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Internal Fault Diagnosis of MMC-HVDC Based on Classification Algorithms in Machine Learning

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INTERNAL FAULT DIAGNOSIS OF MMC-HVDC BASED ON

CLASSIFICATION ALGORITHMS IN MACHINE LEARNING

by

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ABSTRACT

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The University of Wisconsin Milwaukee, 2019
Under the Supervision of Professor Lingfeng Wang

With the development of the HVDC system, MMC-HVDC is now the most advanced technology that has been put into use. In power systems, faults happen during the operation due to natural reasons or devices physical issues, which would cause serious economic losses and other implications. Thus, fault detection and analysis are extremely important, especially in the HVDC system. Existing works in literature mainly focus on the faults detection and analysis on the system side such as short circuit of the AC side, and open circuit of the DC side. However, little attention has been paid to the fault detection and analysis inside the converters. With the technology development of converter devices, replacing the whole converter becomes more expensive. Thus, my research mainly focuses on the detection and classification of the faults within the internal of the MMC module.

In this research, an SPS model of MMC-HVDC is built as the example. Faults including short circuit and open circuit located inside the MMC module are simulated. Machine learning algorithms are chosen as the tool to achieve the goal of detecting faults and locating the fault position inside the MMC module precisely. After comparing the basic characteristics and properly application situations of various methods of machine learning, Coarse KNN, Complex Tree and Bagged Tree (Random Forest) are deployed to solve the problem. The performance of the methods are analyzed and compared, to get the most proper method in solving the

problem.

To

my parents,

my teachers,

and my friends who give me love

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LIST OF ABBREVIATIONS

HVDC	High Voltage Direct Current
LCC	Line-commutated Converters
VSC	Voltage-source Converters
MMC	Modular Multi-Level Converter
NN	Neural Network
TP	True Positive
FN	False Negative
TN	True Negative
FP	False Positive
SPS	SimPowerSystem

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Chapter 1 HVDC system

1.1. Introduction of HVDC

With the integration of renewable energy, Power systems are getting more interconnected, where HVDC technology can play a key role [1].

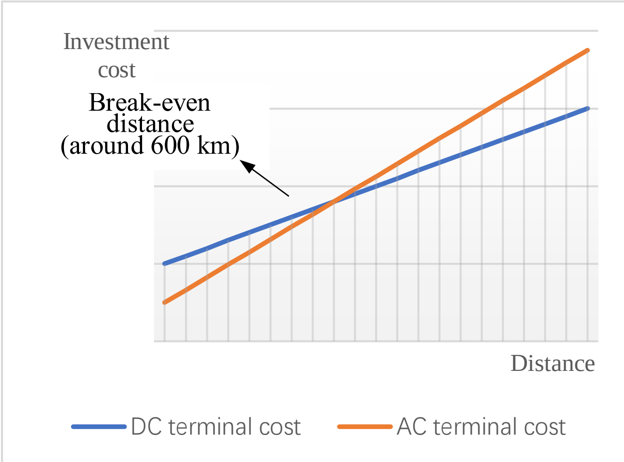
HVDC (High-Voltage Direct Current) is a highly efficient alternative for transmitting large amounts of electricity over long distances and for special situation applications. As a key technology in the future energy system based on renewables, HVDC is truly shaping the grid of the future [2].

HVDC, also known as electric highways or electric highways, is increasingly being integrated into modern power networks. It has been very expensive in history and only preserves the inconvenience of power transmission through traditional alternating current (AC) systems - for example transmission over very long distances, submarine interconnections and transmissions between asynchronous networks. With the development of technology, the economic competitiveness of HVDC transmission systems is becoming stronger and more flexible, leading to a surge in projects [3,4].

Comparing with HVAC, HVDC has some unbeatable natural advantages to some extent, which are shown in the Table 1.1 [5].

Table 1.1 Comparison of HVAC and HVDC

Aspects	Comparison

Investment Cost	
Losses	Skin effect is absent in DC. Also, corona losses are significantly lower in the case of DC. An HVDC line has considerably lower losses compared to HVAC over longer distances.
Controllability	Due to the absence of inductance in DC, an HVDC line offers better voltage regulation. Also, HVDC offers greater controllability compared to HVAC.
Asynchronous Interconnection	AC power grids are standardized for 50 Hz in some countries and 60 Hz in other. It is impossible to interconnect two power grids working at different frequencies with the help of an AC interconnection. An HVDC link makes this possible.
Interference with Nearby Communication Lines	Interference with nearby communication lines is lesser in the case of HVDC overhead line than that for an HVAC line.
Short Circuit Current	In longer distance HVAC transmission, short circuit current level in the receiving system is high. An HVDC system does not contribute to the short circuit current of the interconnected AC system.

As we can see, HVDC transmission system has many more advantages over HVAC, such as stability, controllability etc. For distances longer than the break-even distance, HVDC system becomes more cost effective. Submarine HVDC links can be more suitable for connecting offshore wind farms as they prove to be more efficient and cost effective than undersea HVAC cables. Hence, there is an increasing interest in HVDC transmission. Still, HVAC system will remain much longer as it has its own advantages in transmission and distribution, such as it can be easily stepped up and stepped down. HVDC is actually a complement for AC systems rather than a rival.

1.2. Background of HVDC

AC has been the preferred and most common choice for electrical transmission to homes and businesses for past hundred years. However, high voltage AC transmission has some limitations, starting with transmission capacity and distance constraints, and the impossibility of directly connecting two AC power networks of different frequencies. So here comes HVDC.

The development of electricity began in DC, but it was quickly replaced by AC for a long time. HVDC technology has been in use since the 1950s. After half a century of development, the application of HVDC technology has made great progress. According to incomplete statistics, there are nearly one hundred HVDC transmission projects in the world, including projects under construction, covering more than 20 countries on five continents. [6].

Among them, the Swedish Gotland HVDC transmission project (20MW, 100kV, 90km submarine cable) was completed and put into operation in 1954, which is the world's first high-voltage DC transmission project; The HVDC project with the highest voltage (± 600kV) and maximum transmission capacity (2 * 3150MW) is the Itaipu project in Brazil. The longest transmission distance (1700 km) of HVDC transmission projects is South Africa's Inga-Shaba project; the largest HVDC transmission projects in China, such as Sanchang, Sanguang and Guigang projects, rated DC current is 3000A. Developed HVDC technologies are in Europe and North America, ABB and Siemens have the most advanced HVDC technology, and the United States is the country with the most HVDC projects [6,7].

1.3. Structural Characteristics of HVDC

Today, power generation and power consumption are almost all AC power systems, which determines that in addition to DC transmission lines, HVDC transmission systems should also be equipped with AC-DC converter stations at both ends of the DC line, which means AC is converted to DC at the transmitting end, and then converted to AC after the DC line is sent to the receiving end [8].

The process of converting AC to DC is called rectification, and the process of converting DC to AC is called inversion. The devices that implement rectification and inversion are called rectifiers and inverters, respectively, and the corresponding converter stations are called rectifier stations and inverter stations respectively.

In order to increase the flexibility and reliability of the HVDC system by using ground (or seawater) as a loop, the HVDC system should also have a ground electrode and its leads. In addition, in order to achieve the normal start and stop of the HVDC system, changes in operating mode, adjustment of operating parameters and protection under fault conditions, control and protection systems are also an integral part of the HVDC system.

The converter transformer provides the converter with the appropriate commutation voltage magnitude and phase. When a DC system has a short-circuit fault, its impedance also acts to limit the short-circuit current and avoid damage to the converter. Smooth reactor applications include: (1) suppressing harmonic currents in the DC line, (2) reducing commutation faults of the inverter, and (3) preventing current discontinuity during light loads, (4) Limiting the peak current of the converter when the DC line is short-circuited The AC current of the DC filter is the harmonic current required to filter the converter. The AC filter also provides some of the reactive power required by the converter. The communication system transmits operational control and voice information between the converter stations to achieve coordinated control of the HVDC system [9-11]. The converter is the most important part of the HVDC system.

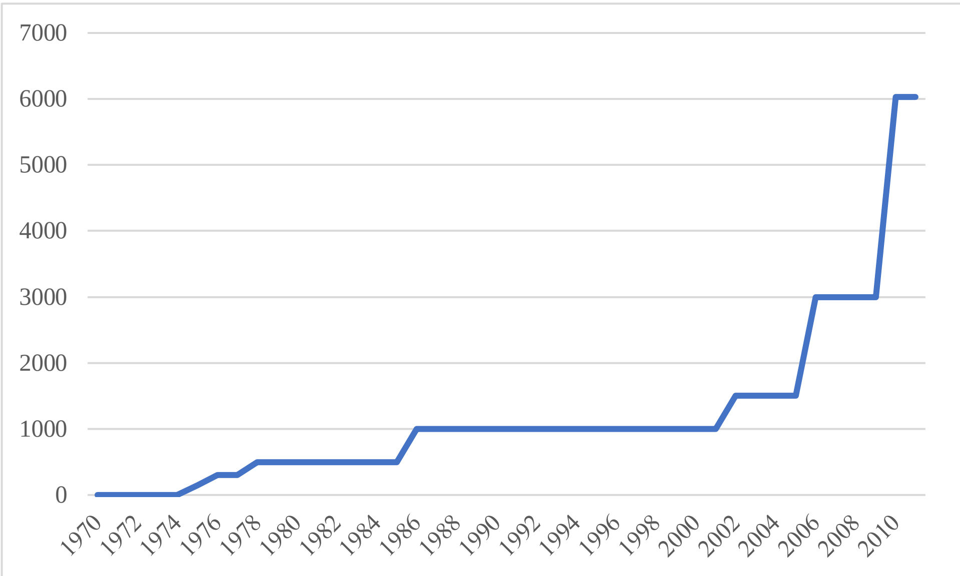


Fig 1.1 The Growth of Transmission Capacity of LCC(MW)

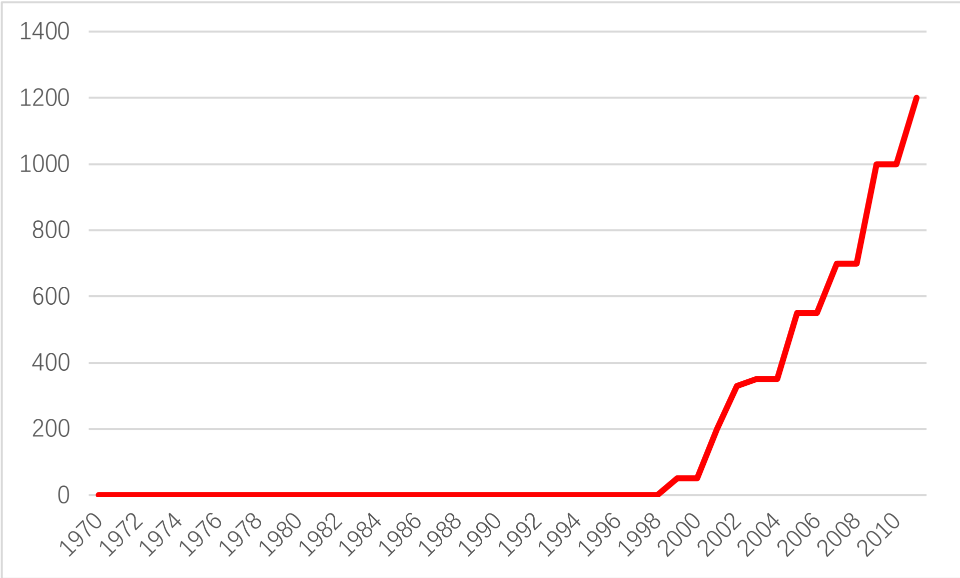


Fig 1.2 The Growth of Transmission Capacity of VSC(MW)

1.4. Converter

The inverter is a device for realizing mutual conversion of AC and DC power. The converter valve is a controllable or uncontrollable switchgear that can realize the function of the converter bridge arm and is the most basic component of the inverter. The inverter is constructed by connecting one or more three-phase bridge converter circuits (also called 6-pulse converters) in series. Change the trigger phase of the converter valve, which can be operated either in the rectified state or in the inverter state. The converter that converts the alternating current to the direct current is called a rectifier, and the inverter that converts the direct current to the alternating current is called an inverter. The rectifier is basically the same as the inverter device and is collectively referred to as the converter [12,13].

HVDC converters come in several different forms. The early HVDC systems built until the 1930s were efficient rotary converters and used electromechanical conversion, where the motor-generators were connected in series on the DC side and in parallel on the AC side. However, all HVDC systems built since the 1940s have used electronic (static) converters. [7].

Electronic converters for HVDC can be divided into two main categories, Line-commutated converters (LCC) and voltage-source converters (VSC), the first one is made with electronic switches that can only be turned on, while the second is made with switching devices that can be turned both on and off. Line-commutated converters (LCC) used mercury-arc valves until the 1970s [7] and from the 1970s to the present day, using thyristors. VSC, which first appeared in 1997, using transistors, usually the Insulated-gate bipolar transistor (IGBT).

As of 2012, both LLC and VSC are important, with LLC used mainly where very high capacity and efficiency are needed, and VSC used mainly for interconnecting weak AC systems, and also for connecting large-scale wind power to the grid or for HVDC interconnections that are likely to be expanded to become Multi-terminal HVDC systems in the future. The market for voltage-source converter HVDC is growing rapidly, in part because of the surge in offshore wind power investments, a special type of converter, and the emergence of modular multilevel converters (MMC) as a leader [14].

1.4.1 LCC-HVDC

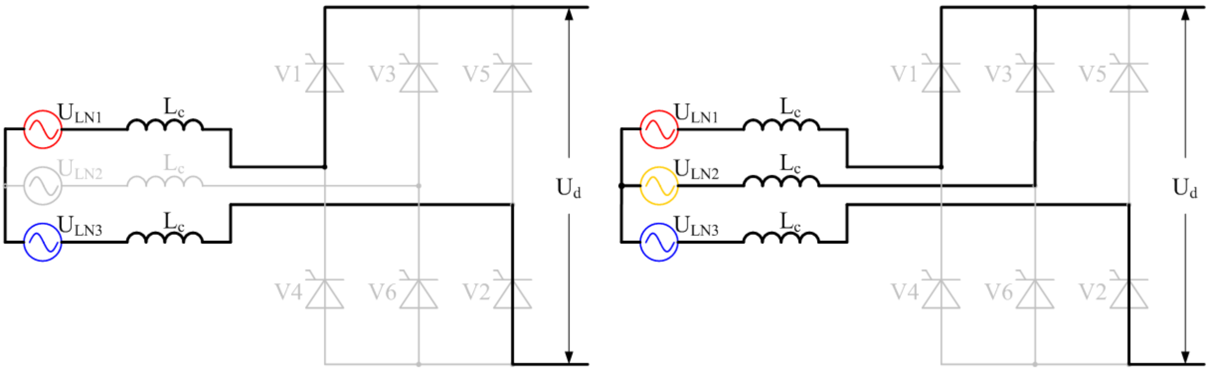
Most HVDC systems currently in operation are based on LCC. The term line commutation indicates that the conversion process relies on the line voltage of the AC system to which the converter is connected to affect the commutation from one switching device to its neighbors [15]. The LCC uses an uncontrolled switching device (such as diode) or can only be turned on by a control action (such as a thyristor).

In LCC, the DC current does not change direction; it flows through a large inductor and can be considered almost constant. On the AC side, the converter appears roughly as a current source, injecting grid frequency and harmonic current into the AC network. Therefore, the line commutating converter for HVDC is also considered to be a current source converter [16]. Since the direction of the current cannot be changed, the reversal of the power flow direction (when needed) is achieved by reversing the polarity of the DC voltage at the two stations.

- Six-pulse bridge

The basic LCC configuration of HVDC uses a three-phase Graetz bridge rectifier or a six-pulse bridge containing six electronic switches, each of which connects one of the three phases to one of the two DC terminals [17]. Often referred to as a complete switching element Typically, two valves in a bridge are electrically conductive at any time: one on the top row and one on the bottom row (from different phases). Two conductive valves connect two of the three AC output voltages in series to the DC terminal. Therefore, the DC output voltage at any given moment is given by the series combination of the two AC phase voltages. For example, if valves V1 and V2 are turned on, the DC output voltage is given by the voltage of phase 1 minus the voltage of phase 3.

The transition from a pair of conductive valves to the next conductive valve does not occur immediately due to the inevitable (but beneficial) inductance of the AC power source. Conversely, when the two valves on the same row of the bridge are simultaneously turned on, there is a short overlap period. For example, if valves V1 and V2 are initially turned on and then valve V3 is open, conduction is transferred from V1 to V3, but both valves are simultaneously conducted [15]. During this time, the DC output voltage is given by the average of the voltages of phases 1 and 2 minus the voltage of phase 3. The overlap angle μ (or u) in the HVDC converter increases with load current, but is typically about 20° at full load..



When V1 and V2 are conducting:
$U_d = U_{LN1} - U_{LN3}$

When V2 is conducting and V1 is commutating to V3:
$U_d = ½(U_{LN1} + U_{LN2}) - U_{LN3}$

Fig 1.3 Working principle of Six-pulse bridge LCC

In other words. When only valves 1 and 2 are turned on, the DC voltage is formed by two of the three-phase voltages. During the overlap period, the DC voltage is formed by all three phase voltages.

- Twelve-pulse bridge

With a phase changes only every 60°, considerable harmonic distortion is produced at both the DC and AC terminals when the six-pulse arrangement is used. An enhanced structure was using 12 valves in a twelve-pulse bridge.

The structure of the twelve-pulse bridge can be regarded as two six-pulse bridges connected in series on the DC side, and a phase shift is placed between their respective AC power sources so that some harmonic voltages and currents are eliminated.

The phase offset between the two AC sources is typically 30°, achieved by using a converter transformer with two different secondary windings (or valve windings). Usually one valve winding is a star (Y-shaped) connection and the other is a delta connection [18]. By connecting each of the two sets of three phases to the twelve valves of the two DC rails, a phase change occurs every 30° and the harmonics are greatly reduced. For this reason, the twelve-pulse system has become the standard for almost all line commutated converter HVDC systems, although HVDC systems constructed with mercury arc valves typically allow for temporary operation, with one of the two six-pulse groups being bypassed.

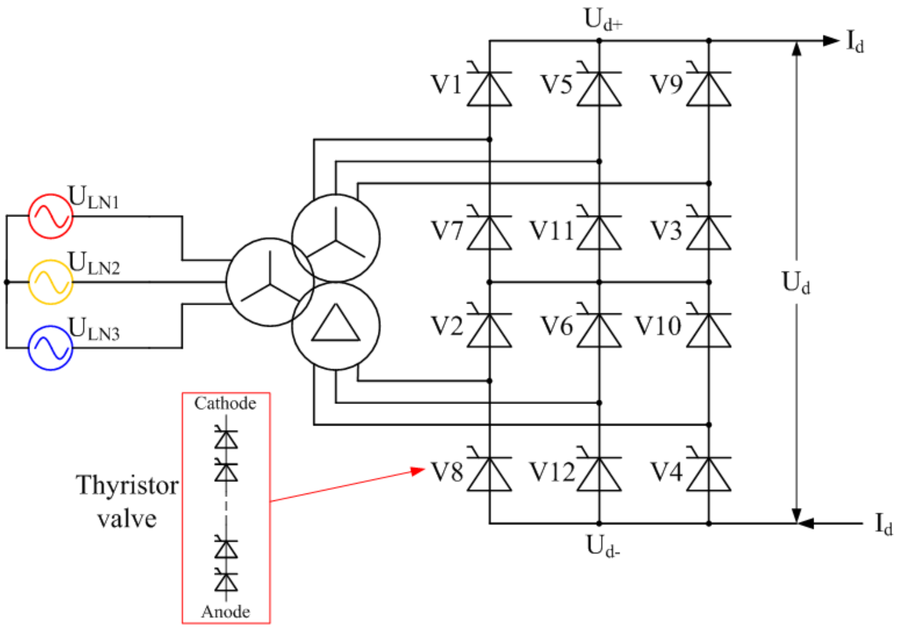


Fig. 1.4 A 12-pulse HVDC converter using thyristor valves

1.4.2 VSC-HVDC

Since the thyristor can only be switched on by control action and relies on an external AC system to affect the shutdown process, the control system has only one degree of freedom - when to turn on the thyristor [15]. This limits the usefulness of HVDC in certain situations because it means that the AC system to which the HVDC converter is connected must always contain a synchronous motor to provide commutation voltage - the HVDC converter cannot feed power into the passive system.

For some other types of semiconductor devices, such as insulated gate bipolar transistors (IGBTs), turn-on and turn-off can be controlled to provide a second degree of freedom. Therefore, IGBTs can be used to fabricate self-commutated converters. In such a converter, the polarity of the DC voltage is usually fixed, and the DC voltage smoothed by the large capacitance can be considered to be constant. Therefore, an HVDC converter using an IGBT is generally referred to as a voltage source converter (or a voltage source converter [18]).

Additional controllability offers many advantages, especially the ability to switch IGBTs multiple times per cycle to improve harmonic performance and (self-rectifying) converters no longer rely on synchronous motors in the AC system for operation. Therefore, the voltage source converter can supply power to an AC network consisting only of passive loads, which is not possible with LCC HVDC.

Voltage source converters are also more compact than line commutator converters (mainly because less harmonic filtering is required) and are better than line commutated converters where space is at a premium, such as on offshore platforms [19].

HVDC systems based on voltage source converters typically use a six-pulse connection because the converter produces harmonic distortion that is much lower than a similar LCC and does not require a twelve-pulse connection. This simplifies the structure of the converter transformer. However, voltage source converters come in several different configurations [19] and research is continuing to evolve into new alternatives.

- Two-level converter

From the installation of the first VSC-HVDC solution (the Hellsjön experimental link [7] commissioned in Sweden in 1997) to 2012, most of the VSC HVDC systems built were based on two-stage converters. The two-level converter is the simplest three-phase voltage source converter [20] and can be thought of as a six-pulse bridge in which the thyristor has been replaced by an IGBT with an anti-parallel diode, the DC smoothing reactor has been replaced by a DC smoothing capacitor. The name of this converter is derived from the voltage at each phase of the AC output switching between two discrete voltage levels, corresponding to the potential of the positive and negative DC terminals.

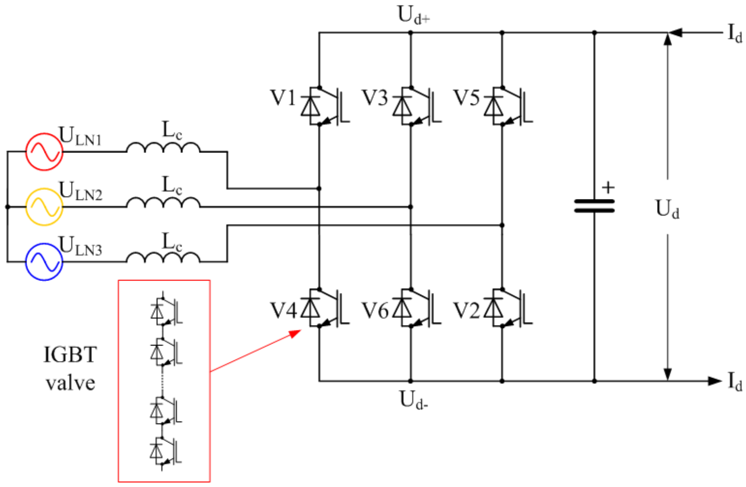


Fig 1.5 Three-phase, two-level voltage-source converter for HVDC

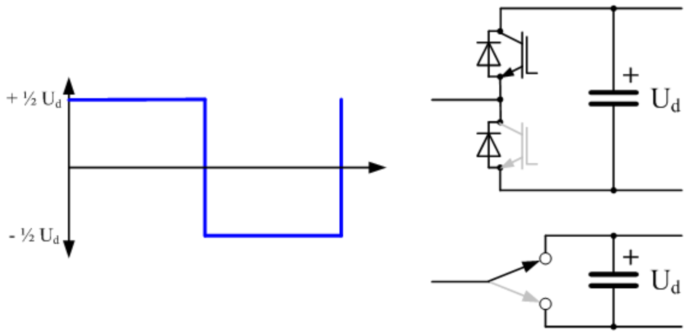


Fig 1.6 Operating principle of 2-level converter

As shown in the above figures, when the upper portions of the two valves in one phase are turned on, the AC output terminal is connected to the positive DC terminal, resulting in an output voltage of +½ U_d with respect to the midpoint potential of the converter. Conversely, when the lower valve in the phase is turned on, the AC output terminal is connected to the negative DC terminal, resulting in an output voltage of --½ U_d. The two valves corresponding to one phase must never be switched on at the same time, as this would result in an uncontrolled discharge of the DC capacitor, which could severely damage the converter device.

But this model does have some key shortcomings, such as high power loss due to conversion time and high levels of electromagnetic interference due to special IGBT types with complex gate drive circuits.

- Three-level converter

In order to improve the low harmonic performance of the two-level converter, some HVDC systems have built a three-level converter.

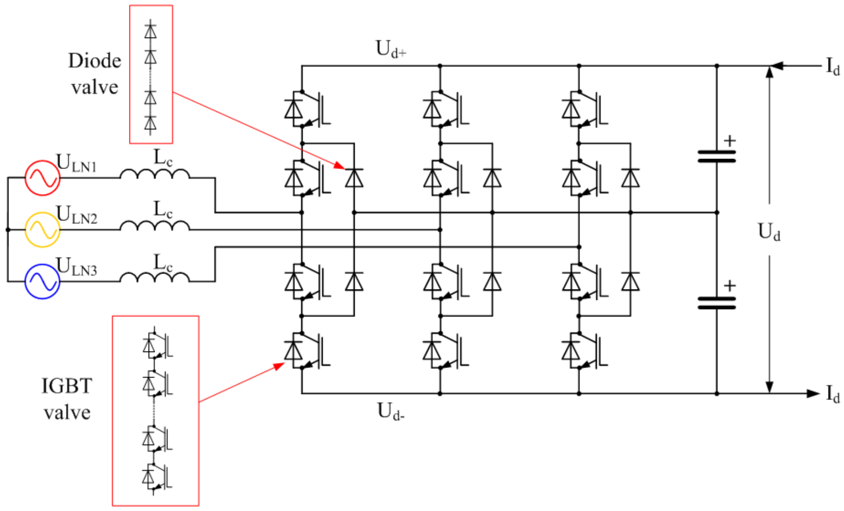


Fig 1.7 Three-phase, three-level, diode-clamped voltage-source converter for HVDC

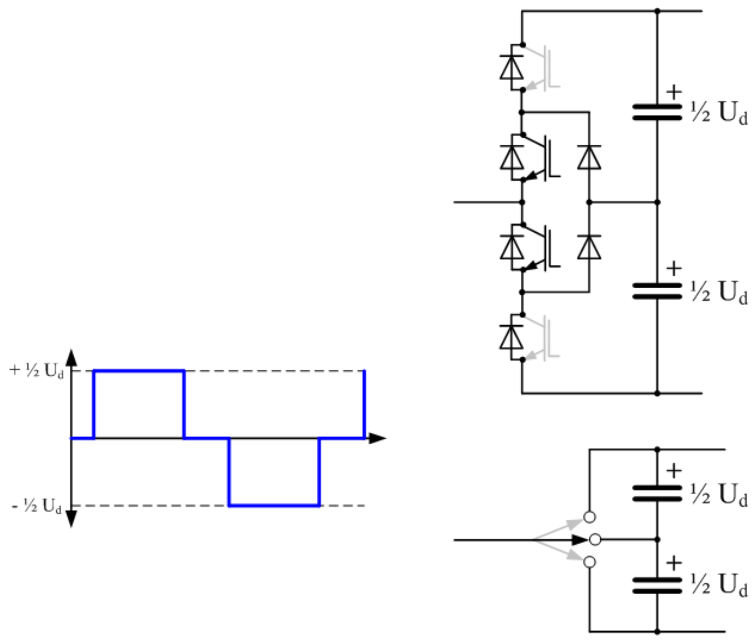
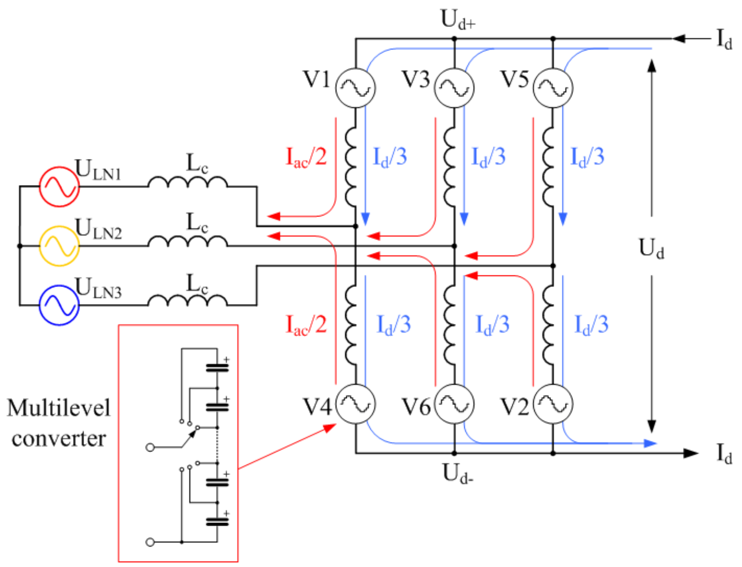


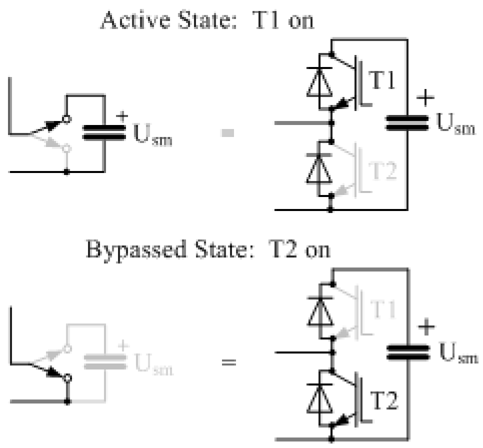
Fig 1.8 Operating principle of 3-level, diode-clamped converter, single-phase representation

The three-level converter can synthesize three (rather than just two) discrete voltage levels at the AC terminals of each phase: +½ U_d, 0 and -½ U_d. A common type of three-level converter is a diode-clamped (or neutral-point clamp) converter in which each phase contains four IGBT valves, half of each rated DC line voltage, and two clamp diode valves [33]. The DC capacitor is divided into two branches connected in series, and the clamp diode valve is connected between the midpoint of the capacitor and between one quarter and three quarters of each phase. In order to obtain a positive output voltage (+½ U_d), the top two IGBT valves open, to get the negative output voltage (-½ U_d), the bottom two IGBT valves open and to obtain a zero-output voltage, the middle two IGBT valves open. In the latter state, the two clamp diode valves complete the current path through the phase.

- Modular Multi-Level Converter (MMC)



(a)



(b)

Fig 1.9 Three-phase Modular Multi-Level Converter (MMC) for HVDC

Like the two-level converter and the six-pulse line commutator, the MMC consists of six valves, each of which connects an AC terminal to a DC terminal. However, in the case where each valve of the two-stage converter is actually a high voltage control switch consisting of a large number of IGBTs connected in series, each valve of the MMC itself is a separate controllable voltage source. Each MMC valve consists of a number of independent converter sub-modules, each containing its own storage capacitor. In the most common circuit form, a half-bridge variant, each sub-module comprising two IGBTs connected in series on the capacitor, a midpoint connection and one of the two capacitor terminals as an external connection [21]. Depending on which of the two IGBTs in each submodule is turned on, the capacitor is bypassed or connected to the circuit. Therefore, each sub-module acts as a separate two-level converter, producing a voltage of 0 or U_{sm} (where U_{sm} is the sub-module capacitor voltage). With a proper number of submodules connected in series, the valve can synthesize a stepped voltage waveform that approximates very closely to a sine-wave and contains very low levels of harmonic distortion.

The MMC differs from other types of converters in that current flows continuously through all six valves of the converter throughout the power supply frequency cycle. Therefore, concepts such as "on state" and "off state" have no meaning in the MMC. The direct current is equally divided into three phases, and the alternating current is equally divided into upper and lower valves of each phase [22]. The current in each valve is therefore related to the direct current I_d and alternating current I_{ac} as follows:

$$\text{Upper valve: } I_v = \frac{I_d}{3} + \frac{I_{ac}}{2} \tag{1.1}$$

$$\text{Lower valve: } I_v = \frac{I_d}{3} - \frac{I_{ac}}{2} \tag{1.2}$$

A typical MMC for HVDC applications consists of approximately 300 sub-modules connected in series in each valve, thus equivalent to a 301-level converter. As a result, harmonic performance is very good, and filters are usually not needed. Another advantage of MMC is that PWM is not required, and as a result, the power loss is much lower than the power loss of the 2-stage converter, which is about 1% at each end [23, 24]. Finally, since the direct series connection of the IGBT is not necessary, the IGBT gate driver does not need to be as complex as a 2-level converter.

MMC has two major drawbacks. First, control is much more complicated than a 2-level converter. Balancing the voltage of each sub-module capacitor is a major challenge and requires considerable computational power and high-speed communication between the central control unit and the valve. Second, the submodule capacitor itself is large and bulky [25]. The MMC is much larger than the equivalent level 2 converter, although this can be offset by saving space without the need for a filter.

As of 2012, the MMC HVDC transmission system with the largest capacity in operation is still a 400 MW cross-bay cable project, but many large-scale projects are under construction, Including underground cable interconnections from France to Spain, including two 1000 MW shunt voltages with a voltage of ±320 kV [26].

1.4.3 Comparison of LCC and VSC

The table 1.2 below shows the difference between LCC-HVDC and VSC-HVDC.

Table 1.2 Comparison of LCC and VSC

LCC-HVDC	VSC-HVDC
Thyristor base technology (turn on only)	IGBT base technology (turn on/off)
The semiconductor can with-stand voltage in either polarity	Withstand current in either direction
Constant current direction	Current direction changes with power
Filter and Shunt capacitor	Small Filter
Energy is stored inductively	Store energy capacitively
Turned on by a gate pulse but rely on external circuit for its turn off	Both turn on and off is carried out without the help of an external circuit
High power capability	Lower power capability
Good overload capability	Has weak overload capability
Requires stronger AC systems for excellent performance	Operate well in a weak AC system
Requires additional equipment for black start operation	Possesses black start capability
Requires AC and DC harmonic filters for	Requires no filter because it generates an

removal of distortion and harmonics	insignificant level of harmonics
Poor in reactive power control	Good reactive power control
Large site area dominated by harmonic filters	A more compact site area
Requires converter transformer	Conventional transformer is used
Lower station losses	Higher station losses
More mature technology	Still at its infancy
Reversal of power is done by reversing the voltage polarity	Power is reverse by changing the current direction
Higher voltage capability of over 1000KV	Lower voltage capability of almost 600KV
Mostly used to transmit bulk power for a long distance	Used for transmitting power from remote area with renewable energy
Suffers commutation failures as a result of a sudden drop in the amplitude or phase shift in the AC voltage, which result in dc temporal over-current Though, the effect has no significant impact on the AC systems as it’s a self-clearing effect within a few power frequency cycles.	Ability to be turned on and turned off of VSC makes it immune to any voltage dips or transient AC disturbance, therefore, it does not suffer commutation failure.
Commutation failures need for change in dc polarity when converter want to change from rectifier to inverter mode make LCC HVDC	Proper for multi-terminal HVDC systems because it does suffer from commutation failures, has independent, multidirectional

more problematic to adopt in a multi-terminal HVDC system. Reason for low number of LCC base technology for multi-terminal HVDC.	power flow, and operate with the same voltage polarity.
During short circuits on the dc line, control of the firing angle of the thyristors valves stop the increase of dc fault current. This converter control and protections reduces the damage caused by the fault current. Incased of overhead lines fault, power transmission is stopped for arc deionization, after which power transmission resumed.	Continuous conduction in the diode will cause an increase in dc fault current even when the IGBTs are turned off. The ac circuit breakers at both VSC HVDC ends must be opened to stop the diode conduction. The converter link must be re-started after fault has been removed.

As a conclusion, we can see the loss of VSC is larger than LCC because the higher switching losses in IGBT. Thus, the future trend of development of HVDC converter is to improve the efficiency of VSC via better topology or better converter design.

Chapter 2 Fault Analysis of MMC-HVDC

In this thesis, we focus on MMC-HVDC, especially the failure of its sub-modules. The sub-module (SM) widely used in engineering is a half-bridge sub-module structure and is the basic unit of MMC. The timely diagnosis of fault conditions and local protection during operation is directly related to the stable operation of the system and has important research significance.

The drive protection circuit on the sub-module controller (SMC) provides some basic sub-module fault diagnosis functions, such as capacitor undervoltage and overvoltage, IGBT overcurrent, over temperature, etc. However, the hardware circuit design is more complicated, and it is impossible to diagnose a certain type of fault, and its diagnostic capability is poor. [27-30].

Therefore, it is of practical engineering significance to study how to realize rapid diagnosis of various faults of sub-modules and realize fast in-situ protection without adding additional measurement points and hardware circuits.

2.1 Sort of Faults

2.1.1. Fault on AC system

The common AC system faults in HVDC projects mainly include the following: Phase-to-phase short-circuit fault or single-phase short-circuit fault on the rectifier side, two-phase short-circuit fault or single-phase short-circuit fault on the inverter-side AC system.

When an interphase short circuit fault occurs in any two phases of the AC system, the two phases are shorted, and a two-phase short circuit current occurs in the AC system. If the rectification fails, due to the loss of the two-phase voltage, the rectifier will not be able to complete the normal commutation operation, causing the current and voltage on the DC line to drop rapidly, and the transmission power will decrease linearly. If there is a fault on the inverter side, the inverter will not be able to reverse direction, eventually causing the DC transmission line current to rise and the AC system current to drop.

When a single system short-circuit fault occurs in the AC system, the short-circuit current directly passes through the inverter-opened converter valve, and then reaches the neutral side of the DC side through the grounding grid and the grounding pole system, thereby forming a short circuit. The fault feature is similar to the short circuit of the converter valve. If a fault occurs on the rectifying side, it is also necessary to prevent DC loop resonance that may be caused by the second harmonic entering the DC line.

2.1.2. Fault on DC side

HVDC transmission projects are mainly used for power transmission across regions. Among the various types of faults occurring on the DC line, the probability of a ground fault short circuit is the highest, accounting for more than 80% of the DC line fault. There are many factors that can cause DC line ground shorts, and frequent lightning strikes, contamination, and branch lines.

When a ground short fault occurs, the current stored in the line is instantaneously released, which causes the current to rise sharply. The magnitude of this current is related to the point at which the fault occurs and the distance between the rectifier stations. The location of the fault comes from the rectifier station. Almost, the smaller the grounding resistance at the outlet of the rectifier station, the larger the short-circuit current.

Lightning strike is one of the main factors leading to DC line faults, especially high-voltage direct current transmission projects that transmit power across regions. Due to the long transmission distance and the complex and varied local environment, the probability of lightning strikes is relatively large [29]. In addition, there are other types of faults, such as wire breaks on DC lines and foreign object impacts.

2.1.3. Sub-module fault characteristics analysis

This article divides common sub-module faults into two categories, namely component fault faults and trigger control faults. Component failure faults include short-circuit faults, open-circuit faults, and storage capacitor faults for power electronics (IGBTs and free-wheeling diodes FWD); trigger control faults are caused by system fault pulses or communication faults between controllers. The following are breakdowns of fault characteristics for several typical faults [31].

2.1.4. IGBT or FWD short circuit fault:

When another normal IGBT is turned on, a short-circuit fault of the IGBT causes the sub-module bridge arms to pass between the circuits. When the complementary IGBT is turned on, the short-circuit fault of the FWD also causes the bridge arm to pass.

Since the time constant is small at this time, the result is that the capacitor is rapidly discharged, the capacitor voltage drops rapidly, and a large short-circuit current flows through the power electronics in the fault sub-module.

2.1.5. IGBT open circuit fault:

When the bridge arm current flows through the sub-module, the IGBT open circuit will change the output voltage of the path and sub-module as well as the charging and discharging of the capacitor. Taking the open circuit of T1 as an example, after the T1 open circuit fault, when the trigger pulse is cut off by the submodule, the running state is the same as when the fault does not occur; when the trigger pulse is the input of the submodule, its working state is as shown in Fig. 2.1.

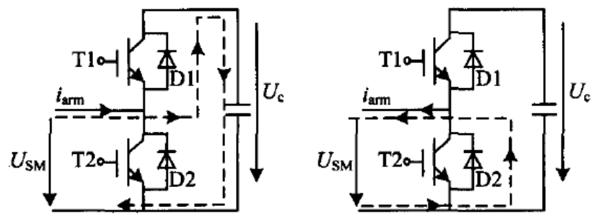


Fig 2.1 Arm Current Path When T1 is Open-circuited

When the arm current I_{arm}>0, a capacitor charging circuit is established which is the same as the normal operating state. When a fault occurs, the capacitor voltage does not cause a discharge loop, the bridge arm current flows through D2, and the outlet voltage is zero.

It can be seen that an open circuit fault of T1 will cause the capacitor voltage of the faulty submodule to continuously rise. Due to the sequencing of the control system, when the capacitor voltage of the faulty submodule rises to a certain value ($i_{arm} > 0$), T1 will no longer turn on to charge the capacitor. However, when $i_{arm} < 0$ and T1 are turned on, the output voltage of the submodule is 0 instead of the normal voltage U_c. At this point, a large circulating current will be generated in the bridge arm, and the sub-module protection must be activated.

Therefore, similarly, when T_2 has an open circuit fault and the trigger pulse is the input of the submodule, the running state is the same as when the fault does not occur; and when the trigger pulse is in the cutting state and $i_{arm} > 0$, the bridge arm current will pass through D_1. The capacitor is charged, and the output voltage is U_c. In this case, the current circuit of the submodule is the same as that shown in Figure 2.1; when the trigger pulse is in the cutting state and $i_{arm} < 0$, the bridge arm current flows through D_2, which is the same as normal operation.

At this time, although the capacitor is abnormally charged and discharged, the capacitor voltage of the faulty submodule can still fluctuate around the rated value due to the sequential equalization effect. Since the output voltage is A instead of 0 when the trigger pulse is in the off state, a large loop is also generated in the bridge arm and the submodule protection must be activated.

2.2 Method of fault diagnosis

Through the research of VSC fault diagnosis technology, fault diagnosis and fault location can be realized quickly and accurately, which provides reliable guarantee for the safe operation of the whole system equipment and the rapid recovery of faults.

At present, the mathematical model, operational characteristics, control strategy and protection method of VSC-HVDC are studied globally [32]. However, little research has been done on fault type diagnosis and fault location for internal circuit faults of VSC equipment.

In paper [33], based on the analysis of the influence of random noise on the fault signal of VSC-HVDC system, the independent component analysis method is used to suppress the noise signal, and the support vector machine is used to complete system fault diagnosis.

For the single-phase ground fault, two-phase short circuit, two relative ground faults, three relative ground faults, and DC line short-circuit faults in the VSC-HVDC system, the literature [34] uses the fault signal as the fault feature vector and uses the artificial neural network to complete the fault diagnosis.

Because the VSC-HVDC system itself is flexible, it can operate at different transmission powers. The paper [35, 36] analyzes the fault diagnosis of the VSC-HVDC system, and does not take into account the interference of the transmission power to the fault signal, so the diagnosis generated depends on the transmission power.

Chapter 3 Neural Network

Artificial neural networks (ANN) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute animal brains [37,38].

Firstly, begin with the basic concept, including samples, features, tags, models, learning algorithms, and more. Take a life experience as an example. Suppose we are going to buy mangoes on the market, but before we have no experience in selecting mangoes, how can we acquire this knowledge through learning?

Firstly, we randomly select some mangoes from the market. The characteristics of each mango, which are also called attributes, including color, size, shape, origin, brand, and the label that we need to predict. Labels can have continuous values (such as a comprehensive score on the sweetness, moisture, and maturity of a mango), or discrete values (such as "good" or "bad").

A mango that marks good features and labels can be thought of as a sample, also called an instance. A collection of samples is called a Data Set. The Data Set is generally divided into two parts: a training set and a test set. The samples in the Training Set are used to train the model, also called the Training Sample, and the samples in the Test Set are used to test whether the model is good or bad, also called the test sample.

We use a d-dimensional vector $x = [x_1, x_2, \ldots, x_d]^T$ to represent a vector of all the characteristics of a mango, which is called a feature vector, where each dimension represents a feature.

Assuming that the Training Set consists of N samples, each of which is identically and independently distributed (IID), that is, independently extracted from the same data distribution, which recorded as

$$D = \{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \dots, (x^{(N)}, y^{(N)})\}. \tag{3.1}$$

Given Training Set D, we hope the computer to automatically find a function $f(x, \theta)$ to establish a mapping between each sample property vector x and label y. For a sample x, we can predict the value of its label by a decision function.

$$\hat{y} = f(x, \theta) \tag{3.2}$$

Or conditional probability of the label,

$$p(y|x) = f_y(x, \theta) \tag{3.3}$$

Where θ is a learnable parameter.

Through a learning algorithm (A), a set of parameters $\theta *$ is found on the training set, so that the function $f(x, \theta^*)$ can approximately reflect the true mapping relationship. This process is called learning or training process, and the function $f(x, \theta)$ is called model. The next time you buy mango (test sample) from the market, you can use the learned model $f(x, \theta^*)$ to predict the quality of the mango based on the characteristics of the mango. For the fairness of the evaluation, we also independently and distribute extract a set of samples as the test set D', and test on all the samples in the test set to calculate the accuracy of the predicted results.

$$Acc(f(x, \theta^*)) = \frac{1}{D'} \sum_{(x,y) \in D'} I(f(x, \theta^*) = y) \tag{3.4}$$

Where $I(\cdot)$ is the indicator function and $|D'|$ is the size of test set.

Figure 3.1 shows the basic concepts of machine learning. For a prediction task, the input eigenvector is x and the output label is y. We choose a function $f(x, \theta)$. We can find a set of optimal parameters θ^* by the learning algorithm A and a set of training samples D, to get the final model $f(x, \theta^*)$. Then we can use this to predict the new input x.

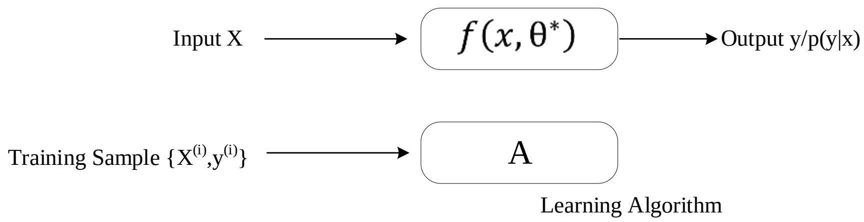


Figure 3.1 Machine learning system example

3.1. Basic Element

Machine learning is a general rule of learning (or "guessing") from limited observational data, and then can apply the summarized rules to unobserved samples. Machine learning methods can be roughly divided into three basic elements: models, learning criteria, and optimization algorithms.

3.1.1. Models

Firstly, the machine learning task needs to be determined its input space X and output space Y. The main difference between different machine learning tasks is the difference in output space. Y = {−1, +1} in the two classification problems, Y = {1, 2, · · ·, C} in the C classification problem, and Y = R in the regression problem.

The workspace is then been formed by input space X and output space Y. For element $(x, y) \in X \times Y$ in sample space, assuming that there is an unknown true mapping function g making $X \rightarrow Y$

$$Y = g(X) \tag{3.5}$$

Or true conditional probability distribution

$$p_r(Y|X) \tag{3.6}$$

To find a model to approximate the true mapping function g(X) or the true conditional probability distribution is the goal of machine learning.

Since we do not know the specific forms of the true mapping function g(X) or the conditional probability distribution $p_r(Y|X)$, we can only empirically determine a set of hypothesis functions F, which is called Hypothesis Space, then choose an ideal hypothesis $f^* \in \mathrm{F}$ by observing its characteristics on the training set D,

Assuming that space F is usually a parameterized family of functions

$$\mathrm{F} = \{\mathrm{f}(\mathrm{x}, \theta) | \theta \in \mathrm{R}^m\} \tag{3.7}$$

Where $\mathrm{f}(\mathrm{x}, \theta)$ is the model in the hypothesis space, θ is a set of learnable parameters, and m is the number of parameters.

The common hypothesis space can be divided into linear and nonlinear, and the corresponding model f is also called linear model and nonlinear model.

a. Linear model

The hypothesis space of a linear model is a parameterized linear function family.

$$\mathrm{f}(\mathrm{x}, \theta) = w^T x + b \tag{3.8}$$

Where the parameter θ contains the weight vector w and the offset b.

b. Nonlinear model

A generalized nonlinear model can be written as a linear combination of multiple nonlinear basis functions $\varphi(\mathrm{x})$.

$$\mathrm{f}(\mathrm{x}, \theta) = w^T \varphi(x) + b \tag{3.9}$$

Where $\varphi(\mathrm{x}) = [\varphi 1(\mathrm{x}), \varphi 2(\mathrm{x}), \cdots, \varphi \mathrm{K}(\mathrm{x})]^T$ is a vector of K nonlinear basis functions, and the parameter θ contains the weight vector w and the offset b.

If $\varphi(\mathrm{x})$ itself is a learnable basis function, such as

$$\varphi_k(\mathrm{x}) = \mathrm{h}(w_k^T \varphi'(\mathrm{x}) + b_k), \forall 1 \leq \mathrm{k} \leq \mathrm{K} \tag{3.10}$$

Where h $(\cdot)$ is a nonlinear function, $\varphi'(x)$ is another set of basic functions, and w_k and b_k are learnable parameters, then f (x, θ) is equivalent to the neural network model.

3.1.2. Learning criteria

Assuming that the training set $D = \{(x^{(n)}, y^{(n)})\}_{n=1}^{N}$ is composed of N Identically and independently distributed (IID) samples, which means each sample $(x, y) \in X \times Y$ is randomly generated from the joint space of X and Y according to an unknown distribution $p_r(x, y)$. It is required here that the sample distribution $p_r(x, y)$ must be fixed (although it may be unknown) and does not change over time. If $p_r(x, y)$ is itself variable, we cannot learn by it.

A good model $f(x, \theta^*)$ should be consistent with the true mapping function $y = g(x)$ for all possible values of (x, y), which is

$$|f(x, \theta^*) - y| < \epsilon, \forall (x, y) \in X \times Y \tag{3.11}$$

Or consistent with the true conditional probability distribution $p_r(y|x)$, which is

$$|f(x, \theta^*) - p_r(y|x)| < \epsilon, \forall (x, y) \in X \times Y \tag{3.12}$$

Where ϵ is a small positive number and $f_y(x, \theta^*)$ is the probability corresponding to y in the conditional probability distribution predicted by the model.

The quality of the model $f(x, \theta)$ can be measured by the Expected Risk $R(\theta)$.

$$R(\theta) = E_{(x,y)\sim p_r(y|x)} \left| \mathcal{L}\big(y, f(x, \theta)\big) \right| \tag{3.13}$$

Where $p_r(y|x)$ is the true data distribution, $\mathcal{L}\big(y, f(x, \theta)\big)$ is the loss function which is used to quantify the difference between the two variables.

3.1.3. Optimization algorithms

After determining the training set D, the hypothesis space F and the learning criteria, how to find the optimal model $f(x, \theta^*)$ becomes an optimization problem. The training process of machine learning is actually the process of solving the optimization problem.

Parameters and hyperparameters: In machine learning, optimization can be divided into parameter optimization and hyperparameter optimization. The θ in the model $f(x, \theta)$ is called the parameter of the model and can be learned by the optimization algorithm. Except for parameters θ that can be learned, there is a class of parameters that are used to define the model structure or optimization strategy. These parameters are called Hyper-Parameter.

Common hyperparameters include: the number of categories in the clustering algorithm, the step size of the gradient descent method, the coefficient of the regular term, the number of layers of the neural network, and the kernel function in the support vector machine. The selection of hyperparameters is generally a combinatorial optimization problem, and it is difficult to learn automatically through an optimization algorithm. Therefore, hyperparameter optimization is an empirical technique for machine learning. It is usually set according to human experience, or through a search method to continuously adjust and correct a set of hyperparameter combinations.

3.2. Machine learning algorithm

Machine learning algorithms can be classified according to different criteria. For example, according to the different functions $f(x, \theta)$, machine learning algorithms can be divided into linear models and nonlinear models; according to different learning criteria, machine learning algorithms can also be divided into statistical methods and non-statistic methods.

But in general, we can classify machine learning algorithms into the following categories according to the information provided by the training samples and the feedback methods:

3.2.1 Supervised Learning

If the goal of machine learning is to establish the relationship between the feature x and the label y of the sample: $y = f(x, \theta)$ or $p(y|x, \theta)$, and each sample in the training set has a label, then This type of machine learning is called Supervised Learning. According to the type of label, supervised learning can be divided into two categories: regression and classification.

a. The label y in the Regression problem is a continuous value (real or continuous integer), and the output of $f(x, \theta)$ is also a continuous value.

b. The label y in the Classification question is a discrete category (symbol). In the classification problem, the model is also called a classifier. Classification problems can be further divided into two types of classification, Binary Classification and Multi-class Classification according to the number of categories.

c. The output of Structured Learning is a structured object, such as a sequence, tree, or graph. Since the output space of structured learning is relatively large, we generally define a joint feature space, mapping x, y to the joint feature vector φ(x, y) in the space, and the prediction model can be written as

$$\hat{y} = \underset{y \in Gen(x)}{\operatorname{argmax}} f(\varphi(x, y), \theta) \tag{3.14}$$

Where Gen(x) represents the input x all possible output target sets. The process of calculating argmax is also called the decoding process, and is generally calculated by a dynamic programming method.

3.2.2 Unsupervised Learning

Unsupervised Learning (UL) refers to the automatic learning of valuable information from training samples that do not contain target tags. Typical unsupervised learning problems include clustering, density estimation, feature learning, and dimensionality reduction.

3.2.3 Reinforcement Learning

Reinforcement Learning (RL) is a kind of machine learning algorithm that learns through interaction. In reinforcement learning, the agent makes an action based on the state of the environment and gets instant or delayed rewards. The agent continuously learns and adjusts the strategy in interaction with the environment to maximize the expected total return.

Table 3.1 Comparison of three types of machine learning

	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Training Sample	Train set $\{(x^{(n)}, y^{(n)})\}_{n=1}^{N}$	Train set $\{x^{(n)}\}_{n=1}^{N}$	Agent and the trajectory τ of the environmental interaction and the cumulative reward Gτ
Optimization Goal	$y = f(x, \theta)$ or $p(y\|x, \theta)$	P(x)or p(x|z) with a hidden variable z	Expectation total return
Learning Criteria	Expected risk minimization Maximum likelihood estimation	Maximum likelihood estimation Minimum reconstruction error	Strategic assessment Strategy improvement

Supervised learning requires labels for each sample, while unsupervised learning does not require labels. In general, supervised learning usually has a large number of tagged data sets, which are generally required to be manually labeled and costly.

Therefore, there are also many methods of Weak Supervised Learning and Semi-Supervised Learning, which hope to fully exploit useful information from large-scale unlabeled data and reduce the requirement for the number of labeled samples.

The difference between reinforcement learning and supervised learning is that reinforcement learning does not need to explicitly give training samples in the form of “input/output pairs”, which is an online learning mechanism.

3.3. Evaluation index

In order to measure the quality of a machine learning model, it is necessary to give a test set, use the model to predict each sample in the test set, and calculate the evaluation score based on the predicted result. For classification problems, common evaluation criteria include correct rate, accuracy, recall rate and F value.

Given the test set $T = (x(1), y(1)),\cdot\cdot\cdot, (x(N), y(N))$, assuming the label $y(n) \in \{1,\cdot\cdot\cdot, C\}$, Using the well-learned model $f(x, \theta)$ to predict each sample in the test set, the result is $Y = \hat{y}(1),\cdot\cdot\cdot,\hat{y}(N)$.

The most commonly used evaluation indicator is Accuracy.

$$ACC = \frac{1}{N}\sum_{n=1}^{N} I\left(y^{(n)} = \hat{y}^{n}\right) \tag{3.15}$$

where $I(\cdot)$ is the indication function.

Corresponding to the accuracy rate is the error rate.

$$E = 1 - ACC = \frac{1}{N}\sum_{n=1}^{N} I\left(y^{(n)} \neq \hat{y}^{n}\right) \tag{3.16}$$

Accuracy is the average of the overall performance of all categories. In order to estimate the performance of each class, the precision and recall ratio need to be calculated. The precision and recall ratio are two metrics widely used in the field of information retrieval and statistical classification and are also widely used in the evaluation of machine learning.

For category c, the results of the model on the test set can be divided into the following four cases:

a. True Positive (TP): The real category of a sample is c and the model is correctly predicted as category c. The number of such samples is recorded as

$$\mathrm{TP}_c = \sum_{n=1}^{N} I\left(y^{(n)} = \hat{y}^{(n)} = c\right) \tag{3.17}$$

b. False Negative (FN): The real category of a sample is c, and the model is incorrectly predicted as other classes. The number of such samples is recorded as

$$\mathrm{F}N_c = \sum_{n=1}^{N} I\left(y^{(n)} = c \wedge \hat{y}^{(n)} \neq c\right) \tag{3.18}$$

c. False Positive (FP): The real category of a sample is other classes, and the model is incorrectly predicted as class c. The number of such samples is recorded as

$$\mathrm{FP}_c = \sum_{n=1}^{N} I\left(y^{(n)} \neq c \wedge \hat{y}^{(n)} = c\right) \tag{3.19}$$

d. True Negative (TN): The real category of one sample is other classes, and the model is also predicted to be other classes. The number of such samples is recorded as $\mathrm{T}N_c$. For category c, this situation generally does not require attention.

Precision, which is also called accuracy or precision, the precision of category c is the ratio of all predictions that are predicted to be category c.

$$R_c = \frac{T\mathrm{P}_c}{T\mathrm{P}_c + F\mathrm{P}_c} \tag{3.20}$$

Recall, which is also called Recall rate. The recall rate for category c is the correct proportion of all real-labeled samples in category c.

$$R_c = \frac{T\mathrm{P}_c}{T\mathrm{P}_c + F\mathrm{N}_c} \tag{3.21}$$

F Measure is a comprehensive index, it's the harmonic average for precision and recall

$$F_c = \frac{(1+\beta^2) \times P_c \times R_c}{\beta^2 \times P_c + P_c} \tag{3.22}$$

Cross Validation is a good statistical analysis method that can measure the machine learning model. It can effectively avoid the impact of the randomness of the training set and test set on the evaluation results. We can divide the original data set into a subset of K groups that are not repeated, each time selecting K − 1 subsets as the training set, and the remaining set of subsets as the verification set. This allows K tests to be performed and K models to be obtained. The average of the error rates of the K models on the respective verification sets as the classifier evaluation.

4.1. The framework of model

To simulate the real fault scenario as much as possible, the model of HVDC system is the first and also one of the most important steps. A SimPowerSystem (SPS) model of HVDC (High Voltage Direct Current) interconnection using VSC (Voltage-Sourced Converters) based on the MMC (Multi-level Converter) technology has been built. The SPS simulation is optimized by using an aggregate MMC model.

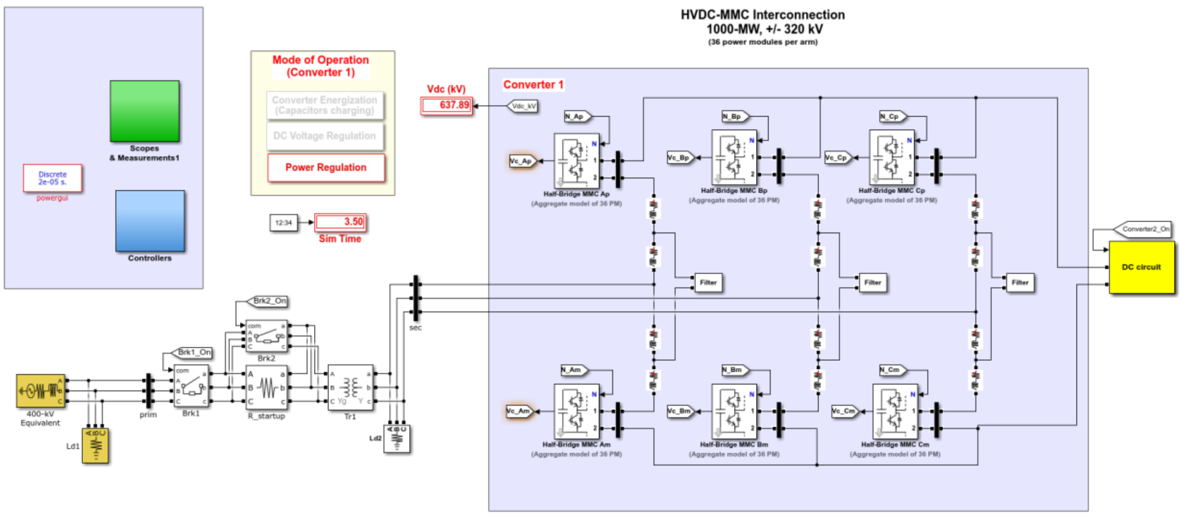


Figure 4.1 Overall figure of the model

In this model, MMC converter is implemented using an aggregate model to simulate 36 power modules per arm. With this aggregate model, control system dynamics, converter harmonics and circulating currents phenomena are all well-represented. However, having only one virtual capacitor to represent the 36 capacitors of the arm, the model assumes that capacitor voltages of all power modules are well-balanced. The aggregate model runs much faster than a detailed model that would use two switching devices and one capacitor for each individual power module. This aggregate model is also well-suited for real-time simulation.

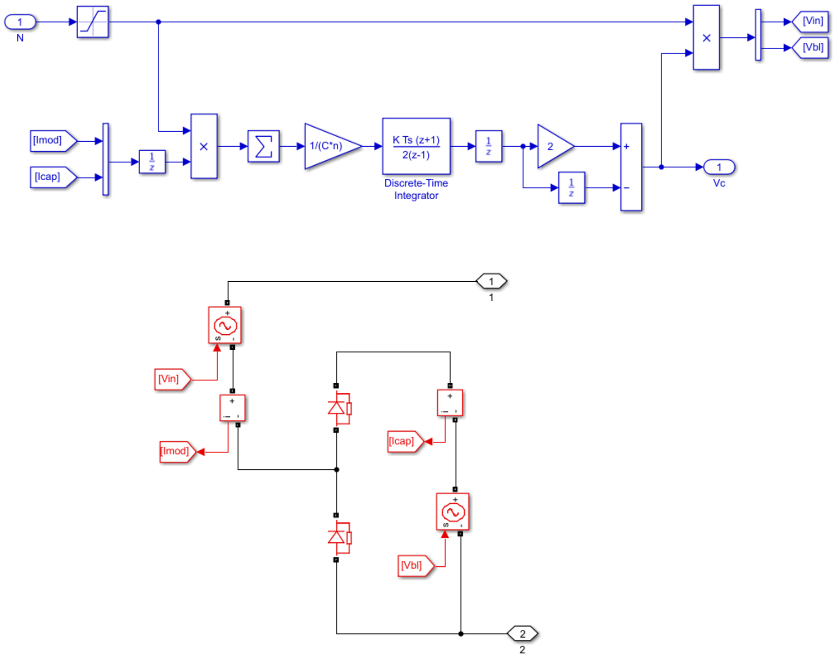


Figure 4.2 Internal structure and control strategy of Submodule

Simulating our SPS model for 3.5 seconds allows observation of the interconnection operation during start-up (capacitor charging), voltage regulation, and power regulation.

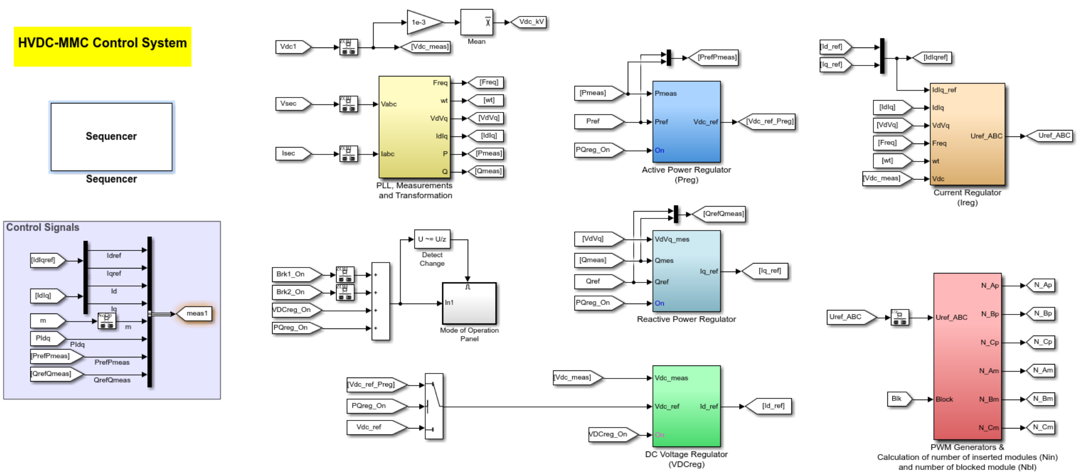


Figure 4.3 Control System of the model

To simplify the model, an equivalent circuit instead of inverter side after DC transmission line has been used.

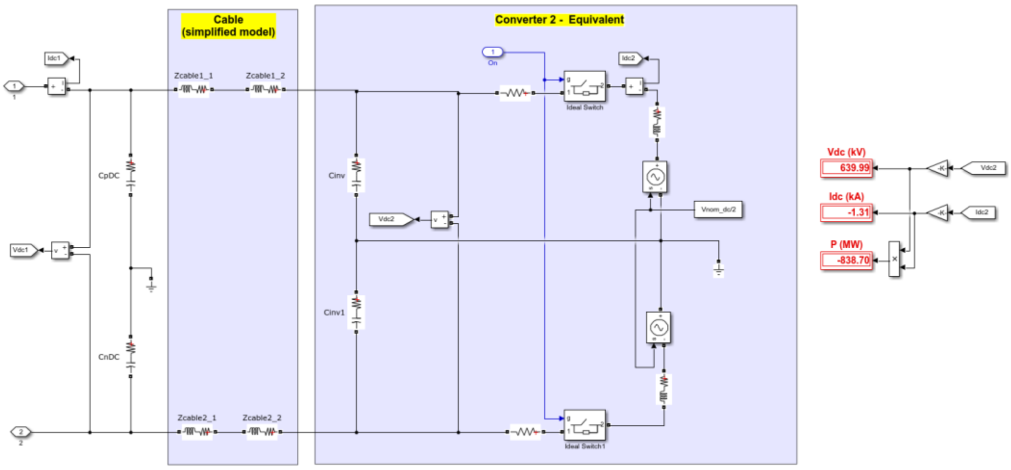
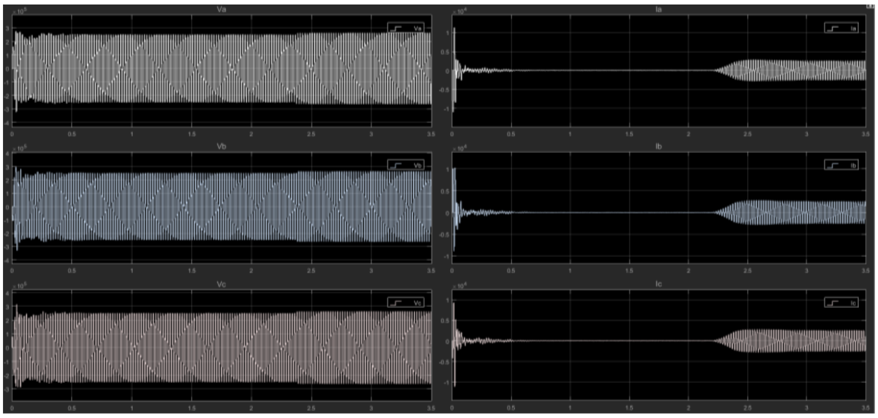
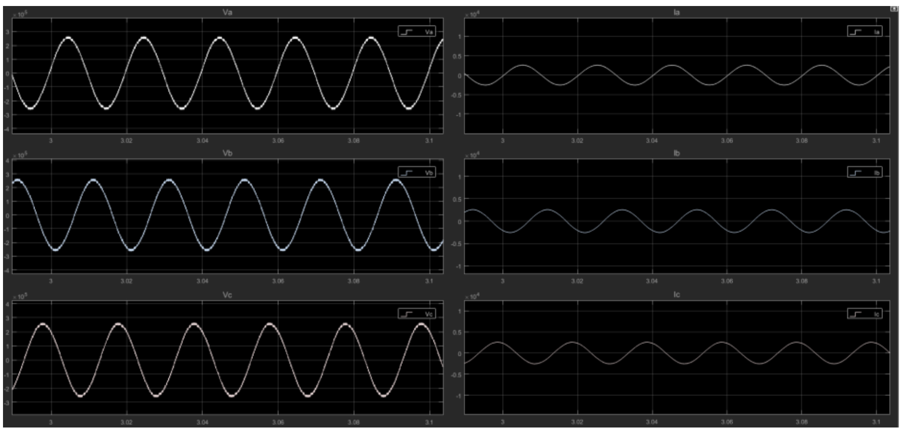


Figure 4.4 DC side of the model

And for the whole system, the total operating time is 3.5s. For the first 2.5s, it's time for control system operation, and after, system would be stable and able to simulate the faults.

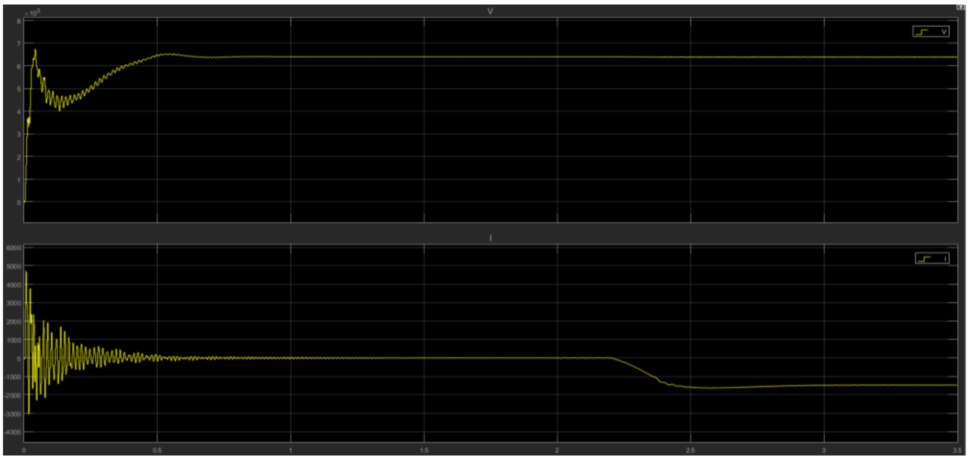


(a)

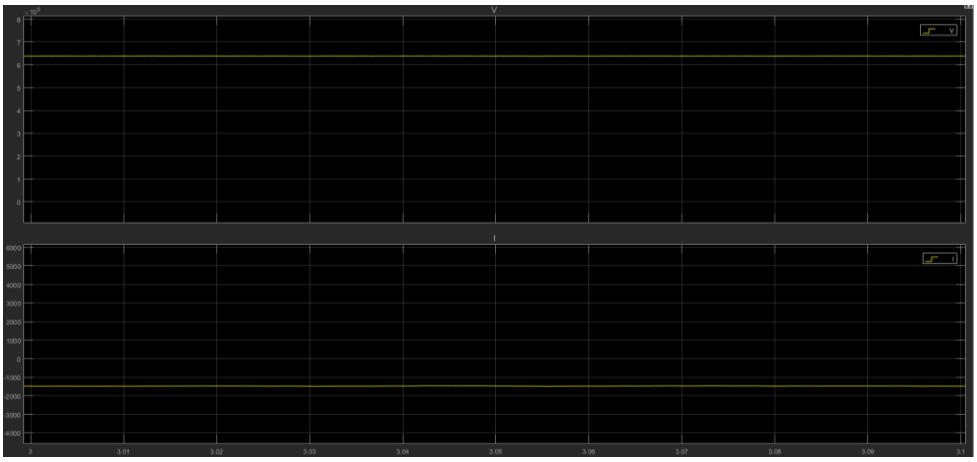


(b)

Fig 4.5 Waveform of Voltage and Circuit of AC Side of Normal Operation



(a)



(b)

Fig 4.6 Waveform of Voltage and Circuit of DC Side of Normal Operation

4.2. Fault simulation

The model comes to stable after 2.5s, the fault start time as 3.0s, while fault end time as 3.1s.

To get enough amounts of datasets for the NN, two parameters of system should be changed separately, voltage of generator and active power regulator limit. Voltage of generator is easy to understand, just to control the voltage of the whole system. But for active power regulator upper and lower limit, this is to control the rated power of DC transmission line. Through adjusting these two parameters, as many as datasets can be collected.

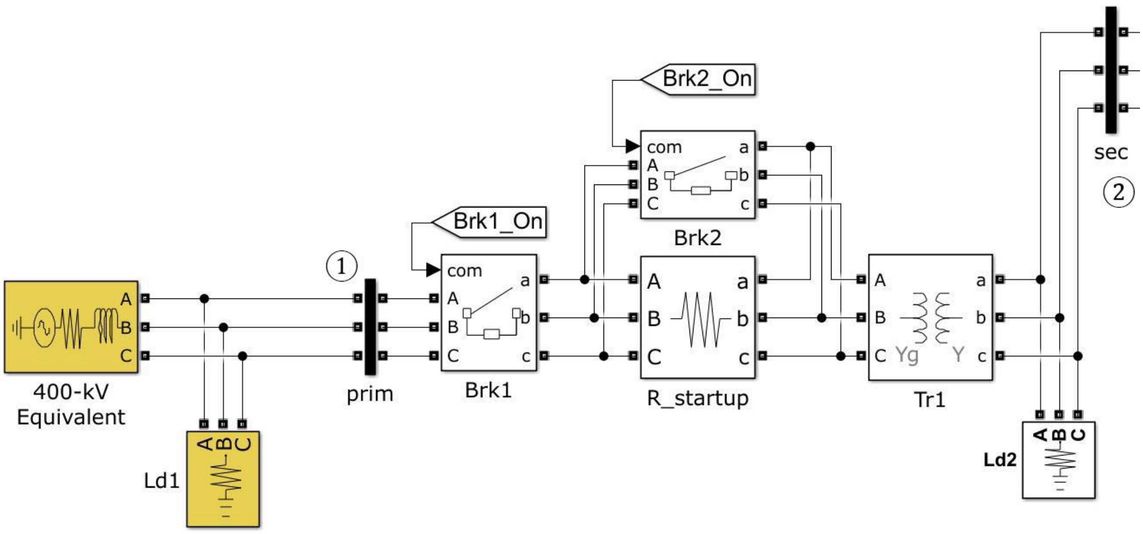
4.2.1 Fault types

In the whole HVDC system, the faults can be generally divided into two parts, one is faults of system side, such as single short circuit of phase A to ground of AC side and single-phase short circuit of DC side, and the other is faults located in MMC module, which is also called internal faults.

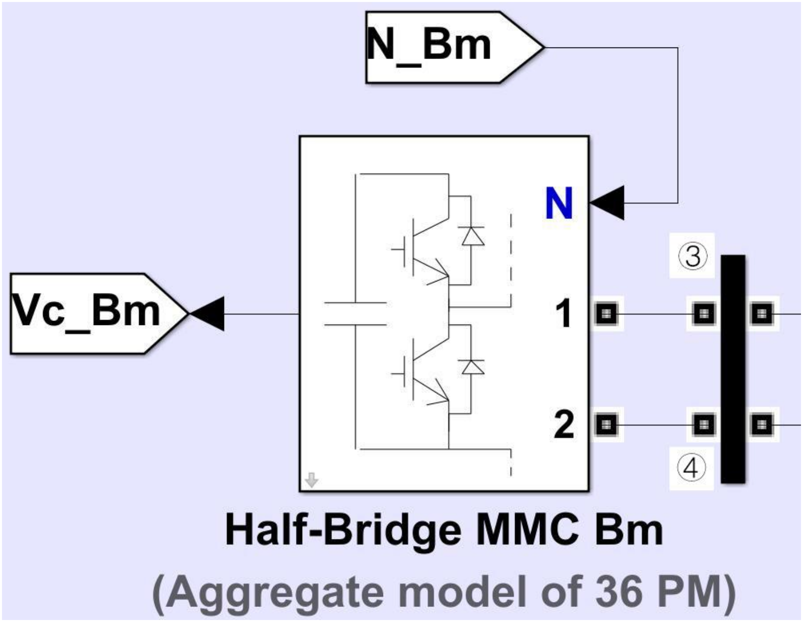
The faults that this thesis focuses on is internal faults including Short circuit of upper and lower arms, Short circuit of DC side of Submodule, open circuit of upper and lower arms and open circuit of DC side of submodule.

4.2.2 Selection of measurement points

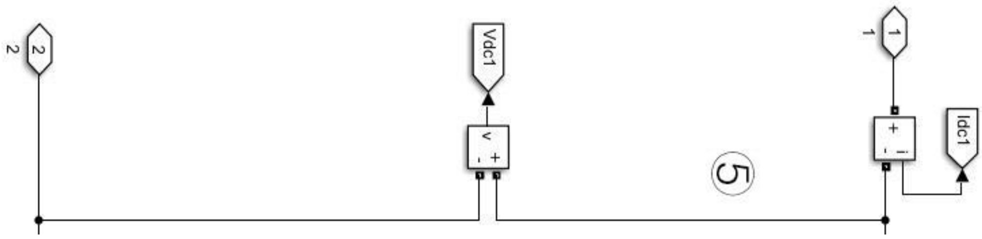
Measurement points can directly affect the accuracy of fault judgement, so selection of measurement points is one of the most important things to achieve fault judgement and analysis. If we can put measurement device in every submodule, of course the collected data could be the most precise and the analysis result could be relatively more accurate. But it's not realistic for either commercial reasons or physical reasons.



(a) AC side



(b) MMC internal (take Bm as example)



(c) DC side

Figure 4.7 Measurement Points

So, these are the measurement points been chosen after comprehensively consideration. ① is the bus that near the generator, before the soft start device, and at ①, voltage and current of three phases are detected; ② is the bus that between the transformer and MMC module, at this location, the parameters that been detected are also voltage and current; Then are the points in the MMC module, take submodule Bm as example, ③ is the measurement point of AC side input, where voltage and current should be detected, ④ is the point located at DC side output of submodule, current is the only parameter that been measured. ⑤ is apparently the DC side point, DC voltage and current are the parameters been detected. Details can be seen in table 4.1.

Table 4.1 Measurement points for data collection

Point	Location	Parameters
1	AC side	Voltage and current
2	AC side	Voltage and current
3	MMC internal	Voltage and current
4	MMC internal	Current
5	DC side	Voltage and current

4.3. Data analysis

The first step is preprocessing them, because the time step of the system is too small, so the datasets are too big to analyze efficiently. To this point, the datasets should be resembled with a proper sample step to compress the memory occupation. And then put into Matlab toolbox Neural Pattern Recognition and Classification Learner for analysis.

In Classification Learner, there are several different models to choose, which includes Decision Trees, Discriminant Analysis, Logistic Regression classifiers, Support Vector Machines, Nearest Neighbor Classifiers and Ensemble Classifiers. The table below shows the proper application situation [39].

Table 4.2 Comparison of Classifiers in Classification Learners

Classifiers	All predictors numeric	All predictors categorical	Some categorical, some numeric	Prediction speed	Interpretability
Decision Trees	Yes	Yes	Yes	Fast	Easy
Discriminant Analysis	Yes	No	No	Fast	Easy
Logistic Regression classifiers	Yes	Yes	Yes	Fast	Easy
Support Vector	Yes	Yes	Yes	Medium for	Easy for

Machines				linear, slow for others	Linear SVM. Hard for all other kernel types
Nearest Neighbor Classifiers	Euclidean distance only	Hamming distance only	No	Slow for cubic, medium for others	Hard
Ensemble Classifiers	Yes	Yes, except Subspace Discriminant	Yes, except subspace	Fast to medium depending on choice of algorithm	Hard

For the first step, the Nearest Neighbor Classifiers, Decision Trees and Ensemble Classifiers are chosen as the classification methods because these are more proper for the datasets.

Table 4.3 Comparison of specific classifier types

Classifier Type	Prediction Speed	Memory Usage	Interpretability	Model Flexibility
Simple Tree	Fast	Small	Easy	Low Few leaves to make coarse distinctions between classes (maximum number of splits is 4).
Medium Tree	Fast	Small	Easy	Medium Medium number of leaves for finer distinctions between classes (maximum number of splits is 20).
Complex Tree	Fast	Small	Easy	High Many leaves to make many fine distinctions between classes (maximum number of splits is 100).
Fine KNN	Medium	Medium	Hard	Finely detailed distinctions between

				classes. The number of neighbors is set to 1.
Medium KNN	Medium	Medium	Hard	Medium distinctions between classes. The number of neighbors is set to 10.
Consine KNN	Medium	Medium	Hard	Coarse distinctions between classes. The number of neighbors is set to 100.
Coarse KNN	Medium	Medium	Hard	Medium distinctions between classes, using a Cosine distance metric. The number of neighbors is set to 10.
Cubic KNN	Slow	Medium	Hard	Medium distinctions between classes, using a cubic distance metric. The number of neighbors is set to 10.
Weighted KNN	Medium	Medium	Hard	Medium distinctions between classes, using a distance weight. The number of neighbors is set to 10.
Bagged Trees	Medium	High	Hard	High — increases with Number of learners setting.
Boosted Trees	Fast	Low	Hard	Medium to high — increases with Number of learners or Maximum number of splits setting.

Comparing with these methods and algorithm firstly by basic characteristics, so Coarse KNN, Complex Trees and Bagged Trees would be used after comprehensively comparison and consideration.

And here are the results.

4.3.1 Fault Type Classification

Firstly, I am aiming at classifying short circuit and open circuit, which is just a binary classification problem. Define short circuit fault as ‘1’ while open circuit fault as ‘0’.

4.3.1.1 With Neural Pattern

Figure 4.8 Result with Neural Pattern

What we can get from figure above with two conclusions, one is about accuracy, which includes these indexes, TP (true positive), FN (false negative), FP (false positive), TN (true negative), the other is confidence level. Both indexes can get to 99.8%, even higher accuracy.

To be detail, accuracy means if the fault is 0, it has 99.76% possibility that can be judged as 0 and 0.23% possibility that can be judged as 1, the possibilities are calls true positive and false negative respectively, and the fault 1 is in the same way.

Table 4.4 Accuracy List

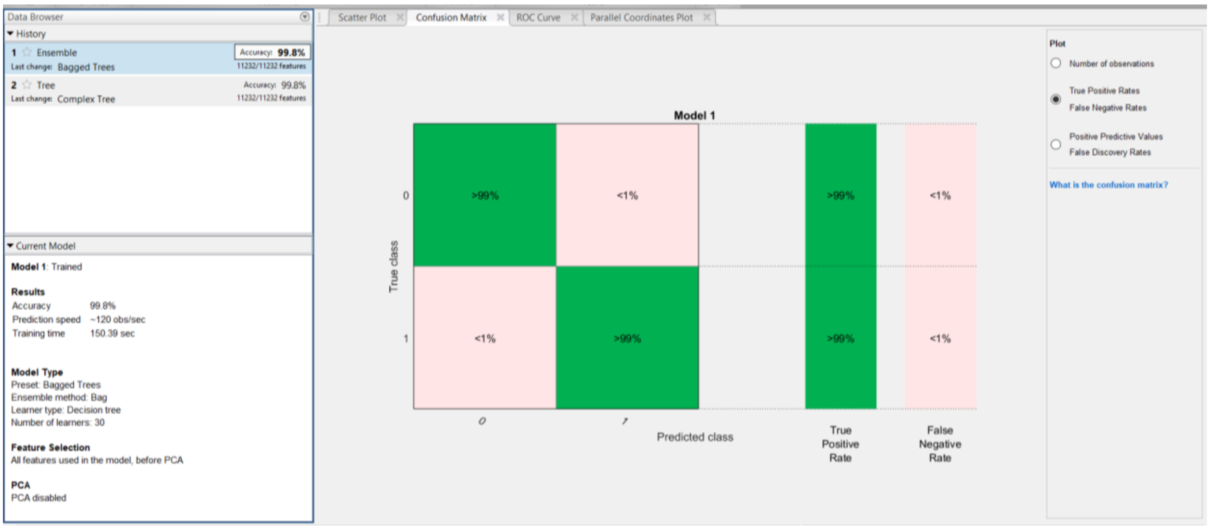
Fault Type	TP	FN
Short circuit	99.74%	0.26%
	TN	FP
Open Circuit	99.78%	0.22%

Table 4.5 Confidence Level

Fault Type	Confidence level
Short circuit	99.76%
Open Circuit	99.74%

4.3.1.2 With the classification learner

(a) Result with Coarse KNN



(b) Result with Bagged Trees

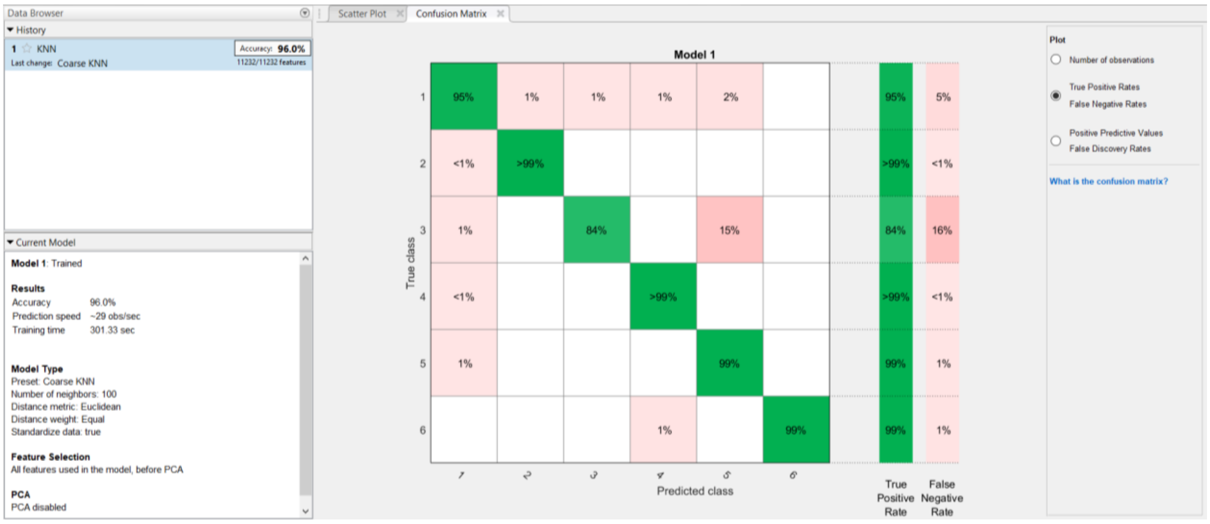
(c) Result with Complex Tree

Figure 4.9 Results with Classification Learner of Fault Type Classification

As can be seen, the accuracy is not that good with Coarse KNN, it's about 95.5%, because KNN is a relatively simple judgement method, so the results can be foreseen. And for other two method, complex trees and random forest, the results are perfect.

4.3.2 Device Location Classification

In this part, we are going to make the fault classification more detailed. For classifying the fault happened in which device (six IGBT in total), Classification Learner is used, whose results are shown as below.



(a) Result with Coarse KNN

(b) Result with Bagged Tree

(c) Result with Complex Tree

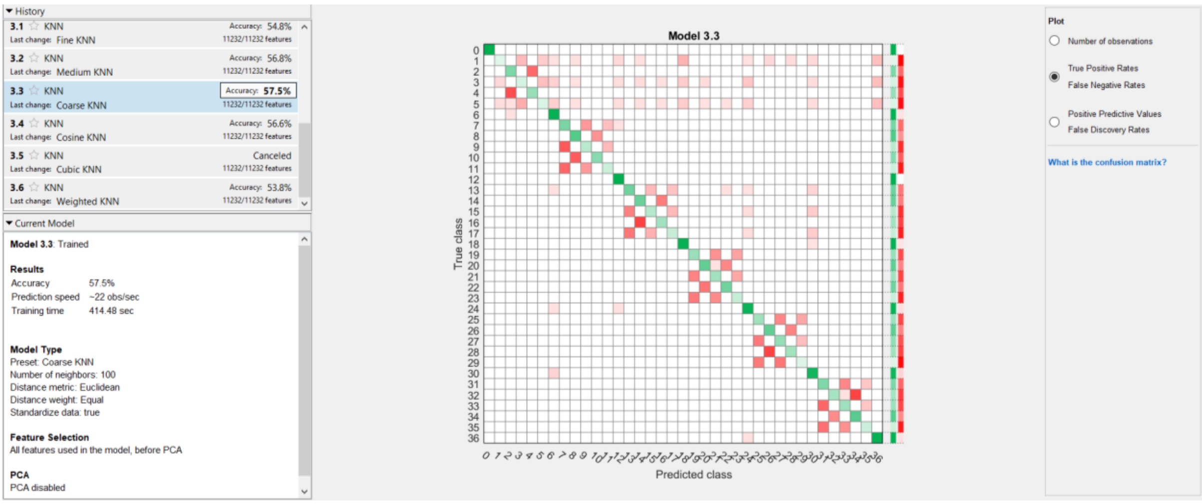
Figure 4.10 Results with Classification Learner of Device Location Classification

This problem is more complex comparing with first one, this is a 6-classification problem. As the results shown, KNN can still solve this kind of problems, with the accuracy of 96%, just little lower than other two methods. Although complex tree and random forest are both with 99.87%, for the training time, complex tree needs more than random forest; and for the memory occupation, complex tree needs less than random forest. Training time and memory occupation are both important reference indicators, short training time can provide control center the fault situation and location first timing and quickly, and memory occupation should be less if the CPU is limited.

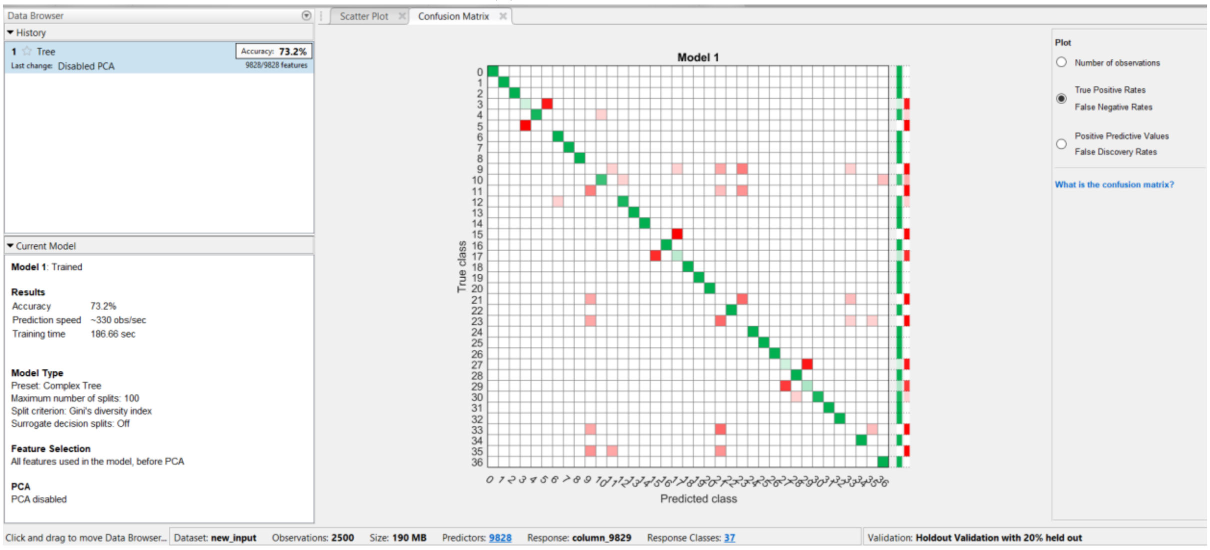
4.3.3 Specific fault point classification

In this part, my aim is to classify the specific fault location inside the IGBTs, and still use the classification learners. There are 3 fault points in each submodule that have been simulated, which means it should be 36 types of faults in total, but for some reason, this part should be divided into two different cases. Case 1 is the normal one, so 36 faults in total. In case 2, the short circuit faults happening at upper and lower bridges are defined as the same fault, which means there are 30 types of faults in this case.

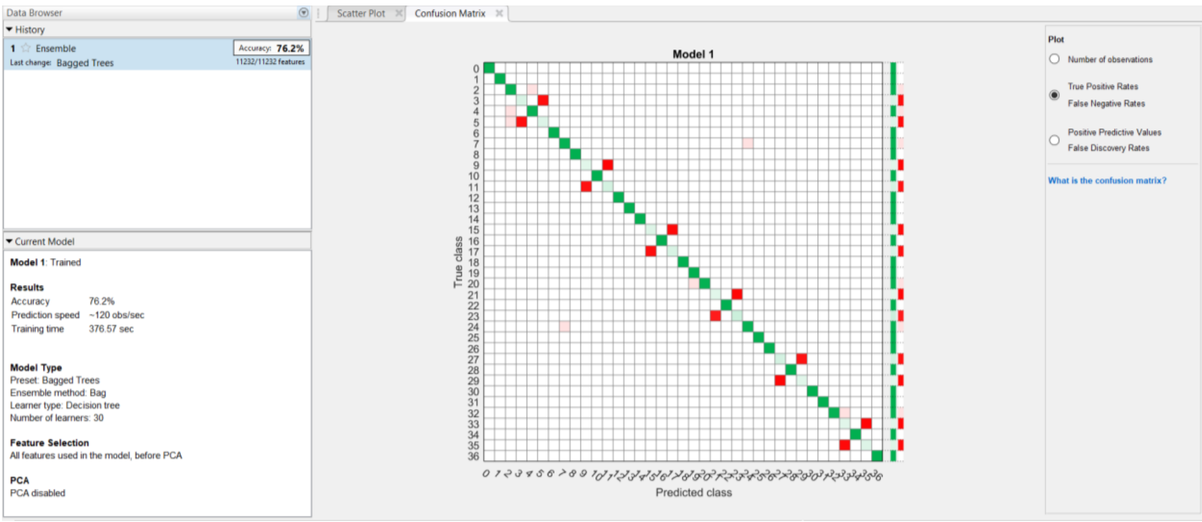
4.3.3.1 Case 1



(a) Result with KNN



(b) Result with Bagged Tree



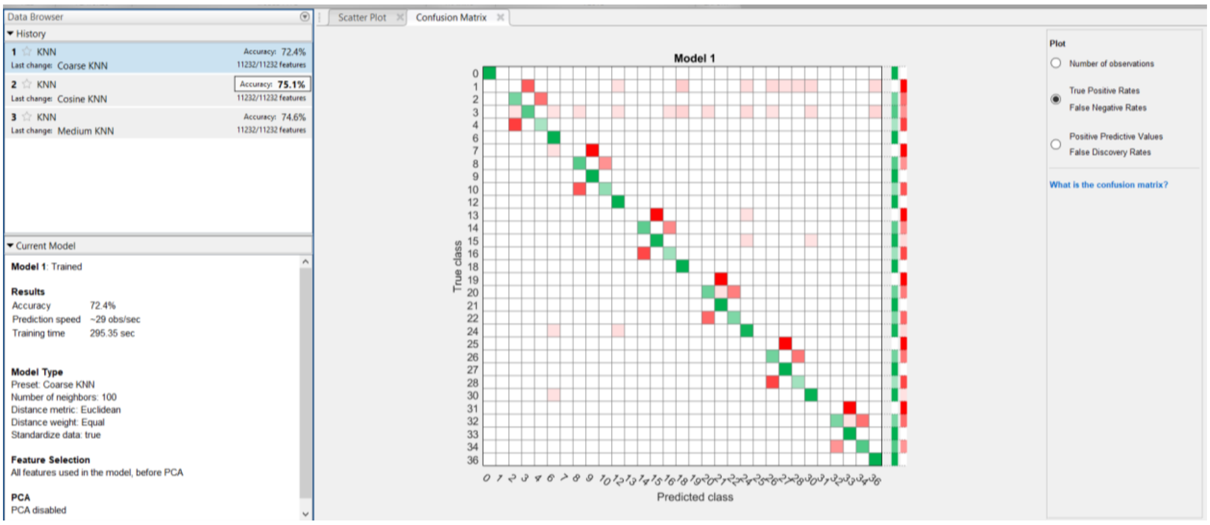
(c) Result with Complex Tree

Figure 4.11 Results with Classification Learner of Specific Faults Location Classification Case 1

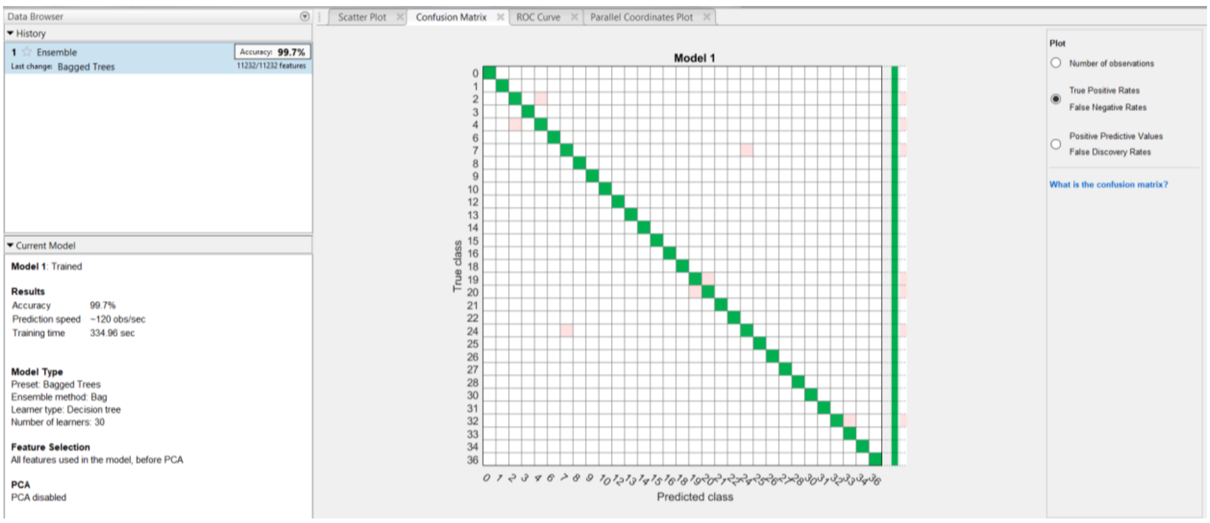
The results for this case is not that good as imagine, from the figure, we could tell that it's hard to recognize short circuit faults happening at upper bridge and lower bridge in the submodules. For now, no proper method could be found to solve this problem, because it's not realistic to equip the measurement devices into the IGBTs. This part will be put into the future works.

4.3.3.2 Case 2

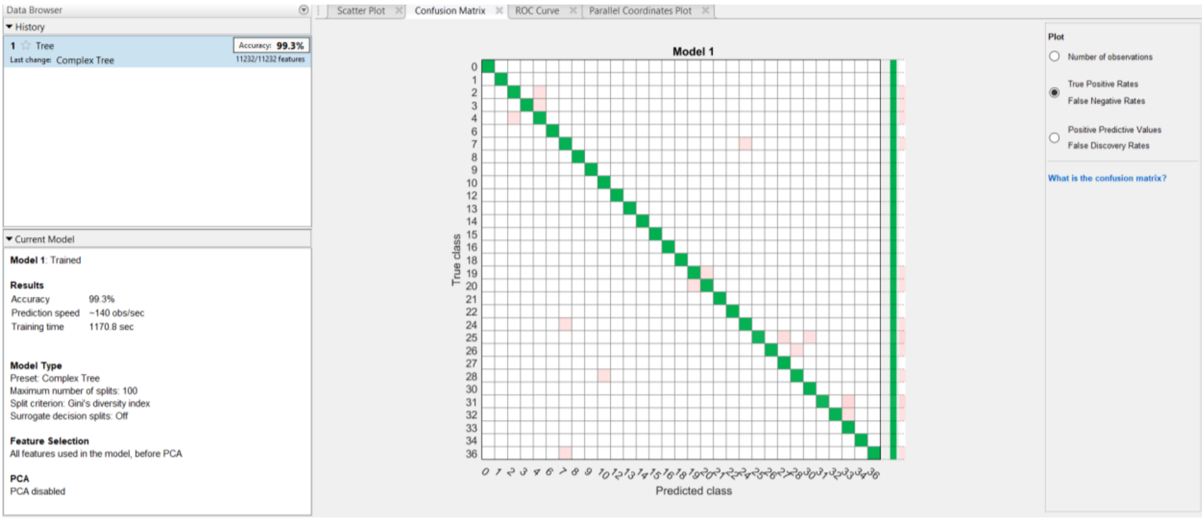
In case 2, short circuit faults happening at upper and lower bridges of each submodule have been defined as same fault.



(a) Result with KNN



(b) Result with Bagged Tree



(c) Result with Complex Tree

Figure 4.12 Results with Classification Learner of Specific Faults Location Classification Case 2

As for conclusion, classification with complex tree and random forest can perfectly solve judge the fault specific location, which are both higher than 99.3%, while the result with KNN is not equally satisfying, which is only 72.4%.

Comparing with Complex Tree and Random Forest, in the system with a large enough memory CPU, Random Forest is a better choice because of the training time is much faster, which means control system can react faster when the fault happens.

Chapter 5 Conclusion and Future Work

5.1. Conclusion

Firstly, to classify short circuit and open circuit faults, KNN, Complex Tree and Random Forest can all meet the requirements of fault type distinguishing. The accuracy of KNN is a little lower than other two methods, but it still can reach 95.5%.

To classify the faults happening in which device, all three methods still have high accuracy which are all higher than 96%, where the result of KNN is still a little bit lower than others.

In order to classify the specific location of faults, we cannot distinguish the faults happening at upper and lower bridges in each certain submodule, the results of the three methods are lower than 75.56%. That may because they are originally the same point in the system. If considering the faults happening at upper and lower bridges in same submodule as the same type of faults, the accurate rates of using Complex Tree and Bagged Tree both can get up to 99.7%. In contrast, the disadvantages of KNN can be shown obviously, the accuracy of which is just 75.1%.

It can be concluded that Complex Tree and Random Forest can both determine the fault location precisely with an accuracy higher than 99.93%. But KNN cannot meet the requirements. Furthermore, because less training time can make protection devices act faster to reduce loss caused by faults and RAM of central control system is limited, these two facts should also be taken into consideration. Complex Tree spends more training time but less memory occupation than Random Forest, so the methods should be chosen based on realistic situation.

5.2. Future Work

Because the short circuit fault cannot be distinguished when located at upper and lower bridges of the same submodule, so my next step is to solve this problem.

Further, it's necessary to put all faults' scenarios together, which means put all faults including the faults on the system sides and faults inside the MMC modules together. After that, fault location on DC transmission line can also be taken into consideration. As such, a more comprehensive framework of the fault detection and classification framework can be achieved.

Furthermore, cyber security is a new area for power systems today. Cyber-attacks can affect the accuracy of the collected data, in this case, the fault detection and classification of the HVDC system under cyber-attacks becomes a valuable research direction.

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