Doctoral Thesis

Model-aided diagnosis for high voltage circuit breakers

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MODEL-AIDED DIAGNOSIS  
FOR HIGH VOLTAGE CIRCUIT BREAKERS

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presented by

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KURZFASSUNG (DEUTSCH)


Deshalb wurde ein Forschungsprojekt über online Zustandsüberwachung und -diagnose für HSLS ins Leben gerufen, mit dem Ziel, ein intelligentes System zu schaffen, das auch zu echter Fehlerdiagnose fähig wäre, d.h. eine leicht verständliche Aussage über Ort, Art und Schwere eines Fehlers liefern könnte. Ein solches System beginnt bei verschiedenen Sensoren am Schalter und endet bei der Benutzeroberfläche, wo dem Anwender die Auswertungsergebnisse mitgeteilt werden. Dazwischen durchlaufen die Daten verschiedene Verarbeitungs- und Übertragungsschritte. Die Literatur zeigt, dass in jedem Teilgebiet große Fortschritte erzielt worden sind; die Verschmelzung der verschiedenen modernen Technologien in ein umfassendes System zur Bestimmung des Zustandes eines HSLS ist jedoch eine noch ungelöste Aufgabe.

Als Grundlage für weitere Arbeiten wurden zunächst Aufzeichnungen von Fehlern an HSLS eines Herstellers statistisch ausgewertet. Die Ergebnisse stimmen generell mit anderen veröffentlichten Statistiken überein, insbesondere mit der von CIGRE Arbeitsgruppe 13.06 durchgeführten. Es wurde wieder bestätigt, dass die meisten Fehler im Antrieb auftreten, und zwar speziell in der Form von Lecks in der
Hydraulik oder Pneumatik. Jede Zustandsüberwachung sollte daher zunächst beim Antrieb ansetzen. – Weitere Ergebnisse lassen den Schluss zu, dass die meisten Fehler durch ein entsprechendes Überwachungssystem mit hauptsächlich handelsüblichen Sensoren erkennbar gewesen wären. Viele Fehler hätten auch vorhergesagt werden können, um so den Betreibern die Gelegenheit zur Wartung zu geben, bevor sich ein ernstes Problem entwickelt hätte.

Vor dem Hintergrund dieser Ergebnisse wurde als Grundlage für ein Diagnosesystem ein Computermodell eines HSLS entwickelt. Es besteht aus Teilmodellen der einzelnen Bestandteile eines Leistungsschalters, wobei das Hauptaugenmerk auf den Antrieb gelegt wurde. Dieser modulare Aufbau erleichtert die Anpassung an HSLS verschiedener Bauarten und Technologien. Das Modell wurde nach der Vorlage eines bestimmten Schalterexemplars erstellt und so abgestimmt, dass es das Verhalten des Originals unter einer Vielzahl von Bedingungen optimal wiedergeben kann. Es eignet sich daher gut zum Einsatz in einem modellbasierten System.


Unter Verwendung des oben beschriebenen Schaltermodells wurde eine einfache Test-Implementierung von MAiD erstellt. Das Diagno-
Abstract (English)

Motivated by economic pressures, power utilities are increasingly looking for new ways of reducing their costs while maintaining the quality of supply. A promising concept is predictive or condition based maintenance of high voltage equipment, based on continuous knowledge of each device’s condition. Power transformers and high voltage circuit breakers (HVCBs) have been the focus of attention in recent years. However, as a survey of available literature indicated, most of the presently available condition monitoring systems for HVCBs offer only limited functionality in providing users with the information they need.

Therefore, research was done into online condition monitoring and diagnosis for HVCBs, with the goal of creating an intelligent system that would perform true diagnosis, i.e. yield a clear statement of the location, nature, and criticality of a detected problem. Such a system starts with various sensors on the breaker and ends at the human-machine interface, where the user is presented with the computation results, with various data processing and transmission stages in between. Literature shows that much progress has been made in each individual discipline, but combining the different state-of-the-art technologies into a comprehensive HVCB condition assessment system remains yet to be done.

As a basis for further work, statistics of problems with HVCBs were compiled from failure records of a manufacturing company. The results do essentially agree with other published statistics, in particular that by CIGRE Working Group 13.06. Again it was confirmed that the greatest number of failures originate in the operating mechanism, in particular due to hydraulic or pneumatic leaks. The operating mechanism is therefore the place to start with condition monitoring.—Other findings indicate that most failures could have been detected by a suitable monitoring system, using mostly sensors that are
readily available today. Many failures could have been predicted, too, thereby allowing the operators to perform maintenance before the problem became serious.

With these results in mind, a computer model of a HVCB was created as a basis for a diagnostic system. It was assembled from models of the individual circuit breaker components, with particular attention to the operating mechanism. This modular construction facilitates adaptation to different breaker types and technologies. Patterned after a specific exemplar of HVCB, the model was tuned to give an optimum representation of its behavior under various circumstances and is therefore suitable for use in a model-based system.

This model was used for implementation of a novel diagnosis strategy, named "Model-Aided Diagnosis" (MAiD). It was developed with the aim of providing diagnostic ability with good flexibility at low computational cost, in order to make it suitable for upgrading existing condition monitoring devices.—MAiD is a combination of the model-based with the case based approach (both known from literature), featuring certain strengths of both while avoiding certain shortcomings. Its main advantage is that the diagnosis itself requires only little computing power and can therefore be used even on a cost-sensitive device such as a HVCB. Of course, it can also be applied to various other kinds of technical devices.

A simple test implementation of MAiD was created, using the circuit breaker model described above. The diagnostic module was tested with simulated data as well as actually measured data on a real circuit breaker in the laboratory, where certain artificial "faults" were introduced into the circuit breaker under observation. In every case, the fault was diagnosed correctly, with no false alarms. This demonstrates the ability of MAiD to reach correct conclusions under a variety of circumstances and is promising for future field installations. Finally, suggestions for integration in an overall monitoring and control system and for possible improvements on the basic MAiD strategy are given. With that, a MAiD-based HVCB condition assessment system can be realized at reasonable effort.
1 Problem Statement

In these times of liberalization and globalization of the electrical energy market, power utilities have come under severe pressure of reducing their costs in order to remain competitive. Reliability-centered and condition-based maintenance strategies are increasingly applied with the aims of reduced life-cycle costs and of increased reliability and availability of power equipment. Within these strategies, online condition monitoring and diagnosis of high voltage apparatus play an essential role by permanently informing substation personnel about the condition of each device, ideally pointing out developing failures even before they become serious.

In this respect, high voltage circuit breakers (HVCBs), as key elements of a transmission network, have been the focus of attention for many years. Numerous studies were conducted to throw light upon the critical components, and manufacturers have been continuously working on increasing reliability. In the last decade, with novel sensors and fiber-optical communication available, several systems for online monitoring of certain quantities on HVCBs were developed and successfully applied. However, the existing systems do not exploit the measured data to their full potential. Essentially, if a deviation from the normal status is detected, the human user is presented mostly with an indication of values exceeding a threshold, possibly augmented by graphs showing the historical development of some measured quantities. From these data, the user needs to determine the source of the problem him- or herself, if he or she possesses the necessary expertise at all. Hence, the monitoring approach to HVCBs must be taken one step further by including automated diagnosis.

Diagnosis, i.e. finding the underlying reason for some abnormal behavior of a device, has been a subject of research in the field of Artificial Intelligence for a long time, and various strategies have been devised. However, no implementation of state-of-the-art technology
for automatic assessment of HVCB condition has been reported so far. This is most likely due to the forbiddingly high costs associated with using any of the modern diagnostic systems commercially available today.

What manufacturers and users ultimately want is a system for intelligent online monitoring and diagnosis of HVCBs. From continuous or periodic measurement of certain quantities on the breaker, this system shall inform the operator about the present status of each breaker, giving the location, nature, and criticality of any detected anomaly. Furthermore, in the case of slowly developing problems such as a small leakage, it shall warn of this situation and give an estimate of the remaining time before necessary maintenance. Of course, the system should be easily adapted to circuit breakers of different technologies and from different manufacturers, be reliable, generate no false alarms, and come at almost no cost.

Since no such system could be found on the market today, a research project was started with the aim of creating an intelligent system with the capabilities listed above. Special attention was paid to the requirement that any algorithm thus found could be implemented on existing condition monitoring equipment with low computing power.
2 State of the Art

2.1 General and Economical Considerations

Since the early 1990s, electrical power utilities have been displaying increasing interest in online Condition Monitoring and Diagnosis (CMD) of their equipment. This is particularly true in North America (partly also in Great Britain [138]), where the deregulation of the electricity market has forced utilities to look for new ways of reducing their operations and maintenance costs while maintaining or even increasing their equipment's availability (see e.g. [133]).

The traditional approach to maintenance has been preventive or periodic maintenance\(^1\), where the equipment is inspected and possibly overhauled at fixed intervals [119]. These intervals were usually prescribed by the manufacturer, based on previous experience [2, 42, 98]. However, investigations have shown that

- the effectiveness of this approach is strongly linked to the frequency of maintenance tests (i.e. useful effectiveness requires frequent testing) [121], and

- with regard to high voltage circuit breakers, many of the failures which are known to occur are neither detected nor decisively affected by this approach [121]. In fact, some utilities specifically refuse the prescribed opening of gas insulated circuit breaker interrupters for the purpose of visual inspection, in order not to introduce additional problems into this sealed environment [131].

\(^1\) For definitions of the terminology related to maintenance see [95], cf. [185].
Runde et al. [145] estimate the costs of a full overhaul between one third and one half of the price of a new circuit breaker, which is a strong argument against unnecessary performance of this procedure.

Nowadays, utilities are increasingly utilizing condition based or predictive maintenance of high voltage switchgear, i.e. performing maintenance only when a need is anticipated [24, 95, 121]. However, this strategy requires continuous, detailed information about the condition of each device, which must be obtained by means of diagnostic tests² [2, 56, 60, 151, 152, 165] or online condition monitoring and diagnostic systems [117, 175], possibly supplemented by statistical estimates [120].

Obviously, in case of an unforeseen problem it is still necessary to conduct maintenance in order to restore normal operations as quickly as possible [24]. This is called corrective [175] or repair maintenance [72], depending on how the problem was found [72], and is not treated in this work. In such events, it is also recommended to complete a failure record, such as the one proposed by IEC [60], which can also help in establishing reliability data [8, 83].

The ultimate goal is to establish sufficient reliability and availability at the lowest overall (life cycle) costs [64, 185] and to extend the equipment life time as far as possible [68]. In 1990, an economical analysis of condition monitoring on high voltage circuit breakers, based on the available and foreseeable systems at that time, came to the conclusion that such an approach would cause actually higher life cycle costs than following the traditional periodic maintenance procedures [2] (cf. [24, 183]). However, this pessimistic view is not generally shared today. In developing a business case for online monitoring systems, Rushford [149] lists a number of direct benefits, most of which boil down to essentially three points, namely,

² Throughout this work, the terminology adopted by CIGRE WG 13.09 for the field of diagnostic techniques is used [76], except for “diagnosis” and related terms, which are used as in the field of artificial intelligence (AI). In addition, the term “online” refers to the respective actions performed with the circuit breaker in service.
1. Reduced maintenance cost (no unnecessary maintenance, reduced time for fault identification and repair);

2. Increased reliability and availability of equipment (pre-warning of developing problems, fewer unplanned outages). More specifically, the probability of a major failure, as defined in [60], is dramatically reduced [61];

3. Improved utilization of equipment (longer service life, possibly higher load).

(See also [15, 16, 49, 50, 69, 75–77, 125, 132, 133, 165] for similar listings of benefits.) All of these can be expressed in financial terms, generally reducing the total life cycle costs [76, 122, 180], as shown in [11, 56, 131] by specific examples. Rajotte et al. [140] even proposed a methodology for evaluating the financial impact of a monitoring system. Blaum et al. [16] also quantify the financial benefits of extended lifetime.—In addition, several indirect benefits such as personnel and public safety [113], customer retention [149], minimizing environmental effects [113], and better understanding of the equipment [49] are anticipated.

For the manufacturers, the data collected by continuous monitoring can help in finding inherent weaknesses of the design. Thus it serves as an aid to building even better and more reliable switchgear [81]. This is particularly relevant for modern circuit breakers with an expected service life in the order of, or even longer than, the entire professional life of the manufacturer's and user's staff responsible for them [122].

Despite all those expected benefits, introduction of CMD into a substation will entail some additional costs [76, 77], namely for

- purchase and installation of the monitoring system;
- training of personnel to use the system;
- maintenance of the monitoring system.

Hence, for any installation the overall costs should be calculated before purchasing any monitoring equipment [180].
Generally, it can be said that managers of power utilities are increasingly viewing condition monitoring as just one aspect of an overall maintenance strategy [194]. Conversely, engineers around the world are expressing high interest in CMD systems [72], which are also expected to assist operating personnel in their sometimes challenging task [31].

A worldwide market survey conducted by GEC Alsthom in late 1995 and continuously updated since then [133] shows that, with regard to switchgear condition monitoring, the philosophies of utilities in North America are fundamentally different from those in Europe. (According to this survey, utilities in the Middle and Far East expressed no short- or medium-term interest in this topic.) Because of the economical pressure, many North American utilities are implementing “Reliability Centered Maintenance” concepts (see e.g. [96, 143, 165]) that require knowledge on the condition of the equipment. In order to keep costs low, they are favoring distributed systems with independent stand-alone devices monitoring specific functions or circuit breakers. Conversely, European utilities do not appear to see an immediate need in this area. Instead, they are considering, in the long run, the digitalization of a power substation as a whole, with the CMD functions as an integral part of the secondary systems (see also [16, 81, 158]).

The common denominator, however, is the desire for concise information rather than data [31, 111, 122]. Utilities do not intend to analyze the raw data produced by a monitoring system, nor do they have the time and the resources (and often the expertise) to do so. Instead, they expect results and decision supporting conclusions which will save them time, work, and thereby money [133], cf. [104]. Hence, an important part of a useful “intelligent” monitoring system is analysis of the data, ideally with a diagnosis that will provide human operators with an assessment of the equipment condition (e.g. OK / need maintenance) and of the severity, location, and probable cause of a malfunction.
Even though continuous online monitoring and automatic diagnosis of technical devices is now reaching maturity and is increasingly accepted, not many applications can be found for power transmission equipment. This is most likely due to the following obstacles:

1. Although manufacturers are willing to offer solutions with new technologies, many utilities seem reluctant to accept innovations, the reliability of which has not been proved in years of experience [72] or which they do not understand; or they see no need for it since they have been satisfied with their existing systems and procedures.

2. Modern switchgear has extremely low failure rates, which often does not justify the additional effort from the utilities' point of view [15]. Hence, the main application would be on older equipment, which is approaching the end of its designated life cycle. However, in many cases the detailed knowledge necessary for a diagnostic expert system is no more available, due to retirement of the designers and/or insufficient record keeping. Therefore, manufacturers are often unable to supply their customers with the information they are really interested in [15].

3. Often, the initial cost is considered to be too high [180] (cf. [10]). Many utilities would gladly utilize an online monitoring system if they didn’t have to pay extra for it (cf. [133, 141]). An often-heard argument is that a modern car is delivered with built-in diagnostics at no extra cost, so why not a high voltage circuit breaker?

With the various types of switchgear found in substations today, it is likely that only the manufacturer knows his equipment well enough to develop a comprehensive CMD system for it [133]. However, the methods used in such a system are mostly the same; the device-specific elements are the data that describe the equipment with its behavior and functionality. Hence, it should be possible to create an intelligent system that can be applied to different kinds of switchgear, given the necessary information about its unique properties.
2.2 High Voltage Circuit Breakers

2.2.1 A Brief Tutorial on High Voltage Circuit Breakers

This subsection gives a brief introduction on the purpose, function, and components of a high voltage circuit breaker. It is primarily aimed at those readers that are not so familiar with this kind of devices, in order to outline the special properties and challenges associated with them. A more detailed treatment of the subject can be found e.g. in [9, 38].

A circuit breaker is an electrical switching device that must be able to make, carry, and interrupt all currents occurring in an electrical energy network, including fault currents. Equally important, it must be able to isolate all voltages when open, including switching and lightning overvoltages. When called upon to operate, it must change unfailingly from conducting to isolating status, or vice versa, normally within a few cycles of the power frequency voltage, even after idling for months or years without operation. Also, it must be able to withstand, and still function reliably under, all other mechanical, electrical, thermal, and chemical stresses [188], as summarized in [148]. Therefore, international standards, most prominently those by IEC [59], prescribe numerous type test for circuit breakers, particularly those for outdoors installation.

By definition, a high voltage circuit breaker (HVCB) is designed to operate at service voltages above 63 kV. It is the primary piece of protection for preventing equipment damage and system instability under fault conditions [19], commonly designed to interrupt rated fault currents in the range 40...63 kA, sometimes even up to 100 kA [59]. Therefore, the demands on its reliability are particularly high because a malfunctioning circuit breaker may also cause damage to other system components.—HVCBs can also be used to perform load switching operations for connecting and disconnecting various components of the power system [9].
A circuit breaker consists of two main parts [61] (cf. [2]) with a linkage between them (Fig. 1):

- primary equipment, i.e. the high voltage part of the switchgear, dedicated to high voltage insulation, current flow and interruption;
- auxiliary equipment, i.e. the low voltage part of the switchgear, dedicated to operation, control, and monitoring of the main components.

![Diagram of a high voltage circuit breaker](image)

Fig. 1: Main functional parts of a high voltage circuit breaker.

The interrupter contains the parts at high voltage potential and is the active part in the network. Normally, it has two sets of contacts, one for carrying the continuous current and one for arcing during opening and closing. Arc extinction for current breaking is facilitated by arc quenching, which makes use of the insulating medium already present within the interrupter housing. The state of the art for HVCBs is \( \text{SF}_6 \) (sulfur hexa-fluoride) for the insulating and arc quenching medium [9, 150]. During current interruption, this gas is blown at the electric arc between the parting contacts in order to facilitate its extinction by cooling. The necessary pressure is generated either by mechanical compression (puffer principle [9, 38, 150]) or by the heat of the arc itself (self-blast principle [9, 90, 150]). The main advantage of the latter technology is a low mechanical energy required for the moving parts, thus reducing the mechanical stresses within the breaker as well as the total reaction forces. In addition, small in-
ductive currents are interrupted more smoothly, also reducing the dielectric stresses on the power system.—Older high voltage interrupter technologies used oil or compressed air; in the medium voltage range (i.e. up to 63 kV), vacuum is widely used, too [9, 38].

The driving force for opening and closing the contacts is supplied by the operating mechanism via a mechanical linkage. Since the mechanism is at ground potential, the linkage must be made of insulating materials, just like the interrupter or the contact mounting, depending on the circuit breaker design. The most common choice of materials is fiber reinforced resin for the operating rod (linkage) and porcelain for the insulating mounting. Recently, composite materials have been promoted for the latter, too.

In the operating mechanism, mechanical energy is stored in a mechanical spring or a compressed pneumatic volume, which is latched by a trigger mechanism. When the mechanism is called upon to operate by energizing one of its trigger coils, this energy is set free and transferred onto the linkage (operating rod), which in turn moves the breaker contacts with the required high velocity (several m/s). The energy transfer can be performed by a mechanical [98], hydraulic [32], or pneumatic system.

Auxiliary components have the duty of assuring physically and logically correct operation of the circuit breaker under all circumstances. Heaters with thermostats or SF$_6$ gas density switches could be given as examples of the first category, whereas the anti-pumping logic, which prevents perpetual Close and Open operations of the breakers in case both the Close and Open coils are permanently energized, serves as an example of the second one.

As with any technical system, the reliability of a HVCB is dictated primarily by its design. With technological progress, the number of components in equally rated circuit breakers has been continuously reduced, leading to an increase in reliability [23, 24]. The expected service life time of modern SF$_6$ circuit breakers is well above 25 years [66] with a mean time between failures (MTBF) estimated in the range between 50 [49] and more than 300 years [61, 160]. Further-
more, the maintenance costs per unit are far lower (by a factor of 3...9) than for older oil or air-blast types [49, 80].

Regardless of technology and design, the basic functions such as current making and interruption are identical for every circuit breaker [61].

### 2.2.2 Failures in High Voltage Circuit Breakers

When it comes to conducting system or substation reliability studies, the circuit breaker is the most difficult component to handle because of the many different breaker functions and associated failure modes [53]. Manufacturers and users of high voltage circuit breakers have long been interested in finding the most common causes for failures in their switchgear. Consequently, extensive studies were conducted internationally, by CIGRÉ [53, 54, 65, 66] (see Fig. 2), as well as nationally, e.g. in Romania [8], West Germany [99] and East Germany [23]. The results are practically identical (see also [16, 80, 120, 121]) and have given direction to research into fault detection and identification [43, 87]. Obviously, the deterioration or failure behavior is different for the various interrupter and mechanism technologies [89], but most failures are mechanical in origin [67].—The findings also show that only a small portion of all failures (below 20%) were found during regular maintenance. To make matters worse, almost 3% of the failures were attributed to incorrect maintenance, i.e. most likely they would not have occurred in the first place, had the circuit breaker been left alone [66]!
Several authors point out that older circuit breakers are often operated closer to their specified limits and have hence greater need for maintenance [11]. Therefore, this is where utilities would most likely want to utilize diagnostic systems [95]. However, such “add-on” systems for older circuit breaker types would probably have to be tailored specifically for the application [34] and are not likely to become available soon [20].
2.3 Data Acquisition, Transmission, and Processing on High Voltage Circuit Breakers

2.3.1 General Remarks

An automatic condition monitoring and diagnosis system generally forms an information chain, the ends of which are fixed: it starts with the sensors located on the primary (and possibly secondary) equipment and ends at the human-machine interface (HMI) where the results are presented to the user. The rest of the chain is mostly left to the creativity of the designers, with due regard to the pertinent standards [81].

Any computer-based system is only as good as the data it receives. Hence, an important part of an automated condition monitoring and diagnosis system for high voltage circuit breakers is the data acquisition, from the sensors to the actual processing unit that derives the diagnosis.—It should go without saying that those parts which are installed in the field must be able to withstand the harsh physical and electromagnetic environment found there [16, 109].

Understandably, power utilities demand that the reliability and expected life time of all monitoring equipment is equal to, or greater than, that of the circuit breaker alone [46, 64], and that it is practically maintenance-free [46]. While some manufacturers are doubtful whether these demands can be fulfilled [133], others are more optimistic and refer to positive experiences with electronic control units accumulated over more than two decades [158]. Self-monitoring functions of each component may accelerate universal acceptance [16]. Still, more reliability data will probably be necessary before the majority of utilities will accept and use digital equipment everywhere in their substations.
2.3.2 Sensors

A sensor (also called transducer in many cases [124]) is a device that transforms one physical quantity (input) into another (output), usually into an electrical one. The relationship between input and output signals must be deterministic and unambiguous in order to be useful.

Sensor data are the basis for any automatic condition assessment of technical apparatus. For purposes of online monitoring and diagnosis, any measurement on a high voltage circuit breaker must be performed not only non-invasive but also with the breaker in service (online), with no human action required. Hence, such measurements as the contact resistance by means of a DC current [169, 146, 152] are hardly suitable for this purpose.

In order not to compromise the functionality and reliability of the primary equipment it is mandatory that any sensor applied to it have [124]

- high reliability and long life time,
- constant long-term behavior,
- small volume,
- immunity to electromagnetic disturbances.

Moreover, it would be desirable that sensors support online calibration if possible. A comprehensive list of requirements to sensors is given in [61].

Selecting the right sensors for the task is crucial to its successful implementation. Operating experience with the existing circuit breaker installations has been providing ample experience on the problematic components and influential factors. However, many older types of switchgear are not constructed to support the fitting of sensors [34]. This may necessitate compromises in the selection or location of the sensor, possibly also compromising the measurements [15].

Over the last decade, manufacturers of both switchgear and monitoring devices have been designing circuit breakers for easy fitting of
sensors [151] as well as sensors for use specifically on high voltage equipment [34].

Particularly for the primary voltage and current, novel sensors are used instead of the conventional voltage and current transformers. For example, capacitive voltage sensors and Rogowski coil current sensors [156] are already standard components in some innovative GIS switchgear [158]. These sensors have a better frequency response and linearity than conventional transformers, making them better suitable for metering and protection purposes. In addition, omission of the magnetic core eliminates not only the saturation problem but also a significant dielectric weakness [156]. With their reduced size and higher reliability, voltage and current sensors are expected to bring economical benefits, too [158].—So far, the main restriction in the application of these new technologies has been the power requirements of conventional control and protection devices. It is expected that the use of non-conventional voltage and current transformers will expand rapidly with the introduction of high-speed digital links [75].

Other available non-conventional sensor types include sensors for

- SF$_6$ gas density [16, 80, 157];
- mechanical vibrations during operations [78];
- partial discharge and moving particles, particularly for GIS [16, 33, 81, 123, 162];
- contact travel [16, 78];
- mechanism spring energy [16];
- static position (to replace the conventional auxiliary contacts) [29, 43];
- temperature [43, 78];
- arcing inside the interrupter [80].

In addition, novel sensor technologies for various quantities, such as passive SAW (surface acoustic waves) sensors [81], were introduced recently.
In air insulated substations (AIS), because of the greater distances within a substation the present trend is towards fiber-optical sensors [71, 93], which offer the following advantages [156]:

- Since they are made of dielectric materials, they are immune to electromagnetic interference;
- the problem of electrical insulation is inherently solved;
- low volume and weight, flexibility with respect to geometric shaping;
- high inherent safety (e.g. no fire hazard since they do not contain any oil).

Fiber-optical sensors for various quantities in high voltage applications are already available and have produced satisfying results in practical use [12, 43, 48, 71, 73, 80, 91, 93, 110, 156, 161]. However, long-term reliability concerns such as the possibility of a light barrier “growing blind” [97] have not been completely resolved, yet.

It should be noted that international standardization activities for high voltage circuit breakers now include recording a no-load travel curve on-site during commissioning (Committee draft of IEC standard 60056 [30]). Consequently, circuit breakers must be designed in a way to allow for this measurement on-site. Among the suggested solutions, one consists in the permanent installation of a travel-curve sensor, thus prescribing an important element of online condition monitoring to the breaker.

2.3.3 Data Acquisition

In most relevant cases, a sensor outputs an electrical signal that is related by a well-known function to the physical quantity observed. Data acquisition denotes the sum of all transformations that make this signal suitable for further processing.

The binary sensors (i.e. sensors that can output only one of two values, e.g. limit switches) on conventional switchgear do not require additional data acquisition; their outputs are usually fed directly into
a digital logic, often still based on electromechanical relay technology. For example, a relay controlled by a low gas pressure limit switch can inhibit open operations and close an alarm contact for local and remote alarm signaling.

For the output from analog sensors (for the sake of simplicity, all signals with more than two possible values are called "analog" in this chapter) usually several steps need to be performed in order to make them suitable for digital processing [184]:

1. Limiting in both amplitude and frequency content (filtering);
2. Analog to digital (A/D) conversion;
3. Intermediate storing before processing, possibly in compressed form [179].

For modern control and monitoring equipment it is desirable to have the data acquisition, together with the initial processing, performed locally at the circuit breaker [34], even in the sensors themselves [3, 75]. Thus, only the relevant or required data need to be transmitted to the substation computer system. In addition, the function of the hardware including sensors can be monitored continuously, providing increased reliability of the entire equipment.

### 2.3.4 Data Transmission

In most cases, the data generated by sensors and other equipment need to be transmitted to other devices and ultimately to a human operator [175]. In traditional substations, many kilometers of copper wires had to be installed for connections between the high voltage apparatus and the supervisory control and data acquisition (SCADA) and protection devices in the station house. The modern approach is toward (mostly optical) process field buses [20, 81, 99, 125, 158, 174] to transmit data in either direction. Because of the high possible transmission rate just a few fibers are sufficient to carry all the traditional data as well as additional sensor data to, from, and within an entire field. The reduction factor in cabling volume is expected to fall in the range between ten [109] and sixty [34]. It is envisioned that
eventually only the power supply for the secondary circuits will be connected by means of traditional copper wires, with all other signals transmitted via serial optical links [109].—Simpler substation wiring also yields the additional advantage of higher reliability [15, 97].

With the modern trends in communication, it is desirable to have standardized communication interfaces and protocols within the entire network [81, 109, 125, 175]. Already this topic is a current subject of work within IEC, in WG20 (SC17A) [75] and TC57/214/INF [122].

Some authors consider condition monitoring functions totally separate from control and supervision, using physically separate communication channels and Human-Machine Interfaces [34, 175]. In this author's opinion, though, the intelligent substation of the future will have all functions integrated into one distributed system, all components cooperating synergistically. Already, attempts for this have been reported [16].

2.3.5 Data Processing

Traditionally, data from the SCADA system within a substation are processed centrally at the control house. This is still a relevant option for many manufacturers and utilities. For example, one recent article discusses the selection of the type of hardware best suited for the task, given different requirements of functionality and others [137].

In modern energy management systems (EMS), the architecture of secondary equipment can be divided into four levels [156, 157]:

1. Process level, i.e. the switchgear itself;
2. Field level or bay level [175];
3. Station level,
4. Network (EMS) level.

Data will be processed at any level. In a well-structured system, all data are processed within each level as far as possible [97, 175]. Only the processing results will normally be passed on to the next
higher level [122], with the option of accessing the raw data if desired. Several general architectures are proposed in [61].

Integrated solutions based on programmable logic controllers were proposed as early as 1994 [19]. Lately, local intelligent interface devices, which are also capable of performing monitoring and diagnostic functions, have become available on the market [20, 158]. —With this decentralized intelligence (including “distributed databases” [174]), a higher functionality can be achieved at each level [109], increasing the reliability and availability [122] (also by added redundancy [34]) as well as making possible intelligent operation of the equipment, e.g. controlled switching [75, 80, 157].

In the long run, it will be necessary to use data from all possible sources, i.e. not from monitoring sensors alone but also from the control and protection systems in order to obtain a comprehensive assessment of the condition of a circuit breaker. It can be expected that in the future the monitoring and diagnostic functions will be no more than software modules in an intelligent circuit breaker control and protection system, sharing the sensors, data transmission channels, and processing devices [19, 65, 75, 81, 88, 123, 189]. In such an integrated system, the data from a monitoring module can in turn provide valuable information for protection and control [170, 189].—State-of-the-art hardware is already capable of doing so, it is merely a matter of developing and implementing the appropriate interconnections and software. Such an integrated system would offer additional cost savings during production as well as during installation, operation, and maintenance [19, 81, 122, 172].

2.3.6 Data Analysis

Before performing a diagnosis, some data acquired from the circuit breaker need to undergo additional analysis. Below is a list of measured quantities together with suggested analysis operations on them.
<table>
<thead>
<tr>
<th>Measured quantities</th>
<th>Suggested analysis</th>
<th>Expected result</th>
</tr>
</thead>
<tbody>
<tr>
<td>SF$_6$ gas density, or gas pressure and temperature</td>
<td>- temperature correction [88, 188], phase state [173] - trend analysis [20, 88]</td>
<td>- true density [20, 174], liquefaction - leakage rate, time until necessary refill</td>
</tr>
<tr>
<td>Primary current in combination with contact travel or auxiliary contact status</td>
<td>- arcing [88]</td>
<td>- contact erosion [7, 104] and nozzle ablation [88]</td>
</tr>
<tr>
<td>All those measured by optical sensors</td>
<td>- chromatic analysis [78, 79]</td>
<td>- behavior in time and frequency domains</td>
</tr>
</tbody>
</table>

Barkan [11] suggests the use of Statistical Process Control procedures of the type developed by Shewhart [107] for the detection of trends or critical deviations in arbitrary monitored quantities. Fox et al. [39] point out that spurious sensor readings and sensor degradation must also be taken into account for correct results.

Furthermore it is often useful to extract features from the processed data, as used e.g. by Gärtner [46] for HVCBs. These features can be used for signal classification and ultimately condition diagnosis. Features are also used in the new diagnostic method described in this work and will be explained in later chapters.
2.3.7 User Interface

After all the computing has been done, the resulting information needs to be presented to a human operator, who has often only limited knowledge of the primary equipment. Hence, the user interface should constitute a “user’s guide”, suggesting the procedures to follow in case of a problem [175]. A simple maintenance request alarm as proposed by Barkan [11] is not sufficient for this purpose because it still requires a human expert for finding the cause of the problem. Rather, the alarm system should indicate [24]

- importance (criticality) of the fault,
- location of the fault,
- type of faulty component,

of which an example can be found in [87].

It makes sense to use one centralized computer, perhaps with several terminals, for the condition monitoring output of all substation equipment, possibly integrated with the control monitoring [16, 175].

2.4 Condition Monitoring and Diagnosis on Technical Equipment

2.4.1 Condition Monitoring

Any type of technical equipment is designed and specified for clearly defined operating conditions. These are formalized by means of acceptable variation ranges regarding a number of influencing factors, e.g. ambient temperature. According to a definition by IEC Working Group SC17A/WG20, as quoted in [175], continuous condition monitoring consists in

1. Measuring the values of influencing factors,
2. Comparing these with specified limits,
3. Indicating any occurrence of a value exceeding its limits.

This can be done for the actually measured values or for those predicted by means of trend analysis. All deviations from the specified limits are indicated by an appropriate alarm.

What is not specifically mentioned in the above definition is taking into account deterministic variations in one quantity based on changes in another. If, for example, a timing value decreases with rising temperature, either the alarm limits have to be set wide enough to cover the entire range, or this influence can be compensated by means of threshold shift [26] or similar means in order to keep the acceptable range as narrow as possible. Fuzzy logic may aid in detecting deviations [155].

A useful condition monitoring system should be able to differentiate between the following operation modes [189]:

- normal operation under normal circumstances,
- normal operation under abnormal circumstances,
- abnormal operation under any circumstances,

where the third type is the critical one.

Generally, condition monitoring techniques can be classified into two categories:

- those more suitable for periodic testing, i.e. carried out at certain intervals (e.g. SF₆ gas analysis [176]),
- those for continuous monitoring throughout the lifetime of the equipment [75].

The former ones require human intervention and possibly taking the equipment out of service, whereas the latter ones provide information that, in principle, can be interrogated remotely at any time. Hence, another distinction can be made in techniques for offline monitoring, for the application of which the equipment must be taken out of service, and for online monitoring, where the data are acquired and processed during undisturbed operation of the equipment [105].
In addition, it makes sense that a condition monitoring system would also monitor its own performance continuously [157] as well as take into account the degradation of its sensors over time [39] for maximum reliability and availability.

### 2.4.2 Diagnosis

Diagnosis, also titled fault isolation by some authors (e.g. [70]), is considered a specialized case of the more general problem of data interpretation. A key part is abduction, the process of determining a cause given a set of observations [57].

Many definitions of diagnosis have been given in literature. A very general one is that by Stefik [166]: “To diagnose is to observe a physical artifact that is malfunctioning or a person who is ill and then determine what is wrong through reasoning and further observations”. In this work, only diagnosis of technical systems is relevant, with the aim of providing information about the fault’s nature and location from a description of the system's external behavior [18] in order to determine the correct procedure to restore the system to normal operation [166].

Some confusion over the correct terminology exists in literature: whereas publications in the field of artificial intelligence (AI) use the word “diagnosis” as defined above, electrical engineers tend to apply “diagnosis” or “diagnostics” to almost any data processing method that can be used to detect anomalies (see e.g. [76, 81, 105, 151]). This terminology problem is also addressed in [22].—Throughout this work, the term “diagnosis” (and “diagnostic” as the associated adjective) has been used in its AI meaning. In this sense, diagnostic systems are classified under intelligent knowledge based systems with their main parts of knowledge base, inference engine, explanation facility, and user interface [112]. This definition excludes neural networks because of their inability to explain the results [186].

The process of reaching a diagnosis consists of essentially three sub-tasks [1, 22, 28, 166]:
1. Symptom detection, i.e. finding a discrepancy between the observed and the normal behavior;

2. Suspect generation, i.e. creating hypotheses which component may be faulty;

3. Suspect discrimination, i.e. checking each suspect whether or not it can explain, or is consistent with, the observations.

These basic functions are implemented into a reasoning engine, which should be generic with respect to the application. The application-specific data are contained in a separate knowledge base. Both components together form the diagnostic system.

It should be noted that the number $N$ of possible diagnostic hypotheses rises exponentially with the number $k$ of system components [166], namely

$$N \geq 2^k.$$

The problem of finding the final diagnosis quickly and efficiently is still the subject of worldwide research [178]. Often, the assumption of a single fault holds and can be used to reduce the number of hypotheses [57, 108].

As with other software solutions, the successful utilization of a diagnostic system is highly determined by its integration into the control and monitoring environment of the system under supervision. This concerns not only the hardware and user interface but also the easy (perhaps even automatic) incorporation of any changes in that system [27]. Furthermore, several authors suggest that a diagnostic system should also propose steps for repairing the fault, and/or operations for minimizing the impact of the fault [40, 57, 175].

For selecting the type of knowledge representation, the intended use of the system should be taken into account [135]. The basic approaches to knowledge representation have been classified into “shallow” and “deep” knowledge [177]. Shallow (symptom-based) knowledge essentially consists of empirical inference rules, often shortcuts, to solving a problem. Conversely, “deep” (specification-
based) knowledge is based upon physical laws and is therefore also referred to as “reasoning from first principles” [22]. Here, too, a wide variety on the terminology can be found in literature (see e.g. [159]).

Three basic approaches to condition diagnosis exist in the Artificial Intelligence (AI) community today, namely (in the order of development [139])

1. Rule-based diagnosis,
2. Model-based diagnosis,
3. Case-based diagnosis.

They shall be explained briefly in the following subsections. For a hierarchical treatment of these diagnostic paradigms see [116].

2.4.2.1 Rule-based diagnosis (RBD)

Rule-based diagnosis is an attempt of capturing a human expert’s diagnostic knowledge—often a blend of theoretical knowledge, rules of thumb and experiences—in a set of association rules [108], relating symptoms to faults for a specific system.

Based on the available information, a RBD engine determines which one of the rules is applicable; the result is used as additional input for the next rule(s), and so on. When several rules are applicable at the same time, the system must have a way of selecting which one to execute next. This selection task is called “conflict resolution” and can be influenced by different factors which depend on the application and implementation of the system [40].

Strengths of RBD [108]:

- Ability to use experiential knowledge acquired from human experts. This is particularly important in domains that have not been well formalized.
- Very efficient in domains with limited dimensions and options.
- The modularity of rules makes the knowledge base fairly easy to construct, test, and debug.
Shortcomings of RBD [108]:

- The effort for gathering all information necessary for building a somewhat complete rule base is substantial [21, 57], as described by an actual example in [39].
- It is practically impossible to handle unexpected situations.
- Updating a rule base to reflect increased knowledge or a change in the system involves more than just adding a few rules. Rather, the entire rule base must be examined for consistency with the newly added information [57].
- In most cases, the knowledge base cannot be reused for other applications.
- If symptoms are in the form of sensor readings, a large number of rules are needed solely to verify the sensor data, in order to rule out a sensor failure [57].

2.4.2.2 Model-based diagnosis (MBD)

The significant problems associated with the shallow knowledge used in RBD led researchers to devise other reasoning methods, based on deep knowledge, of which the model-based is one of the most promising ones. A diagnostic system that is to use deep knowledge needs essentially three ingredients [21],

1. domain knowledge (what basic components exist, how do they work, what are the laws of the domain, etc.),

2. a model of the device to diagnose (what components constitute the system, how are they connected, where are they located, etc.),

3. a general diagnosis method (how to detect discrepancies between the model’s and the real system’s behavior).

A fourth item, observations of the behavior of the device, needs to be added for use in diagnosis [22].

If the system model, equipped with the first two items from the above list, is implemented correctly it can predict and/or simulate all
possible behaviors of the system, even those unforeseen by the designers [114]. However, its predictive power is always limited by the simplifying assumptions that it is based upon [31]. Then again, with highly complex systems not every possible event or interaction can be taken into account, as illustrated by the example of wires in electronic/electronic systems [166]. The important matter, here, is to make the model “pragmatically good enough” [22] for the application.

In diagnostic systems, the model is used to determine which non-standard component behavior could make the output values of the model match those of the physical system [41]. In addition, it can be used for monitoring the system [92] and for confirming or refuting a tentative diagnosis [57].

There are different kinds of models, e.g. functional [85], causal, physical structural, logical, constraint, or process models [58]. For example, Abu-Hanna uses the functional type in his system called “Faulty-II” for diagnosis of a video camcorder [1].—Another approach is the use of qualitative models, which has been found effective in situations where only inexact data are available or exact results are not required (see [58], which contains numerous application examples and further references).

An introduction to model-based reasoning can be found in [57]; a description of several model-based systems is given in [166].

Strengths of MBD [108]:

- The model contains “deep” knowledge, based on the physical principles governing operation of the system under observation. Hence, the diagnostic system is able to correctly handle a variety of problems, including those that may not have been anticipated by its designers [41], and to explain its reasoning to the user.

- For component-oriented models it is possible to gain access to “hidden” quantities (i.e. not accessible to direct measurement) in the system through simulation.

- The knowledge base is flexible in adjusting to changes in the system, e.g. a new component or an extra sensor, because all it
takes is updating the model to reflect the changes. Knowledge can be re-used by storing the component models in component libraries from where they can be copied to the model of another system that contains equal or similar components [27, 41]. A hierarchical model reduces the complexity at any given level and allows well-aimed refinement where necessary [57].

- Since the model simulates the behavior of the system under all possible conditions it can be used with novel systems right from the start because no operational experience is necessary [41, 57, 100]. It may even be used to improve the design during the development phase, saving the costs for expensive prototyping.

- The sensor validation problem [154] is inherently solved as long as the sensors are included in the system model [57].

Shortcomings of MBD [108]:

- The initial effort for creating a model and adjusting its parameters to the real-world system is substantial. It requires detailed knowledge of both the system under observation with its underlying physical principles and of computer modeling. Some authors even argue that a MBD system for real-world systems is likely to use an incomplete or incorrect device model [36, 108]. It has also been stated that model-based reasoning is inappropriate for physical systems that are too complex to model properly or for domains that lack a well defined scientific theory, such as medical diagnosis, financial applications, or weather forecasting [22, 57].

- Quantitative simulation of analog devices requires very high computing power. (However, certain approaches for speeding up the diagnostic process have been reported, e.g. [4, 41].) In addition, commercially available software tools, even those based on qualitative reasoning, are not only expensive but typically require a high-end workstation for each installation. Hence, up to this time model-based diagnosis has not been feasible for cost-sensitive applications such as high voltage circuit breakers.
• Faults that change the structure of the system, such as a bridging fault between two wires, cannot be simulated with reasonable effort and are hence impossible to predict [108]. Alternatively, including every conceivable change would make the model too complex for practical application [36].

The reasoning abilities of MBD systems can be enhanced by including fault models which describe the manners in which a device may fail, thus excluding physically impossible diagnoses such as a “faulted” wire generating electricity [171]. However, this may also lead to limitations in the presence of unforeseen problems [36].

Additional benefits from creating a model for a technical system include the following:

• A model preserves knowledge which otherwise would be lost as soon as the designers of the technical system are no more available, e.g. due to retirement. The latter has been a major obstacle with implementing MBD for older types of high voltage equipment because in many cases even the manufacturers do not have the required depth of knowledge about them.

• Models can also be used to improve the design of a system, train operating personnel, and facilitate failure mode and effect analysis (FMEA) [27].

A comprehensive overview of the fundamentals and the state of the art in MBD systems is given in [27].

2.4.2.3 Case-based diagnosis (CBD)

Case-based diagnosis uses an explicit database of past fault cases and their causes to find a solution for a new problem situation. As opposed to the rule-based and model-based approaches, the knowledge base for CBD does not need to be assembled explicitly by a human expert, rather it is generated “automatically” by analyzing actual cases from the past and generalizing them for future use. When a new problem arises, the system retrieves the cases most similar to the current problem, then combines and adapts them to derive and criti-
cize a solution. After the problem is solved, a new case can be created and stored in the case base.

Case-based reasoning is used by humans in many areas of expertise, e.g. medicine (diagnosing an illness) or law (finding precedents to a law case). Luger and Stubblefield argue that “the ability to reason from cases is fundamental to human intelligence” [108]. Furthermore, the case-based approach is the only one that is able to learn from experience, because every new case presented to the expert system enhances its knowledge base.

A more detailed introduction to case-based reasoning can be found in [57].

Strengths of CBD [108]:

- The knowledge base can be generated almost automatically from case histories, repair logs, or similar sources, eliminating the need for intensive knowledge acquisition with a human expert.
- The diagnostic system “learns” with every new case added to the knowledge base.
- High efficiency if an appropriate case is present in the knowledge base.
- Presuming proper implementation and data entry, the knowledge base has a low probability of errors because the knowledge is encoded automatically by the expert system, with little human interaction.

Shortcomings of CBD [108]:

- A history of actual problems and their solutions must be present in order to create a knowledge base. Hence, this approach is hardly suitable for new systems for which no service experience exists.
- A case base lacks deeper knowledge of the system under observation. Hence, there is no way of proving the correctness of a diagnosis.
• It is not easy to devise good criteria (features) for storing, retrieving, and matching the cases. Currently, the retrieval and matching algorithms must be handcrafted carefully, outweighing many of the advantages with respect to knowledge acquisition.

2.4.2.4 Combined Techniques

Traditionally, each diagnostic paradigm (RBD, MBD, and CBD) has been considered and implemented separately. However, attempts of imitating a human expert's reasoning process by combining two approaches into a single diagnostic system were considered and implemented as early as 1986 [37, 70] and have been the subject of research since then [40]. Luger and Stubblefield give a theoretical overview of such combinations with their respective strengths and shortcomings [108]. An actual implementation with numerous references to other published works can be found in [36]. Several authors propose “blackboard systems” for integrating various different forms of knowledge representation into one intelligent system [57, 118].

In this author's opinion, such combined systems are even less suited for online condition diagnosis of cost-sensitive devices, because of the increased memory and computing requirements.

2.5 Condition Monitoring and Diagnosis on High Voltage Circuit Breakers

Since the early 1980's, various attempts to determine the internal mechanical condition of gas-insulated high voltage circuit breakers (dead tank) without opening it were reported, using different techniques such as low-speed operation [62] or the accumulated breaking load [8]. Originally initiated by equipment manufacturers, soon an increasing number of power utilities began expressing the same interest, too (see e.g. [162]). However, the condition monitoring systems available in the 1980s were not sufficiently reliable and cost-saving for utilities [10]. Indeed, it seems a challenging task to create
a system that will meet all the demands summarized in [11, 48, 190], that a circuit breaker monitor must

- be simple in application and interpretation;
- be economical in initial cost, installation, and operation;
- operate automatically and continuously online;
- be capable of detecting a broad range of circuit breaker failure modes;
- function reliably in the adverse electrical and physical environment of an electrical substation; in other words, its reliability should be equal to or greater than that of the circuit breaker [64], without human intervention [189];
- not affect the operation of any component of the power system when operating normally or even in a failed condition (cf. [49]);
- be easily adapted to changing configurations of the substation and to advances in technology;
- supported by its suppliers over its entire lifetime [25].

A methodology of developing such a system, used for a specific example, is proposed in [189].

Augustin’s conclusion that “too sophisticated” condition monitoring would not be justified [7] is probably mainly applicable to hardware. In this author’s opinion, the software of a condition monitoring system does require a certain level of sophistication in order to produce useful results.

Only recently have a number of condition monitoring systems entered the market which attempt to satisfy the requirements listed above. They will be discussed later.

As far as diagnosis in power transmission is concerned, however, most applications are found in electric fault location within the network (see e.g. [14, 27, 111, 136] and numerous references in [86]). This is mostly due to the fact that the first diagnostic systems for technical systems (e.g. GDE/Sherlock [94], see [22, 47, 84] for ex-
tended lists) were created for assessing digital systems. To such systems, locating a fault within a transmission network based on control and protection data—i.e. binary information on which relays initiated a trip, or the open/closed status of each circuit breaker—offers itself as a natural application. The first expert systems were rule based and had an interactive user interface, asking the operator questions about the network status and finding a conclusion from the answers [136].

Automated monitoring and diagnosis of substation equipment, first investigated in the 1980's (see e.g. [46]), is still the subject of worldwide research, with the main focus on power transformers [49, 89, 92, 105, 132, 153, 187] and high voltage circuit breakers (see below). One difficulty in creating a generally applicable diagnostic system for HVCBs is the vast variety of circuit breaker technologies and designs, which have confined most attempts to a certain brand and model of circuit breakers. Thuries [175] even states that condition monitoring functions are “by nature” dependent on the apparatus’ technology and design. CIGRÉ Working Groups 23.10 and 23.05 take a less restricting view by permitting some generic “diagnostic” (in the electrical engineering sense of the word, cf. Section 2.4.2) techniques for gas-insulated switchgear (GIS), such as partial discharge detection [75].

A general consensus, supported by CIGRÉ Working Groups 13.06 [65], 13.09 [76], 23.03 [180], and 23.10 together with 23.05 [75], seems to exist on the importance of monitoring the following quantities in a high voltage circuit breaker:

- Contact position (travel) and/or velocity [5, 7, 15, 24, 34, 43, 46, 69, 80–82, 98, 120, 175];
- Continuity of trip and close circuits [15, 20, 157], or trigger coil operating current [43, 82, 120];
- Insulating and arc quenching medium, e.g. SF₆ gas density [5, 7, 15, 19, 24, 34, 43, 44, 46, 66, 69, 80–82, 120, 174, 175] and purity [10, 120, 131];
- Contact wear based on accumulated switching duty [5, 7, 10, 34, 44, 69, 80, 81, 120, 157, 175];
- Timing of switching operations [24, 43, 46, 120, 123, 174];
- Current of mechanism charging motor [19, 20, 43];
- Charging time of the mechanism [120];
- Self-test of the entire monitoring system including sensors [20, 24, 75, 80, 120].

Comprehensive lists of circuit breaker failures, together with suggested monitored signals for detecting them, are proposed in [11, 48, 56, 102, 104, 128, 190, 193] and also by CIGRE Working Groups 13.06 [65] and 23.03 [180]. The first two articles point out that certain failures are practically impossible to detect, let alone predict, such as a rusted cabinet or a leaking oil-filled bushing. The first one also suggests a few qualitative rules as an example of condition assessment from measured data.

Some research has also been conducted into analysis of the vibrations during circuit breaker operations [43, 45, 55, 101, 126, 130, 134, 145-147, 169, 182]. While this is certainly an interesting method, it has only been used for offline testing so far, not for continuous online monitoring. Furthermore, the interpretation of the data requires complex mathematical operations and is strongly dependent on the mechanical fine points of each circuit breaker pole [130, 145]. Therefore, in this author's opinion, it is presently not suitable for online diagnostic purposes; albeit, it appears quite promising for offline testing.

Other approaches to online condition assessment of high voltage circuit breakers include evaluation of data from control and protection systems [93, 189] as well as partial discharge monitoring and moving particles/parts detection [5, 15, 82, 91, 129, 132, 162, 163, 180, 183, 190, 191] or evaluation of vibrations due to contact problems [127] in metal-clad GIS.

Here again, the limiting factor in applying online condition monitoring and diagnosis is very often economical considerations which limit
monitoring functions to that which is strictly necessary in the eyes of the utility. Often it is decided that the high reliability of modern HV switchgear does not warrant the additional expense for an extra monitoring and diagnostic system [95], except for breakers which are frequently operated or located in critical nodes of the network [56]. However, most users will gladly accept it when it comes as part of the circuit breaker or control system without any additional cost (cf. [15]).

### 2.5.1 Application Examples

This subsection lists a number of actually implemented systems for on-line condition monitoring and, in a few instances, diagnosis of high voltage circuit breakers. They are sorted in chronological order of publication. In this list, an asterisk (*) in the “References” column indicates a product description published by the manufacturer.

<table>
<thead>
<tr>
<th>Location or name</th>
<th>Breaker type</th>
<th>Complexity</th>
<th>Monitored quantities</th>
<th>Diagnosis</th>
<th>Ref’s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Japan GIS</td>
<td>low</td>
<td>gas density, surge arrester leakage current</td>
<td>no</td>
<td>[128]</td>
<td></td>
</tr>
<tr>
<td>East Germany air-blast</td>
<td>high</td>
<td>interrupter air pressure, primary current, contact position, interrupter temperature, operating times</td>
<td>signal classification</td>
<td>[46, 124]</td>
<td></td>
</tr>
<tr>
<td>“AM1000” by Doble</td>
<td>low</td>
<td>interrupting time, contact wear</td>
<td>no</td>
<td>[50]</td>
<td></td>
</tr>
<tr>
<td>Russia air-blast</td>
<td>medium</td>
<td>primary voltage and current, ambient temperature, air pressure, contact position</td>
<td>no</td>
<td>[13]</td>
<td></td>
</tr>
</tbody>
</table>

---

3 This is a subjective assessment by the author.
4 As defined in Section 2.4.2.
<table>
<thead>
<tr>
<th>Location or name</th>
<th>Breaker type</th>
<th>Complexity</th>
<th>Monitored quantities</th>
<th>Diagnosis</th>
<th>Ref's</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>SF$_6$ (GIS)</td>
<td>medium</td>
<td>primary voltage and current, mechanism travel, spring energy, gas density, partial discharge</td>
<td>no</td>
<td>[16]</td>
</tr>
<tr>
<td>“CMU” by ABB Power T&amp;D</td>
<td>single pressure SF$_6$</td>
<td>medium</td>
<td>phase current, SF$_6$ pressure and temperature, motor current and voltage, heater current and resistance, trigger coil current and continuity, contact (linkage) travel, auxiliary contacts</td>
<td>no</td>
<td>[87, 88, 141, 192, 193]</td>
</tr>
<tr>
<td>Australia</td>
<td>any</td>
<td>high</td>
<td>mechanical vibrations</td>
<td>neural network</td>
<td>[182]</td>
</tr>
<tr>
<td>“Insite” by Doble</td>
<td>bulk oil, air-blast, single and dual pressure SF$_6$</td>
<td>high</td>
<td>ambient temperature, auxiliary contacts, mechanism travel, motor current, air or gas pressure, mechanism pressure, trip coil continuity, trigger coil current, primary current; optionally heater operation and current, battery voltage</td>
<td>rule-based</td>
<td>[189, 141] (* )</td>
</tr>
<tr>
<td>Location or name</td>
<td>Breaker type</td>
<td>Complexity</td>
<td>Monitored quantities</td>
<td>Diagnosis</td>
<td>Ref's</td>
</tr>
<tr>
<td>---------------------</td>
<td>--------------</td>
<td>------------</td>
<td>-------------------------------------------------------------------</td>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>“Star 2000” by Barrington Consultants</td>
<td>any</td>
<td>low</td>
<td>operation times</td>
<td>no</td>
<td>(*)&amp;</td>
</tr>
<tr>
<td>“Star 10000” by Barrington Consultants</td>
<td>any</td>
<td>low</td>
<td>operation times</td>
<td>no</td>
<td>(*)&amp;</td>
</tr>
<tr>
<td>“Argus”</td>
<td>any</td>
<td>medium</td>
<td>various</td>
<td>no</td>
<td>[184]</td>
</tr>
<tr>
<td>“Moniteq” by IREQ</td>
<td>air-blast, single and dual pressure SF₆</td>
<td>high</td>
<td>operating rod travel, air or SF₆ pressure, pneumatic or hydraulic drive pressure, moisture in SF₆ gas, primary current, trigger coil currents, various temperatures, auxiliary contacts, auxiliary voltages, pump motor current, hydraulic oil level</td>
<td>no</td>
<td>[140, 102–104]</td>
</tr>
<tr>
<td>China</td>
<td>oil</td>
<td>medium</td>
<td>trigger coils voltage and current, contact travel and speed</td>
<td></td>
<td>[144]</td>
</tr>
<tr>
<td>Location or name</td>
<td>Breaker type</td>
<td>Complexity</td>
<td>Monitored quantities</td>
<td>Diagnosis</td>
<td>Ref's</td>
</tr>
<tr>
<td>----------------------------------</td>
<td>--------------</td>
<td>------------</td>
<td>---------------------------------------------------------------------------------------</td>
<td>-----------</td>
<td>-----------</td>
</tr>
<tr>
<td>“BCM-200” by Hathaway</td>
<td>any</td>
<td>medium</td>
<td>primary current, trigger signals, trigger currents, station battery voltage, auxiliary contacts; optionally SF₆ gas density, motor operations, contact travel</td>
<td>no (*)</td>
<td></td>
</tr>
<tr>
<td>“SM6” series by Consolidated Electronics</td>
<td>SF₆</td>
<td>configurable</td>
<td>SF₆ pressure and temperature; optionally motor operations, heater function, contact wear (from external module), mechanism pressure, trigger coil continuity</td>
<td>no (*)</td>
<td></td>
</tr>
<tr>
<td>“OLM” by ABB Switchgear</td>
<td>SF₆</td>
<td>medium</td>
<td>primary current, trigger signals, travel curve, auxiliary contacts, trigger coil currents, SF₆ density, spring charge, motor current, supply voltage, operations counter, ambient temperature, mechanism temperature</td>
<td>no (*)</td>
<td></td>
</tr>
<tr>
<td>“SICU”</td>
<td>SF₆</td>
<td>low</td>
<td>SF₆ density, contact travel, etc.</td>
<td>no [133, 175]</td>
<td></td>
</tr>
<tr>
<td>Location or name</td>
<td>Breaker type</td>
<td>Complexity(^3)</td>
<td>Monitored quantities</td>
<td>Diagnosis(^4)</td>
<td>Ref's</td>
</tr>
<tr>
<td>------------------</td>
<td>--------------</td>
<td>------------------</td>
<td>----------------------</td>
<td>-----------------</td>
<td>-------</td>
</tr>
<tr>
<td>“ICM”</td>
<td>SF(_6)</td>
<td>high</td>
<td>contact travel, SF(_6) density, contact wear, trigger coils integrity; self-monitoring</td>
<td>no</td>
<td>[133, 175]</td>
</tr>
<tr>
<td>“HVMC” by ABB ADDA</td>
<td>SF(_6)</td>
<td>medium</td>
<td>primary current, trigger signals, auxiliary contacts, SF(_6) density, trigger circuit continuity, motor energization, DC control voltage, internal errors</td>
<td>no</td>
<td>(*)</td>
</tr>
</tbody>
</table>

\(^{(*)}\) product description by the manufacturer.

### 2.6 Conclusions

Numerous articles in literature, listed above, are strong evidence that there is high interest worldwide in intelligent online condition monitoring of high voltage circuit breakers, and that it is expected to yield not only technical but also economical benefits. However, the existing systems are unable to fully satisfy this demand because they do not exploit the full potential of the data gathered. Neither is a useful interpretation of the data given, nor is it possible to infer hidden quantities i.e. those that are not directly measured.

This shortcoming is not brought about by the absence of sophisticated methods for condition assessment; they have been known for decades. Rather, the application of these methods appears too costly in their present form. In addition, it seems that the manufacturers and users of high voltage switchgear are reluctant to use novel technologies in their systems as long as their usefulness and reliability have not been proved by extensive field experience. Obviously, the latter obstacle is not expected to be overcome soon. The former one,
however, could probably be alleviated by developing and implementing low-cost diagnosis strategies with still sufficiently high performance. A low-price monitoring system with a diagnostic functionality which is easy to understand and operate will probably be well acceptable to the users of high voltage circuit breakers.
3 Research Goal

As stated above, there is still great potential for intelligent condition monitoring and diagnosis of high voltage circuit breakers (HVCBs). The overall aim of the current research work is to exploit this potential to its fullest, from both the scientific and the practical sides. With this in mind, the specific goals of this work were defined as follows:

1. Investigation of failure statistics of HVCBs. Many manufacturers, users, and independent organizations have been collecting data on failures of their equipment for years. The knowledge about which parts of a HVCB are more likely to fail was expected to guide subsequent efforts toward a useful tool for condition assessment.

2. Finding the best fault diagnosis method for this application. In the field of artificial intelligence, several methods for condition assessment are known. These should be examined and evaluated. Also part of the work is to explore possible combinations of existing methods.

3. Practical application of the best method (found in the previous step) to the problem, i.e. creating a usable diagnosis system. The latter should be verified with respect to feasibility and efficiency. The attribute "best" here does refer not only to the selected method's performance but also to its cost of implementation.

The author's contributions to each of these tasks will be set forth in the following chapters.
4 Failure Statistics of High Voltage Circuit Breakers

4.1 Description

Manufacturers and users of high voltage circuit breakers have long been interested in finding the most common causes for failures in their switchgear. While the former want to know how to improve their products, the latter need this information for selecting switchgear and for developing maintenance strategies. As a consequence, numerous empirical studies were conducted; the resulting worldwide and national failure statistics are cited in Subsection 2.2.2. Published results contain general data about failure modes, causes, and probabilities.

For more detailed information, two divisions of a large circuit breaker manufacturer made available their collected failure records of HVCBs to the author. Of all existing failure records, only those of HVCBs using SF₆ interrupter technology were taken into account, covering manufacturing years from 1972 to 1996. They are equipped with pneumatic, spring-hydraulic, or spring-mechanical operating mechanisms.—The resulting collection comprises a total of 267 records, gathered during the years of 1988...1996.

Even though these failure records were collected by a single company, the data can be considered representative for the majority of HVCBs in service today, for the following reasons:

- This manufacturing company, as constituted today, is the outcome of several acquisitions and mergers. It is therefore responsible for different product lines of circuit breakers, which were developed independently. This fact is reflected in the failure records.
• Various types of the two basic designs of air-insulated switchgear are represented, namely live tank breaker (LTB, with the interrupter housing at high voltage potential) and dead tank breaker (DTB, interrupter housing at ground potential).

• Other companies have been using similar technology, according to the published state of the art, often differing only in minor details.

The original intention was to derive the same statistics as those used in the Second International Enquiry by CIGRE [66]. However, since certain important information were not included in the original failure records, information such as analysis of failures depending on circuit breaker location (indoors/outdoors), service voltage, or mechanism type are not available. Furthermore, in many cases only the nature of the fault is given but not its cause. Therefore, the resulting statistics are focused mainly on the nature and location of the faults, also trying to extract some further interesting details.

The terminology and abbreviations used in the CIGRE report have been adopted here, too. In particular, the following abbreviations from [60] will be used:

MF ..... Major Failure, defined as “failure of a circuit breaker which causes the cessation of one or more of its fundamental functions.”

mf ..... minor failure, defined as “any failure of a constructional element or a subassembly which does not cause a major failure of the circuit breaker.”

All results given in this chapter are in absolute numbers of failure records, i.e. circuit breakers.
4.2 Statistical Results

4.2.1 Fault Locations

The following table gives an overview of which component was responsible for the recorded failures. The categories are slightly different from those used in the CIGRE study, for two reasons:

1. the divisions are somewhat smaller, giving more detailed information.
2. they conform better to the circuit breaker model which will be introduced in Chapter 5.

<table>
<thead>
<tr>
<th>Component responsible for failure / defect</th>
<th>mf</th>
<th>MF</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Operating mechanism</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>actuators</td>
<td>12</td>
<td>18</td>
<td>30</td>
</tr>
<tr>
<td>energy storage</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>energy transmission</td>
<td>6</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>damping devices</td>
<td>4</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>hydraulic/pneumatic system</td>
<td>68</td>
<td>12</td>
<td>80</td>
</tr>
<tr>
<td>charging motor</td>
<td>0</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>compressor / pump</td>
<td>3</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>mechanical linkage</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>indicators / gauges</td>
<td>3</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td><strong>Electrical control and auxiliary circuits</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>circuit breaker control</td>
<td>2</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>trip/close coils</td>
<td>0</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>auxiliary contacts</td>
<td>3</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>limit switches</td>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>current transformers</td>
<td>2</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>density monitor</td>
<td>4</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>heaters</td>
<td>4</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>wiring</td>
<td>1</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Component responsible for failure / defect</td>
<td>mf</td>
<td>MF</td>
<td>total</td>
</tr>
<tr>
<td>------------------------------------------------------------</td>
<td>----</td>
<td>----</td>
<td>-------</td>
</tr>
<tr>
<td>Components at service voltage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>grading capacitors</td>
<td>41</td>
<td>27</td>
<td>68</td>
</tr>
<tr>
<td>SF&lt;sub&gt;6&lt;/sub&gt; gas system</td>
<td>26</td>
<td>5</td>
<td>31</td>
</tr>
<tr>
<td>main insulation to earth</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>interrupter</td>
<td>10</td>
<td>18</td>
<td>28</td>
</tr>
<tr>
<td>closing resistors with interrupters</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>other</td>
<td>2</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>total</td>
<td>161</td>
<td>106</td>
<td>267</td>
</tr>
</tbody>
</table>

### 4.2.1.1 Conclusions

- The subassembly responsible for most of the failures is the operating mechanism, followed by the components at service voltage. All in all, the mechanical and electrical components (other than those at service voltage) account for approx. two thirds of all failures.
- The most frequent failures are associated with some kind of leakage, either of the SF<sub>6</sub> gas system or of the hydraulic or pneumatic system in the operating mechanism. Possible remedies can be found in better selection and handling of the seals as well as in design measures such as fewer seals by simplified design.

### 4.2.2 Fault Types

Having found the most critical components with respect to failure frequency, the general types of problems encountered were investigated, too. These results are summarized in the table below.
## Description of failure

<table>
<thead>
<tr>
<th>Description of failure</th>
<th>mf</th>
<th>MF</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>electrical breakdown leading to failure of a CB pole</td>
<td>1</td>
<td>13</td>
<td>14</td>
</tr>
<tr>
<td>resistance of main contacts too high</td>
<td>8</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>failure to operate (properly)</td>
<td>1</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>timing or velocity of contact travel out of boundaries</td>
<td>6</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>SF₆ gas leak, including blown rupture disc</td>
<td>21</td>
<td>2</td>
<td>23</td>
</tr>
<tr>
<td>SF₆ gas liquefaction</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>SF₆ gas moisture</td>
<td>4</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>hydraulic/pneumatic leakage in operating mechanism</td>
<td>72</td>
<td>17</td>
<td>89</td>
</tr>
<tr>
<td>dirt in critical mechanism location</td>
<td>4</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>broken component</td>
<td>3</td>
<td>10</td>
<td>13</td>
</tr>
<tr>
<td>loose component (nuts, electrical plugs, etc.)</td>
<td>9</td>
<td>12</td>
<td>21</td>
</tr>
<tr>
<td>moving component stuck</td>
<td>3</td>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>other mechanical defect</td>
<td>4</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>misadjusted limit switch or auxiliary contact</td>
<td>6</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>burnt component (motor, coil)</td>
<td>0</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>electrical problem (open/short circuit, malfunctioning auxiliary contact)</td>
<td>9</td>
<td>13</td>
<td>22</td>
</tr>
<tr>
<td>explosion (other than interrupter) for unknown reason</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>other</td>
<td>9</td>
<td>3</td>
<td>12</td>
</tr>
<tr>
<td>total</td>
<td>161</td>
<td>106</td>
<td>267</td>
</tr>
</tbody>
</table>

### 4.2.2.1 Conclusions

- By far the most frequently encountered problem is a hydraulic or pneumatic leakage in the operating mechanism, which is in agreement with Subsection 4.2.1. This points to design problems of the mechanism types used.

- Next in frequency are SF₆ gas leaks, followed by electrical problems and by loose components. Most of the latter can probably be eliminated through greater care during erection and maintenance of the circuit breaker.
4.2.3 Causes for Failures

A very valuable information when looking at failure statistics is the cause of the failure. Unfortunately, more than two thirds of the failure records available did not contain this information. From the author’s experience with HVCBs, it was possible to unequivocally assign a general cause category to some of them. The rest was classified as “unknown” in the table below.

<table>
<thead>
<tr>
<th>Cause of failure</th>
<th>mf</th>
<th>MF</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>aging</td>
<td>8</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>design</td>
<td>3</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>installation, commissioning, or maintenance</td>
<td>6</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td>manufacturing</td>
<td>62</td>
<td>19</td>
<td>81</td>
</tr>
<tr>
<td>operator errors</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>overstress (mechanical, electrical, thermal, ...)</td>
<td>5</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>transport to site</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>unknown</td>
<td>75</td>
<td>63</td>
<td>138</td>
</tr>
<tr>
<td><strong>total</strong></td>
<td>161</td>
<td>106</td>
<td>267</td>
</tr>
</tbody>
</table>

4.2.3.1 Conclusions

- By far the majority of failures were attributed to manufacturing, which was defined to include assembly of the circuit breaker at the factory. Hence, as of 1996 there exists great potential for improvement in this area.

- Another significant portion of the failures was caused by human errors, during installation, commissioning, maintenance, or regular operation. This problem rate may be reduced by better training of personnel or by improving the procedures defined for conducting these processes.

- More accurate record keeping, to include the reason for every problem discovered, will help improve equipment reliability in the long run.
4.2.4 Time of Failure

Another interesting information to be gleaned from the failure records is the time when the problem was discovered. This is best expressed in years since manufacturing, as summarized in Fig. 3.

![Graph showing distribution of circuit breaker years from manufacturing date until discovery of the problem.](image)

*Fig. 3: Distribution of circuit breaker years, from manufacturing until discovery of the problem. See text for details.*

For interpreting this graphic it is important to know that numerous circuit breakers were placed into regular service up to two years after manufacturing. Therefore, the majority of failures contained in the first three categories were found during, or shortly after, commissioning.—Along with this, the two years’ warranty period on new circuit breakers must be taken into account. Obviously, the owner of a new HVCB will have most problems fixed by the manufacturer during that period. Thus, practically every little failure goes on record. After the end of the warranty period, many problems will be corrected by the utility’s maintenance personnel if possible and are hence not brought to the manufacturer’s attention.

Since the oldest HVCBs included in the failure records were manufactured in 1978, all failure times are in the range from 0 to 17 years. 17 failure records did not give the manufacturing date of the circuit breaker; these data were omitted from the diagram.
An essential information to accompany the histogram from Fig. 3 is the year when the failure was discovered. As can be seen from Fig. 4 below, most of the records were created during a span of only six years, which must be taken into account if using these data for reliability considerations.

![Histogram of failure record creation years](image)

Fig. 4: Distribution of failure record creation years.

4.2.4.1 Conclusions

- Most of the problems encountered were found during commissioning, or shortly afterwards. This is consistent with the findings from Subsection 4.2.3. However, this only holds for newer circuit breaker types since no failure records from before 1988 were available.

- The practice of keeping failure records has improved significantly over the last ten years.

4.2.5 Possibilities to Detect, Identify, and Predict Failures

Particularly within the context of this work, it is desirable to know how many of the failures occurring on HVCBs could have been de-
tected, identified, or predicted by means of online condition monitoring and diagnosis.

From his experience with HVCBs and condition monitoring systems for them, the author made an estimation on the possibility to detect, identify, or predict the fault described on every failure record. Due to the scarce information contents of some failure records, this was often not possible. In these cases, the assessment “maybe” indicates the need for additional data. For example, in the case of pneumatic pressure loss in a circuit breaker mechanism it would be necessary to know whether this problem had occurred suddenly (e.g. caused by a broken valve) or whether it was the result of slow degradation.

The following table lists the numbers of failures that could have been detected by an appropriate monitoring system. Here, “detecting” was defined as finding out that something is wrong with the circuit breaker, i.e. it behaves differently from normal.

<table>
<thead>
<tr>
<th></th>
<th>yes</th>
<th>no</th>
<th>maybe</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>detect mf</td>
<td>115</td>
<td>23</td>
<td>23</td>
<td>161</td>
</tr>
<tr>
<td>detect MF</td>
<td>98</td>
<td>1</td>
<td>7</td>
<td>106</td>
</tr>
<tr>
<td><strong>total detectable</strong></td>
<td><strong>213</strong></td>
<td><strong>24</strong></td>
<td><strong>30</strong></td>
<td><strong>267</strong></td>
</tr>
</tbody>
</table>

The next table shows how many of the detectable failures could also have been identified correctly—i.e. pinpointed the location and nature of the problem—given an appropriate diagnosis system in addition to the monitoring system.

<table>
<thead>
<tr>
<th></th>
<th>yes</th>
<th>no</th>
<th>maybe</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>identify mf</td>
<td>104</td>
<td>27</td>
<td>30</td>
<td>161</td>
</tr>
<tr>
<td>identify MF</td>
<td>78</td>
<td>6</td>
<td>22</td>
<td>106</td>
</tr>
<tr>
<td><strong>total identifiable</strong></td>
<td><strong>182</strong></td>
<td><strong>33</strong></td>
<td><strong>52</strong></td>
<td><strong>267</strong></td>
</tr>
</tbody>
</table>

Finally, the number of failures that could have been predicted, meaning to issue a warning of a developing problem before it became serious.
### 4.2.5.1 Conclusions

- Given an appropriate monitoring and diagnosis system, it would be possible to detect almost 80% of all problems and to identify more than 67%. At least one third of all failures could have been predicted, allowing the users to schedule maintenance to correct the problem before it became serious.

- Again, the need for accurate record keeping is manifested by the high number of “maybe” ratings in the predictability table.

### 4.2.6 Sensors for Detecting the Failures

Having established the possibilities to find (i.e. detect, identify, or predict) failures on HVCBs, the question arises how to do that. Generally, these tasks require hardware and software facilities, from sensors down to the user interface, as outlined in Section 2.3.

Based on his experience with HVCBs and existing monitoring systems for them, the author has derived a list of sensors required for detecting, identifying, or predicting the various faults, given in the table below. It presumes that suitable data acquisition and processing hardware as well as sufficiently intelligent algorithms for processing the sensor data are available.

This list gives the number of faults from the failure records that could have been found by means of each sensor. Taking the first row as an example, a measurement of the breaker voltage would have been required for finding 20 faults (“mandatory” column) and helpful for finding 6 additional faults (“supplemental” column), making a total of 26 faults. The “mandatory” figures are not exclusive, though: for example, it is assumed that many problems can be found by monitoring either the travel curve or the status of the auxiliary contacts, or both.

<table>
<thead>
<tr>
<th></th>
<th>yes</th>
<th>no</th>
<th>maybe</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>predict mf</td>
<td>71</td>
<td>37</td>
<td>53</td>
<td>161</td>
</tr>
<tr>
<td>predict MF</td>
<td>13</td>
<td>42</td>
<td>51</td>
<td>106</td>
</tr>
<tr>
<td>total predictable</td>
<td>84</td>
<td>79</td>
<td>104</td>
<td>267</td>
</tr>
<tr>
<td>Sensor for</td>
<td>Mandatory</td>
<td>Supplemental</td>
<td>total</td>
<td></td>
</tr>
<tr>
<td>------------------------------------</td>
<td>-----------</td>
<td>--------------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td>Breaker voltage</td>
<td>20</td>
<td>6</td>
<td>26</td>
<td></td>
</tr>
<tr>
<td>Breaker current</td>
<td>21</td>
<td>23</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>Travel curve</td>
<td>47</td>
<td>7</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>Auxiliary Switches</td>
<td>33</td>
<td>21</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>Gas pressure/density</td>
<td>38</td>
<td>1</td>
<td>39</td>
<td></td>
</tr>
<tr>
<td>Gas humidity</td>
<td>4</td>
<td>0</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Energy storage level</td>
<td>106</td>
<td>19</td>
<td>125</td>
<td></td>
</tr>
<tr>
<td>Trigger voltage</td>
<td>46</td>
<td>14</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>Trigger current</td>
<td>20</td>
<td>12</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>Coil continuity</td>
<td>7</td>
<td>26</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td>Motor voltage</td>
<td>117</td>
<td>5</td>
<td>122</td>
<td></td>
</tr>
<tr>
<td>Motor current</td>
<td>16</td>
<td>104</td>
<td>120</td>
<td></td>
</tr>
<tr>
<td>Heater voltage</td>
<td>6</td>
<td>3</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>Heater current</td>
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<td>2</td>
<td>9</td>
<td></td>
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<tr>
<td>Ambient temperature</td>
<td>0</td>
<td>24</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>Mechanism temperature</td>
<td>3</td>
<td>5</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>Tank/interrupter/gas temperature</td>
<td>4</td>
<td>34</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>Operation lockout due to low</td>
<td>20</td>
<td>92</td>
<td>112</td>
<td></td>
</tr>
<tr>
<td>mechanism energy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operation lockout due to low</td>
<td>38</td>
<td>0</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>SF\textsubscript{6} gas density</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total</td>
<td>553</td>
<td>398</td>
<td>951</td>
<td></td>
</tr>
</tbody>
</table>

In 43 cases, analysis of the mechanical vibrations might have been helpful for detecting or even predicting the failure. In addition, 16 faults could have been found using special sensors that are not generally available for online monitoring of HVCBs, e.g. sensors for moisture in the SF\textsubscript{6} gas or for the resistance of the primary contacts in closed position.

**4.2.6.1 Conclusions**

- The highest number of failures could have been found by monitoring quantities related to the energy storage and transmission
system of the operating mechanism. This is consistent with the findings of the previous sections.

- Due to its complexity, the operating mechanism requires the highest number of sensors for comprehensive monitoring of a HVCB. This means that most sensors will be applied at or near ground potential, without the need for special high voltage insulation other than the usual EMC measures.

- It is possible to detect, identify, or predict numerous failures by exploiting the signals already available on a conventional HVCB, such as breaker current, auxiliary contacts, or operation lockouts.

4.3 General Conclusions

From the analysis of the failure records presented above, the following conclusions can be drawn:

1. The results of these failure statistics are basically identical with those of the second enquiry by CIGRE [66] and other surveys listed in Subsection 2.2.2.

2. The record keeping itself can be improved. Most failure records contain only the problems that were found during investigation but not the reason that led to it. Certainly the manufacturer as well as the user would be interested in knowing whether the malfunction of a circuit breaker component was caused by a manufacturing fault, by incorrect installation or maintenance, excessive stress, or simply by aging or wear.

3. Condition monitoring can help with establishing comprehensive failure records that are really useful to both manufacturers and users. Conversely, failure records can also help to tailor a condition monitoring system to the HVCBs of a certain manufacturer.

4. Improvements in design and manufacturing are expected to yield an increased reliability of circuit breakers.
5 MODELING A HIGH VOLTAGE CIRCUIT BREAKER

5.1 General Model

As a basis for various diagnostic functions and experiments, it is very helpful to employ a computer model of the device under observation. For high voltage circuit breakers, a very coarse “model” was shown in Section 2.2.1 (Fig. 1), comprising only the three main functional parts. When examined more closely, each part consists of several different components, which can be modeled individually. Out of these considerations, a general model of a HVCB with its relevant components was developed; it is presented in Fig. 5.

This model is generic with respect to the technology of each component. It can represent a modern live-tank SF₆ self-blast breaker with hydraulic mechanism just as well as an old metal-clad bulk oil breaker with pneumatic mechanism. Its purpose is to visualize the
individual functions contained in a HVCB and to serve as a foundation for computer modeling.

5.2 Specific Computer Model

5.2.1 Circuit Breaker to Be Modeled

As a basis for further work, the generic component-oriented HVCB model described above was implemented in Simulink, a graphical simulation tool for analog and discrete models. In consequence of the different HVCB designs in existence today, all circuit breaker types have their own characteristic behavior. Hence, a specific type had to be chosen, namely the ABB ELF SP 6-2 [106, 168] with an AHMA 8 drive mechanism.

The ELF SP is an SF₆-insulated puffer (self-blast assisted) high voltage AC circuit breaker with up to four interrupters per phase. The 6-2 type has two interrupters on one column, in T shape, and was designed for 420 kV nominal voltage, 4 kA rated continuous current, and 63 kA rated fault current.

The AHMA 8 [142] is an hydraulic-mechanical drive where the mechanical energy for the operations is provided by a plate spring assembly, which pressurizes a hydraulic volume. Energization of a control coil actuates a change-over valve which in turn applies or removes the system pressure to/from the main piston head, causing it to move from Open to Closed position or vice versa. The oil volume lost from the high pressure storage is replaced by a hydraulic pump, which is controlled by the position of the spring column via a limit switch. This particular specimen has a total stored energy of 8 kJ and can perform a COCO (C = close, O = open) switching sequence without recharging the spring.

---

5 Simulink Version 2.2.1 © 1998 The MathWorks, Inc.
5.2.2 General Description of the Computer Model

The Simulink model was created on the basis of the general model introduced in Section 5.1. It was designed to give a good representation of the behavior of the ELF SP 6-2 circuit breaker under various normal and abnormal operating conditions. The entire model contains nine integrators and has a total of 47 inputs to reflect internal parameters as well as external inputs. Each functional component of the entire circuit breaker was implemented individually; later the component models (called “subsystems” in Simulink) were assembled into the complete model and connected through the various data paths (Fig. 6). The model inputs and 42 of its parameters were realized as external connections, making it possible to control each value at runtime. A simple MATLAB® function initializes the model, starts the simulation, and displays the results if desired.

This model implementation was designed to be normalized, i.e. the normal values of every input and output quantity are 1. This allows easy adaptation to various real circuit breakers, where the measured values simply need to be divided by their normal values.

Because of its modular construction, this model can be adapted for other circuit breaker types with moderate expenditure. Only those components which differ from the ones used in the ELF SP 6-2 need to be modeled anew, in the form of separate Simulink subsystems. These new component models will then replace those of the present model.

---

6 MATLAB Version 5.2.1 © 1998 The MathWorks, Inc.
Fig. 6: Implementation of circuit breaker model in Simulink. 

R = resistance, CB = Circuit Breaker, CT = Current Transformer, TC = Trip Coil. Other abbreviations on port names refer to the origin or destination block of the signal, e.g., motor voltage supply, pump delivery.
5.2.3 Model Components

Each functional component of the circuit breaker under consideration was modeled as an independent subsystem in Simulink. It would be possible to re-use each of these components in a model of a different circuit breaker, only requiring adjustment of its parameters.

The individual components were modeled as follows.

5.2.3.1 Control Circuit

![Control Circuit Diagram]

**Description:** Logical connection of control signals (Open, Close), auxiliary contacts, and control voltage, to represent the relay logic in a conventional circuit breaker.

The control voltage is only passed to a trigger coil output if the control signal is present, the corresponding auxiliary contact is closed, and the secondary circuit breaker is on.
**Inputs:**
1. control voltage, nominal value 1.0.
2. Close signal, 0 or 1.
3. auxiliary contact 52b electrical position, 0 (open) or 1 (closed).
4. Open signal.
5. auxiliary contact 52a electrical position.
6. status of circuit breaker in close circuit, 1 (on) or 0 (fallen).
7. status of circuit breaker in trip circuit.

**Outputs:**
1. Close voltage to close coil.
2. Trip voltage to trip coil.

### 5.2.3.2 Close and Trip Coils

**Description:** Trigger coils for close or open operations, which actuates the changeover valve. Modeled as a non-ideal inductor with moving core (and thus time-varying inductance).

**Inputs:**
1. trigger voltage from control circuit, nominal value 1.0.
2. position of changeover valve, between 0.0 (open position) and 1.0 (closed position).
3. electrical resistance of coil, nominal value 1.0.
Outputs:  1. coil current.
        2. mechanical force on changeover valve.

5.2.3.3 Changeover Valve

Description: This valve applies the hydraulic system pressure to, or removes it from, the bottom of the main piston, depending on its position: 0 = Open, no pressure on piston; 1 = Close, full pressure on piston. These limits are adjustable for simulating mechanical problems.

It is actuated by the close and trip coils: the close coil pushes it towards the Close position, the trip coil towards the Open position. In every case, the valve is self-holding, so a certain threshold force must be exceeded for any movement.

        2. Trip coil mechanical force.
        3. Acceleration factor, corresponding to the mechanical coupling to the trigger coils.
        4. Initial position of valve, normal value 0.0 or 1.0.
        5. Motion limit on Close side, normal value 1.0.
        6. Motion limit on Open side, normal value 0.0.

Output: Position of changeover valve.
5.2.3.4 Hydraulic Cylinder

Description: This cylinder contains the main piston, which moves the circuit breaker contacts. For opening operations, the hydraulic pressure is applied to the top of the piston only, moving it to the Open position. For close operations, both sides of the piston are pressurized; due to the area difference it is moved towards the Closed position.

Inputs:
1. Hydraulic system pressure.
2. Position of changeover valve.
3. Mass of moving system, including piston, linkage, and contacts.
4. Mechanical damping in mechanical chain.
5. Initial position of piston, normal value 0.0 or 1.0.
6. Motion limit on Closed side, normal value 1.0.
7. Motion limit on Open side, normal value 0.0.
8. End position damping on Closed side, normal value 1.0.
9. End position damping on Open side, normal value 1.0.
**Outputs:**
1. Loss of hydraulic fluid from high pressure system due to piston movement.
2. Piston position.

5.2.3.5 Mechanical Linkage

**Inputs:**
1. Piston position from cylinder.
2. Moving mass of mechanical system.
3. Total mechanical damping.
4. OK-status of mechanical linkage: 1 = OK, 0 = broken.
5. Mechanical friction of linkage, normal value 0.01.

**Outputs:**
1. Contact side position of linkage.
2. Effective moving mass (0 if broken).
3. Effective total damping.

The mechanical linkage transfers the movement from the hydraulic piston to the main contacts, as long as it is in working order. No movement is transferred if it is broken.
5.2.3.6 Primary Contacts (Interrupter)

**Description:** This is a simple model of the primary contact system of a high voltage circuit breaker. Current starts flowing as soon as the momentary voltage across the contacts exceeds the dielectric withstand (depending on contact distance and SF₆ gas pressure) and is extinguished at a current zero when the contacts are separated. No fault current or transient pressure related phenomena were modeled because this would have increased the complexity of the model immensely. Since fault current interruption is a rare event during a circuit breaker's life time, only load current switching was taken into account.
**Inputs:**
1. Voltage at source side (busbar) of the breaker.
2. Voltage at load side of the breaker.
3. Current through the circuit breaker.
4. Contact position from linkage.
5. Insulating SF$_6$ gas pressure, normal value 1.0.
6. Friction of main contacts, normal value 0.2.
7. Resistance of main contacts, normal value $10^{-6}$.
8. Moving mass of contact system, normal value 1.0.

**Outputs:**
1. Arcing voltage between contacts.
2. Contact resistance.
3. Contact status: 1 = contacts closed or arcing, 0 = no current flow possible.
4. Moving mass of contact system.
5. Effective damping of moving contact system.

### 5.2.3.7 Line System

**Description:** This subsystem represents a simple power system, consisting of an ideal generator with sinusoidal voltage output, the circuit breaker, and a non-ideal inductance as load. Its purpose is to represent the interactions between the circuit breaker and the power network.
**Inputs:**
1. Arc voltage from contacts.
2. Contact resistance.
3. Contact status.
4. Reciprocal inductance of load, normal value 100.
5. Online status of circuit breaker: 0 = disconnected, 1 = online.

**Outputs:**
1. Source side (busbar) voltage.
2. Load side (inductor) voltage.
3. Circuit breaker current.

### 5.2.3.8 Auxiliary Contacts Linkage

**Description:** This linkage transfers the piston movement to the auxiliary contacts block, as long as it is in working order.

**Inputs:**
1. OK-status of linkage: 1 = OK, 0 = broken.
2. Piston position.

**Output:** Linkage position on auxiliary contacts side.

### 5.2.3.9 Auxiliary Contacts
**Description:**

The auxiliary contacts are actuated by the main piston via a separate linkage. The toggle position of every contact can be individually adjusted.

When the circuit breaker is open, a type A contact is open and a type B contact is closed. Among other purposes, they are used to interrupt the trigger coil current after a circuit breaker operation.

**Inputs:**

1. Linkage position from auxiliary contacts linkage, normally in the range 0...1.
2. Alignment, i.e. linkage position where the contact toggles, plus/minus a mechanical hysteresis of 0.01. Normal values here are 0.93 for the type A contact and 0.26 for the type B contact.

**Output:**

Electrical contact status: 1 = closed, 0 = open.

---

5.2.3.10 Motor Limit Switch

**Description:**

When the position of the main spring falls below a threshold level, the motor limit switch turns on the pump motor in order to replenish the hydraulic fluid lost from the high pressure volume. The trigger lever is actuated by a guide bar moving with the spring piston.

The model of this limit switch includes a primitive representation of mechanical inertia (namely, a velocity limiter) and a mechanical hysteresis of 0.03.
**Inputs:**
1. Motor supply voltage, normal value 1.0.
2. Spring position.
3. Alignment of limit switch, i.e. the threshold for toggling the contact. Normal value 1.0.

**Output:**
Switched voltage to pump motor.

### 5.2.3.11 Pump Motor

The motor drives the hydraulic pump which transports hydraulic fluid from the low pressure reservoir into the high pressure volume, building up pressure against the main spring.

This motor was modeled as a simple DC machine.

**Inputs:**
1. Supply voltage from pump limit switch.
2. Mechanical load on motor.
3. Electrical conductance of motor, normal value 1.0.
4. Initial rotational speed (at start of simulation), normal values 0.0 or 1.0.

**Outputs:**
1. Rotational speed of motor.
5.2.3.12 Pump Gear

**Description:** The pump gear transfers the mechanical torque from the pump motor to the pump itself, as long as it is in working order.

**Inputs:**
1. Rotational motor speed.
2. Mechanical load on the gear, from the pump.
3. OK status of gear: 1 = OK, 0 = broken.
4. Mechanical friction of gear, normal value 0.05.

**Outputs:**
1. Rotational speed of gear.
2. Load from gear on the motor.

5.2.3.13 Hydraulic Pump

**Description:** The hydraulic pump transports hydraulic fluid from the low pressure reservoir into the high pressure volume, building up pressure against the main spring.
Inputs:  
1. Gear speed.  
2. Hydraulic pressure in high pressure volume.  
3. Oil delivery of pump, normal value 1.0. This value represents the condition of the pump: values below 1 indicate a problem, a value of 0 means no oil is delivered at any speed.

Outputs:  
1. Amount of hydraulic fluid pumped into the high pressure volume.  
2. Mechanical load on the gear.

5.2.3.14 High Pressure Volume

Description: This is the part of the hydraulic system that is pressurized by the main spring. The hydraulic fluid delivered by the pump is stored here until the circuit breaker is operated.

Inputs:  
1. System pressure applied by the main spring.  
2. Amount of fluid delivered by the pump.  
3. Position of changeover valve. This is used to allow for the loss of fluid when the valve is between its end positions.  
4. Main piston position. Used for the loss of fluid during operation of the circuit breaker.  
5. Size of hydraulic leak, normal value 0.0.
Output: Amount of hydraulic fluid entering the high pressure volume. A negative value indicates a loss, which would have to be replenished by the pump.

5.2.3.15 Main Spring

Description: The spring pressurizes the hydraulic high pressure volume, thus it is the power source for operations of the circuit breaker. The non-linear pressure over position characteristic is entered by means of a lookup table.

Inputs:
1. Oil flow into high pressure volume.
2. Initial spring position at start of simulation, normal value 1.0.
3. Motion limit on charged side of the spring, normal value 1.0.
4. Motion limit on discharged side of the spring, normal value 0.0.
5. Strength of spring (spring constant), normal value 1.0.

Outputs:
1. Spring position.
2. Hydraulic pressure generated by spring force.
5.2.3.16 Potential and Current Transformers

Description: Basically, the current or voltage transformers are modeled as transducers that do or don't transmit the input signal to the output. The motor current transformer has an additional limiting characteristic to represent the saturation of the current probes used for the measurements.

Inputs: 1. Input voltage or current.
2. Transformation ratio, normal value 1.0. A value of 0.0 indicates a malfunctioning sensor, -1.0 represents wrong polarity connection.

Output: Output voltage or current.

5.2.3.17 Travel Sensor

Description: Just like the current and voltage transformers, the travel sensor is modeled as a transducer that does or doesn't transmit the travel position signal to the output.

Inputs: 1. Linkage position.
2. Sensor operation, normal value 1.0. A value of 0.0 indicates a malfunctioning sensor, -1.0 represents wrong polarity connection.

Output: Contact position signal.
5.2.3.18 Stop logic

![Logic diagram]

**Description:** The purpose of this subsystem is to stop the simulation after a certain time, or when the pump motor stops running.

**Inputs:**
1. End time of simulation, normal value 0.3 seconds.
2. Current simulation time
3. Motor energization status (0 = off, 1 = on).

**Output:** Stop signal (1 = stop simulation).

5.2.4 Using the Computer Model

With the model structure created, the model parameters need to be adjusted in order to match the particular circuit breaker under observation. This was done manually, using information from the manufacturer as well as data from the measurements, so that it represents operation of the breaker as closely as possible.

Each model input (the numbered oval elements with lines emerging from them in Fig. 6) represents a variable model parameter. The default values for normal operation were given in the previous section. Each input value can be changed individually to simulate malfunction of any circuit breaker component.

The model features thirteen outputs, which correspond to the sensors on a real circuit breaker. After a simulation run, the model returns a
matrix containing the trajectories of each output over the entire simulation. The outputs are,

1. source side voltage,
2. load side voltage,
3. circuit breaker current,
4. travel curve of linkage/contacts,
5. Close voltage before auxiliary contact 52b,
6. Trip voltage before auxiliary contact 52a,
7. voltage across close coil,
8. voltage across trip coil,
9. current through close coil,
10. current through trip coil,
11. voltage across pump motor,
12. current through pump motor,
13. position of main spring.

An example for simulation results under normal and fault conditions is shown in Fig. 7. The contact travel trajectory is shown for two opening operations; the measurements on the real circuit breaker are displayed for comparison. At first everything was in normal condition (a). Then an artificial fault was introduced, namely the hydraulic flow cross-section for opening operations was reduced by turning a throttle screw, resulting in dramatically slower motion of the contacts (b). It can be seen that the measured and simulated curves match very well, which is also the true for the other quantities measured on the real circuit breaker. Thus, the model is a suitable foundation for diagnostic tasks on the particular circuit breaker.
5.3 Discussion

It has been shown that it is possible to create a computer model of a high voltage circuit breaker from individual component models. Experiments have proved its accurate agreement with the behavior of the original circuit breaker. It can therefore be used as the basis for a quantitative monitoring and diagnosis system.

For application of the model in practical use, the following improvements are suggested:

- Adaptation of model parameters to each circuit breaker specimen. For the test implementation described in this work, the model parameters were adjusted manually. For commercial use, it would make sense to have the exact model parameters determined automatically, e.g. during commissioning. Of course, this is only necessary if the variations between circuit breakers are significant, which would need to be investigated first.

- On the basis of the existing model, a component library can be created, containing the different variants of HVCB parts. For ex-
ample, the operating mechanism can be delivered with an energy storage in the spring of 1 kJ, 4 kJ, or 8 kJ; this would be reflected by different “spring” subsystems.—By means of a simple model construction tool, the component models could be easily assembled into a complete model of the specific circuit breaker to be monitored.
6 Model-Aided Diagnosis: A Novel Strategy for Condition Diagnosis

With the application of condition assessment of high voltage circuit breakers in mind, various strategies for diagnosis were examined. Based on an analysis of the strengths and shortcoming of each diagnosis strategy (Section 2.4.2), the author has come to the conclusion that in principle a model-based monitoring and diagnosis system would be the best solution for online condition assessment of high voltage circuit breakers. However, the cost and the computational complexity of presently available systems are forbiddingly high. Hence, a compromise was sought which would offer the principal advantages of MBD at much lower expense.

To this end, a novel strategy for diagnosis was developed; the author named it “Model-Aided Diagnosis” (MAiD). It is a combination of the model-based and the case-based approaches and offers several advantages of each while avoiding some of the disadvantages. The concept of MAiD was first published in [164].

6.1 Basic Concept

Model-aided diagnosis is based on a functional computer model of the device under observation. This model can accurately simulate the system’s behavior under normal and fault conditions. Its operation depends on internal parameters (e.g. an electrical impedance or a spring constant) as well as external inputs (operating conditions such as power supply voltage of the device or ambient temperature). When the model is presented with a combination of parameter and input values, it will yield the same data as would be measured by the sensors on the real-world system under the same conditions.
From the sensor data or simulation results, meaningful quantities for assessing the condition of the system are extracted; they are called \textit{features}. These features should be sensitive to certain changes in the system. The set of all these features at a given time is called \textit{system status}. In addition, it is helpful to compensate for dependencies of the extracted features on environmental influences such as temperature before further processing.

The basic strategy for MAiD is two-fold. First the computer model is used to simulate all possible faults; the resulting fault cases are stored in a database. Then, this database is used online for finding the most likely diagnosis when a deviation from normal operation has been detected. This is explained in detail in the next section.

\section*{6.2 General Strategy of Model-Aided Diagnosis}

The process of reaching a diagnosis by the model-aided approach shall first be explained in structogram form. Then each step will be elaborated individually.

The first part of model-aided diagnosis (Fig. 8) is executed offline on a workstation computer. It needs to be performed only once for every type of device.
Make a list of all possible (anticipated) combinations of the model input values.

For every feasible combination of input values from the list:

- Run a simulation on the computer model.
- Extract the system status from the resulting data.
- Store the system status, together with the input values that led to it, in a database for later reference.

Fig. 8: Part 1 (preparation) of MAiD.

The second part (Fig. 9) is performed on the target monitoring computer. It uses the database from Part 1.

- From the sensor data, extract the current system status.
- Current system status deviates from expected status? yes
- Look up the best matching simulated system status in the database from Part 1.
- Present the result as the current diagnosis.
- (Optional.) If possible, run additional simulations to refine the result.

Fig. 9: Part 2 (diagnosis) of MAiD.

Each step will be further explained in the following sections.
6.3 Part One: Preparation

This part of MAiD is executed off-line, on a computer which holds the model of the system to be monitored. Since quantitative simulation of analog systems requires a high performance computer, this could well be a high-end workstation. The computation results form a database, which is transferred to the target system (the computer that actually monitors operation of the device); there it is used to perform the actual diagnosis.

6.3.1 List of Model Inputs and Parameters

As a first step, MAiD requires a list of input and parameter values for the model. A model input describes an external influence on the system, e.g. the ambient temperature or the level of a supply voltage. These can usually be measured through appropriate sensors. Conversely, a model parameter describes a condition inside the system, such as a bearing friction or the strength of a spring (spring constant). In many cases, these parameters are not directly accessible for measurement and only manifest themselves through their influence on the system behavior. This holds true for the examples given above.

Every list entry contains either the entire set of input values or those parameters which deviate from their default value only. It is important to also include the no-fault case. For example, consider a mechanical circuit breaker model with a total of five inputs or parameters, each of them with normal values of 1.0. One of these parameters (#4) represents the strength of a spring i.e. the spring constant. To simulate a reduction in this parameter to a fault value of 0.1 using the first approach (entire set), the corresponding list entry would be of the form

\[ 1.0 \ 1.0 \ 1.0 \ 0.1 \ 1.0 \]

For the second approach (deviations only) it would be something like
The list should be exhaustive for the anticipated possible faults of each component, making it roughly equivalent to the fault models in model-based diagnosis [171]. Variations with time must be taken into account. With high voltage circuit breakers, the assumption of single or at the most double faults, i.e. only one or no more than two components fail simultaneously, is usually justified. With that, the number of combinations and thus the length of the list rises only with the first or second power of the number of inputs.

Using the fault list created above, the following steps are executed for every list entry.

### 6.3.2 Simulation

The computer model is presented with the input and parameter values from one list entry and a simulation run is started. The model generates the same outputs (data) that would be read from the sensors under the same external and internal operating conditions. One simulation is conducted for each item on the list, under all possible normal operating conditions.

Using the example from Subsection 6.3.1 for application on a HVCB, this means that the fault of reduced spring strength must be simulated e.g. for closing or opening the circuit breaker, with the CB connected to the net or not, etc. The same procedure is followed for every other fault in the list.

---

7 Dvorak [31] has pointed out that this is often not the case in operation of very large systems, where repair of known minor faults is deferred until a convenient time.
6.3.3 Model Status (Feature Extraction)

From the simulation results (model outputs), the model status is created. It consists of a set of $N$ numbers, the “features” of the data series.

Every model output, just like a sensor on the real system, creates a series of “readings”, a trajectory or time series, of the observed quantity. A feature is a single number that reflects one interesting aspect of this trajectory, or of several trajectories combined. An example of $N = 5$ features extracted from a contact travel curve on a HVCB include initial and final positions $p_i$ and $p_f$, initial delay $T_d$, total travel time $T_t$, and maximum travel velocity $v_m$ (Fig. 10).

![Figure 10: Contact travel curve with extracted features of position (initial and final), timing (delay and total), and velocity.](image)

It makes sense to select features of the kind that will change noticeably with variations in the model inputs and parameters. Combining the above example with that from Subsection 6.3.1, such a dramatic reduction in the strength of the main spring will significantly reduce the contact velocity and thereby the value of the $v_m$ feature. Therefore, this is a useful feature with the added advantage that it is also
meaningful to a human operator, who will more likely trust the diagnosis if he or she can duplicate the reasoning that led to it.

### 6.3.4 Generating the Diagnostic Database

The model status from the previous step, together with the model inputs and parameters, forms a new case in the diagnostic database for use in diagnosis. Again, either the entire set of features or only those parameters which deviate from their normal values are included. The information thus saved is essentially of two kinds:

1. Information that is equivalent to, or can be derived from, monitored quantities in the system, regardless whether it relates to an internal or an external parameter. These features are called “visible” features.

2. Information that cannot be derived from the monitored quantities, referred to as “hidden” features.

The data records (one for each case) should therefore be structured so that the visible and the hidden features, respectively, are grouped together, with easy lookup on the hidden from the visible ones. This is explained in greater detail below. Also, the analog (continuous) and digital (binary) features should be kept together to facilitate calculation later (Subsection 6.4.3). Note that this database should be in a format which can be conveniently transferred to and processed by the diagnosis computer.

For example, using the five-inputs model from Subsection 6.3.1 and the features from Subsection 6.3.3, it is assumed that the normal value of each feature is also 1.0. With that, two of the data records might contain the following data:

<table>
<thead>
<tr>
<th>Par. number</th>
<th>Par. value</th>
<th>Analog features</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>1.0 1.0 1.0 1.0 1.0</td>
</tr>
<tr>
<td>4</td>
<td>0.1</td>
<td>1.0 1.0 1.1 7.7 0.1</td>
</tr>
</tbody>
</table>

The first row is the no-fault case, which is indicated by parameter number 0. The second one is the fault case discussed above.
At first glance, this database bears some resemblance to the concept of "Fault Dictionaries" (see e.g. [41]). However, the fundamental difference is that MAiD does not attempt to simulate and record all possible faults, which is impossible for analog systems, anyway. Rather, the idea is to include a number of selected cases that may occur in reality; then, the best match needs to be found for the diagnosis.

6.4 Part Two: Diagnosis

This part of MAiD is executed on-line and automatically by the diagnostic computer. It uses the diagnostic database created in Part 1 to find the most likely cause of a detected anomaly.

6.4.1 Extract System Status

From the sensor data, the same $N$ features as in Subsection 6.3.3 are extracted, forming the system status. Obviously, only the visible features (Section 6.3.4) can be obtained; the aim is to derive the corresponding invisible features, too. For continuous monitoring, the data need to be partitioned chronologically such that every section is equivalent to a simulation run. These sections may overlap.

Example: For condition assessment of a hydraulic operating mechanism's spring and charging system, the motor voltage and motor current are monitored. As long as the motor is off there is no need to analyze its voltage and current. The only quantity that needs to be measured during that time is the interval between two motor energizations. On the other hand, as soon as the motor is switched on, the voltage and current trajectories are recorded to yield such features as running time, peak current, and steady state current. In addition, it is important to distinguish whether the motor was energized in consequence of a switching event or because of gradual pressure loss (assuming the pressure or spring position is not monitored directly). Hence, an obvious segmentation point of the measured data in this case is at every motor start or switching event (where the latter is expected to precede the former by a few milliseconds).
6.4.2 Detect Deviations

The system status is tested for deviations from the normal or expected values; these deviations are called symptoms. In many cases a simple threshold check will be sufficient. For features which are dependent on other quantities, such as the variation of operating times with temperature, the dependencies must be compensated beforehand, or the threshold must be shifted accordingly [26].

It is possible to omit this step and feed the entire system status, as extracted from the sensor data, directly into the next step. This has advantages for processing speed but is detrimental to full documentation of the diagnostic process, i.e. to explain to the user the reasoning that led to the final decision.

6.4.3 Find Case in Database

The system status, or collection of \( N \) symptoms/features, is now looked up in the database. However, it is unlikely that all analog values will exactly match any case from the simulations. Therefore, it makes sense to choose the case that resembles the current system status "most closely" as the diagnosis. From a theoretical viewpoint, this is a simplification of the CBD case matching problem [36].

This notion of similarity can be interpreted geometrically by considering every case in the database as well as the current system status a vector in \( N \)-dimensional space, where each dimension represents one of the \( N \) features contained in each case. That case vector which has the least distance from the system status vector is the one selected as current diagnosis. This approach is called the single nearest neighbor (1-NN) method in classification theory [63].

Generally, the 1-NN method is to assign a new object (vector) \( \mathbf{x} \) to one of a number of predetermined groups of objects such that the selected group contains the nearest neighbor of \( \mathbf{x} \). The low statistical significance of the single-element group structure used in MAiD (one model status per simulated fault) was shown not to impair the performance of this method. See Appendix A for details.
A simple graphical example for two features is presented in Fig. 11.

In this figure, the axes represent the features that are used for diagnosis. Three cases with different values of the features are depicted together with the current system status. It is obvious that even though the current system status has the same value for Feature A as Case 3 and its Feature B value is almost equal to that of Case 1, it is “closest” to Case 2. Hence, with these measurements Case 2 would be chosen as the current diagnosis.

The calculation of the distance between two feature vectors is not a trivial task. Literature on classification and cluster analysis (e.g. [17, 51, 167, 181]) contains numerous methods for doing so. Some of them are outlined in Appendix B.

Let the system status ($N$ features) be contained in vector $\mathbf{y}$ with elements $y_k$, and the features of the $c$th simulated case in vector $\mathbf{x}_c$ with elements $x_{c,k}$. It has been found that the distance metrics best suited for MAiD—giving the best results at low calculation effort—are the “city block” metric [51, 167, 181]

$$
\left(1\right)
$$

$$
d_1 = \sum_{k=1}^{N_a} |y_k - x_{c,k}|
$$
for analog (continuous valued) features and the “total distance” metric [167, 181]

\[ d_T = \frac{B + C}{A + B + C + D} = \frac{B + C}{N_b} \]  

(2)

for binary features. The values \(A\ldots D\) in (2) are taken from the contingency table [167, 181]

\[
\begin{array}{c|cc}
\_ & \_ & \_ \\
\_ & 1 & 0 \\
\_ & 1 & A & B \\
\_ & 0 & C & D \\
\end{array}
\]  

(3)

where \(B\) is the number of elements that are 1 in vector \(x_c\) and 0 in vector \(y\), etc.

The analog and binary distance measures are then combined into a single distance figure \(d\) by means of weighted addition [167],

\[ d = w_1d_1 + w_Td_T \]  

(4)

where \(w_1\) and \(w_T\) (the weight factors for the analog and binary distances \(d_1\) and \(d_T\), respectively) are either unity or the number of features contained in each vector. For a detailed explanation of the symbols used here refer to Appendix B, which is devoted to the topic of distance calculation and also points out some practical aspects.

This distance is calculated between the current system status and every case in the database. The output of this step is the best matching case, or a list of cases, selected from the database. It contains not only the visible features, derived from the sensor readings, but also the corresponding hidden features. Thus it yields valuable information about quantities that are not normally accessible to inspection.
6.4.4 Report Diagnosis

The diagnosis (or list of probable diagnoses) found in the previous step can now be reported to a supervisor, in most cases a human operator. However, this diagnosis as it comes out of the database is just a set of numbers, which will probably not be very meaningful to the person receiving the problem report. The result needs to be processed in order to plainly show the nature and location of the diagnosed problem.

Since the simulated fault situation has been known at the time of creating the problems list (Subsection 6.3.1) it should be easy to include a text field describing the problem with each record in the database. This text can be presented to the user, together with a list of the most significantly deviating parameters. That way, the operator is informed of the situation and can initiate the necessary steps to restore the system to proper operation.

6.4.5 Additional Simulations (optional)

If the features of the simulated case selected as diagnosis do not match the system status exactly, as is likely to be the case, it is possible to run additional simulations to pinpoint the problem more precisely. Since the general location and type of the fault are already known, one or two simulation runs should be sufficient for an exact assessment of the situation.

For example, consider a friction parameter with a default value of 1; the database contains simulated cases with fault values of 10 and 100. If during matching these two cases were found as most likely diagnoses, additional simulation runs could be performed with parameter values of 3, 30, and 300; the results, compared with the system status, should produce an even better match for the final diagnosis.

Obviously, this step is only possible if the model and simulation software are accessible to the user. This might be the case at a larger plant containing several pieces of equipment (such as a high voltage
substation), where a single installation on one supervisory computer is sufficient, because the probability of a fault occurring in more than one piece of equipment simultaneously is very low.
7 Application of MAiD to High Voltage Circuit Breakers

This chapter describes the application of the theoretical knowledge from the previous chapters to high voltage circuit breakers (HVCBs).

7.1 Test Implementation of Model-Aided Diagnosis

Using the model described above, a test implementation of MAiD was created using MATLAB. It is a stand-alone application, tailored specifically to the application of diagnosing the condition of a high voltage circuit breaker. With that, the diagnostic database was created and used on the high voltage circuit breaker described above.

7.1.1 Fault List

In creating the fault list for MAiD, the single fault assumption (Section 2.4.2) was used, i.e. only one fault was considered at a time. Each entry contains only those parameters that deviate from the default values (cf. Section 6.3.1). A total of 83 faults were included in the list.

For as complete coverage as possible, eight operation modes were considered for simulation, namely all possible combinations from

- circuit breaker closing or opening
- breaker online or offline, and
- spring fully or half charged.

Whereas the fault list is explicitly contained in a text file, the operation modes are an implicit part of the simulation module, which is described below.
7.1.2 Data Base Generation

For generating the database, the fault list is read from the file. The operation mode is combined with the current list entry to form the complete input parameters vector for the model. Every fault or operation mode is simulated by a combination of model inputs, therefore the procedure is as follows:

1. Load the default values for simulation.
2. Adjust the parameters for the operation mode.
3. Modify the parameters for the fault to be simulated.

A plausibility check assures that only logically possible combinations can be entered, e.g. the piston cannot assume an initial position of 2 if its upper motion limit is 1.

This parameter vector is passed to the model and a simulation run is started. It returns the trajectories of the model outputs (see Subsection 5.2.4). From these, the selected features are extracted and stored in the database.

The database consists of three text files. The first contains the complete vector of features for each simulation run. The second contains the combination of operation mode and fault that was used for each simulation run. The third one contains a description of which features are analog and which are binary; this information is necessary for distance calculation in the diagnosis part (cf. Section 6.4.3).

7.1.3 Diagnosis

Since no online connection to a real circuit breaker was available for this test implementation, it was designed to read its input data from a file. In case these data are from real measurements, they are scaled to the standard value range of 0...1, in order to match the model outputs, before further processing.—It is conceivable that this strategy would be followed in an online implementation, too, where the data acquisition module writes the measured data to a file, from where they are retrieved and analyzed by the MAiD module.
From the trajectories of the data, a number of features are extracted to form the circuit breaker status (Section 6.4.1). All the features used here are described in detail in Appendix C.—Due to the virtually unlimited number of methods for data processing it is impossible to find the theoretically optimum set of features for abducting a diagnosis. Hence, the main criteria for selecting the features were,

- low effort for calculation,
- good indication of change in the circuit breaker’s behavior,
- meaningful to maintenance personnel without scientific training.

In the next step, the distance of the circuit breaker status—formed by the set of features—from each of the cases contained in the data base is calculated. As described in Section 6.4.3, the “city block distance” is used for the analog features (after scaling to zero mean and unity variance) and the “total distance” for the binary ones. The distinction between analog and binary is made by means of the data in the third file of the database (Section 7.1.2). Missing values are omitted from the calculation (cf. Appendix B).

The results are written into a list of distances, sorted in ascending order. Hence, the first case in this distance list points to the case that best matches the circuit breaker status. This is the one that is returned as the most likely diagnosis.

The output of the diagnosis consists in a set of seven numbers. They are,

1. circuit breaker operation (detected from the data),
2. online status of circuit breaker,
3. initial charge status of main spring (fully or half),
4. number of model input responsible for the fault,
5. matched value of model input responsible for the fault,
6. calculated distance between circuit breaker status and best matching case,
7. pointer to matched case in database.
For better understanding, these numbers can be translated into plain text briefly describing the diagnosis result.

7.1.4 Confidence of Diagnosis

In every application of computerized diagnosis it is desirable to know how "sure" the diagnosis is, i.e. how much confidence the diagnosis engine has in its own conclusions. This is particularly relevant for this test implementation of MAiD, where only one diagnosis is reported as the result even if more than one case match the system status rather closely.

For assessing the credibility of each diagnosis, a "confidence value" $c_i$ ($0 \leq c_i \leq 1$) was introduced. If all possible diagnoses are ordered by their distance from the system status in ascending order, where the best match has index 1 ($x_1$), this confidence value is defined as

$$c_i = \frac{d_i - d_1}{d_i}, \quad i > 1$$

$d_1$ ....... distance between observation vector (system status) $y$ and best matching case $x_1$ in database,

$d_i$ ....... distance between observation vector (system status) $y$ and $i^{th}$ best matching case $x_i$ in database.

This is an empirical estimate of the non-ambiguity of the diagnosis. Normally it is calculated for $i = 2$. A value of $c_i = 1$ means the best matching simulated diagnosis agrees exactly with the observation, $c_i = 0$ indicates there were at least $i$ equally applicable diagnoses found.

7.1.5 User Interface

In order to facilitate the use of this MAiD implementation, a simple user interface was created. Depending on the application on simulated or actually measured data, the user is prompted for the name of a file containing the recorded trajectories. The data in this file are evaluated according to the MAiD strategy and the results are pre-
presented in a tabular window on the screen (Fig. 12). It gives the
circuit breaker online status and operation, and the diagnosis in the
form: faulty component, component parameter responsible for the
fault, and component parameter value (default, and matched from
database). In addition, all the features derived from the data with
their normal, measured, and matched values can be viewed. This is
intended to help the user understand the decisions made by the di-
agnostic system. The results can be viewed for the best and for the
second-best matching cases (called “first diagnosis” and “second di-
agnosis”).

![Image of user interface](image)

**Fig. 12**: User interface for diagnosis result in test implementation
of MAiD, shown with sample diagnosis of real measured data. See
text for description of window elements.
7.2 Test Results

7.2.1 Tests with Simulated Data

To establish the initial accuracy of the MAiD system, the same faults that are contained in the fault list were used to simulate a problem with the HVCB under observation. White Gaussian noise of varying intensities (standard deviations of zero and from $10^{-6}$...$10^{-1}$, the latter corresponding to signal to noise ratios of 120...20 dB) was added to the simulated trajectories before they were fed into the diagnostic module\(^8\). The tests were conducted at numerical resolutions—for both the fault cases and the new simulations—of 8, 12, and 16 bits, and at the full accuracy of MATLAB (64 bit IEEE floating point format).

As expected, as long as the noise was below the numerical resolutions, every simulated fault was identified practically without error. With increasing noise, the number of misclassifications rose, too, until it was practically useless at S/N ratios of 40 dB and below.

These results from the noisy data could be significantly improved by applying digital filtering to the trajectories before feature extraction. The filter used is of the moving average type

$$\tilde{y}_k = \sum_{m=-l}^{l} w_m y_{k+m}, \quad l \geq 0 \quad (6)$$

where:

- $w_m$...... weight of data point $y_{k+m}$,
- $l$ ......... length of window on either side of $y_k$,

with symmetrical triangular weighting of the data points (Fig. 13),

$$w_m = \frac{1 - \frac{|m|}{l+1}}{l+1}, \quad w_{-m} = w_m \quad (7)$$

\(^8\) With added noise, this is not only a test for the usefulness of the MAiD strategy, but even more so for the robustness of the diagnostic features used in this implementation.
which has the advantages of not changing the energy content of the filtered signal, and of not introducing any time delay into level changes. However, use of this filtering technique is only recommended if an identical filter is used for building the database, because some features may be changed, e.g. narrow peaks will be flattened.

![Triangular window for moving average.](image)

**Fig. 13:** Triangular window for moving average, shown for \( l = 1 \) (dotted line), 2 (solid line), and 3 (dashed line). For any \( l \), the sum of all \( w_m \) is always 1.

In several cases without added noise, the wrong type of fault was reported as the diagnosis, apparently a misdiagnosis. However, a closer look revealed that this only surfaced a problem inherent to all automated diagnosis systems: if two different faults are manifested by identical symptoms there is no way of finding the correct one without additional information. Statistical data on the likelihood of the various faults may help in making a decision. Still, the diagnosis thus found cannot be proved correct.—For example, with the sensors or model outputs used in the test implementation, a fallen circuit breaker in the close circuit cannot be distinguished from a severe maladjustment of the type B auxiliary contact such that it will never close. This is a significant argument for displaying a list of the most likely diagnoses in a practical implementation of MAiD.—Apart from this ambiguity, all simulated faults without noise were diagnosed correctly with confidence 1.
7.2.2 Laboratory Test on a Real High Voltage Circuit Breaker

One pole of the same HVCB that served as template for the model was used for experiments with the MAiD implementation. Since several sensors are permanently installed on it, it was an almost ideal test object.

For the experiments, the circuit breaker was disconnected from any high voltage source. The following quantities were measured on the breaker: close and trip coil energization (before the auxiliary contacts), close and trip coil voltage (after the auxiliary contacts), close and trip coil current, linkage travel, motor voltage, motor current. These quantities were recorded by means of a PC-based monitoring system (12 bit resolution, 10 kSamples/s on each channel, recording time 300 ms) and evaluated off-line at a later time. No spring travel sensor was available, hence the spring position after each operation was estimated by the operator. It is believed that monitoring this quantity directly would have further increased the diagnostic confidence.

Several abnormal operating conditions were applied to the circuit breaker, namely,

1. The hydraulic flow cross-section was reduced by turning the throttle screw one or three turns, causing a low opening velocity (cf. Fig. 7).

2. A differently aligned pump motor switch was used for controlling the motor, namely the one normally used for CO lockout, to simulate misalignment of the spring limit switch, which resulted in low spring charge.

3. The control voltage for opening or closing the breaker was changed from the default value of 110 V to 80 V or 130 V, respectively.

At first, one change was made at a time; later, up to three changes were applied simultaneously. Altogether, 66 experiments were made, with three each under identical circumstances, i.e. the circuit breaker
was closed and opened three times after every change. A summary of the experiments together with the diagnosis results is presented in Table 1.

Table 1: Results of laboratory test of MAiD on real high voltage circuit breaker. Abnormal conditions are flagged with an asterisk. See text for details.

<table>
<thead>
<tr>
<th>Operating conditions</th>
<th>Diagnosis</th>
<th>conf.</th>
<th>next best match</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>best match</td>
<td>(first diagnosis)</td>
<td>(second diagnosis)</td>
</tr>
<tr>
<td>operation voltage</td>
<td>spring</td>
<td>velocity</td>
<td></td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>2.8%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full full</td>
<td>no problem</td>
<td>2.1%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>3.2%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full full</td>
<td>no problem</td>
<td>2.2%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>42.5%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 110 V half* full</td>
<td>limit switch misaligned</td>
<td>15.2%</td>
<td>no problem</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>24.9%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* full</td>
<td>limit switch misaligned</td>
<td>10.3%</td>
<td>no problem</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>28.6%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* full</td>
<td>limit switch misaligned</td>
<td>10.3%</td>
<td>main contacts friction increased</td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>0.6%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full medium*</td>
<td>hydraulic damping increased</td>
<td>35.2%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Operating conditions</td>
<td>Diagnosis</td>
<td>conf.</td>
<td>next best match (second diagnosis)</td>
</tr>
<tr>
<td>-----------------------</td>
<td>--------------------</td>
<td>----------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td></td>
<td>best match (first diagnosis)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>2.8%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full medium*</td>
<td>hydraulic damping increased</td>
<td>27.3%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>2.9%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full medium*</td>
<td>hydraulic damping increased</td>
<td>35.5%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>3.5%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full low*</td>
<td>hydraulic damping high</td>
<td>31.7%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>3.1%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full low*</td>
<td>hydraulic damping high</td>
<td>35.4%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 110 V full full</td>
<td>no problem</td>
<td>3.4%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V full low*</td>
<td>hydraulic damping high</td>
<td>30.9%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>24.9%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* low*</td>
<td>hydraulic damping high</td>
<td>15.2%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>24.0%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* low*</td>
<td>hydraulic damping high</td>
<td>18.9%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>33.5%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* low*</td>
<td>hydraulic damping high</td>
<td>14.4%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>29.1%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Operating conditions</td>
<td>Diagnosis</td>
<td>conf.</td>
<td>next best match (second diagnosis)</td>
</tr>
<tr>
<td>----------------------</td>
<td>-----------</td>
<td>-------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td><strong>Operating voltage</strong></td>
<td><strong>Spring velocity</strong></td>
<td><strong>Diagnosis best match (first diagnosis)</strong></td>
<td><strong>Control voltage low (breaker online)</strong></td>
</tr>
<tr>
<td>Open 110 V half* medium*</td>
<td>hydraulic damping increased</td>
<td>2.9%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>28.2%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* medium*</td>
<td>hydraulic damping increased</td>
<td>4.6%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 110 V half* full</td>
<td>limit switch misaligned</td>
<td>35.7%</td>
<td>spring motion limit (low) displaced</td>
</tr>
<tr>
<td>Open 110 V half* medium*</td>
<td>hydraulic damping increased</td>
<td>0.1%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 90 V* full full</td>
<td>control voltage low</td>
<td>33.8%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 90 V* full medium*</td>
<td>hydraulic damping increased</td>
<td>18.2%</td>
<td>control voltage low</td>
</tr>
<tr>
<td>Close 90 V* full full</td>
<td>control voltage low</td>
<td>30.1%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 90 V* full medium*</td>
<td>hydraulic damping increased</td>
<td>15.8%</td>
<td>control voltage low</td>
</tr>
<tr>
<td>Close 90 V* full full</td>
<td>control voltage low</td>
<td>28.1%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 90 V* full medium*</td>
<td>hydraulic damping increased</td>
<td>16.8%</td>
<td>control voltage low</td>
</tr>
<tr>
<td>Close 90 V* half* full</td>
<td>control voltage low</td>
<td>2.3%</td>
<td>control voltage low (breaker online)</td>
</tr>
<tr>
<td>Open 90 V* half* medium*</td>
<td>control voltage low</td>
<td>3.1%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 90 V* half* full</td>
<td>control voltage low</td>
<td>3.9%</td>
<td>control voltage low (breaker online)</td>
</tr>
<tr>
<td>Open 90 V* half* medium*</td>
<td>control voltage low</td>
<td>2.9%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 90 V* half* full</td>
<td>control voltage low</td>
<td>11.2%</td>
<td>control voltage low (breaker online)</td>
</tr>
<tr>
<td>Operating conditions</td>
<td>Diagnosis</td>
<td>conf.</td>
<td>next best match</td>
</tr>
<tr>
<td>----------------------</td>
<td>-----------</td>
<td>------</td>
<td>----------------</td>
</tr>
<tr>
<td>Open 90 V* half* med*</td>
<td>control voltage low</td>
<td>3.8%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 130 V* full full</td>
<td>control voltage high</td>
<td>40.5%</td>
<td>(breaker online)</td>
</tr>
<tr>
<td>Open 130 V* full med*</td>
<td>hydraulic damping increased</td>
<td>14.5%</td>
<td>main contacts friction increased</td>
</tr>
<tr>
<td>Close 130 V* full full</td>
<td>control voltage high</td>
<td>43.9%</td>
<td>(breaker online)</td>
</tr>
<tr>
<td>Open 130 V* full med*</td>
<td>hydraulic damping increased</td>
<td>12.5%</td>
<td>main contacts friction increased</td>
</tr>
<tr>
<td>Close 130 V* full full</td>
<td>control voltage high</td>
<td>47.1%</td>
<td>(breaker online)</td>
</tr>
<tr>
<td>Open 130 V* half* med*</td>
<td>hydraulic damping increased</td>
<td>14.2%</td>
<td>main contacts friction increased</td>
</tr>
<tr>
<td>Close 130 V* half* full</td>
<td>control voltage high</td>
<td>5.2%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 130 V* half* med*</td>
<td>hydraulic damping increased</td>
<td>3.1%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 130 V* half* full</td>
<td>control voltage high</td>
<td>7.9%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 130 V* half* med*</td>
<td>hydraulic damping increased</td>
<td>1.4%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 130 V* half* full</td>
<td>control voltage high</td>
<td>7.0%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 130 V* half* med*</td>
<td>control voltage high</td>
<td>5.4%</td>
<td>linkage friction high</td>
</tr>
<tr>
<td>Close 130 V* half* full</td>
<td>control voltage high</td>
<td>20.4%</td>
<td>no problem</td>
</tr>
<tr>
<td>Open 130 V* half* low*</td>
<td>hydraulic damping high</td>
<td>12.4%</td>
<td>hydraulic damping increased</td>
</tr>
<tr>
<td>Close 130 V* half* full</td>
<td>control voltage high</td>
<td>9.3%</td>
<td>no problem</td>
</tr>
</tbody>
</table>
### 7.2.2.1 Discussion of Results

In every case, the abnormal condition (or one of them in case of multiple faults) was correctly identified from the measured data. Obviously, the confidence values were higher for the single fault cases than for the multiple faults. In addition, the confidence was further increased by quantizing the simulation results to match the resolution of the measured data. The maximum confidence values achieved were above 40%, values around 20% still indicate a good match.

With 100% correct fault identifications and no false alarm, the performance of this simple MAiD implementation is good. Confidence values above 10% for the first diagnosis can be considered sufficient. Conversely, the cases with lower values call for closer examination. Here it can be helpful to take a look at the second diagnosis.

- In many cases from Table 1, the second diagnosis describes a fault mode that cannot be distinguished from the first one given the respective operating conditions. Most notably, this is true for a slightly misadjusted lower motion limit of the main spring (“spring motion limit (low) displaced”). Normally, the spring only moves within the upper portion of the possible range (roughly within [0.7, 1] in the normalized model). A lower motion limit of 0.3 would therefore produce the same features as the no fault case and would only be manifested under unusual circumstances where the spring was almost completely discharged.
• In a few cases, the first and second best matches both read “control voltage high/low”. Here, the second diagnosis assumed that the breaker was online (connected to high voltage), which of course was not correct. This error can be explained as follows: The only features that give an indication whether or not the breaker is online are the final status (on or off) and the times of status change of the primary load voltage and current trajectories (see Appendix C for details). In offline mode, no change times can be detected, thereby removing these missing features from the distance calculation (cf. Subsection 7.1.3). From this, two simple methods for improving confidence can be envisioned:
  a. introduce a feature that unmistakably gives the online status of the circuit breaker, or
  b. determine the initial conditions of the breaker (e.g. online or not) first, and use only the corresponding portion of the database for diagnosis.

• In the multiple fault cases involving an only halfway charged spring, this condition (or rather the misadjusted limit switch that led to it) is not among the first two diagnoses. This calls for an analog spring position sensor on the mechanism, which is expected to significantly increase the discriminatory power of MAiD or, for that matter, of any HVCB condition monitoring and diagnosis system.

• In some multiple fault cases, increased hydraulic damping was mistaken for increased friction in the linkage as second diagnosis. This is due to the inherent difficulty of discerning the source of increased friction in a mechanical chain without intermediate measuring points. Therefore, it is practically impossible to improve the diagnosis for this case.

Over all, with only correct diagnoses and no false alarm, the performance of this simple MAiD implementation is good. In case of a fault diagnosis with low confidence, the displayed features can help to confirm the diagnosis, either by the operator or the manufacturer.
7.3 Discussion of MAiD

MAiD is a powerful combination of the model-based and case-based approaches to diagnosis. Originally developed for diagnosing high voltage circuit breakers, it can be used for condition assessment of most kinds of technical equipment with moderate expenditure as long as a functional model of the device exists. Results with a simple test implementation on simulated and actually measured data have been promising for practical application.

The development of MAiD was part of an overall effort to create an intelligent online monitoring and diagnosis system for high voltage circuit breakers. The major challenge is certainly to develop a system that will convince potential customers by its performance and competitive price. With its flexibility and low demand on the diagnostic computer’s resources, MAiD offers itself as an able but low cost choice of diagnosis engine.

7.3.1 Strengths

• Much like true model-based diagnosis, MAiD permits access to quantities that are not or cannot be directly measured in the system, helping to really pinpoint the location and kind of the problem.

• MAiD can be used for new types of equipment even before any operational experience has been gained since all conceivable faults can be simulated beforehand. Thus, a powerful system for condition monitoring and diagnosis can be supplied with the device from its first installation.

• With reasonable effort, the knowledge base can be made inclusive of all conceivable faults in the system. This completeness is facilitated by the fact that the model designer only needs to consider the possible faults of one component at a time and can set them down in the input (fault) list immediately.
MAiD exploits the data already present in a condition monitoring system. Hence, implementation is a matter of software only, which keeps the costs low.

The actual diagnosis (Part 2 of the algorithm) requires no more than finding the best matching case in a pre-defined database. As long as no sophisticated computations are used for data preprocessing or distance calculation it can be executed on a local supervisory computer with low computing power. Or, for even lower computing demands on the peripheral computer, only the feature extraction can be performed locally and the actual diagnosis performed by a central diagnosis computer, which may hold the databases of several pieces of equipment.

Adaptation to similar types of equipment can be performed fairly easily by modifying the model operating parameters to suit the new application. After that, all that needs to be done is generating a new database and installing it onto the diagnostic computer. Since the database is generated automatically the information contained therein should always be consistent and “clean” (i.e. free from measuring errors etc.).

If a fault not originally considered is encountered later it can easily be added to the local database if desired, provided the diagnosis software allows for this option. Thus the diagnostic system can learn from experience. In order to maintain consistency with other installations, though, the recommended procedure is to incorporate this fault into the input list or into the model if necessary, redo the simulations, and install the new database on the diagnosis computer.

7.3.2 Shortcomings

The initial effort for creating the computer model is still substantial. However, if it can be assumed that the model can be used for diagnosis on many similar systems the cost per installation (possibly including adaptation of the model parameters for a particular device) will decrease rapidly.
• As with true MBD, it is practically impossible to identify structural changes of the system or other faults that have not been incorporated into the model.

• MAiD works best for analysis of processes which display significant changes in the trajectories of the measured data within a short period of time. The reason is simply that when values change it is easy to derive meaningful features such as event timing, event duration, or rate of change. For supervision of normally constant or slowly changing processes, it is necessary to define events for conducting the diagnosis, either periodically or from certain changes in system operation. This is due to the fact that simulation of the operating condition needs to be conducted beforehand and can only cover a finite period. However, careful pre- and post-processing of the sensor and simulation data as well as selection of the features for diagnosis can to a large extent mitigate this limitation.

• If the occurrence of more than one fault at the same time shall be taken into account the database can grow very large, increasing the storage requirements on the diagnostic system. The same is true for high resolution of the simulated faults (i.e. the inputs are varied with very small intervals), although this is rarely necessary because in many practical applications a sufficient diagnosis comprises no more than the location and general type of the fault.

### 7.3.3 Possible Improvements

The following suggestions are envisioned as further improvements of the MAiD strategy.

• Algorithms for pre- and post-processing of the measured data for deriving additional features. This is particularly relevant for normally constant or slowly changing quantities such as the gas pressure in a high voltage circuit breaker, which has been assumed constant in the test implementation.
• Strategies for finding the correct diagnosis more quickly. With the present algorithm, every case in the database is examined as a possible candidate for diagnosis. Based on the features and perhaps failure statistics, it may be possible to eliminate certain faults from the start.—When doing so, the tradeoff between execution speed and the anticipated computational complexity must be considered.

• Automatic adaptation of the model parameters to the specific unit to be supervised. With that, a universal model could be used for many exemplars of a device, e.g. a high voltage circuit breaker, each of which varies slightly from the others.

• A learning facility, which would function something like this: Whenever a fault has been detected and verified, the operator is asked for an explanation of the problem. This description, together with all the features from the measured data, is added to the database as a new case for future reference.—Presumably, these data would also be of great interest to the manufacturer.

**7.3.4 Practical Aspects for Implementation**

In many cases, human operators are not willing to accept a computer’s solution to a detected problem at face value. Therefore, it is advisable to present the user with as detailed information as desired. For example, the first display may only indicate that a problem has been found and give the most likely diagnoses. With any of these selected, the corresponding most significant symptoms can be displayed to explain the reasoning that led to this conclusion.

Experiments with simulated and real data indicate that the optimum numerical resolution for the measured data is 12 bits. At higher resolutions, small statistical fluctuations may distort the results; at lower resolutions, details of the trajectories may get lost.—In addition, the highest confidence values were achieved when the resolution was equal for the simulated and the measured data.
7.3.5 Integration

MAiD is not intended as a stand-alone system but rather as an intelligent module of a larger monitoring and diagnostic system. In accordance with Section 2.3, other modules of such a system would include

- sensors,
- data acquisition and transmission,
- trend analysis and other methods of data analysis,
- information storage,
- user interface with data visualization.

While some examples of each of the above modules already exist, integration of them all, together with a diagnosis system, remains yet to be done.
8 CONCLUSIONS AND OUTLOOK

Failure statistics compiled from failure records of a specific circuit breaker manufacturing company have confirmed the results of the Second International Enquiry on Circuit Breaker Reliability by CIGRÉ. Again it was shown that most failures on high voltage circuit breakers (HVCBs) are mechanical in nature and are located in the operating mechanism. Therefore, the mechanism is the most important part to monitor in a HVCB.

It was also shown that many of the failures encountered could be detected, identified, or even predicted by a suitable condition monitoring and diagnosis system, using mostly commercially available sensors. Using such a system can therefore reduce the costs for maintenance of HVCBs.

A computer model of a HVCB was developed, consisting of submodels of the individual components. Its accuracy was demonstrated by comparing its outputs with the data from a real circuit breaker under various operating conditions. With that, it can serve as the knowledge base in a model-based diagnosis system.

Model-Aided Diagnosis (MAiD), a new diagnosis strategy introduced in this work, was developed with the aim of providing advanced diagnostic capabilities with low computing power. Specifically, it is aimed at implementation in existing condition monitoring devices, in order to assist the operator in identifying acute or incipient problems.

A rudimentary implementation of MAiD, using the HVCB model described above, was tested in computer simulations and in a laboratory test, using measured data from a real circuit breaker. In both cases, MAiD proved effective in correctly identifying all of the faults encountered, without any false alarm. The set of sensors installed on the laboratory circuit breaker proved sufficient for diagnosis, with one exception: an analog spring position sensor should be added to
increase the discriminatory power. Over all, the results are promising for future field installations.

In order to make the basic MAiD strategy even more useful for practical application, a few additional issues will need to be addressed. In particular, these include pre- and post processing of the sensor data (including time series partitioning and trend analysis), automatic adaptation of the model parameters to the specific device (HVCB) under observation, and a learning facility for updating the knowledge base. Also, a carefully designed user interface will help the operators understand and gain confidence in the diagnosis results of the MAiD system.
9 LITERATURE


10 Curriculum Vitae

Personal Information

Born on 21 February, 1965, in Vienna, Austria.

Citizen of Austria.

Married to Ilse Barbara Horwath since January 1999.

Education

1971-1975    Volksschule der Stadt Wien, Steinlechnergasse, Vienna, Austria.


1993-2000    Vienna University of Technology, Austria, and Swiss Federal Institute of Technology Zurich, Switzerland: Ph.D. studies (electrical engineering).
**Professional Experience**

1983-1984  Österreichisches Bundesheer: mandatory military service, 8 months.


1993-1997  Institute of Switching Devices and High Voltage Technology, Vienna University of Technology, Austria: research assistant.

1997-1998  High Voltage Laboratory, Swiss Federal Institute of Technology Zurich, Switzerland: research assistant.

1998 to present  ABB High Voltage Technologies Ltd., Switzerland: development engineer.

**Recognitions**

Swiss Electrotechnical Association, Switzerland: Innovation Award of the Power Engineering Society, 1998, for work on a device for controlled switching of high voltage circuit breakers.
A. **Case Classification**

From a theoretical point of view, finding the best matching fault case for a given system status is a classification task of the diagnostic type [35]. Classification, the assignment of an object to one of a number of predetermined groups [63], has been an essential research tool for a long time. With the arrival of capable computers, it is now possible to widely apply the theoretical methods that have been developed over the years.

Generally, the basic classification problem can be defined as follows. Let \( x \) be an object consisting of \( N \) features (numbers, measurements). Given \( G \) groups (also called strata or clusters [35]) of objects of the same type, the task of classification is to assign \( x \) to the group \( G_i \) "where it belongs", using the features of \( x \) and of all other objects. The goal is to develop an algorithm for this task, called classifier, which will perform this task automatically for all new objects \( x \). The classifier is usually designed to minimize the rate of misclassifications, i.e. of objects assigned to a wrong class. For that, the theoretical optimum can be achieved by applying Bayes' rule [63], which is to assign \( x \) to that group \( G_i \) where

\[
P (G_i|x) > P (G_j|x) \quad \text{for all } j \neq i. \tag{8}
\]

Here, \( P (G_j|x) \) is probability of \( x \) belonging to \( G_j \) or, more formally, the conditional probability of an object belonging to group \( G_j \) given the object is \( x \).

The practical obstacles to obtaining the probabilities necessary for applying Bayes' rule have given rise to numerous classification strategies. Most of these do not achieve the theoretical optimum in error rate but still yield good enough results for practical use. As James [63] put it, "In practice, it is never incorrect to use a classifier that works. Equally, there is no point to use a poor but theoretically
correct classifier." Even so, it is important to have an idea of the error rate of the classifier used.

A practical classifier with a good theoretical foundation is the "nearest neighbor method" (NN method) [63]. It amounts to assigning the new object to the group that the majority of its $K$ nearest neighbors belong to; therefore it is usually called "K-NN method". (The notions of nearness and neighbors deserve special attention and are treated in Appendix B.) Apart from being intuitively appealing, this method has two important advantages:

1. It can be used without knowledge of the distribution of the objects.

2. The error rate of Bayes' rule can be estimated fairly well, to allow comparison of the K-NN method with the theoretical optimum.

James [63] quotes some evidence that out of all possible values for $K$, the classifier with $K = 1$ has the lowest error rate. This 1-NN classifier simply assigns $x$ to the group that contains its nearest neighbor.

For the reasons outlined above, a 1-NN classifier was chosen for the diagnostic part of MAiD. An additional advantage of this method is that, subject to the choice of distance measure, it does not involve extensive mathematical operations such as matrix multiplication or inversion. Thus it also contributes to the goal of making the diagnosis suitable for systems with low computing power.

In MAiD, part of the basic strategy is to perform one simulation for each entry in the fault list. From the classification point of view, every model status thus derived is a member of a group of faults. Depending on how detailed the model and the fault list are, there will be a few groups of more than one elements (faults) that cannot be distinguished on the basis of the sensor signals given. However, most groups will consist of only a single fault case. Therefore, the nearest neighbor to a new system status is already the solution, the diagnosed problem.
Obviously, the fact of most groups consisting of only one vector assigns a low statistical significance to this classifier (cf. [35]). It would be possible to increase this significance by performing additional simulations with slightly modified model parameters. However, the group structure used was shown to perform well in all tested examples (see Section 7.2). Therefore it was not deemed necessary to increase the group size artificially.

This special configuration also makes it difficult to calculate the error rate. Out of the common estimators for classification error, only the "apparent error rate" [63] is feasible. It is obtained by classifying the same data that were used to construct the classifier, in this case all the simulated fault cases, and counting the number of misclassifications. As reported in Subsection 7.2.1, all simulated cases were classified correctly, hence the apparent error rate is zero. However, for finite sample sizes the apparent error rate always gives an estimate that is biased toward lower values, i.e. it is too optimistic. The true error rate can only be determined by evaluation of a large number of diagnosis results gathered in practical use, which were not available at this time. Then, if too many errors are encountered, the reason lies probably in the inaccuracies of the model. This may trigger an optimization cycle which can eventually yield a highly accurate diagnosis system.
B. Distance Calculation

In this chapter, generally applicable methods for calculating various measures of distance between two vectors are presented, with regard to application within a 1-NN classifier (cf. Appendix A) as used in model-aided diagnosis (MAiD). A few practical aspects such as missing values or the combination of analog and binary values are also discussed.

B.1 Definitions and Notation

\( y \) ........observation vector, containing the system status from the latest measurement.

\( y_k \) ........\( k^{th} \) element of \( y \), or \( k^{th} \) feature of system status.

\( a_y \) ........analog portion of \( y \), containing only the analog features \( a_y \).

\( b_y \) ........binary portion of \( y \), containing only the analog features \( b_y \).

\( x \) ........database containing the fault cases in vector form.

\( x_c \) ........fault case number \( c \) from \( x \).

\( x_{c,k} \) ........\( k^{th} \) element of \( x_c \), or \( k^{th} \) feature of case number \( c \) in \( x \).

\( a_{x_c} \) ........analog portion of \( x_c \), containing only the analog features \( a_{x_c} \).

\( b_{x_c} \) ........binary portion of \( x_c \), containing only the analog features \( b_{x_c} \).

\( N \) ........length of both vectors \( x_c \) and \( y \), or number of features used for distance calculation.

\( N_a \) ........length of both vectors \( x_c \) and \( y \), or number of analog features used for distance calculation.

\( N_b \) ........length of both vectors \( x_c \) and \( y \), or number of binary features used for distance calculation.
**B.2 Distance Measures for Analog Features**

For calculating the vector distance between two features, the Euclidean distance [17, 51, 167, 181]

\[ d_2 = \sqrt{\sum_{k=1}^{N_a} (y_{k} - x_{c,k})^2} \]  \hspace{1cm} (9)

is the choice with which users are most familiar. James [63] does not even mention any alternatives to it. However, there are other distance measures which may be used, such as the general Minkowski distance [51, 167, 181]

\[ d_L = \left[ \sum_{k=1}^{N_a} |y_{k} - x_{c,k}|^L \right]^{\frac{1}{L}}, \ L > 0 \]  \hspace{1cm} (10)

which is a generalization of the Euclidean distance. Here, \( L \) denotes the degree of the function; larger discrepancies in individual features are emphasized stronger with higher values of \( L \).

A different special case of the Minkowski distance, with \( L = 1 \), is the so-called city block distance [51, 167, 181]

\[ d_1 = \sum_{k=1}^{N_a} |y_{k} - x_{c,k}| \]  \hspace{1cm} (11)

which is particularly suitable for low-performance computers because no powers and roots need to be calculated.

Several authors, e.g. [167, 181], point out that, strictly mathematically, use of the Minkowski distance metrics is only permitted for uncorrelated features (orthogonal axes in vector space), which is not the case in most diagnostic applications. However, this is only a theoretical drawback. On the contrary, experiments with simulated and real data have shown that other distance measures that remove correlations between the features, such as the Mahalanobis distance [17,
are less robust against noise on the sensor data, and remove the "inherent weighting" of the data [181].

Another mathematical requirement is identical scaling of the features (axes) [167]; otherwise the features with the highest absolute values have the greatest influence on the resulting distance measure [181]. This effect is not desired, hence it is necessary to scale the data to zero mean and unity standard deviation by

$$\bar{x}_{c,k} = \frac{x_{c,k} - \bar{x}_k}{\sigma_k}$$  \hspace{1cm} (12)

where $\bar{x}_k$ is the empirical mean and $\sigma_k^2$ the empirical variance of feature $k$, as defined in [17, 167],

$$\bar{x}_k = \frac{1}{M} \sum_{c=1}^{M} x_{c,k}$$

$$\sigma_k^2 = \frac{1}{M} \sum_{k=1}^{M} (x_{c,k} - \bar{x}_k)^2$$

$M \ldots \ldots$ number of cases in database.

Of course, the system status vector $y$ needs to be scaled accordingly, too, before computing the distance.

**B.3 Distance Measures for Binary Features**

For binary features such as the status of a contact it is possible to define measures equivalent to the distance of analog vectors.

Let $x$ and $y$ be binary vectors, i.e. the elements are either 0 or 1, of identical length $N_b$. The agreements and disagreements of the corresponding elements are counted and arranged in the contingency table below:
Here, $B$ is the number of elements that are 1 in vector $i\mathbf{x}_c$ and 0 in vector $i\mathbf{y}$, etc. Based on this table, many similarity and dissimilarity coefficients have been defined. The most suitable “distance” measure for this purpose, placing equal emphasis on mutual ones and zeros in both vectors, is the “total distance” metric [167, 181], cf. [17, 51],

$$d_T = \frac{B + C}{A + B + C + D} = \frac{B + C}{N_b}.$$  

Note that always $0 < d_T < 1$, hence there is no need for scaling.

### B.4 Combining Analog and Binary Distance Measures

In literature, distance measures for analog and binary features are always treated separately. However, in a real world system such as a high voltage circuit breaker there are usually both kinds of quantities measured. Therefore, finding the “closest” case for a given system state is not a trivial task. In computer experiments with model-aided diagnosis it has proven effective to calculate the analog distance ($d_a = d_1$ or $d_a = d_2$, each with standardized values) and the binary distance ($d_b = d_T$) separately and combine them by means of weighted addition [167],

$$d = w_ad_a + w_bd_b$$

where $w_a$ and $w_b$ (the weight factors for the analog and binary distances $d_a$ and $d_b$, respectively) are either unity or the number of fea-
tures contained in each vector. This method has been shown to yield a figure well suited for comparing the simulated cases to the system status and thus finding the current diagnosis.

**B.5 Missing Values**

In gathering statistical information, researchers are often confronted with the problem that some data are missing from their records. For example, an interviewed individual may be unwilling to disclose a personal information, or some archived data may be incomplete. The question here is how to best use the available information without disturbing the overall results.

In practical application of automated diagnosis, too, it is possible that a data set (fault case)—simulated or measured—is missing one or more elements. Take for example a high voltage circuit breaker's time from close coil energization to the instant of contact touch (referred to as “closing time”) as one feature for distance calculation. If, for reason of some fault, the breaker never closes at all, the closing time cannot be measured, it is a “missing value”.

In principle, there are two methods of dealing with a missing value:

1. Assign it a value that allows meaningful processing [167]. In the above example, the user may decide to stop measurement of the closing time after one second and use this value as an indication of “breaker did not close”. This approach requires knowledge on why the value is missing, assuming that the occurrence of a missing value is in itself a valuable information. If this is the case, an appropriate value substitution may be applied. For automatic processing, it can only be recommended as long as a-priori only one reason for a missing value exists. Of course, the value to be assigned must be carefully selected in order not to disturb the results.

2. Omit the value in distance calculation. Several authors [17, 181] propose a modification of the Euclidean distance (9) to use only the $p$ elements containing available data in both vectors,
\[ p \, d_2 = \frac{1}{p} \sqrt{\sum_{k=1}^{p} (y_k - a_{x_c,k})^2}. \] (14)

This makes the results comparable even at varying numbers of features. \( p \) needs to be determined individually for each pair of vectors. The same type of modification can be applied to the other Minkowski type (10) distance metrics [167].

Other approaches to handling missing values, e.g. those based on the conditional densities of each feature [51], are computationally more expensive and are therefore not considered further here.
C. Diagnostic Features in Test Implementation of MAiD

The selection of features for diagnosis (or, more generally, for classification) is not a trivial task and has also received some attention in literature. For example, James [63] gives some methods for combining measured variables to give an optimum set of features, and for omitting the least relevant variables.—In application on time series, this matter is further complicated by the virtually unlimited number of mathematical operations that can be performed on the trajectories, each of them yielding a single feature. Hence, it is impossible to find a theoretically optimum set of features.

The strategy followed in the implementation of MAiD was therefore to use only such features which are meaningful to substation operation and maintenance personnel without advanced knowledge of mathematics or statistics. No optimization of the set of features was attempted. With that, it is more likely that the persons who will eventually use MAiD in their daily work will have greater confidence in the results it produces.

C.1 Definitions and Notation

The diagnostic features used in the test implementation of MAiD are derived from the (measured or simulated) signal trajectories from the circuit breaker. The data of each trajectory are contained in a vector, which is designated in bold italic type (e.g. \( p \) for the contact position or \( i_L \) for the load current). Every vector contains \( N+1 \) elements, sampled at equidistant times. Therefore, each vector element is implicitly time-stamped.

The elements of each vector are identified by a subscript index to the normal italic type symbol, e.g. \( i_{L,k} \) is the \( k \)th element of vector \( i_L \). The
first element of each vector, measured at the beginning of the observation interval, bears the index 0. The last one has the index \textit{N}.

Normally, the observation interval begins with energization of (i.e. applying voltage to) either the Close or the Open trigger coil. All times are measured relative to this event.

For the signals related to circuit breaker status or contact position, the values of 0 and 1 denote the fully open and closed positions, respectively.

A feature value of \textit{NaN} (Not a Number, a MATLAB constant) indicates that it was not possible to calculate a feature from the signals as defined. For example, a contact toggle time feature is calculated as \textit{NaN} when the contact wasn't toggled at all during the observation interval.

Below, each feature is described individually, together with the signals from which it is derived. The mathematical formula or algorithm is only given if it cannot be deduced readily from the text.

\textbf{C.2 Analog Features}

The value of these features can theoretically be any real number that can be represented by the computer running the MAiD algorithm.

\textbf{C.2.1 Toggle Time of Load Side Voltage}

\textbf{Description:} Time of first or last zero crossing in the load side voltage signal. \textit{NaN} if the load side voltage was on or off over the entire observation interval.

\textbf{Signals used:} Load side voltage \textit{u}_t.

\textbf{Calculation:} Definition of zero crossing: Data point \textit{u}_{t,t} is defined as zero crossing if \(|\text{sgn}(u_{t,t}) - \text{sgn}(u_{t,t-1})| > 0.

C.2.2 **Toggle Time of Load Current**

**Description:** Time of first or last zero crossing in load side voltage signal. *NaN* if the load current was on or off over the entire observation interval. The definition of a zero crossing is identical to that given above for the load side voltage.

**Signals used:** Load current $i_L$.

C.2.3 **Initial Static Contact Position**

**Description:** Position of the primary contacts before operation. The normal values are 0.0 in open position and 1.0 in closed position.

**Signals used:** Contact position $p$.

**Calculation:**

$$\frac{1}{L} \sum_{k=0}^{L-1} |p_k|,$$

where $L$ is the number of the first data points in $p$ for which $|p_k - p_0| < \Delta_T$ holds ($\Delta_T$ is the threshold value).

C.2.4 **Final Static Contact Position**

**Description:** Position of the primary contacts after the end of an operation. The normal values are 0.0 in open position and 1.0 in closed position.

**Signals used:** Contact position $p$.

**Calculation:**

$$\frac{1}{L} \sum_{k=N-L+1}^{N} |p_k|,$$

where $L$ is the number of the last data points in $p$ for which $|p_k - p_N| < \Delta_T$ holds ($\Delta_T$ is the threshold value).
C.2.5 Time to Beginning of Contact Motion

Description: Time until the primary contact first moves beyond the static position determined in C.2.3, in milliseconds.

Signals used: Contact position \( p \).

C.2.6 Time to End of Contact Motion

Description: Time until the primary contact first enters the static position determined in C.2.4, in milliseconds.

Signals used: Contact position \( p \).

C.2.7 Travel Velocity in Acceleration Phase

Description: Average velocity of main contact in the interval of 5...20% of its total stroke during this operation.

Signals used: Contact position \( p \).

Calculation: \[ \frac{|p_{20\%} - p_{5\%}|}{t_{20\%} - t_{5\%}} \]

C.2.8 Travel Velocity in Constant Phase

Description: Average velocity of main contact in the interval of 20...72.5% of its total stroke during this operation.

Signals used: Contact position \( p \).

Calculation: \[ \frac{|p_{72.5\%} - p_{20\%}|}{t_{72.5\%} - t_{20\%}} \]
C.2.9 Travel Velocity in Deceleration Phase

**Description:** Average velocity of main contact in the interval of 72.5...95% of its total stroke during this operation.

**Signals used:** Contact position $p$.

**Calculation:**
$$\frac{p_{95\%} - p_{72.5\%}}{t_{95\%} - t_{72.5\%}}$$

C.2.10 Overshoot at End of Contact Movement

**Description:** Maximum value of contact position divided by total stroke.

**Signals used:** Contact position $p$.

C.2.11 Maximum Velocity (First Derivative)

**Description:** Maximum of first derivative of contact position, using a multi-point finite difference formula for the differentiation of non-exact data.

**Signals used:** Contact position $p$.

**Calculation:**
$$\max \frac{dp}{dt}.$$ See [6, 52] for details on calculating the derivative.

C.2.12 Maximum Acceleration (Second Derivative)

**Description:** Maximum of second derivative of contact position, using a multi-point finite difference formula for the differentiation of non-exact data.

**Signals used:** Contact position $p$.

**Calculation:**
$$\max \frac{d^2p}{dt^2} = \max \frac{d}{dt} \left( \frac{dp}{dt} \right),$$ see C.2.11.
C.2.13 Time of Contact Touch or Separation

Description: Since the instant of contact touch or separation cannot be measured directly, it is assumed to occur at a specific contact position. Here, this position was arbitrarily chosen 0.6.

Signals used: Contact position $p$.

C.2.14 Time of Auxiliary Contact Toggle

Description: Time when the auxiliary contact status changes from 0 to 1 or vice versa. This feature is calculated individually for the type A and B contacts.

Signals used: Auxiliary contact status $s_A$ or $s_B$.

C.2.15 Auxiliary Contact Alignment

Description: Main contact position when the auxiliary contact toggles. This feature is calculated individually for the type A and B contacts.

Signals used: Auxiliary contact status $s_A$ or $s_B$, main contact position $p$.

C.2.16 Duration of Coil Voltage Signal

Description: Time when the voltage signal is removed from the energized trigger coil (Close or Open, cf. Section C.1). The threshold is 50% of the nominal voltage. This feature is calculated individually for the Close and Open coils.

Signals used: Coil voltage $u_c$ or $u_o$. 
C.2.17 Peak Level of Coil Voltage

Description: Maximum value of coil voltage in observation interval, divided by nominal voltage. This feature is calculated individually for the Close and Open coils.

Signals used: Coil voltage $u_c$ or $u_o$.

C.2.18 Accumulated Coil Voltage

Description: Sum of all coil voltage data points in observation interval, divided by nominal voltage. This feature is calculated individually for the Close and Open coils.

Signals used: Coil voltage $u_c$ or $u_o$.

C.2.19 Time Delay of Coil Current

Description: Time when the coil current first reaches 10% of its nominal steady state value. This feature is calculated individually for the Close and Open coils.

Signals used: Coil current $i_c$ or $i_o$.

C.2.20 Total Duration of Coil Current

Description: Time during which the coil current signal exceeds 50% of its nominal value. This feature is calculated individually for the Close and Open coils.

Signals used: Coil current $i_c$ or $i_o$.

C.2.21 Peak Level of Coil Current

Description: Maximum value of coil current in observation interval, divided by nominal current. This feature is calculated individually for the Close and Open coils.

Signals used: Coil current $i_c$ or $i_o$. 
**C.2.22 Accumulated Coil Current**

**Description:** Sum of all coil current data points in observation interval, divided by nominal current. This feature is calculated individually for the Close and Open coils.

**Signals used:** Coil current $i_c$ or $i_o$.

**C.2.23 Peak Level of Coil Power**

**Description:** Maximum value of coil power (i.e. element-by-element product of coil voltage and current) in observation interval, divided by nominal current. This feature is calculated individually for the Close and Open coils.

**Signals used:** Coil voltage $u_c$ or $u_o$, coil current $i_c$ or $i_o$.

**Calculation:** $\max_k (u_{ck} \cdot i_{ck})$ for Close coil, $\max_k (u_{ok} \cdot i_{ok})$ for Open coil.

**C.2.24 Energy Dissipated in Coil**

**Description:** Sum of all coil power data points (as defined in C.2.23) in observation interval, divided by nominal voltage and nominal current. This feature is calculated individually for the Close and Open coils.

**Signals used:** Coil voltage $u_c$ or $u_o$, coil current $i_c$ or $i_o$.

**C.2.25 Time of Motor Energization**

**Description:** Time when the pump motor voltage first exceeds 50% of its nominal value. 0 if the motor has been switched on before the start of the observation interval.

**Signals used:** Motor voltage $u_M$. 
C.2.26 Time of Motor Deenergization

**Description:** Time when the pump motor voltage first drops below 50% of its nominal value.

**Signals used:** Motor voltage $u_M$.

C.2.27 Initial Motor Current

**Description:** Peak level of pump motor current signal, assuming only one peak, which occurs shortly after energization.

**Signals used:** Motor current $i_M$.

C.2.28 Steady State Motor Current

**Description:** The steady state current is defined here as the first current value that is maintained within an adjustable tolerance range for at least 50 milliseconds.

**Signals used:** Motor current $i_M$.

C.2.29 Time to Steady State Value of Motor Current

**Description:** Time when the steady state value of the motor current, as defined in C.2.28, is first reached.

**Signals used:** Motor current $i_M$.

C.3 Binary Features

These are features that can assume only the binary values of 0 or 1. Generally, 1 indicates that a signal is present, a contact is closed, etc.
C.3.1 Status of Source Side Voltage after Operation

**Description:** Indicates whether or not the source side voltage signal can be detected after a circuit breaker operation. Normally it should be 1 if the circuit breaker is online and 0 if it is disconnected.

**Signals used:** Source side voltage $u_s$.

**Calculation:**

$$1 \text{ if } \frac{1}{L} \sum_{k=N-L+1}^{N} |u_{S,k}| > U_{Th},$$

where $U_{Th}$ is an adjustable threshold value. $L$ is the number of data points contained in the averaging window; in this implementation, $L$ is chosen so that this window contains $\frac{1}{6}$ of the power frequency period.

C.3.2 Status of Load Side Voltage after Operation

**Description:** Indicates whether or not the load side voltage signal can be detected after a circuit breaker operation. For successful operations with the circuit breaker online it should be 1 after a closing and 0 after an opening operation.

**Signals used:** Load side voltage $u_L$.

**Calculation:**

$$1 \text{ if } \frac{1}{L} \sum_{k=N-L+1}^{N} |u_{L,k}| > U_{Th},$$

where $U_{Th}$ is an adjustable threshold value. For the definition of $L$ see C.3.1.
C.3.3 Status of Load Current after Operation

Description: Indicates whether or not the load current signal can be detected after a circuit breaker operation. For successful operations with the circuit breaker online it should be 1 after a closing and 0 after an opening.

Signals used: Load current $i_L$.

Calculation: $1$ if $\frac{1}{L} \sum_{k=N-L+1}^{N} |i_{L,k}| > I_{Th}$, where $I_{Th}$ is an adjustable threshold value. For the definition of $L$ see C.3.1.

C.3.4 Auxiliary Contact Initial Status

Description: Indicates whether the auxiliary contact is closed (1) or open (0) at the start of the observation interval. This feature is calculated individually for the type A and B contacts.

Signals used: Auxiliary contact status $s_A$ or $s_B$.

Calculation: $s_{A,0}$ or $s_{B,0}$

C.3.5 Auxiliary Contact Final Status

Description: Indicates whether the auxiliary contact is closed (1) or open (0) at the start of the observation interval. This feature is calculated individually for the type A and B contacts.

Signals used: Auxiliary contact status $s_A$ or $s_B$.

Calculation: $s_{A,N}$ or $s_{B,N}$
**C.3.6 Initial Status of Pump Motor**

**Description:** Indicates whether or not the pump motor is energized (voltage above 50% of nominal value) at the start of the observation interval.

**Signals used:** Motor voltage $u_M$.

**Calculation:** $u_{M,0}$

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**C.3.7 Final Status of Pump Motor**

**Description:** Indicates whether or not the pump motor is energized (voltage above 50% of nominal value) at the end of the observation interval.

**Signals used:** Motor voltage $u_M$.

**Calculation:** $u_{M,N}$