J. Indian Inst. Sci., May–June 1990, 70, 249–268.

Expert system approach to fault diagnosis of HVDC systems

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Received on January 9, 1989; Revised on July 27, 1989.

Abstract

This paper describes a new approach to fault diagnosis of high-voltage direct current (HVDC) systems and important features in developing a fault diagnosis expert system (FDES). The logical behaviour exhibited by the converter under normal and abnormal conditions forms the basis of the expert system. The logical behaviour of the converter represented in terms of the valve conduction pattern is used to detect and diagnose faults on the converter. Logical analysis of the converter behaviour provides a set of relations which are used for fault diagnosis. The FDES is implemented in TURBO-PROLOG for various faults on the converter.

Key words: Fault diagnosis, ac/dc converter, power systems, artificial intelligence, and expert systems.

1. Introduction

HVDC power transmission constitutes an important and integrated part of ac power systems. With the increasing complexity of dc systems and consideration for implementation of multi-terminal dc (MTDC) systems, fault detection and diagnosis of dc systems play an important role in the reliable operation of the power system as a whole. Fault detection and diagnosis (FDD) of HVDC systems should be fast and efficient, and much of it has been achieved through microprocessors which monitor continuously the operation of the converter under different conditions[1].

Whenever a fault occurs on a power system, it has to be detected, identified and isolated immediately so that power is restored to its normal state and the outage time reduced. Operation engineers in energy control centres or energy management centres (EMS) perform this task of fault diagnosis from known or reported symptoms obtained from relays and circuit breakers. Diagnosis by the operator by 'human reasoning process' is satisfactory but is not always reliable, as many factors like prolonged stress and stringent constraints affect the fault diagnosis and decision-making performance of the human expert[2,3]. Hence it is felt necessary to gather and emulate the human reasoning process of the expert during diagnosis and decision making. Expert systems (ES) or knowledge-based systems (KBS) are intelligent computer systems which come to the aid of the operator during diagnosis and decision making. Expert system is a computer-based system that searches for a solution within a set of statements or body of knowledge formulated by the domain experts in a specific area.

In the recent decade, many expert systems using artificial intelligence have been developed and proposed in different areas of power system planning, operation and control, especially in fault diagnosis to solve complex and ill-structured problems[4]. Various expert systems for power system fault diagnosis are described[5-8].

Feasibility of application of expert systems to HVDC systems was first reported by Kalra[9], where different areas are identified for expert system application. Fault diagnosis was justified to be one of the important areas for expert system application[10], as there exists different control strategies at various hierarchical levels and decision has to be made regarding the selection of the appropriate control strategy for fast system restoration during and after a disturbance. In this paper a new approach to fault diagnosis of HVDC systems using expert systems based on the logical behaviour of the converter is described and implemented in TURBO PROLOG for various faults on the converter.

2. Fault diagnosis of HVDC systems

Fault analysis and diagnosis of HVDC systems are usually performed with the help of microprocessors which continuously monitor the operation of the converter during normal and abnormal conditions[11-14]. The microprocessor which monitors the operation of the converter during normal and faulted conditions, detects the fault from the valve conduction pattern (VCP) which contains information regarding the type of fault. Fault diagnosis of HVDC converters using valve conduction pattern[15-19] mainly consists in detecting the ON/OFF states of the valves and the duration of conduction with respect to the voltage phase cross-over points[19]. This method is used for accurate and unambiguous discrimination of converter faults. Faults are also detected from the logical signals obtained from converter waveforms[13]. Diagnosis of the response of the dc system to symmetrical and unsymmetrical faults using valve conduction pattern has recently been reported[20].

In this paper a new approach to fault diagnosis of HVDC systems using expert systems based on the logical behaviour of the converter is described. Logical behaviour of the converter under normal and faulted conditions[11] provides a set of relations and conditions which are used for diagnosis of faults in the converter.

The relations[21] are given below for reference.

$$FT_i \subset V_{i+2} V_i (C_{i-1} - C_{i+2})(P_{i+2} - P_{i+3})$$

$$CF_i \subset V_{i+2} V_i (C_{i-1} - C_{i+3})(P_{i+2} - P_{i+3})$$

$$MFR_i \subset V_i V_{i-2} (P_i - P_{i+2})$$

where FT_i is fire through of valve i, CF_i, commutation failure of valve i, MFR_i, misfire of valve i, V_i, conducting valves, C_i, voltage zero crossing or phase cross-over points, and P_i, pulse availability zone.

The three components, namely, the phase cross-over points, the pulse availability zone, and the conducting valves which constitute the valve conduction pattern of the converter can be effectively and efficiently used to detect and identify converter faults. Commutation failure is the most commonly occurring fault at the inverter and is considered in detail.

2.1. *Fast detection of commutation faiulre*

Continuous monitoring of the commutating voltage zero-crossings, the firing pulses to the valves and the conduction state of the valves provide sufficient information for the detection and discrimination of all converter faults[1,11,21].

Figures 1a and b show the six-pulse converter configuration and alternating voltage waveshapes. Valve V_1 can commutate the current from valve V_5 during the time interval starting at zero-crossing C_1 and ending at zero-crossing C_4. Commutation failure of valve V_1 can be detected earliest at C_4, since at this instant valves V_5 and V_6 are conducting and after C_4, V_5 is more positive than V_1 and even if V_1 were fired, the current would commutate back to V_5. Commutation failure of valve V_1 is detected before the firing of V_2. In general, commutation failures of valve V_i are detected at the voltage zero-crossing $C_{(i+3)}$ if at this instant valves $V_{(i-1)}$ and $V_{(i-2)}$ are conducting. This detection of commutation failure which is easily implemented using logic circuits can be effectively and efficiently represented symbolically with the help of the logic programming language PROLOG for fault diagnosis.

3. Fault diagnosis using expert systems

Diagnosis is defined as the process of assessing the internal status of a physical system from behavioural symptoms and physical findings[22,23]. The objective of diagnosis is either classification, localization or both. Experience with building diagnostic expert systems has

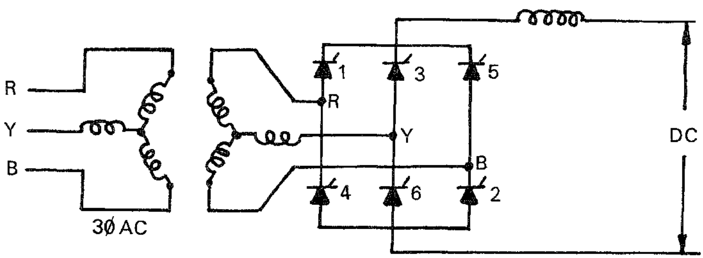


FIG. 1a. Six-pulse converter configuration.

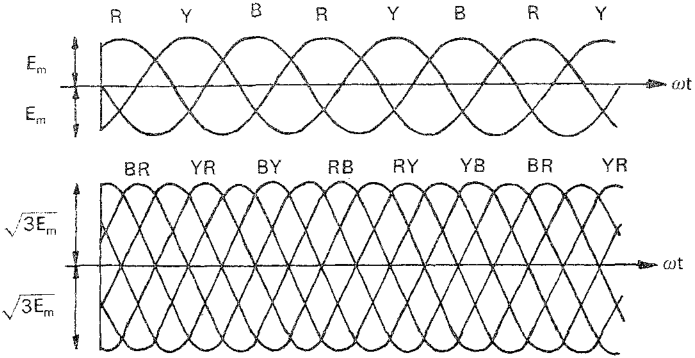


FIG. 1b Alternating voltage waveforms

shown that it is a knowledge-driven approach. Problem-solving performance of an expert system is determined to a large extent, by what knowledge (diagnostic) is used and how it is organized and utilized.

Diagnostic reasoning is generally accepted to be sequential hypothesize-and-test (hypothetico-deductive) process during which the diagnostician conceptually constructs a model of the underlying causative symptoms. This model or hypothesis is based largely on what manifestations are known to be present and postulates the presence of one or more symptoms that could explain the given manifestations.

Several problems of diagnosis have been successfully handled by first generation expert systems which use judgemental knowledge of human experts in the form of a monolithic set of production (IF ... THEN ...) rules. A typical rule is a heuristic association between observed data patterns and final or intermediate diagnostic conclusions. These associations are generally based on the judgemental knowledge of the experts which in turn is derived empirically.

Reasoning is the process of constructing a dynamic inference chain which starts from a given data and ends at diagnostic conclusions. Given a specific case, the diagnostic conclusions are those that have the strongest association with the given symptoms.

3.1. *Diagnostic expert systems*

Various approaches are used for representing and processing knowledge in expert systems for diagnostic problem solving and can be broadly classified as shown in Table I.

In the statistical pattern classification approach, the knowledge base typically consists of tables of probabilities and the inference mechanism involves the calculation of posterior probabilities of disorders using formulas such as Bayes theorem. Expert systems of this

Table I
Approaches for diagnostic expert systems

Method	Theoretical basis	Application
Statistical pattern classification	Probability theory	Medical diagnosis
Rule-based reduction	First-order predicate calculus	Medical diagnosis
Frame-based abduction	Abductive inference	Medical diagnosis

type have achieved expert level performance at times outperforming human diagnosticians.

Diagnostic expert systems using rule-based deduction typically have a knowledge base consisting of conditional rules and an inference mechanism based on *modus ponens* or resolution, the latter written in PROLOG. Diagnostic expert systems of this type have clearly been demonstrated to exhibit an expert level performance in empirical reasoning. They also have a strong theoretical foundation in first-order predicate calculus.

Diagnostic expert systems of the frame-based abduction type inherently involve abductive inference. Abductive expert systems aim for a higher level of performance and often attempt to model the underlying reasoning of the diagnostician. Information in the knowledge base is generally represented in an object-oriented fashion and a sequential hypothesize-and-test inference process is used. Frame-based abductive expert systems do not have a readily identifiable, well-developed theoretical foundation. Generalized set covering model[24,25] attempts to develop a theoretical basis for abductive expert systems.

In most diagnostic systems, in order to reach the performance level and flexibility of human experts, more than judgemental knowledge is necessary. Knowledge based on the structural and functional (causal) models is required for efficient diagnostic problem solving. Diagnostic knowledge can be basically divided into two broad categories: empirical and model knowledge.

The reasoning process corresponding to the above approaches is referred to as 'shallow' and 'deep' or 'symptom-based' or 'specification-based' reasoning. There are several approaches to modelling diagnostic expert systems. The methods of knowledge representation ranges from production rules and predicate logic for empirical knowledge to semantic networks and frames for model knowledge. Table II shows the approaches, reasoning and knowledge representation methods for diagnostic expert systems.

In most of the diagnostic expert systems, a combination of the two types of knowledge is effectively used for problem solving. 'Shallow knowledge' is initially used. When the knowledge is not sufficient enough for better explanation, reasoning or conclusions to be reached, 'deep knowledge', consisting of the knowledge based on structure and behaviour of the system, is used for better problem-solving performance.

Diagnostic expert systems integrate the phenomenological and fundamental knowledge for diagnostic problem solving[26]. Phenomenological knowledge deals with the relation among phenomena and is equivalent to what is called 'experiential'[27] or 'shallow knowledge'. Fundamental knowledge deals with the mechanisms underlying phenomena and is

Table II
Diagnostic expert systems—methods of approach, reasoning and knowledge representation

	Empirical knowledge	Model knowledge
Reasoning	Shallow or symptom-based	Deep or specification based
Representation	Production rules or predicate logic	Semantic networks or frames

equivalent to what is called 'structural' or 'deep knowledge'[27,28]. Diagnostic expert systems often employ phenomenological knowledge in the first place and resort to fundamental knowledge when phenomenological knowledge fails to arrive at a good solution[29]. An adaptive model which combines phenomenological knowledge and fundamental knowledge is developed to achieve system performance in terms of accuracy, efficiency and explanation capability[26].

4. Diagnostic approaches and strategies

4.1. *Approaches*

Approaches for fault diagnosis using expert systems can be broadly classified as: set covering model, deep and shallow methods, and qualitative simulation.

A diagnóstic problem can be defined as a problem in which one is given a set of abnormal findings (manifestations) for some system and must explain why these findings are present. A model prepared for diagnostic expert system[24,25] based on the concept of minimal set covers, captures several intuitively plausible features of human diagnostic inference, addresses the problem of multiple simultaneous disorders and provide a theory for diagnostic inference.

In expert-system problem-solving situations, two different kinds of knowledge are employed. These are referred to as 'shallow', 'surface', 'compiled' or 'low-road' knowledge or 'deep' or 'high-road' knowledge[27]. Diagnostic problem solving using deep and shallow knowledge approaches[28,30] essentially consists of the classification task[31]. Shallow knowledge consists of rules of thumb often in the form of condition-action pairs, that has been acquired by the expert through first-hand experience. These rules tell the user what to conclude in a given situation, but do not provide any kind of inherent reason for the relation between the conditions and the conclusions beyond satisfaction. These rules which are short cuts or compilation of the deeper understanding of the problem tend to be experiential and model the decision-making process of the expert in the problem domain. Deep knowledge, on the other hand, provides the lower level causal, functional and physical information in a problem-solving situation. It models how the domain itself works based on the structure and behaviour of the system. Often such deep knowledge is not used by the expert in a particular problem-solving situation. Shallow knowledge is sometimes all that is needed for problem solving however, when a new problem appears that the expert has never encountered before, deep knowledge is used. Expert system technology currently employs the shallow knowledge model for diagnostic problem solving[32].

A qualitative model is a symbolic representation of a system. It is the most basic description of a component. A component is described in terms of its connections to other components and its behaviour. Behaviour is described in terms of the physical variables that are present at its connections. The differentiation between the structural description (connection) and the behavioural description is particularly important for ensuring the robustness of a qualitative model. Diagnostic reasoning described by Davis[33] uses qualitative simulation for problem solving. The system has built-in knowledge of the structure and expected behaviour of the individual components of the circuit. Using simulation rules which are not production rules, the program predicts the output of a circuit based on its input. The system begins the diagnostic process by creating a dependency record and detects the discrepancy of the value expected by simulation. A new algorithm, called candidate generation by constraint suspension, is used to accomplish the identification problem of suspected malfunctioning devices.

4.2. *Strategies*

Strategies for diagnostic problem solving can be broadly classified as: logical structure and function; qualitative reasoning; and first and second principles.

Diagnostic reasoning based on knowledge of structure and function has been used in the domain of digital circuit trouble shooting. The basic principle is in designing a formal scheme to model the logical structure of circuit and their functional behaviour. A technique called constraint suspension is used for candidate generation based on discrepancy detection. The overall process is guided by a strategy for trouble shooting that consists of progressive relaxation of underlying assumptions.

Qualitative causal reasoning is used in the analysis of a broad variety of physical systems where functional relationships cannot or need not be described quantitatively. This approach attempts to explain the behaviour of a physical system by 'qualitative simulation' or environment process. This process, when given a qualitative description of the causal relationships between components of a mechanism and some utilization information, produces a description of the mechanism's overall behaviour.

Any generic knowledge underlying a domain includes fundamental theorems, *i.e.*, first principles and their derivatives *i.e.*, second principles. These can be used to conduct both quantitative and qualitative reasoning depending on the view point. Knowledge represented as a rule like format is natural and practical in the context of diagnosis. Second principles are commonly used by electronic engineers to assign responsibilities to faulty components in analog circuit trouble shooting[34].

Chandrasekaran and Mittal[35] decouple the structural and functional representation of devices from diagnostic expertise, where they use a formal representation for describing devices and suggest compiling a set of production rule for diagnosis in a systematic manner.

Milne[32] discusses various strategies for diagnosis and interaction among them. Diagnostic strategies, classified as structural, behavioural, functional and pattern matching, essentially consist of an abstraction process which involves a hierarchical organization and representation of the relation between function and structure.

5. Fault diagnosis of power systems using AI

In the recent past, many expert systems have been developed and proposed to solve complex, fuzzy and ill-structured problems in different areas of power systems, the most prominent being *fault diagnosis*. Expert system technology has obtained wide-ranging attention of the power engineering community, researchers at universities, organization and engineers and operating personnel of electric power companies. Currently expert systems in power engineering are prototypes of demonstration, research or field tests, whereas some expert systems have been in practical use since 1980 in USA and Japan.

It has been observed from the generic types of expert systems in power industry on comparison with other industries, that *diagnosis* plays a predominant role as expert system in power industry accounting to about 41% of the total application[36]. Diagnostic problems are best suited for expert system application because there exists no established theory. Also diagnostic problems are difficult to process numerically during system operation.

Expert system for fault diagnosis of power systems[5,6,37–39] make use of the following methods for problem solving: set covering method; general problem solver; discrete event simulation, and physical objective model.

A hybrid approach to synthesising solutions for fault diagnosis and set covering problems for power system operation is discussed by Talukdar and Cardozo[40], where a combination of the expert system (written in a rule-based language OPS5) and algorithmic programs (written in C and LISP) run in parallel in a network of computers for real-time application. Hypothesis generation by a set of programs using patchwork synthesis for constructing the hypothesis tree is described. Distributed processing scheme to allow multiple hypotheses to be expanded in parallel using distributed problem-solving kennel (DPSK) is described in detail.

The use of general problem solver (GPS) architecture for fault diagnosis of power systems is proposed by Sakaguchi[37] as a background of the knowledge intensive expert system. The GPS architecture solves problems by characteristic search in problem space. When a knowledge base is complete at each step of diagnosis, the system can decide what to do next and diagnosis is made the same way as knowledge-intensive method without any search. When incomplete, the system cannot decide what to do next at some step of diagnosis, and the GPS architecture takes over the knowledge-intensive method, making general heuristic search in a fault problem space.

The use of discrete event simulator (DES) in designing the knowledge base for network fault diagnosis is discussed by Sakaguchi and Komai[4] where the event simulator used for verification of fault hypothesis created by on-line measurements is described. Initially, as many fault hypotheses as are possible are created with the on-line data. Then each hypothesis is verified by comparing the output of the event simulator or network fault protection. The event simulator and the meta-knowledge on how to use it, are implemented in the rule-based language OPS5.

A new method to estimate the fault section using information from protective relays and circuit breakers based on knowledge and physical objective model is discussed by Fukui and Kawakami[7] where fault diagnosis using 'physical model' is described. The physical model contains the graphical representation of a power system network and a description of various electrical phenomena observed on the network. All inference on fault environment is derived from fundamental principles. The physical model creates necessary inference rules and facts from a basic principle when required. Physical model has the advantages of: (1) separation of domain-specific knowledge and principle of knowledge on phenomena makes it possible for the fault detection system to apply various types of networks, (2) reduction in the total amount of knowledge as the result of exclusion of domain-dependent rules, (3) ability to cope with the changes of configuration which occur when the fault area propagates.

6. Expert system approach to fault diagnosis of HVDC systems

Expert system for HVDC systems is a new area of research and quite a few researchers have proposed or developed new approaches or strategies for problem solving. Application of expert system for fault diagnosis of HVDC systems was first investigated by Kalra[9,10], where different features are discussed and statistical and frequency domain techniques are described for fast fault detection and discrimination. More emphasis has been placed on the techniques underlying fast fault detection and discrimination.

The process of fault detection, discrimination and diagnosis of HVDC systems should be fast in the order of its fast controllability of power. Various control strategies at different hierarchical levels exist for the operation and control of HVDC systems during and after the disturbance[18]. The selection of these control strategies for different fault situations is an important task and depends largely on the diagnostic results regarding the type, location and classification of the fault. Fault location, its features and characteristics (symptoms) help the operator in diagnosis and decision making regarding the selection and implementation of control strategies. These fault characteristics (symptoms) constitute the knowledge base of the expert system.

The converter is the basic and important component which converts power from ac to dc and *vice versa*. Figure 1a shows the usual configuration of a six-pulse converter. The switching sequence of the converter is sequential and periodic (cyclic) under normal conditions (fig. 2a) but tends to be complex or unpredictable under abnormal or faulted conditions (fig. 2b). Various factors, internal and external to the converter, affect its operation. These include faults and malfunctions of system components. Analog and digital techniques are used for detection of malfunctions and faults. Microprocessors are best suitable for fault detection and are widely in use. Microprocessors perform the task of fault diagnosis

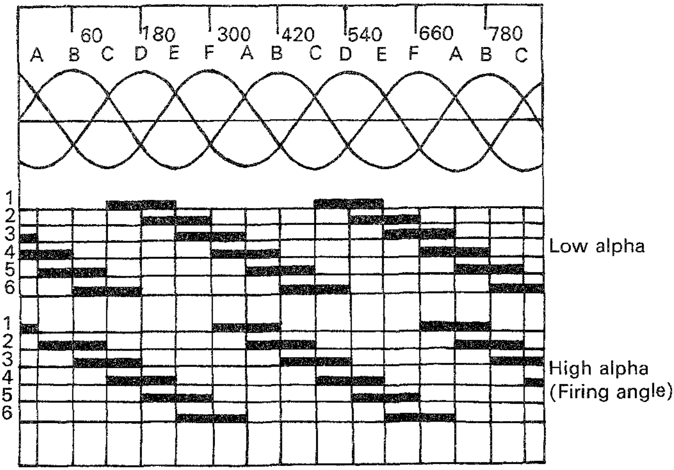
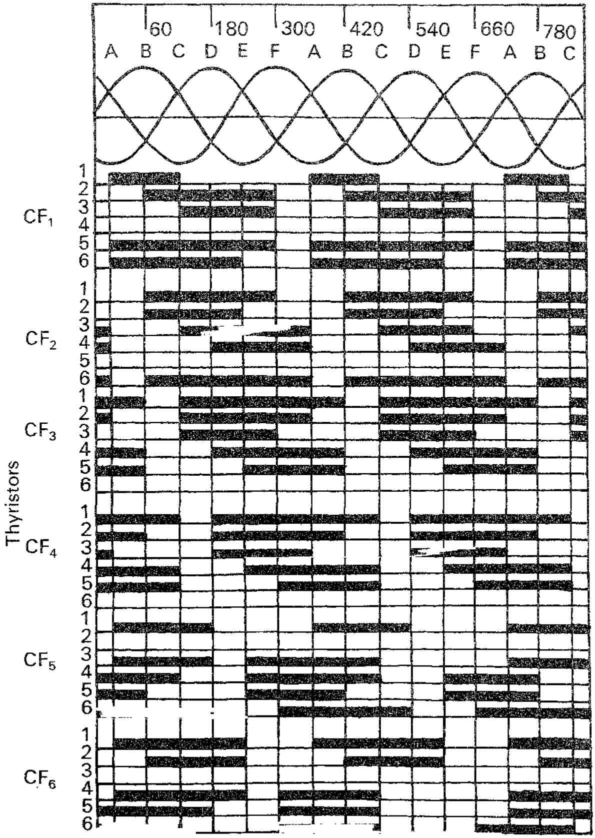


FIG. 2a. Valve conduction pattern for normal operation.

by monitoring the valve conduction pattern of the converters. The valve conduction pattern consisting essentially of the conduction of the valves and the duration of conduction contain information regarding the type and location of the fault. The principles of valve conduction pattern and the logical behaviour exhibited by the converter are used in developing the fault diagnosis expert system[41].

Figure 2a shows the phase voltages, the conducting pattern of the valves for a six-pulse converter under normal conditions for low and high values of firing angles. It can be observed from the figure that the VCP is periodic under normal conditions, and is disturbed and distorted for abnormal or faulted conditions. The problem formulation of diagnostic expert systems consists essentially of representing the faulted state of the converter in terms of the valve conduction pattern, which in turn is represented as a combination of the voltage crossover points, the firing pulse availability and conducting valves. The valve conduction pattern of the converter essentially consists of the following three components: 1. voltage available across the valve (termed as VOLTZONE), 2. firing pulse available for the valve (termed as PULSZONE), and 3. conducting thyristors (termed as CONDUCTION).

It is possible to represent the operation of the converter under normal and faulted conditions using the above three components. Figure 3a shows these components of valve conduction patterns for normal operation. Figure 4b shows the fault tree for fault diagnosis of HVDC systems using valve conduction patterns.



Valve conduction pattern of thyristors for single commutation failure (SCF) of valve 1, for firing angle alpha less than 120°.

FIG. 2b. Valve conduction pattern for faulted condition.

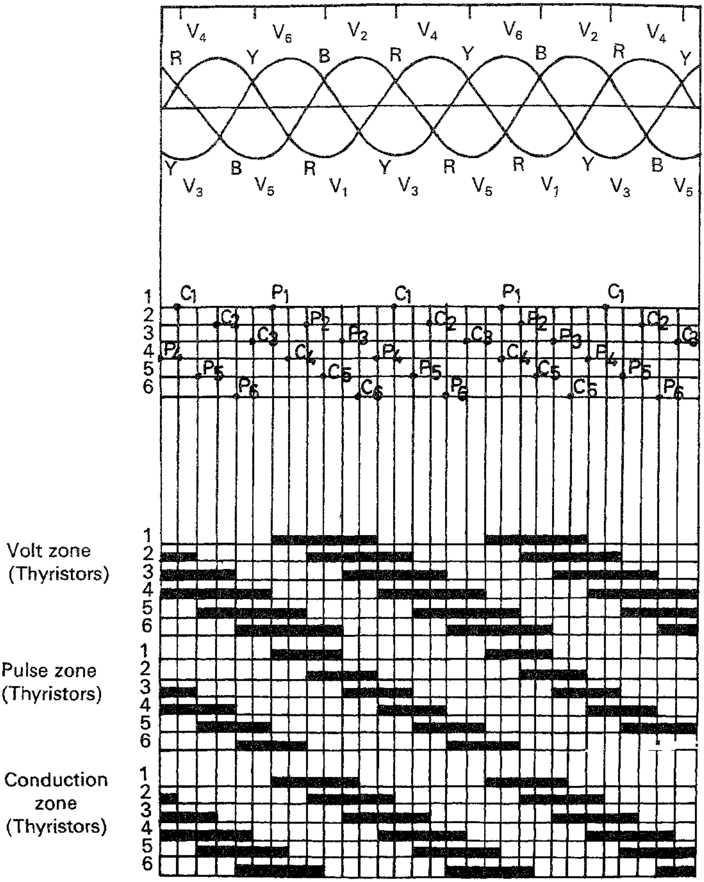


FIG. 3. Components of conduction pattern used for fault diagnosis; C_i = Voltage crossover point corresponding to thyristor i; P_i = Pulse firing instant of thyristor i.

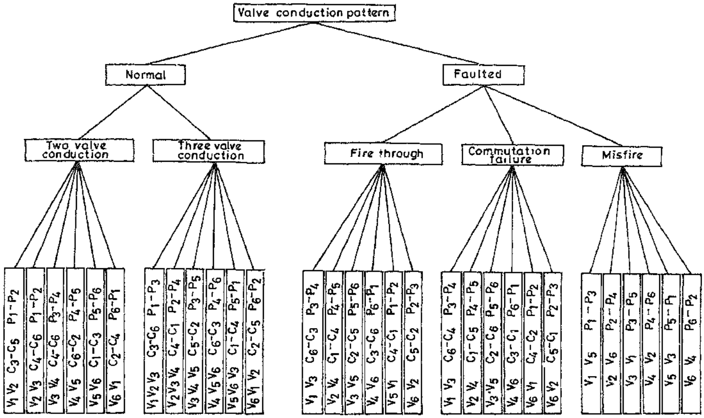


FIG. 4. Fault tree for diagnosis of HVDC converter systems.

Table III
Logic behaviour of converter

		P_1-P_2	P_2-P_3	P_3-P_4	P_4-P_5	P_5-P_6	P_6-P_7
Normal operation		(5)61	(6)12	(1)23	(2)34	(3)45	(4)56
SCF of valve	1	56(1)AD	5(6)2BE	(5)23CF			
	2		61(2)BE	6(1)3CF	(6)34DA		
	3			12(3)CF	1(2)4DA	(1)45EB	
	4				23(4)DA	2(3)5EB	(2)56FC
	5	(3)61AD				34(5)EB	3(4)6FC
	6	4(5)1AD	(4)12BE				45(6)FC

6.1. *Problem formulation*

It has been mentioned earlier that the converter exhibits logical behaviour which can be used to detect and identify faults in the converter. The logical behaviour of the converter can be represented in terms of the valve conduction pattern (VCP) and *vice versa.* Logic behaviour of the converter for a single commutation failure is given in Table III and the corresponding valve conduction pattern is shown in fig. 2b. The VCP consists of three basic components, namely, 1. phase cross-over points; 2. availability of firing pulses, and 3. conducting valves.

The operation of a converter in terms of VCPs under various operating conditions can be represented by these components termed as 'predicates' in AI terminology.

7. Expert system developement

An expert system is an intelligence computer program that uses knowledge and inference procedures to solve problems that are difficult enough and require significant human expertise for their solution. The expert system simulates the performance of the human expert in a specific, narrow field or domain[42]. The important features in expert system development are: knowledge acquisition, knowledge representation, and problem solving.

7.1. *Knowledge acquisition*

Knowledge acquisition is one of the preliminary stages and time-consuming tasks in expert system development. Knowledge is either acquired from experts in a particular domain or from books and literature. Knowledge acquisition using generic tasks for knowledge-based reasoning[36] provides the interaction problem between the initial and goal states of knowledge-acquisition process. Knowledge is acquired here for the diagnostic expert system from the results obtained from digital simulation and logical analysis of the converter behaviour during normal and faulted conditions. Results obtained from digital simulation in the form of VCPs for various faults at different locations form the knowledge base of the expert system. The acquisition process constitutes the knowledge-based simulation of the expert system, which is the ongoing research of the authors in this area.

7.2. *Knowledge representation*

Knowledge representation is the most important feature and determines the efficiency and accuracy of the expert system. Knowledge representation methods for expert system development are basically categorized as: 1. Production rules, 2. Predicate calculus, 3. Semantic networks, and 4. Frames.

Production rule is widely used for knowledge representation and is described in detail.

7.2.1. *Production rules*

Production rules constitute the major knowledge representation strategy in many of the expert systems, termed as rule-based systems. In a rule-based system, the knowledge representation takes the form of a collection of conditional statements of the form 'IF ⟨condition⟩ THEN ⟨conclusion⟩'[43–45]. Diagnostic knowledge of a human expert can be effectively represented as production rules[2]. Rules of the form IF ... THEN ... condition can be written in PROLOG to infer new facts from existing facts. A rule in PROLOG is an expression which indicates that the truth of a particular fact depends upon one or more facts. General form of representation of a rule in PROLOG is as follows

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Hypothesis (Conclusion):-
    Symptom (Condition 1),
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Symptom (Condition 2),
Symptom (Condition n).

Knowledge acquired in the form of VCPs is represented with the help of the following predicates

VOLTZONE (Voltage cross-over period and duration)
PULSZONE (Firing pulse availability period)
CONDUCTION (Conducting valves in the above period)

Table IV
Voltzone, pulszone and conduction periods for different fault situations

Valve	Conduction	Voltzone	Pulszone
1	$V_1 V_2$	C_3-C_5	P_1-P_2
2	$V_2 V_3$	C_4-C_6	P_2-P_3
3	$V_3 V_4$	C_5-C_1	P_3-P_4
4	$V_4 V_5$	C_6-C_2	P_4-P_5
5	$V_5 V_6$	C_1-C_3	P_5-P_6
6	$V_6 V_1$	C_2-C_4	P_6-P_1

Normal two valve conduction

Valve	Conduction	Voltzone	Pulszone
1	$V_1 V_2 V_3$	C_3-C_6	P_1-P_3
2	$V_2 V_3 V_4$	C_4-C_1	P_2-P_4
3	$V_3 V_4 V_5$	C_5-C_2	P_3-P_5
4	$V_4 V_5 V_6$	C_6-C_3	P_4-P_6
5	$V_5 V_6 V_1$	C_1-C_4	P_5-P_1
6	$V_6 V_5 V_1$	C_2-C_5	P_6-P_2

Normal three valve conduction

Valve	Conduction	Voltzone	Pulszone
1	$V_1 V_3$	C_3-C_6	P_3-P_4
2	$V_2 V_4$	C_5-C_4	P_4-P_5
3	$V_3 V_5$	C_2-C_5	P_5-P_6
4	$V_4 V_6$	C_3-C_6	P_6-P_1
5	$V_5 V_1$	C_4-C_1	P_1-P_2
6	$V_6 V_2$	C_5-C_2	P_2-P_3

Fire through

Valve	Conduction	Voltzone	Pulszone
1	$V_1 V_2$	C_6-C_4	P_3-P_4
2	$V_2 V_4$	C_1-C_5	P_4-P_5
3	$V_3 V_5$	C_2-C_6	P_5-P_6
4	$V_4 V_6$	C_3-C_1	P_6-P_1
5	$V_5 V_1$	C_4-C_2	P_1-P_2
6	$V_6 V_2$	C_5-C_3	P_2-P_3

Commutation failure

Valve	Conduction	Voltzone	Pulszone
1	$V_1 V_5$		P_1-P_3
2	$V_2 V_6$		P_2-P_4
3	$V_3 V_1$		P_3-P_5
4	$V_4 V_2$		P_4-P_6
5	$V_5 V_3$		P_5-P_1
6	$V_6 V_4$		P_6-P_2

Misfire

Typical rule for single commutation failure of valve is given below

FAULT (Commutation failure, converter, type 1, valve i):

VOLTZONE (C_{i-1}, C_{i+3}),

PULSZONE (P_{i+2}, P_{i+3}),

CONDUCTION (V_i, V_{i+2}).

The rule is interpreted as follows.

A fault on the converter is said to be a commutation failure of type 1 on value i, if the thyristors V_i and V_{i+2} conduct during the voltage cross-over points C_{i-1} and C_{i+3} with firing pulses available during the period P_{i+2} to P_{i+3}.

Further predicates, like for instance, Detect, Locate, Identify and Classify are used for detection, location, identification and classification of faults. The knowledge base constitutes similar rules for different faults and location, and consists of 252 rules for normal and faulted conditions of converter operation.

7.3. *Problem solving*

Many of the problems that fall within the purview of artificial intelligence are too complex to be solvable by direct techniques, rather, they must be attacked by appropriate search methods. The goal in problem solving is to find the best search technique which locates a solution path efficiently and effectively by limiting the number of data items or paths examined. Problem solving generally consists of: 1. general search methods, 2. control strategies, and 3. additional reasoning techniques.

7.3.1. *Diagnosis problem solving*

Generic tasks[28,32,35,46] are very useful as building blocks for the construction and understanding of knowledge-based systems. These elementary tasks cover a wide range of existing expert systems in diagnosis and design. Any diagnostic problem can be implemented as an integration of the three generic tasks of problem-solving types given below: 1. Hierarchical classification, 2. Hypothesis matching, and 3. Knowledge-directed information.

The first two generic tasks are considered here for diagnosis problem solving and are explained in detail.

7.3.2. *Hierarchical classification*

The process of diagnosis can be thought of as a classificatory problem. This leads to considering the nature and organization of knowledge and the control process required for hierarchical classification. Hierarchical classification can be best described as an examination of the tree structure by searching top-down manner from rough hypothesis to precise hypothesis[1].

7.3.3. *Hypothesis matching*

Hypothesis matching is an important generic task which requires distinctly separate forms of knowledge organization and control. This task involves hierarchical symbolic abstraction.

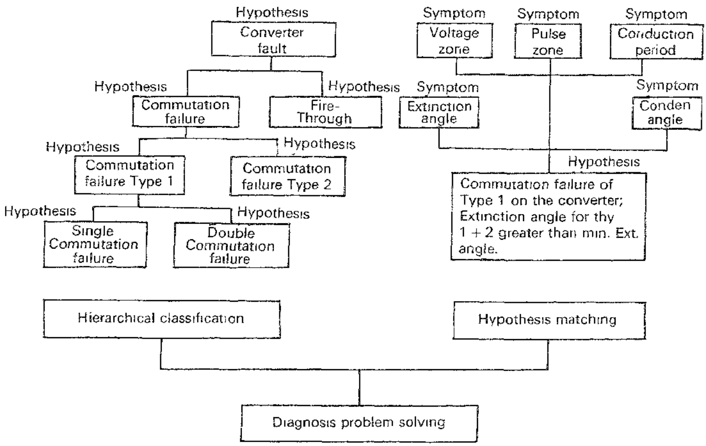

FIG 5. Diagnosis problem solving using hierarchical classification and hypothesis matching.

The problem of matching hypothesis against data is a general sub-type of reasoning useful in a number of different contexts. Hypothesis matching can be described as a method of testing a given hypothesis with bottom-up manner by matching a hypothesis and symptoms related to it.

Diagnosis problem solving is achieved using hierarchical classification and hypothesis matching. Diagnosis problem solving using hierarchical classification and hypothesis matching for a typical converter fault is shown in fig. 5.

8. Conclusions

Fault diagnosis of HVDC systems using artificial intelligence and in developing a diagnostic expert system based on the logical behaviour of the converter is discussed. Valve conduction pattern, the representation formalism of the converter behaviour, is used for fast fault detection and diagnosis. Generic tasks are used for problem solving. The diagnostic expert system is implemented in PROLOG for converter faults. Additional information regarding the fault characteristics improve the performance of the expert system. Problem solving using generic tasks constitutes the shallow knowledge of the expert system and therefore 'deep knowledge' based on the structure and behaviour of the system (converter in question) should be employed. This can be achieved through 'model-based diagnosis' which relies on the structure and behaviour of a properly functioning system. Research is in progress in developing a diagnostic expert system using the model-based approach.

Knowledge-based simulation and knowledge-based pattern recognition are proposed to be used for fault detection, discrimination and diagnosis. Extension of the fault diagnosis expert system to MTDC (multi-dimensional dc) systems is in progress.

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