layer (usually a spread vector)

b is the bias term.

The soft max function for the output layer is as follows :

$$y_i = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (4)$$

where

e is the base of the natural logarithm

y_i is the probability of the output, indicating the probability that the sample belongs to class i .

z_i is the raw score (logit) input to the soft max function, usually the raw score obtained at the last layer of the neural network

C is the total number of category labels, indicating the number of categories the model can discriminate.

$\sum_{j=1}^C e^{z_j}$ is Calculate the exponential sum of all categories, which is used for normalization to ensure that the probability of the output sums to 1.

After convolution, an activation function (e.g., ReLU) introduces non linearity.

$$\text{ReLU}(x) = \max(0, x) \quad (5)$$

3.2.2 Generative Adversarial Network (GAN)

GAN is a novel algorithmic approach to training generative models, using two neural networks to create synthetic data. First proposed by Ian Goodfellow in 2014 [96]. The GAN model comprises a generator and a discriminator. The generator produces samples the discriminator finds challenging, while the latter differentiates between the generated samples and the true data during training. These two models

reach a Nash equilibrium where the generator produces samples aligned with the true data's distribution, as shown in the Figure12 [97].

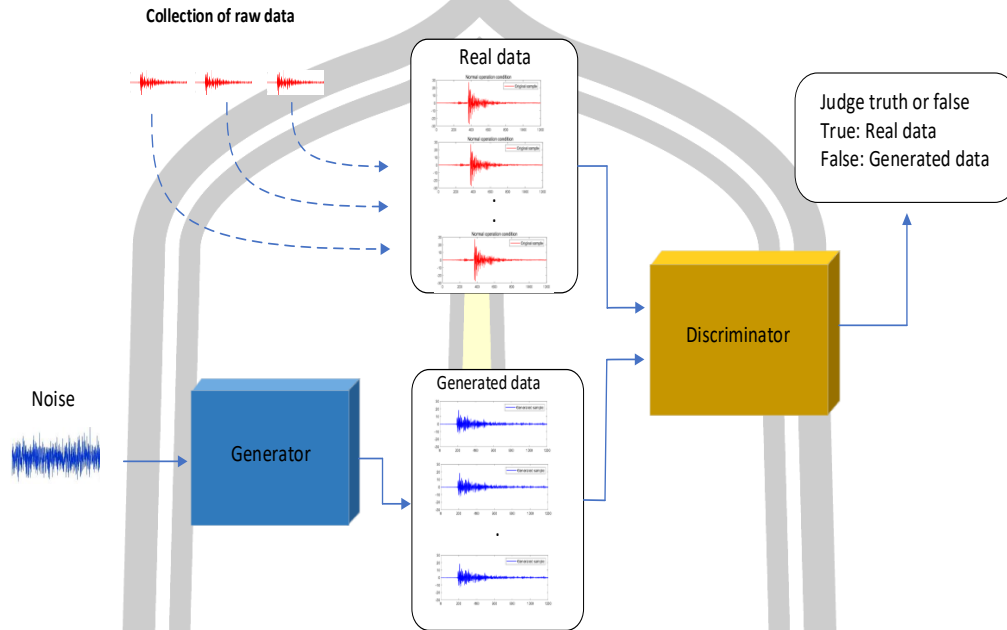


Figure 12 The principle structure of GAN[97]

The objective of training a GAN is to maximize the probability that the discriminator will correctly classify a sample, while simultaneously minimizing the probability that a sample generated by the generator will be classified as a real sample. The GAN optimization objective can be expressed as Eq1 [96] :

$$\min_G \max_D V(D, G) = E_{x \sim p_{\text{data}}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (6)$$

Where: $V(D, G)$ is the objective function; G is the generator; D is the discriminator; x is the real data, whose distribution is $p_{\text{data}}(x)$; z is the random noise of the input G , whose distribution is $p_z(z)$; $D(x)$ is the probability that the discriminator decides the input is the real data; $G(z)$ is the generator data; and $D(G(z))$ is the probability that the discriminator decides the input is the generator data.

3.2.3 Conditional Generative Adversarial Network(CGAN)

The conditional generative adversarial network (CGAN) improves the traditional generation adversarial network (GAN) algorithm. Compared with the traditional Gan, the generator and discriminator of CGAN accept random noise as input, and also accept conditional information (category labels or feature vectors) [98]. Its principle structure is shown in the following Figure 13 [99].

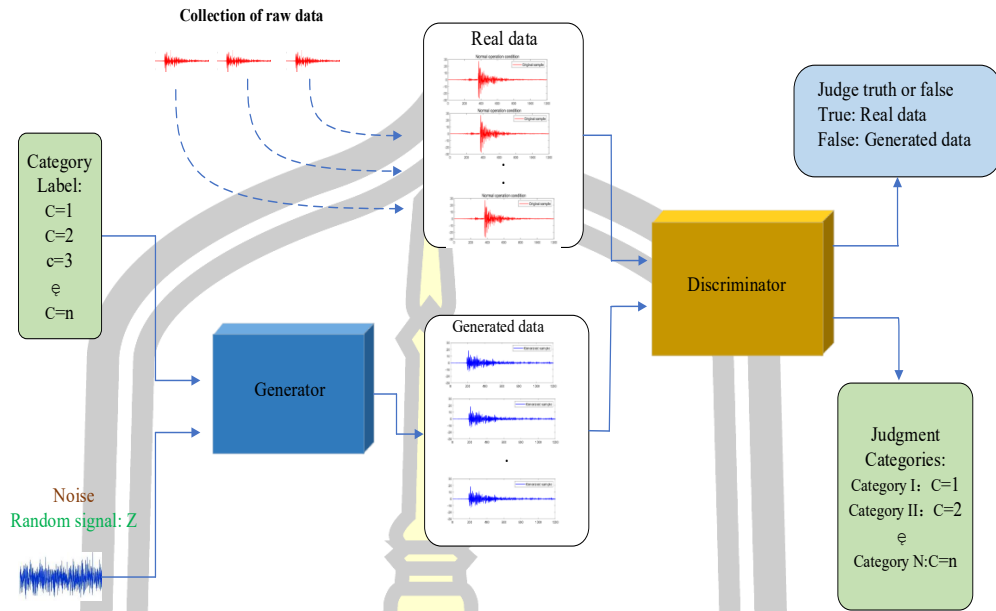


Figure 13 The principle structure of CGAN[99]

The goal of CGAN is to minimize the probability that the conditional samples generated by the generator will be judged as false by the discriminator, and to maximize the probability that the discriminator will correctly distinguish between the real samples and the generated samples. In this way, CGAN can control the specific attributes of the generated data in the generation task, such as generating images or text with specified characteristics. The specific loss function can be expressed as [98]:

$$\min_G \max_D V(D, G) = E_{x \sim p_{\text{data}}(x)} [\log D(x|y)] + E_{z \sim p_z(z)} [\log (1 - D(G(z|y)|y))] \quad (7)$$

Where: $D(x|y)$ represents the probability estimation of the discriminator that the input x is real data under condition y . $G(z|y)$ represents the sample generated by the generator with noise Z under condition y .

3.2.4 Platform construction

This paper takes the ZN63A high-voltage vacuum circuit breaker as the research object. Under no-load conditions, the high-voltage switch mechanical characteristic tester is connected to the circuit breaker, and a 220V AC power supply is used for power supply to collect and analyse the test data. The high-voltage circuit breaker test platform primarily consists of: a power supply module, a signal acquisition module, a control module, and a host computer. The host computer runs the Windows operating system, enabling real-time data acquisition, processing, and storage, as well as data analysis as required. In this study, a high-voltage switch

mechanical characteristic tester is used to control the circuit breaker's operation. The hardware block diagram of the test platform is shown in Figure 14.

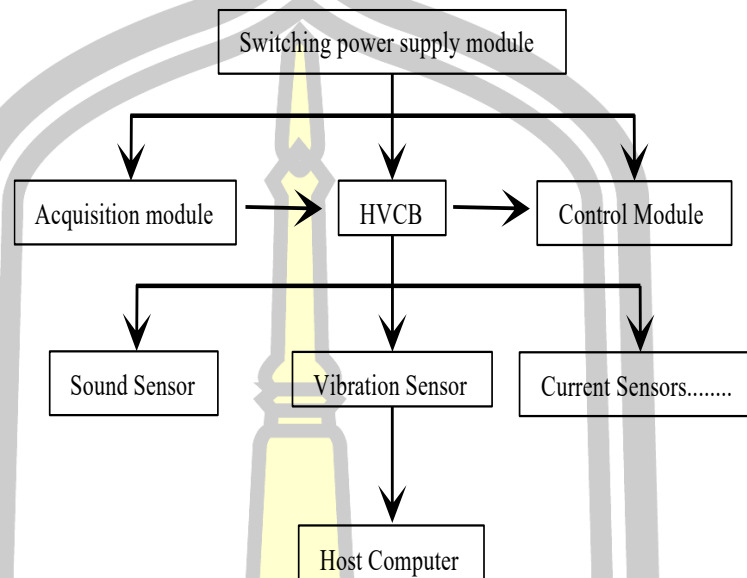


Figure 14 High voltage circuit breaker test platform hardware block diagram

After systematic research, the MPS series data acquisition cards were selected to synchronously collect data from five channels: the three-phase contact position signals of the circuit breaker, the travel of the moving contacts, and the current of the closing and opening coils. Specifically, three channels are used to collect the contact position signals of phases A, B, and C, while the remaining two channels are used to collect the current of the closing and opening coils and the travel of the moving contacts in phase A. The collected data is then transmitted to the host computer. As shown in the Figure15 below.

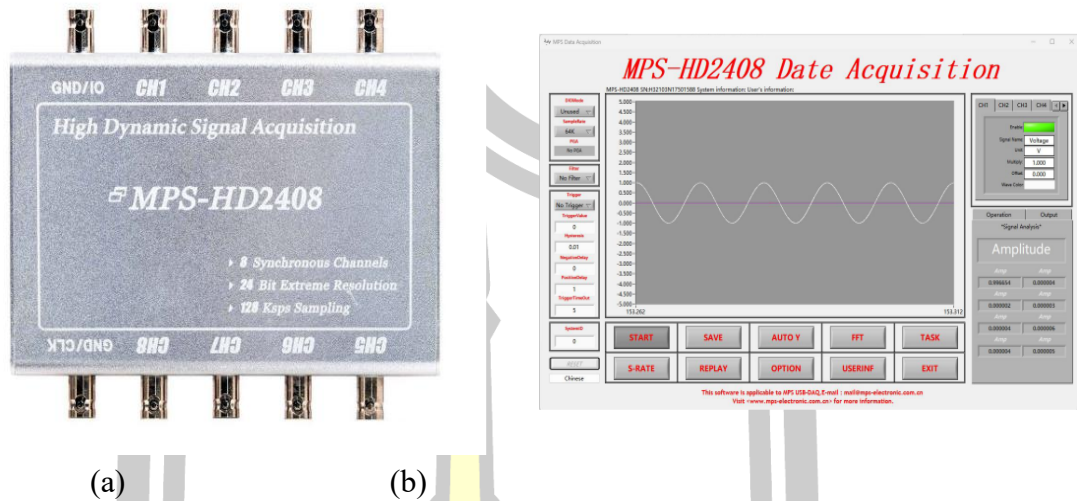


Figure 15 Acquisition module with (a) MPS series data acquisition card and (b) data collection screen

High-voltage vacuum circuit breakers need to pass multiple tests to verify their performance and reliability. When selecting a tester, the instrument's action time test, withstand voltage test, mechanical life test, opening and closing times test, electrical performance test and other performances should be considered to ensure the reliability and safety of vacuum circuit breakers in various states. After comprehensive evaluation, the high-voltage switch characteristic comprehensive tester shown in the Figure16 below was finally selected.

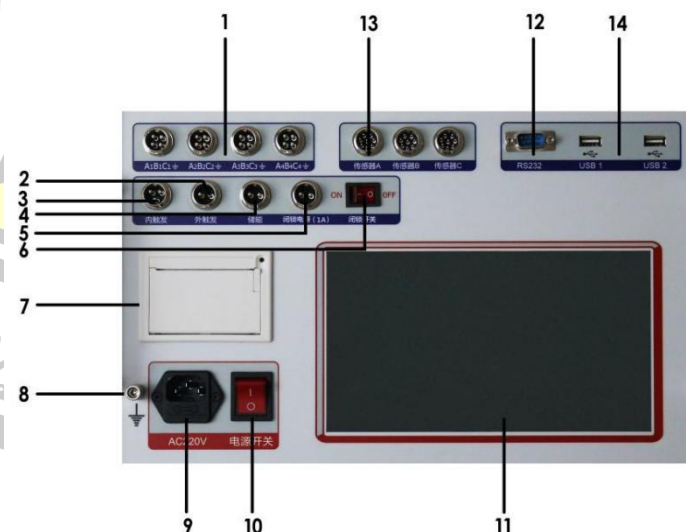


Figure 16 High-voltage switch characteristic comprehensive tester

The mechanical vibrations of high-voltage circuit breakers typically occur within a low-frequency range (1 Hz to several hundred hertz), such as vibrations from electromagnetic operating mechanisms or spring-driven mechanical systems. Therefore, when selecting vibration sensors for monitoring the operating mechanisms of high-voltage circuit breakers, it is essential to comprehensively consider multiple critical factors, including frequency response range, sensitivity, measurement range, accuracy, and linearity, as well as interference resistance. After testing, the experimental platform adopted the CT1000L to collect vibration signal currents, as shown in the Figure17 below.

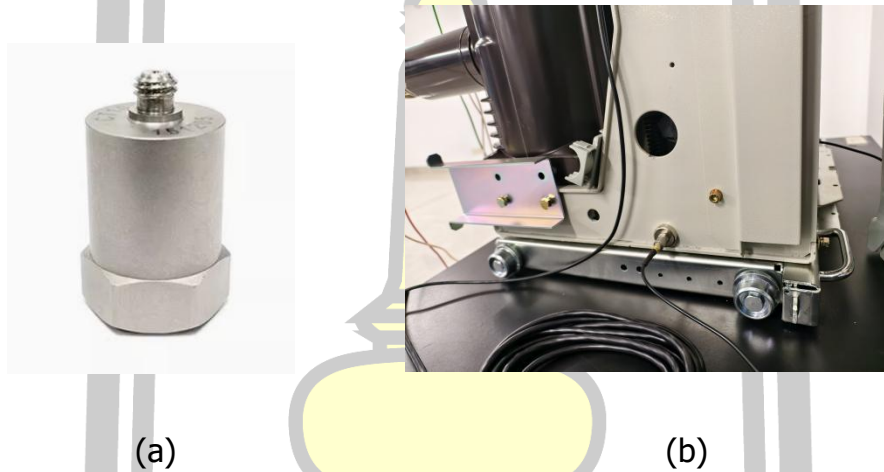


Figure 17 Vibration Sensor with (a) CT1000L sensor and (b) installation location

Its technical parameters are listed in the Table 2 [100].

Table 2 Vibration Sensor technical parameters [100]

Electric Sensitivity (mV/g)	5	Dimensions (mm)	φ11*20
Common Frequency (kHz)	40	Non linearity Range	±0.1%
Operating Frequency Range (Hz)	1 ~ 15000	Settling Time (sec)	±2
Maximum Lateral Sensitivity Ratio	<5%	Output Swing (±Vp)	±5Vp
Overload Shock (g)	10000	Measurement Range (g)	±1000
Noise (μV):	<3	Output Resistance (ohm)	<150
Constant Current Source	2-10mA/18~30VDC	Use Temperature Range (°C)	-20 ~ 100

After completing the sensor selection and installation, other device selection, and circuit connection design, a test platform was constructed under no-load conditions of the high-voltage circuit breaker. A fault simulation was performed on the test platform, and test data under normal and fault conditions were collected.

Figure 18 shows the high-voltage circuit breaker test platform, Figure 19 shows the signal acquisition principle diagram.

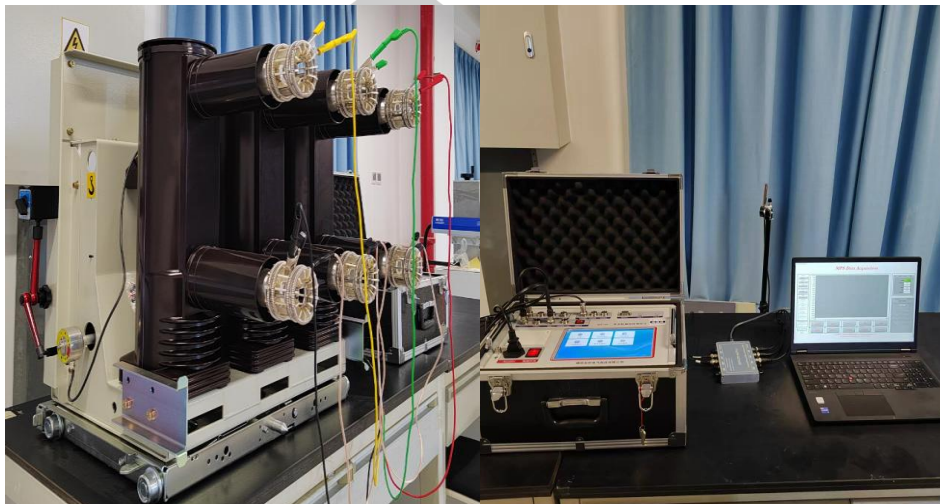


Figure 18 HVCB test platform

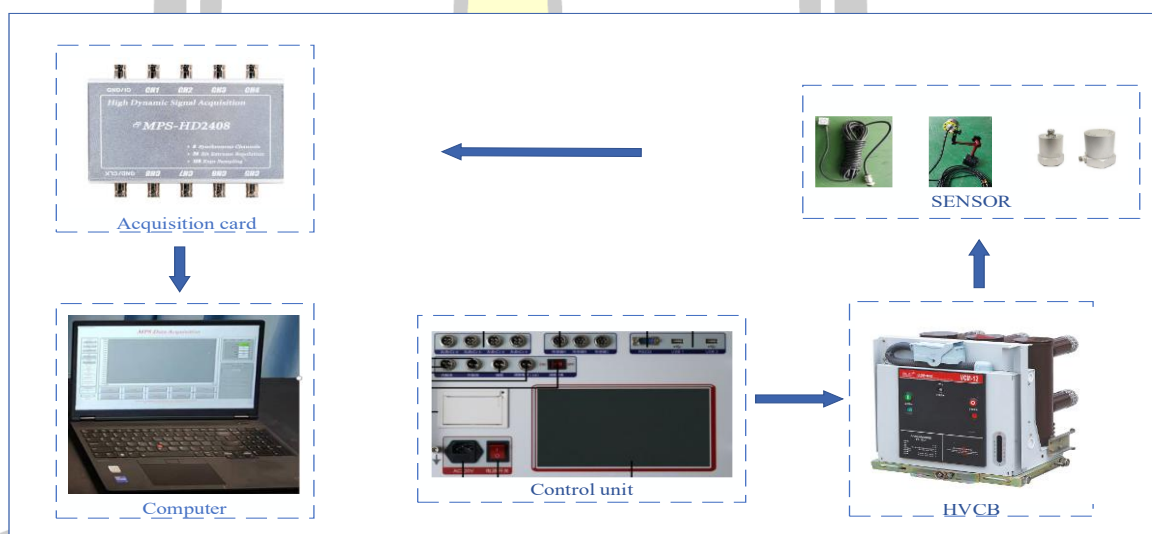


Figure 19 Signal acquisition principle diagram

A simulation experiment was conducted on a 12kV spring-operated high-voltage circuit breaker to simulate the following fault conditions: Normal operation, Instantaneous trip upon closure, Coil burn out, Contact bounce, Coil sticking, and Stuck Energy storage mechanism.

Figure 20 shows Instantaneous trip upon closure fault: Re-secure (move upward) the components shown in the figure below to disengage the closing trip mechanism.



Figure 20 Instantaneous trip upon closure

Figure 21 shows Coil burnout fault: Each time the closing and opening coils are energized during operation, they generate heat, accelerating ageing and increasing coil resistance. As shown in the figure, remove the trip coil, simultaneously close the trip button, and keep the trip coil energized for an extended period until its surface turns charred and emits a burnt odour but does not completely burn out, simulating a trip coil breakdown fault.



Figure 21 Coil burnout

Figure 22 shows Contact bounce fault: Adjust the compression of the over travel spring.



Figure 22 Contact bounce

Figure 23 shows Coil sticking fault: Due to environmental factors, the electromagnetic components of high-voltage circuit breakers are subject to inevitable corrosion and ageing, leading to sticking faults. As shown in Figure a, disassemble the closing coil, wrap a layer of insulating tape around the top bar to increase friction during movement, thereby simulating a closing coil sticking fault.

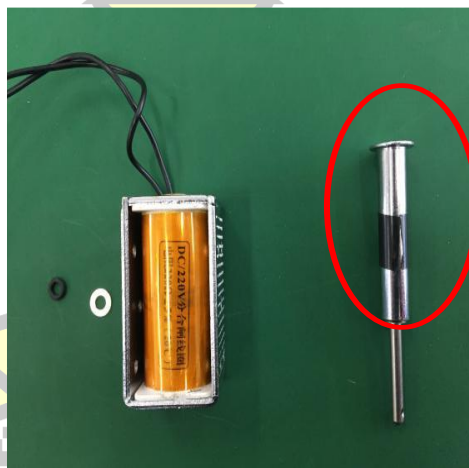


Figure 23 Coil sticking

Figure 24 shows stuck Energy storage mechanism fault: Remove the wire coil, wrap a layer of insulating tape around the top bar to increase its friction during movement.



Figure 23 Stuck Energy Storage Mechanism

After the platform was set up, 80 sets of closing data were collected from high-voltage circuit breakers in normal operating conditions. Without damaging the internal structure of the circuit breakers, five different types of faults were simulated and data was collected based on the actual site conditions. The faults were then classified and labeled as shown in the table below. The five types of fault conditions are: Instantaneous trip upon closure, coil burnout, contact bounce, coil sticking, and stuck energy storage mechanism sticking. The labels and fault types are shown in the Table 2 below.

Table 3 Data Conditional Label Configurations

State Type	Real sample data	Faulty label
Normal operation condition (NOP)	80	1
Instantaneous trip upon closure (ITUC)	80	2
Coil burnout (CBT)	80	3
Contact bounce (CBE)	80	4
Coil sticking (CS)	80	5
Stuck energy storage mechanism (SESM)	80	6

Sample 80 instances of each fault, with each sample containing 12,001 data points. Resample the raw data, set the target sample point count (1,201 points) and the original sample point count, and calculate the resampling ratio. Use the resample function to resample each data sample, adjust each sample to the target length standardized data format, and retain the original data characteristics to improve model training efficiency. As shown in Figure 25 below.

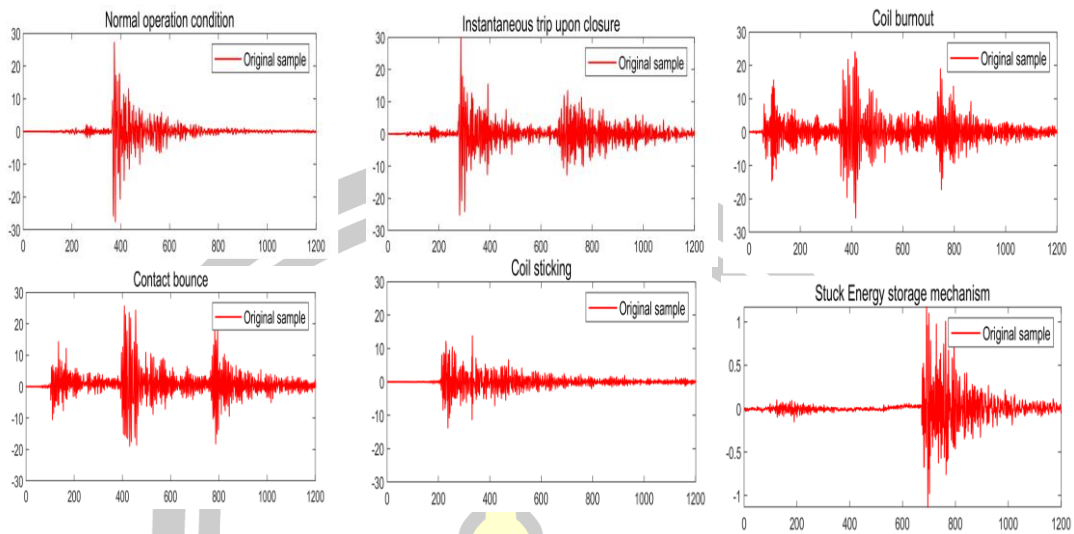


Figure 24 Original sample in 6 states

In summary, the entire study is built based on MATLAB and Simulink and uses the data enhancement capability of adversarial generative training and the feature extraction capability of convolution-neural networks to achieve high-precision fault diagnosis of high-voltage vacuum circuit breakers. The specific process is shown in Figure 26.

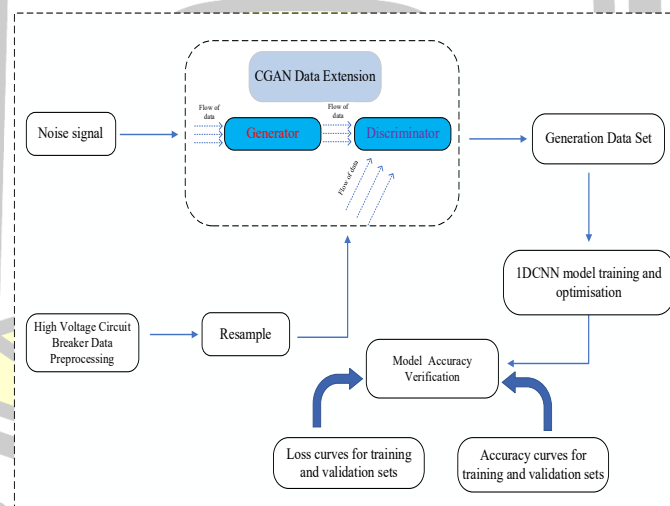


Figure 25 Design diagram of HVCB fault diagnosis framework

The convolution-neural network achieves efficient extraction of fault features by learning the operating characteristic data of the circuit breaker; the adversarial generative network generates high-quality sample data through adversarial optimization of the generator and the discriminator to enhance the diversity of the training data set. In order to improve the diagnostic efficiency of the model, this paper combines deep learning with adversarial generative training to construct a fault diagnosis method framework that can adapt to complex working conditions.

Chapter 4 Results and Discussion

4.1 Training the CGAN model

To understand the model training process, the down-sampled data-set is used as the real sample set for the CGAN model. The down-sampled data-set is used as the real sample set for the CGAN model. The generator is fed with 6×200 -dimensional Gaussian noise and outputs generated samples. The discriminator then classifies the real samples and generated samples. During training, the CGAN achieves adversarial learning between generated samples and real samples by alternately optimizing the loss functions of the generator and discriminator. The optimization algorithm uses the Adam optimizer to minimize the loss of the generator and discriminator through gradient descent, ultimately generating realistic samples. During training, the original and smoothed scores of the generator and discriminator in the CGAN model are shown in Figure 27.

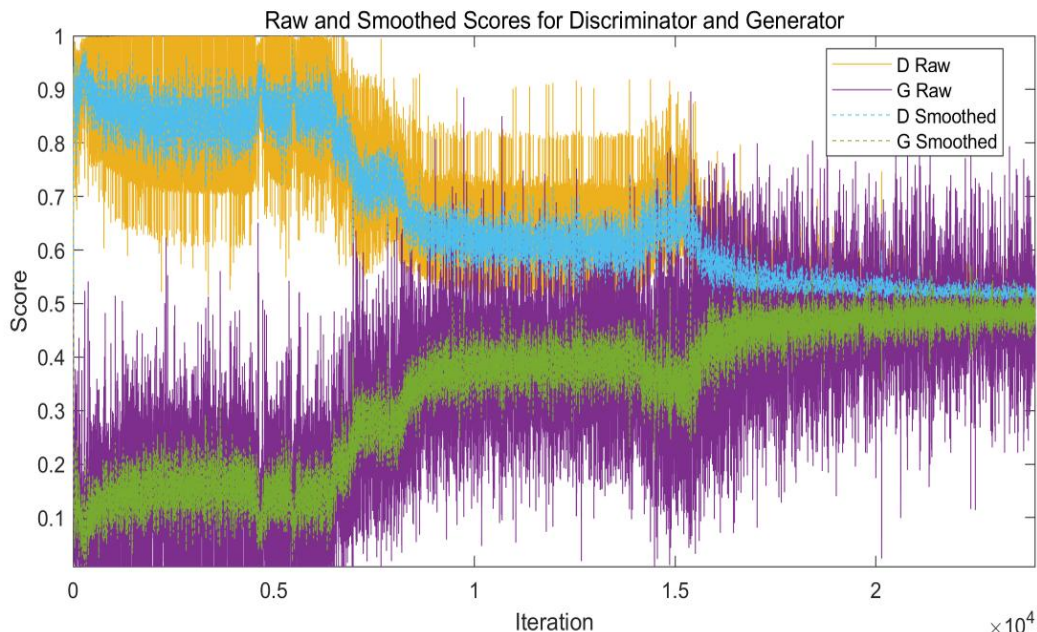


Figure 26 Raw and Smoothed Scores for Discriminator and Generator

The discriminator's score fluctuates significantly in the early stages of training but rapidly decreases and stabilizes as training progresses. The generator's score also experiences significant fluctuations in the early stages before gradually increasing and stabilizing. After approximately 20,000 iterations, the score stabilizes around 0.5. This indicates that after multiple rounds of adversarial training, the generator and

discriminator gradually reach a Nash equilibrium state, ultimately generating realistic samples. This aligns with the basic expectations for training a Generative Adversarial Network (GAN) model.

After training, the comparison between real samples and generated samples is shown in the Figure 28.

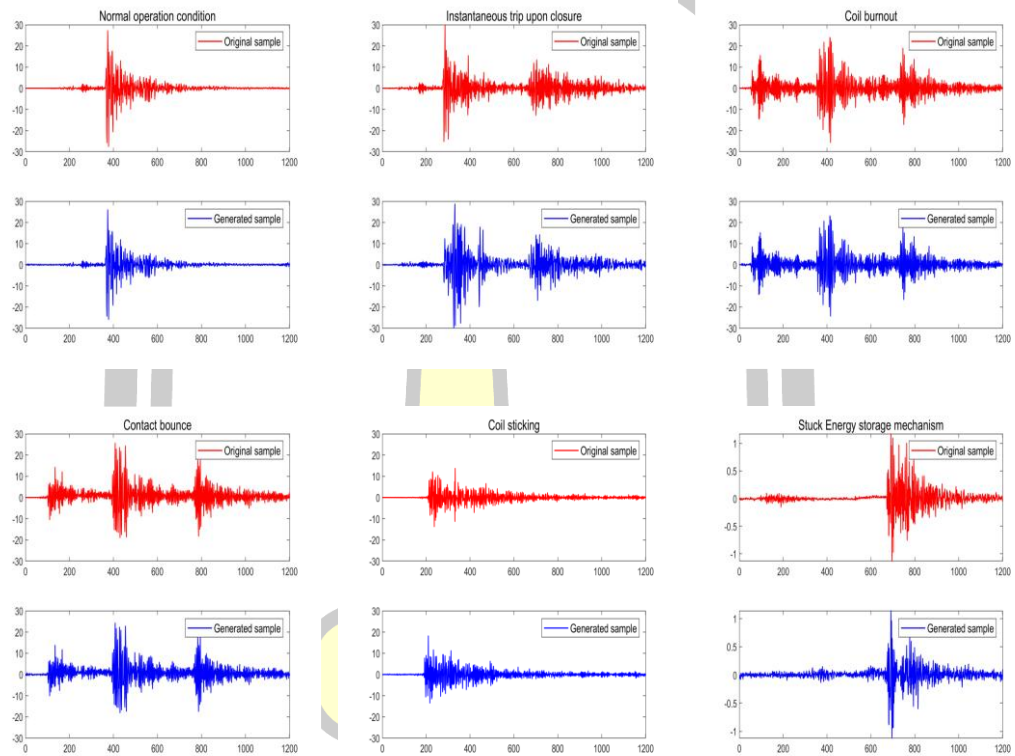


Figure 27 CGAN - Comparison of generated samples and real samples

It can be seen from the figure that the model training optimization is basically complete, and the generated samples are basically close to the real samples. The dataset generated using CGAN is 2.5 times the original data, which is 200 samples for each of the six fault types.

To further stress the superiority of CGAN-generated samples, samples generated by KDE and MCMC were compared with those generated by the CGAN network, as shown in Figure 29 and 30 below.

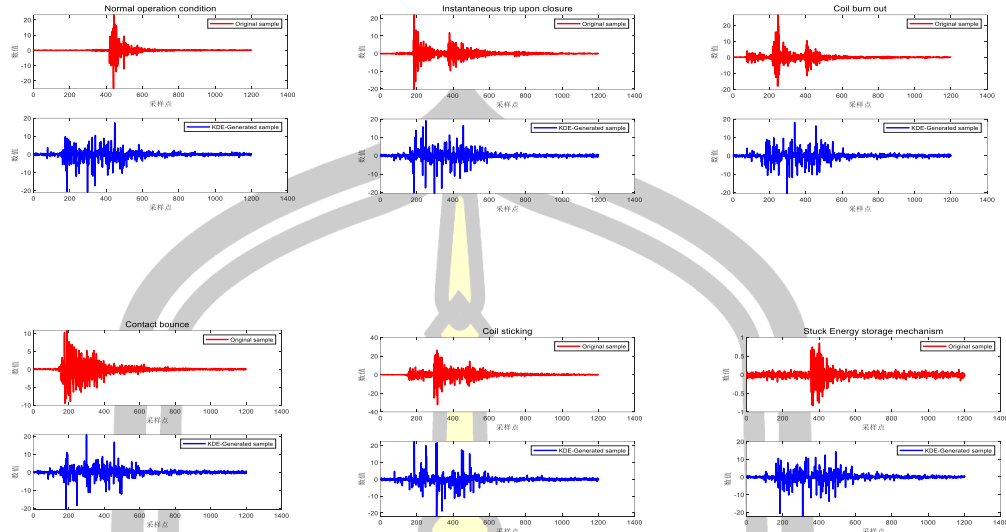


Figure 28 KDE - Comparison of generated samples and real samples

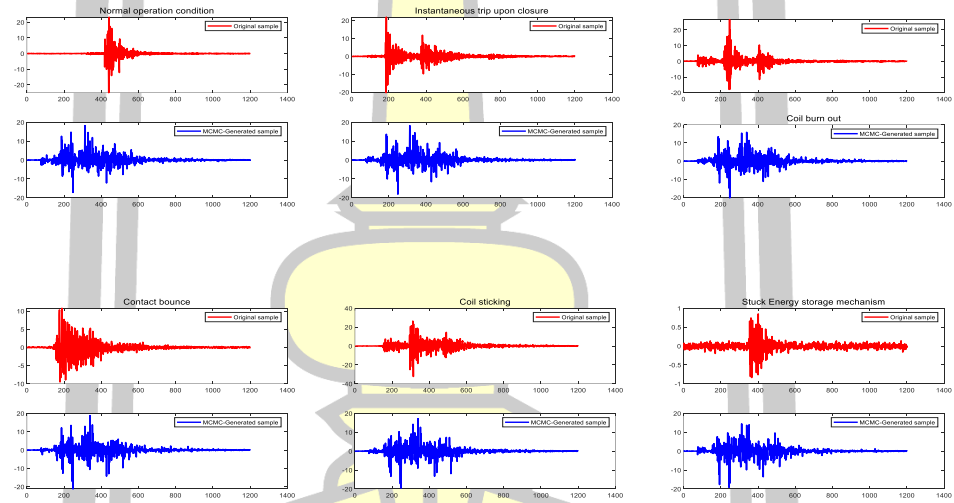


Figure 29 MCMC - Comparison of generated samples and real samples

From the comparison figures above, it can be seen that the sample signals generated by the KDE and MCMC networks are numerically similar, but there are obvious deviations in the shape of each type of signal, indicating that KDE and MCMC are less effective than CGAN in modelling and generating high-dimensional data and complex distributions, especially when handling large-scale data, where their efficiency and effectiveness are typically poorer.

For HVCBS normal state and five fault state samples, each type consists of 80 real samples corresponding to 200 synthetic samples. To compare the sample quality generated by CGAN, KDE, and MCMC, the three networks were evaluated using FID

and MMD metrics to quantitatively analyse the quality of the generated samples. The comparison results are shown in the Figure below.

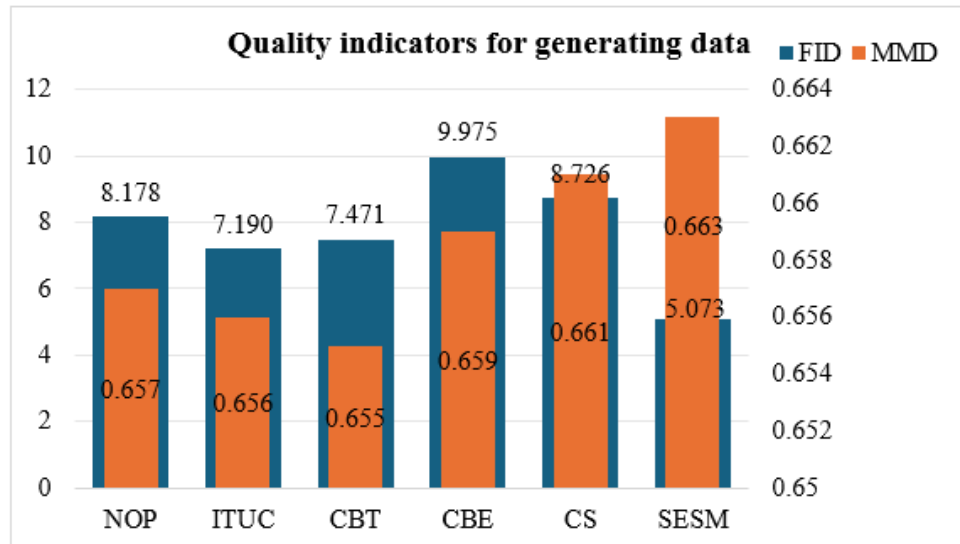


Figure 30 CGAN model metrics

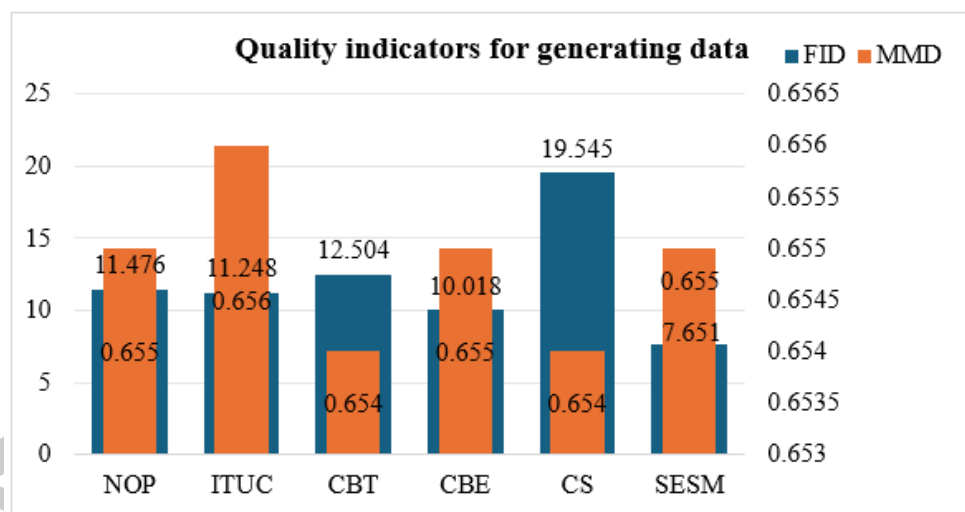


Figure 31 KDE model metrics

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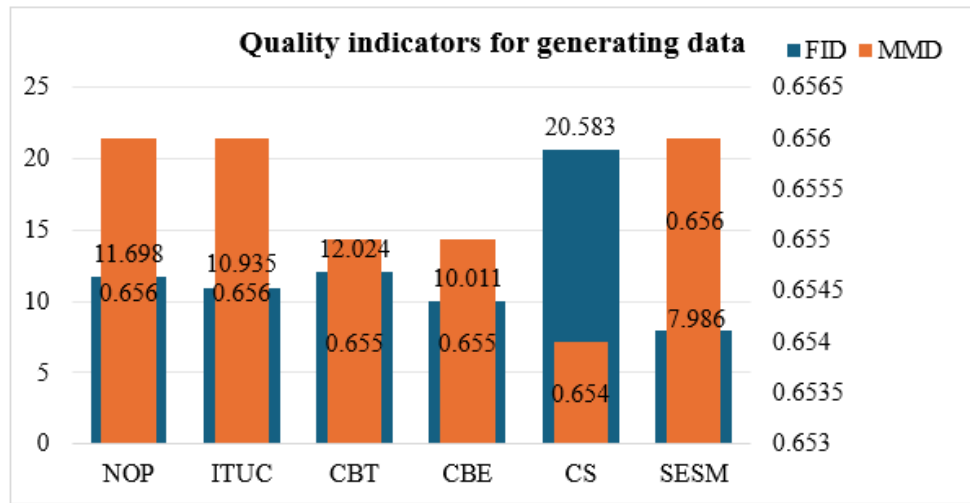


Figure 32 MCMC model metrics

As can be seen from the figure, the MMD metrics of the three models are similar and close to 0, indicating that the distribution differences between the generated data and the real data are small. The FID metrics of the three models are close to 10 or even greater than 10, indicating that the generative models are not sufficiently trained. Although CGAN is more powerful than traditional generative models, it may also generate samples that differ significantly from real samples if not sufficiently trained or with inappropriate hyper-parameters. The FID values for normal states and the five fault states in CGAN are slightly lower, indicating that these five states are generated most effectively. Fault data may be highly complex, containing multiple nonlinear and noisy features that are difficult for traditional generation methods such as KDE and MCMC networks to capture. Additionally, CGAN networks may also face challenges in certain training stages, resulting in FID values approaching 10 in the CGAN model. However, when distinguishing between the five fault states, the FID values of CGAN remain lower than those of KDE and MCMC, indicating that CGAN-generated samples exhibit superior quality compared to traditional generation methods. The quality metrics of samples generated by different models are presented in Table 4.

Table 4 Quality indicators table for samples generated by different models

Metric	CGAN	KDE	MCMC
NOP (FID)	8.178	11.476	11.698
NOP (MMD)	0.657	0.655	0.656
ITUC (FID)	7.190	11.248	10.935
ITUC (MMD)	0.656	0.656	0.656
CBT (FID)	7.471	12.504	12.024
CBT (MMD)	0.655	0.654	0.655
CBE (FID)	9.975	10.018	10.011
CBE (MMD)	0.659	0.655	0.655
CS (FID)	8.726	19.545	20.583
CS (MMD)	0.661	0.654	0.654
SESM (FID)	5.073	7.651	7.986
SESM (MMD)	0.663	0.655	0.656

4.2 Training results for the 1DCNN model

During the one-dimensional convolution training of the data-set, the data-set was divided into a training set (70%) and a test set (30%). The data-set contains 729 samples (including 600 generated samples and 129 original real samples, with each sample consisting of 1,201 data points). The data-set is trained with a learning rate of 0.001, a batch size of 12, and 40 training rounds. After each training round, the model is validated, and the loss curve and accuracy curve of the training set and validation set are plotted to determine the model's performance at different training rounds. As shown in Figure 34.

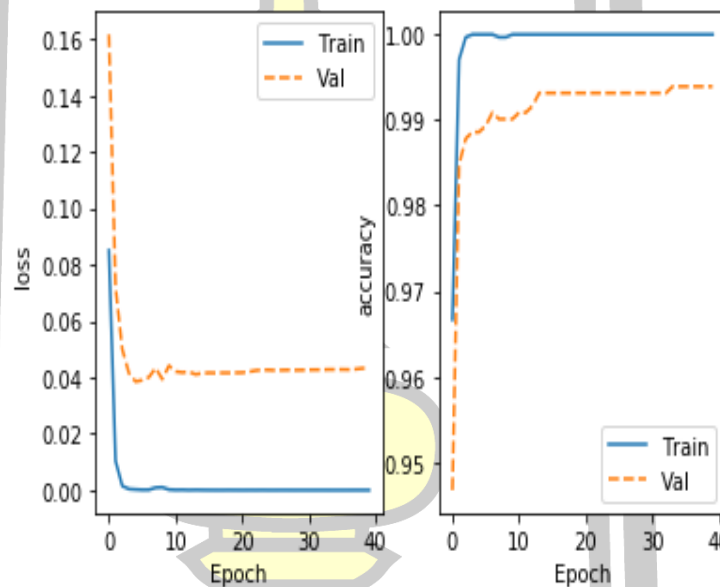


Figure 33 Loss and accuracy curves of train and validation

As can be seen from the figure, during training, the training set loss decreases rapidly and then stabilizes in the initial stage, while the validation set loss decreases in the initial stage, fluctuates slightly, and then gradually stabilizes. The validation set accuracy of the model rises rapidly in the initial stage of training and then gradually stabilizes. This shows that the model has strong generalization ability after fitting the data, and the validation set accuracy fluctuates in the early stage and then stabilizes, indicating that the model performs well in fault detection tasks.

The original sample data-set and the expanded high-voltage vacuum circuit breaker sample data-set were input into the constructed 1DCNN diagnostic model for

fault diagnosis classification. The model structure and parameters are shown in the Figure 35.

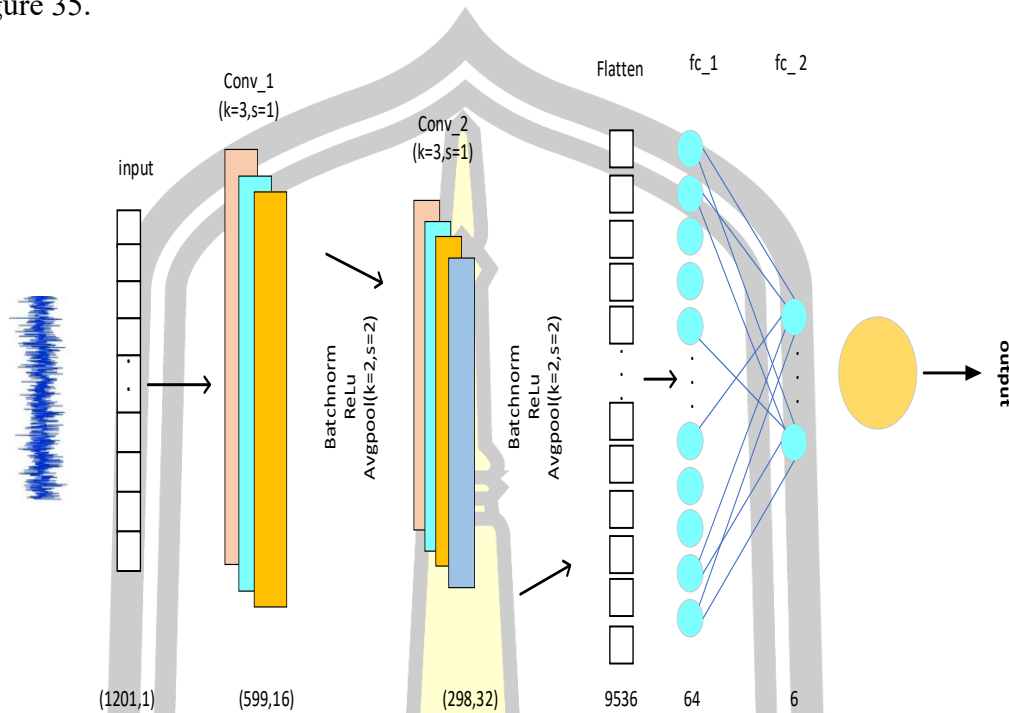


Figure 34 Model structure and Parameters

The model structure uses the Adam optimizer for parameter optimization, with a binary cross-entropy loss function. It consists of one input layer, two convolution layers, two pooling layers, one fully connected layer, and one output layer. The two convolution-layers contain 16 and 32 sets of convolution-kernels, respectively, with ReLU activation functions. The pooling operation uses 2×1 average pooling, followed by feature flattening, and is connected to a fully connected layer with 64 neurons. After training, the model outputs the 6-class classification data-set.

4.3 Model fault diagnosis verification

The classification accuracy of the CNN model under the sample set input method is represented by a confusion matrix. After calculating the model, it can be concluded that the classification accuracy of the model reaches 98.17%. In order to compare the accuracy of different classification algorithms in an unbalanced sample scenario, The sample set was simultaneously input into three classification diagnostic models: the k-nearest neighbour (KNN) algorithm, the extreme gradient boosting tree (XGBOOST), and the random forest (RF) model. The confusion matrix was used to

display the accuracy of each category's samples in the classification task. The results are shown in the Figure 35.

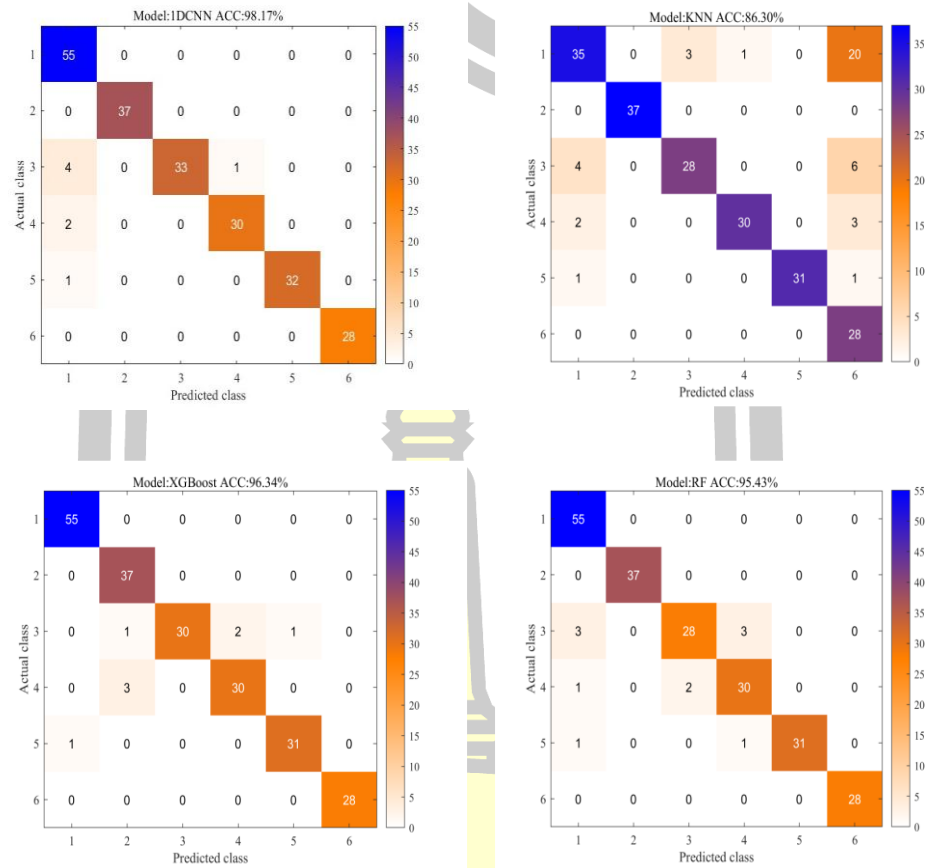
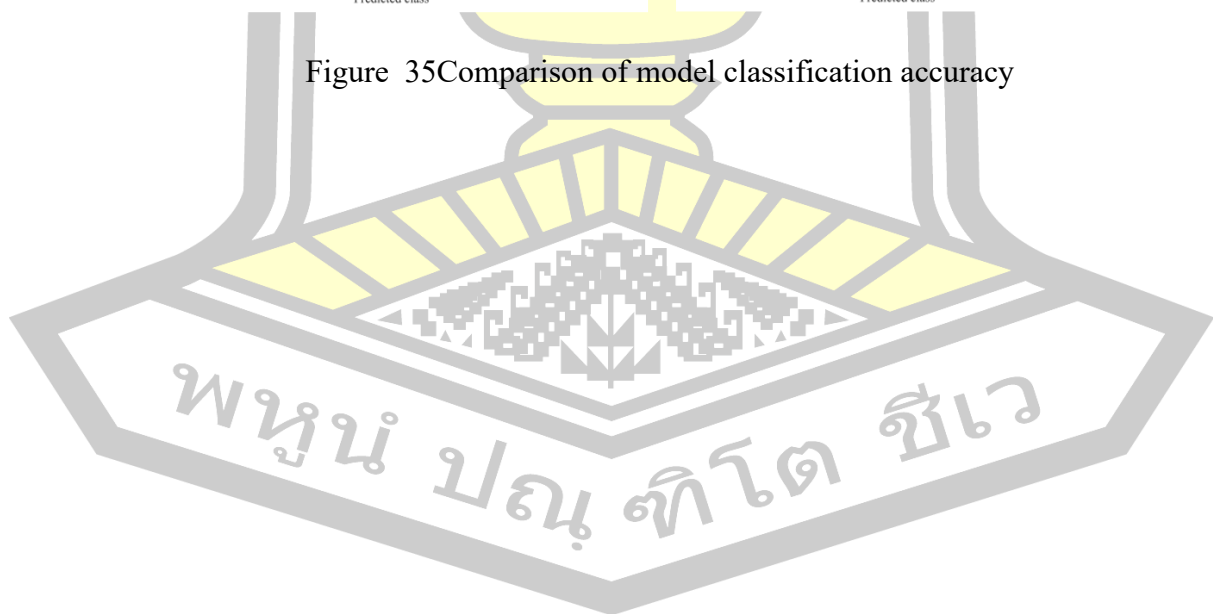


Figure 35 Comparison of model classification accuracy



Chapter 5 Conclusions

5.1 Summary of the research

This study primarily utilizes conditional generative adversarial networks to simulate real high-voltage vacuum circuit breaker fault data and generate similar data. As the number of fault sample data increases, fault patterns are identified among the numerous fault data, thereby facilitating the resolution of high-voltage vacuum circuit breaker faults. The core of this research lies in using the model to generate vibration signals of high-voltage vacuum circuit breakers in both healthy and faulty states, while employing a 1DCNN classification model to validate the reliability of the data. Ultimately, this provides the fault diagnosis system with more diverse training data.

In conducting the research, this design established an experimental platform and simulated corresponding fault conditions, collecting relevant data that included signal data under both normal and fault conditions. To ensure the comparability of the data in subsequent analyses, this study first randomly selected data samples and then performed standardization processing on them. Given the insufficient amount of fault signal data, a conditional generative adversarial network model was specifically designed. This model primarily consists of a generator and a discriminator: the generator is responsible for generating high-voltage vacuum circuit breaker signals under both healthy and fault conditions, while the discriminator is tasked with distinguishing between the generated signals and real signals.

During the network construction process, the generator utilized transposed convolution layers and batch normalization layers to ensure that the generated signals had a high quality standard. The discriminator employed a multi-layer convolutional network to effectively distinguish between generated signals and real signals. After entering the training phase, the Adam optimizer was selected to update the network parameters using the back propagation algorithm. As a result, the quality of the generated signals continues to improve, and the discriminator's ability to distinguish between generated and real signals gradually enhances.

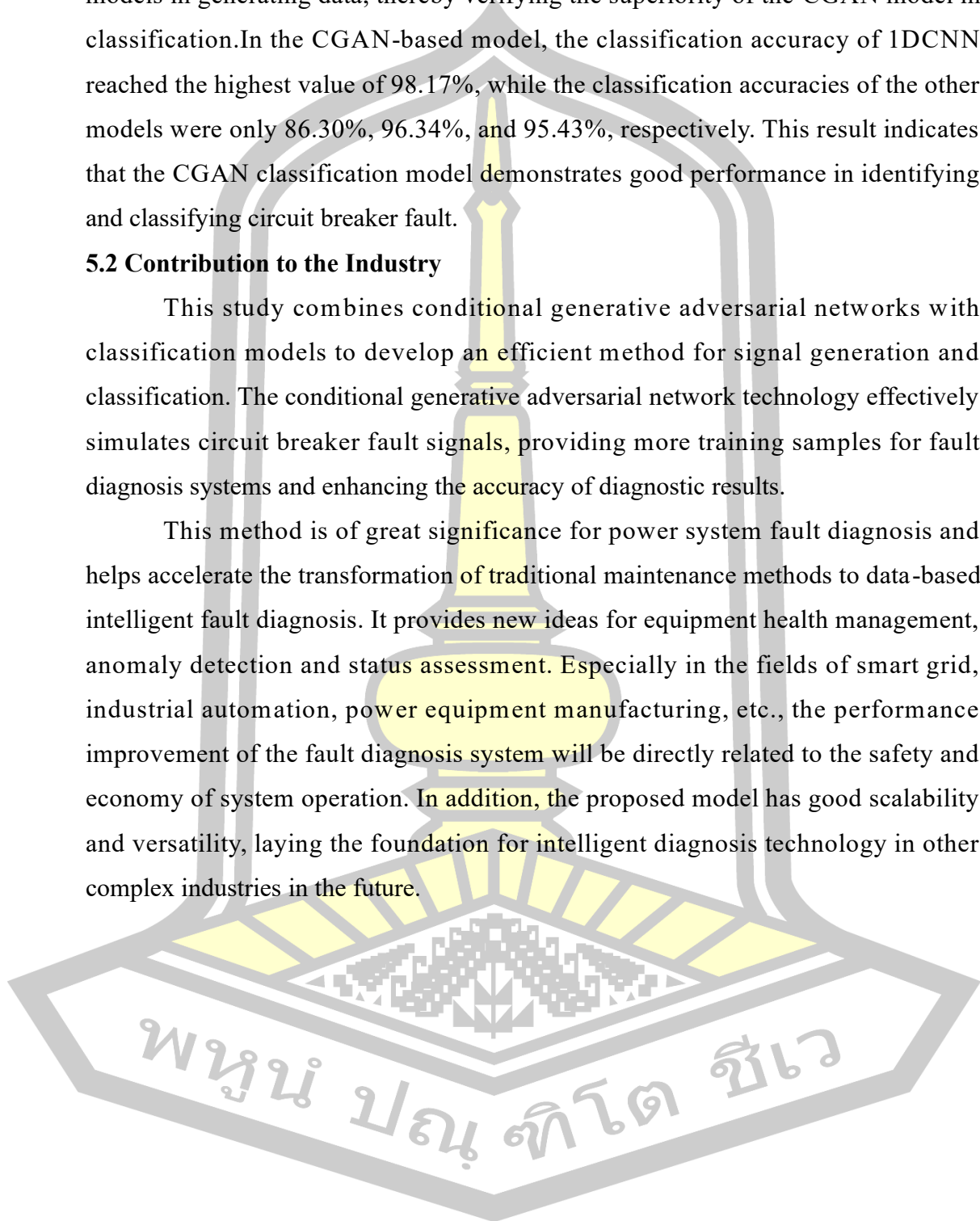
To validate the effectiveness of CGAN-generated signals in actual fault diagnosis applications, both real signals and generated signals were used as training sets. Classification analysis was performed using 1DCNN, KNN, XGBOOST, and RN

classification algorithms to compare the performance of CGAN, KDE, and MCMC models in generating data, thereby verifying the superiority of the CGAN model in classification. In the CGAN-based model, the classification accuracy of 1DCNN reached the highest value of 98.17%, while the classification accuracies of the other models were only 86.30%, 96.34%, and 95.43%, respectively. This result indicates that the CGAN classification model demonstrates good performance in identifying and classifying circuit breaker fault.

5.2 Contribution to the Industry

This study combines conditional generative adversarial networks with classification models to develop an efficient method for signal generation and classification. The conditional generative adversarial network technology effectively simulates circuit breaker fault signals, providing more training samples for fault diagnosis systems and enhancing the accuracy of diagnostic results.

This method is of great significance for power system fault diagnosis and helps accelerate the transformation of traditional maintenance methods to data-based intelligent fault diagnosis. It provides new ideas for equipment health management, anomaly detection and status assessment. Especially in the fields of smart grid, industrial automation, power equipment manufacturing, etc., the performance improvement of the fault diagnosis system will be directly related to the safety and economy of system operation. In addition, the proposed model has good scalability and versatility, laying the foundation for intelligent diagnosis technology in other complex industries in the future.



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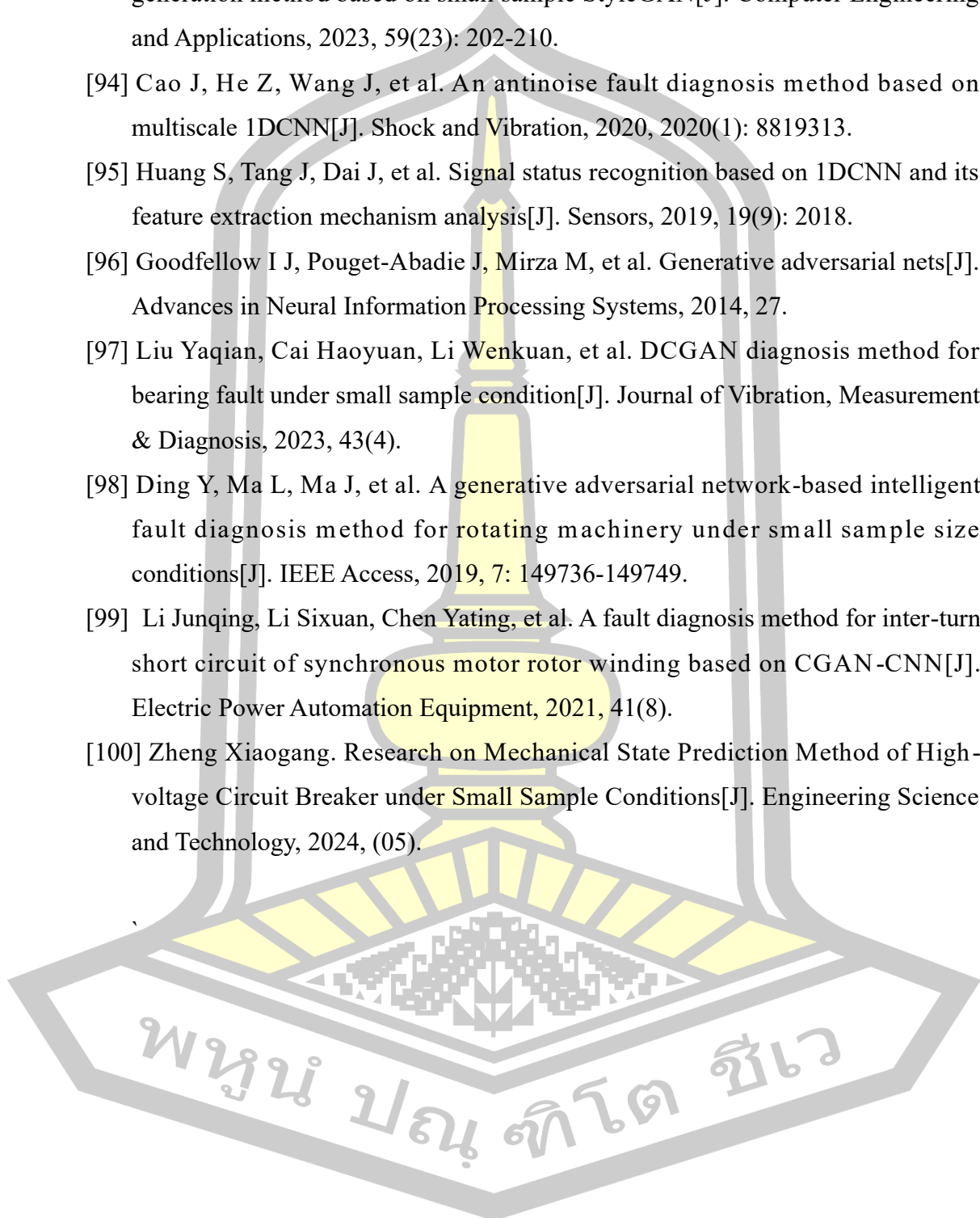
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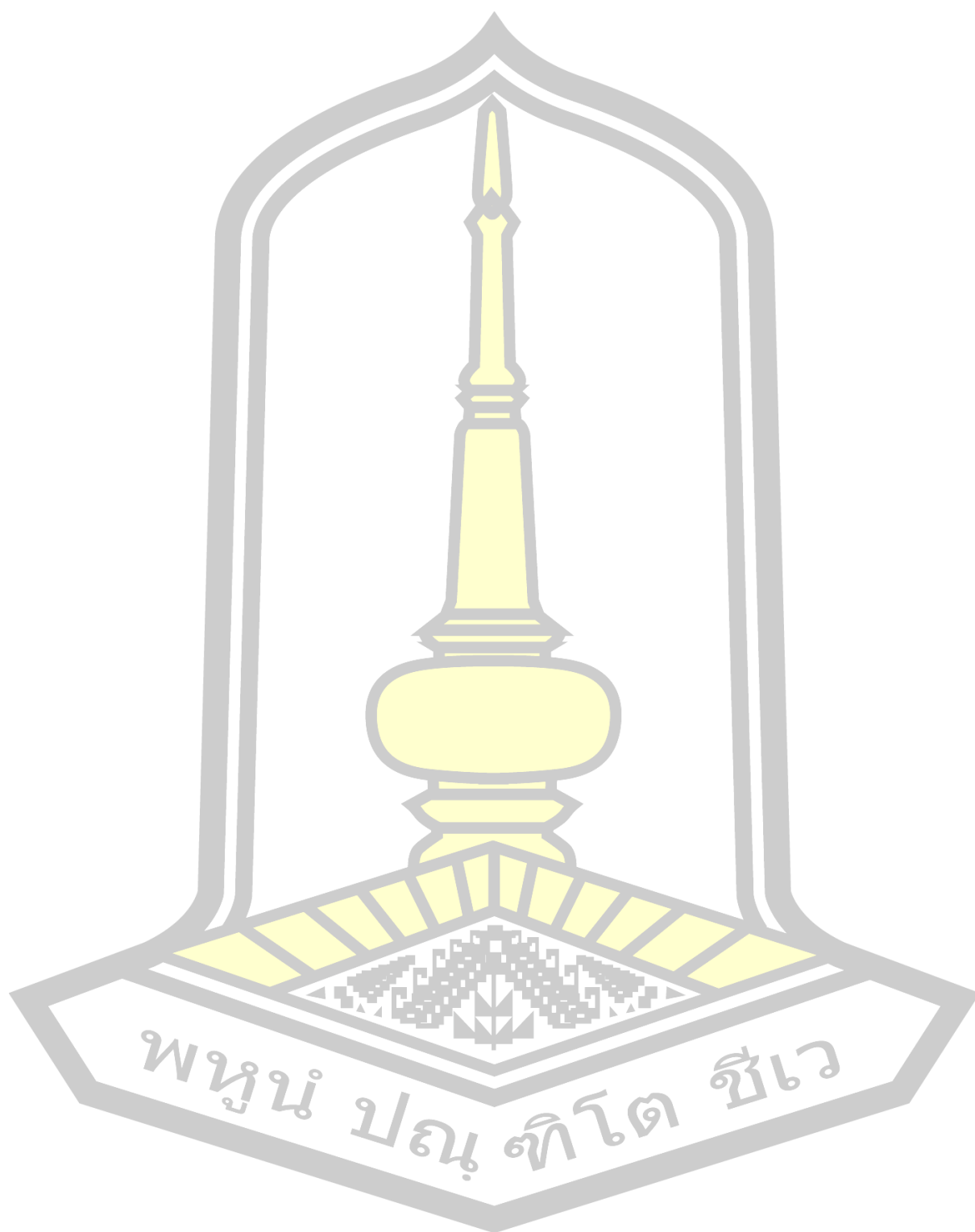
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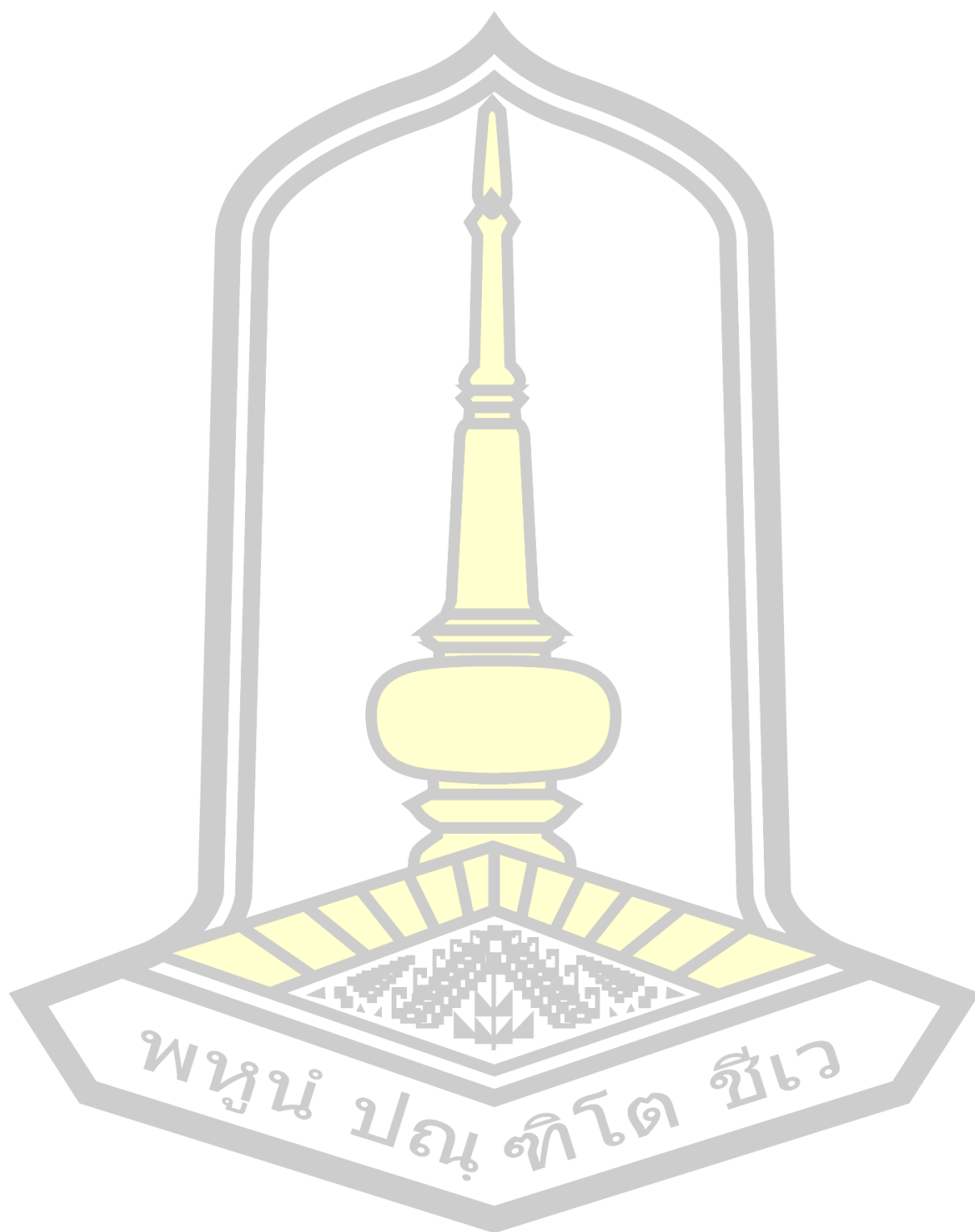
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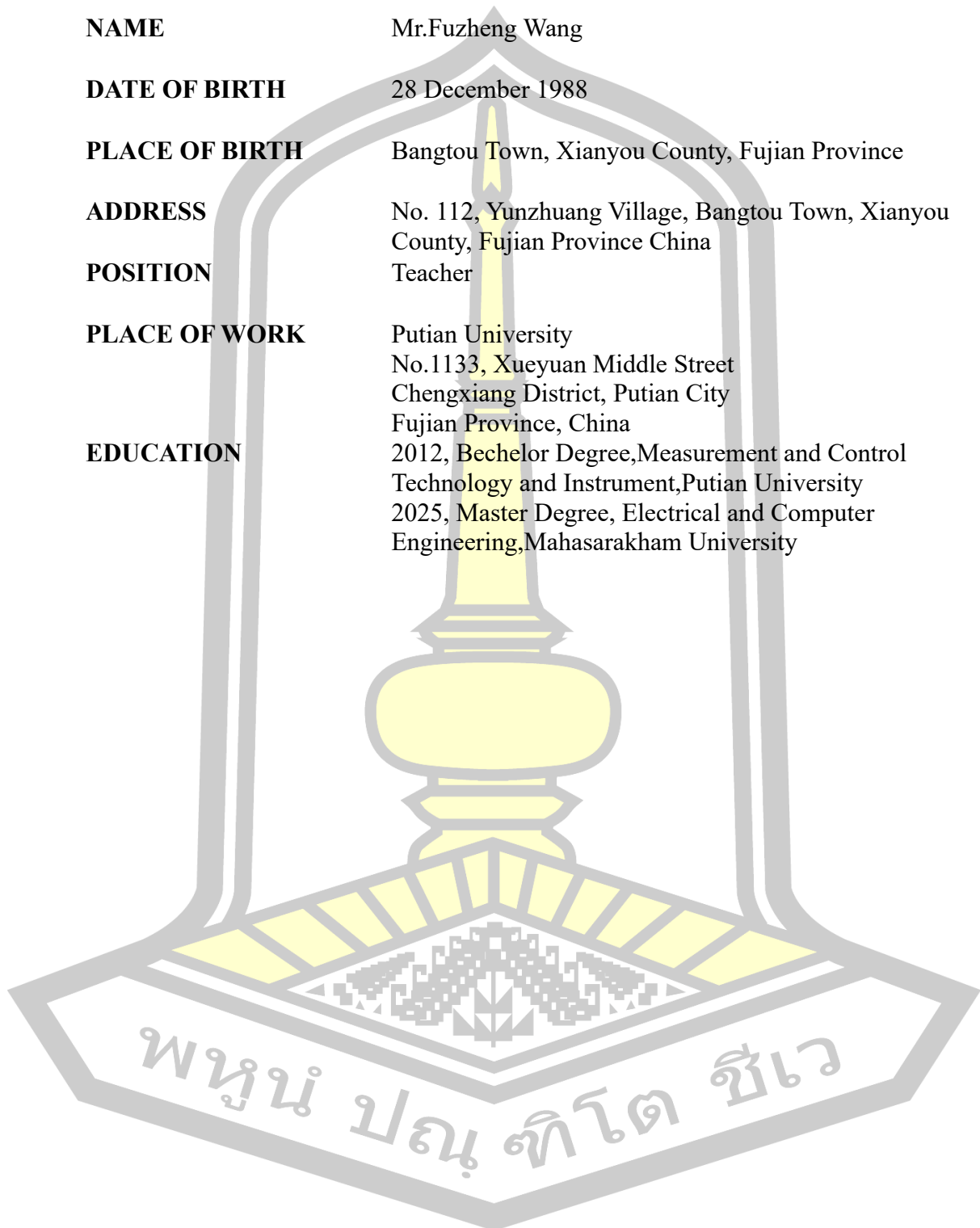
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