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ANFIS based HVDC control and fault identification of HVDC converter

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Abstract

This paper presents computationally simple and accurate expert system for fault identification of HVDC Converter and Control of HVDC system. Adaptive Neuro-Fuzzy Inference System (ANFIS) is applied and discussed in detail. Instead of using separate fault identifier for each valve, an integrated fault identifier is developed which is effective for complete bridge Converter. Fault identifiers are tested for HVDC with strong and weak ac sides. Fault identification methods are applicable in both inversion and rectification mode. ANFIS based current control is also developed for a HVDC system. Several digital simulation results are presented to validate the procedure outlined in the paper. ANFIS based control can be easily combined with the fault identifier to form integrated system, which can improve dynamic response of HVDC systems.

Keywords: ANFIS, HVDC converter, fault diagnosis, HVDC control.

1 Introduction

In recent years artificial intelligence based on Neural network, Fuzzy system, Adaptive neuro-fuzzy inference system (ANFIS), genetic algorithm, etc. have met growing interest in many industrial applications.

Fault diagnosis of systems is a major subject of expert systems applications. The past two decades have revealed great advances in the application of artificial intelligence to power systems [1,2].

A trend that is growing in visibility relates to the use of fuzzy logic in combination with neuro-computing and genetic algorithms. More generally, fuzzy logic, neuro-computing, and genetic algorithms may be viewed as the principal constituents of what might be called soft computing. Unlike the traditional hard computing, soft computing is aimed at an accommodation with the pervasive imprecision of the real world. Number of papers are available that deal with the application of artificial intelligence in the area of power systems. In [3], a hybrid scheme using Fourier linear combiner and fuzzy expert system for the classification of transient disturbance waveform in power system is presented. An integrated fuzzy expert system is presented in [4] to diagnose different faults in a regional transmission network and substations. In the recent paper [5], different methods based on Artificial Neural Network (ANN) to identify various faults that may occur in HVDC converter, are presented.

An exhaustive survey of application of Neuro and fuzzy systems to the power system problem can be found in [6].

Wavelet - based fuzzy reasoning approach to the power quality disturbance recognition is presented in [7]. In [8] a comparison between proportional and fuzzy controllers for a power converter is proposed.

Modern controls based on Artificial Neural Network, Fuzzy system and Genetic algorithm are found fast, reliable, can be used for protection against the line and converter faults and are gaining more interest in the field of HVDC transmission.

HVDC systems traditionally use PI controllers with fixed gains. Although such controllers have certain disadvantages, they are rugged and operate satisfactorily for perturbations within a small operating range. On the other hand, ANN controllers have some specific advantages whereby the use of ANN controller has been shown to introduce flexibility and fault tolerance into the performance of the controllers.

ANN has attracted a great deal of attention because of their pattern recognition capabilities and their ability to handle noisy data. However, its ability to perform well is greatly influenced by the weight adaptation algorithm and the amount of noise in the data. The neural network architecture suffers from a large number of training cycles and computational burden. Neural network has the shortcoming of implicit knowledge representation, whereas fuzzy logic systems are subjective and heuristic.

Fuzzy inference systems and neural networks are complementary technologies in the design of adaptive intelligence system. Artificial Neural Network (ANN) learns from scratch by adjusting the interconnections between layers. Fuzzy Inference System (FIS) is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. Design of a simple fuzzy logic controller for HVDC transmission line is presented in [9] for fast stabilization of transient oscillations. Unlike both adaptive and variable structure controllers, which require, at least functionally, an accurate model of the system dynamics, the fuzzy controller does not require a mathematical model of the system to estimate the control input under disturbance conditions.

A neuro-fuzzy system is simply a fuzzy inference system trained by a neural network- learning algorithm. The learning mechanism fine-tunes the underlying fuzzy inference system.

Fuzzy system faces difficulties like a lack of completeness of the rule base and a lack of definite criteria for selection of the shape of membership functions, their degree of overlapping, and the levels of data quantization. Some of these problems can be solved if the neural technique is used for fuzzy reasoning.

The integrated neuro-fuzzy system combines advantages of both ANN and FIS. Application of both technologies are categorized into following four cases:

1. NN's used to automate the task of designing and fine tuning the membership functions of fuzzy systems.

2. Both fuzzy inference and neural network learning capabilities acting separately.

3. NN's work as correcting mechanisms for fuzzy systems.

4. NN's customizes the standard system according to each users preferences and individual needs.

The integrated neuro-fuzzy system combines advantages of ANN and FIS. Some of the major works in the area of neuro-fuzzy system are GARIC, FALCON, ANFIS, EfuNN, dmEEuNN, etc.

The HVDC system traditionally uses PI controllers to control the DC current thereby keeping the power (current) order at the required level. Although these controllers undoubtedly are robust and are operating satisfactorly for many years, they are prone to changes in system parameters, delays or other non-linearities in the system and suffer from some limitations. This paper describes fault identification and protection of a HVDC converter using ANFIS based fault identifier (ANFLBI). A fuzzy logic based current controller (ANFLBC) for the fast and flexible control of an HVDC transmission link is also designed. Unlike other controllers, ANFIS controller does not require a mathematical model of the system to estimate control input under disturbance conditions. ANFLBC can be easily combined with ANFLBI to form integrated system. Power system reliability improves when HVDC converter faults are detected and eliminated before they deteriorate to a severe state.

The paper is organized as follows. HVDC system under study is defined in Section 2. Section 3 gives introduction on ANFIS system. Application of ANFIS for HVDC control is given in Section 4. Section 5 presents use of ANFIS for fault identification. Simulation and test result is discussed in Section 6. Conclusions are given in Section 7.

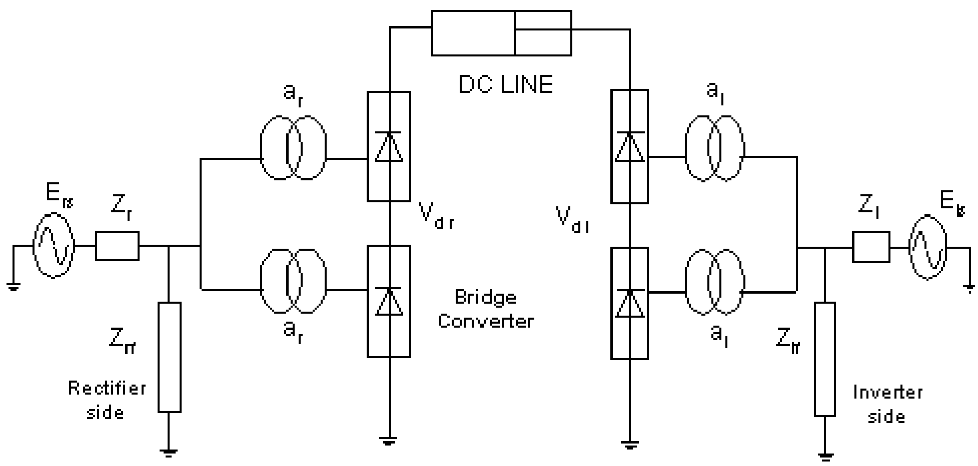

Figure 1: HVDC system - schematic diagram.

2 HVDC system model

The HVDC system used here as a test system is a 12-pulse, 1000 MW (500 kV-2kA) 50/60 Hz HVDC transmission system (S. Casoria; Hydro-Quebec (IREQ). A 1000 MW (500 kV, 2kA) DC interconnection is used to transmit power from the 500 kV, 5000 mVA, 60 Hz network to 345 kV, 10000 mVA, 50 Hz network. The converters are interconnected through a 300 km distributed parameter line and smoothing reactor of 0.5 H. The reactive power required by the converters is provided by a set of filters (Capacitor bank plus 11th, 13th and high pass filters; total 600 MVAR on each side). Fig. 1 shows a typical HVDC system using 6 pulse Graetz's Bridge configuration. Two 6-pulse bridges in series constitute a 12-pulse converter.

3 Adaptive neuro-fuzzy inference system (ANFIS)

Fuzzy systems are generally used in cases when it is impossible or too difficult to define crisp rules that would describe the considered process or system, which is being controlled by a fuzzy control system. Thus, one of the advantages of fuzzy systems is that they allow to describe fuzzy rules, which fit the description of real-world processes to a greater extent.

Another advantage of fuzzy systems is their interpretability; it means that it is possible to explain why a particular value appeared at the output of a fuzzy system. In turn, some of the main disadvantages of fuzzy systems are that expert input or instructions are needed in order to define fuzzy rules, and that the process of tuning of the fuzzy system parameters (e.g., parameters of the membership functions) often requires a relatively long time, especially if there is a high number of fuzzy rules in the system. Both these disadvantages are related to the fact that it is not possible to train fuzzy systems. A diametrically opposite situation can be observed in the field of neural networks. User can train neural networks, but it is extremely difficult to use a priori knowledge about the considered system and it is almost impossible to explain the behaviour of the neural system in a particular situation.

In order to compensate the disadvantages of one system with the advantages of another system, several researchers tried to combine fuzzy systems with neural networks. A hybrid system named *ANFIS* (*Adaptive-Network-Based Fuzzy Inference System or Adaptive Neuro-Fuzzy Inference System*) has been proposed in [10].

ANFIS is the fuzzy-logic based paradigm that grasps the learning abilities of ANN to enhance the intelligent system's performance using a priori knowledge.

Using a given input/output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modeling.

These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks.

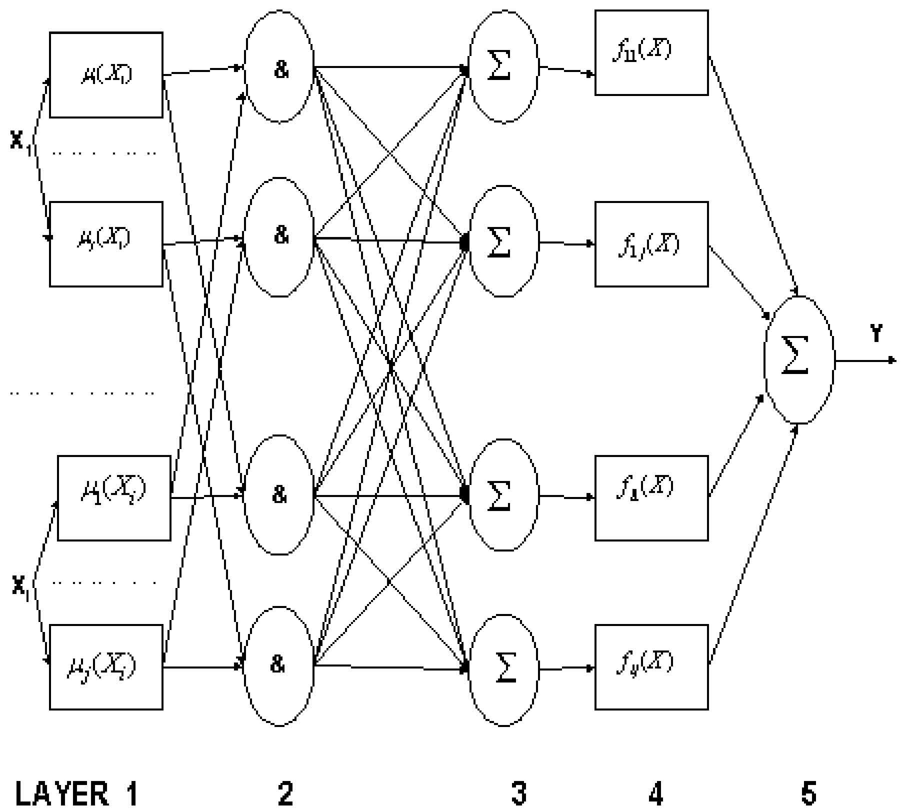

Figure 2: ANFIS structure.

Fig. 2 shows the basic structure of the ANFIS algorithm for a first order Sugeno-style fuzzy system. It is worth noting that the Layer-1 consists of membership functions described by the generalized bell function

$$\mu(X) = (1 + ((X - c)/a)^{2b})^{-1} \tag{1}$$

where a, b and c are adaptable parameters. Layer-2 implements the fuzzy AND operator, while Layer-3 acts to scale the firing strengths. The output of the Layer-4 is comprised of a linear combination of the inputs multiplied by the normalized firing strength w :

$$Y = w(pX + r) \tag{2}$$

where p and r are adaptable parameters. Layer-5 is a simple summation of the outputs of Layer-4. The adjustment of modifiable parameters is a two-step process. First, information is propagated forward in the network until Layer-4 where the parameters are identified by a least-squares estimator. Then the parameters in Layer-2 are modified using gradient descent. The only user specified information is the number of membership functions in the universe of discourse for each input and output as training information.

ANFIS uses back propagation learning to learn the parameters related to membership functions and least mean square estimation to determine the consequent parameters. Every step in the learning procedure includes two parts.

The input patterns are propagated, and the optimal consequent parameters are estimated by an iterative least mean square procedure. The premise parameters are assumed fixed for the current cycle through the training set.

The pattern is propagated again, and in this epoch, back propagation is used to modify the premise parameters while the consequent parameters remain fixed.

To use ANFIS for classification problem, the designer needs to perform the following steps:

1. Design a Sugeno FIS appropriate for the classification problem.
2. Hands optimize the FIS, given actual input classification data.
3. Set up training and testing matrices. The training and testing matrices will be composed of inputs and the desired classification corresponding to those inputs.
4. Run the ANFIS algorithm on the training data.
5. Test the results using the testing data.

ANFIS has a network-type structure similar to that of a neural network which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied to adjust parameters that will reduce some error measure (usually defined by the sum of the squared differences between actual and desired response).

ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation. The next section describes application of ANFIS for HVDC control.

4 ANFIS based HVDC control

The rule-based linear fuzzy logic controller can be used to achieve the desired transient performance of the HVDC link connected to a weak ac system. Unlike other controller, the fuzzy controller does not require a mathematical model of the system to estimate control input under disturbance conditions.

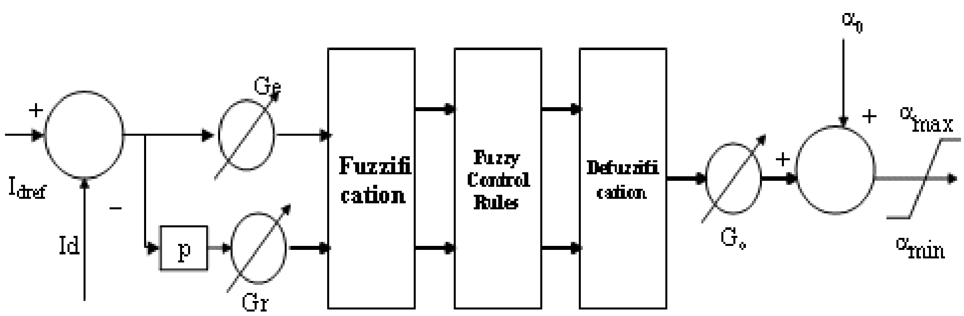

Figure 3: FLC block diagram.

The input of the constant current simple type fuzzy controller (FLC) is the DC current error and the rate of change of the error and output is the change in alpha order ($\Delta\alpha$). The linguistic variables used as two inputs are the error I_e and the rate of change of error $I_e p$ as shown in Fig. 3.

A rule base with only four rules can be designed. As the rule base contains very few rules and membership functions are not optimized, the response of this simple type of fuzzy controller is not satisfactory which is evident from the response depicted in Fig. 4.

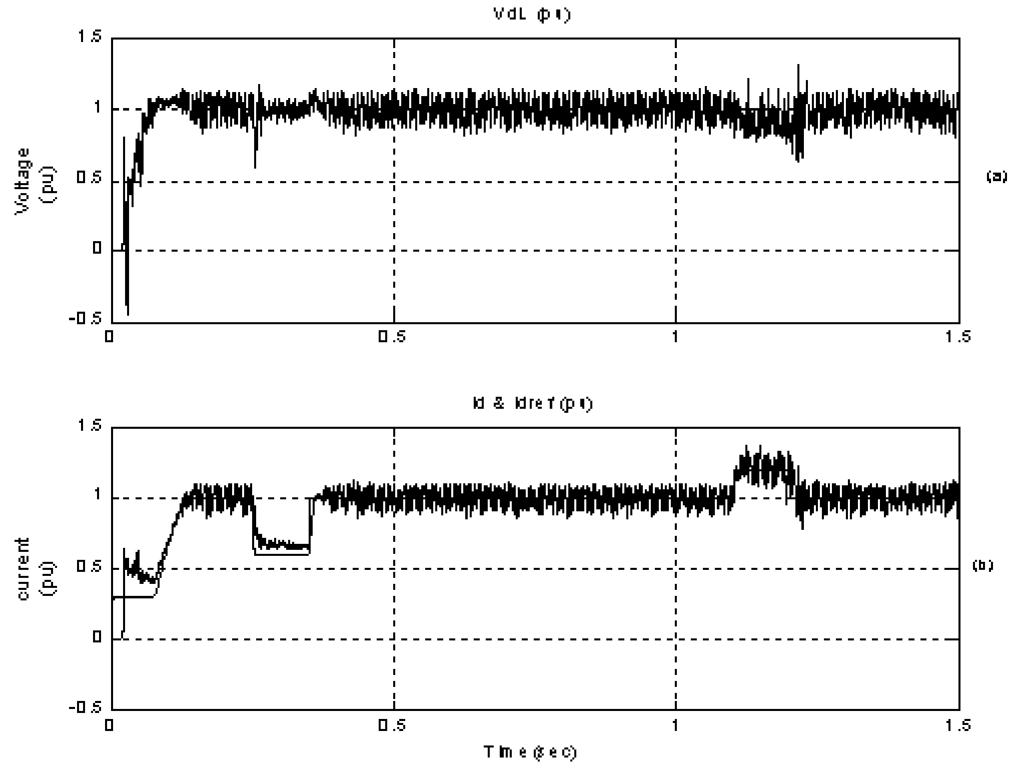

Figure 4: Response of a simple fuzzy controller: a) DC line voltage; b) DC current I_{dc} and I_{dref}.

Extending of the rule base and proper tuning of membership functions can enhance performance of the fuzzy controller. But its performance relies on selection of proper membership functions and fine-tuning. To avoid these problems, in this paper ANFIS based current controller is presented which preserves all the advantages of fuzzy systems and uses neural network at the front end to optimize performance of the overall system. To train ANFIS based control, training data is obtained from HVDC system, which is equipped with a conventional PI based constant current controller (see Fig. 5). ANFIS is trained using 70% of the data while 30% is used for testing and validation.

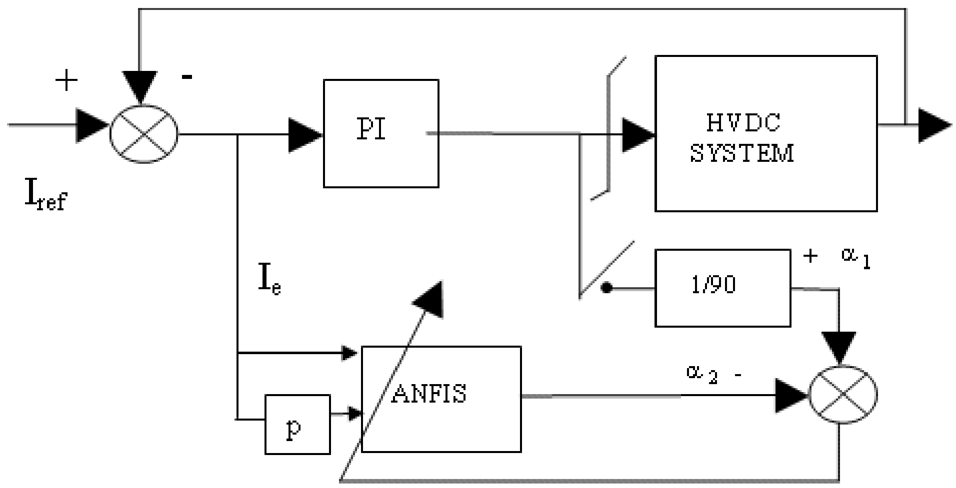

Figure 5: Off-line trained ANFIS control.

Response of the designed ANFIS current controller is shown in Fig. 6 for variation in DC reference current (I_{dref}). Performance of HVDC system improves if faults within converter are detected and fault development control initiates some corrective action. The next section deals with use of ANFIS for fault identification.

5 ANFIS based fault identification

As the data in HVDC system are highly uncertain and the power disturbance monitoring is a pattern classification problem, therefore ANFIS based expert system is adopted for designing fault identifier.

The existing method available for converter fault identification may give a very quick indication of the converter fault with the assumption that the overlap angle μ is limited up to 60 degrees. But the accuracy of the identifier totally relies on the proper selection of the delay time, i.e. the delay time exceeding the expected overlap angle μ may give false indication of fire-through and false indication of commutation failure if the delay angle is not sufficient. To overcome this problem, fault identifiers are designed using artificial neural network to detect commutation failure, firethrough, and other faults within the converter bridge [5], in which three different methods are presented to detect various faults in HVDC converter using the artificial neural network and comparison is made between different methods. But in these methods, one identifier per valve is required, i.e. six identifies are required for a Graetz bridge converter.

To eliminate this problem, an integrated type of fault identifier is proposed in this paper, which is based on an adaptive neuro-fuzzy inference system.

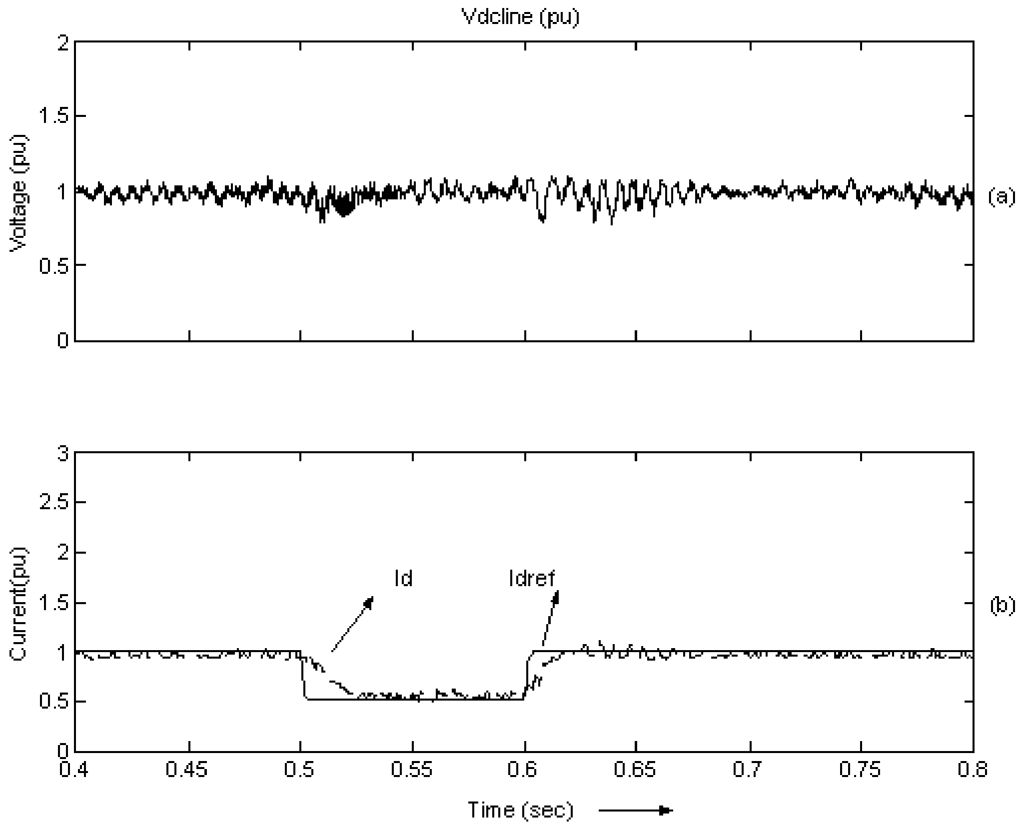

Figure 6: Performance of ANFIS control for change in I_{dref}: a) DC line voltage; b) DC current I_{dc} and I_{dref}.

The fault identification is based on the fact that every operation of the converter valve (normal or abnormal) is associated with a set of conduction pattern of the valves.

An integrated fault identifier with 12 inputs and one output is proposed and will be utilised for a complete bridge converter. The structure of this fault identifier is depicted in Fig. 7.

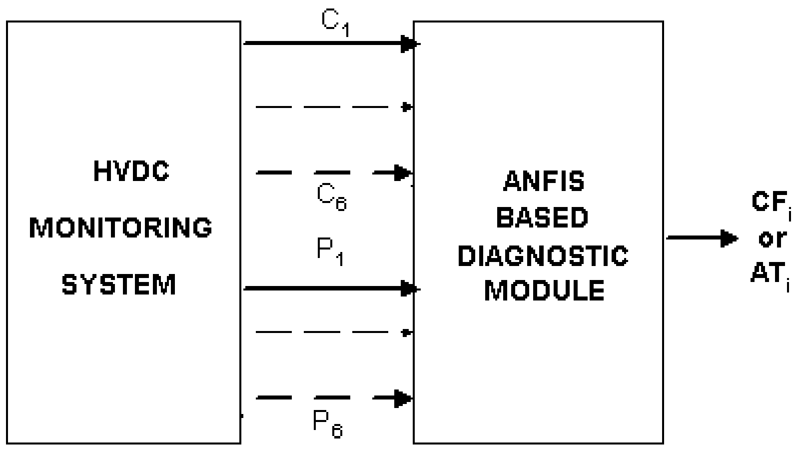

Figure 7: Integrated fault identifier.

Here P_i= firing pulse of i^{th} valve

C_i = current through i^{th} valve.

CF_i = commutation failure of i^{th} valve

AT_i = arc-through / firethrough of i^{th} valve

$i = 1$ to 6

C_i signal is derived from a valve, and P_i (gate firing pulses) are obtained from the converter control circuit.

The signature that is used to recognize commutation failure of i^{th} valve is given by

$$C_{(i-2)} \wedge P_{(i+1)}. \tag{3}$$

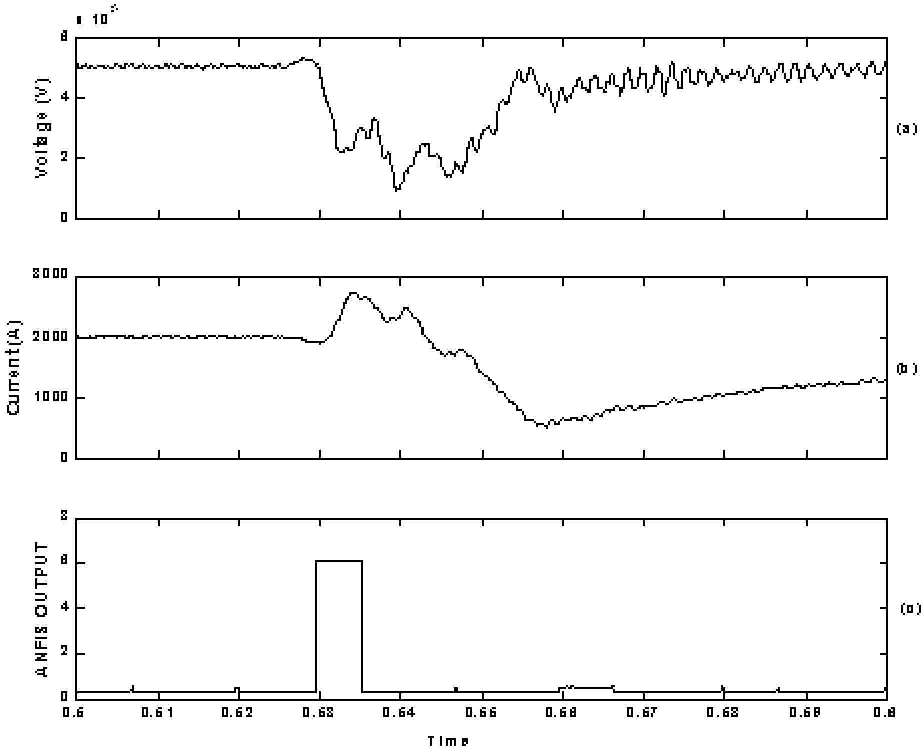

Figure 8: ANFIS – CF6 response: a) DC line voltage; b) DC current Id; c) output from ANFIS-CF.

Thus the conduction of valve number 4 in pulse zone P_1 is recognized as a commutation failure of valve 6 (CF_6).

It is important to note that integrated identifier also can be designed as a simple fuzzy system but for the present problem it is not easy to select number of membership functions and fine-tune them. Instead, this paper uses ANFIS approach to the design of system overcoming various problems related to simple fuzzy systems.

The proposed method is highly reliable and gives unambiguous indication of converter faults.

To design the proposed ANFIS based CF identifier (ANFIS-CF), input-output training data are constructed using the signature stated earlier and some of the data are reutilized as test data.

It is found that this ANFIS model contains 18 rules. Training time and learning epochs for the ANFIS are definitely less than those required for designing similar identifier using pure neural network.

Fig. 8 (a,b,c) shows voltage at DC line, DC current I_d, and output from ANFIS-CF when the commutation failure of valve 6 occurs in the system at $t = 0.528$ sec.

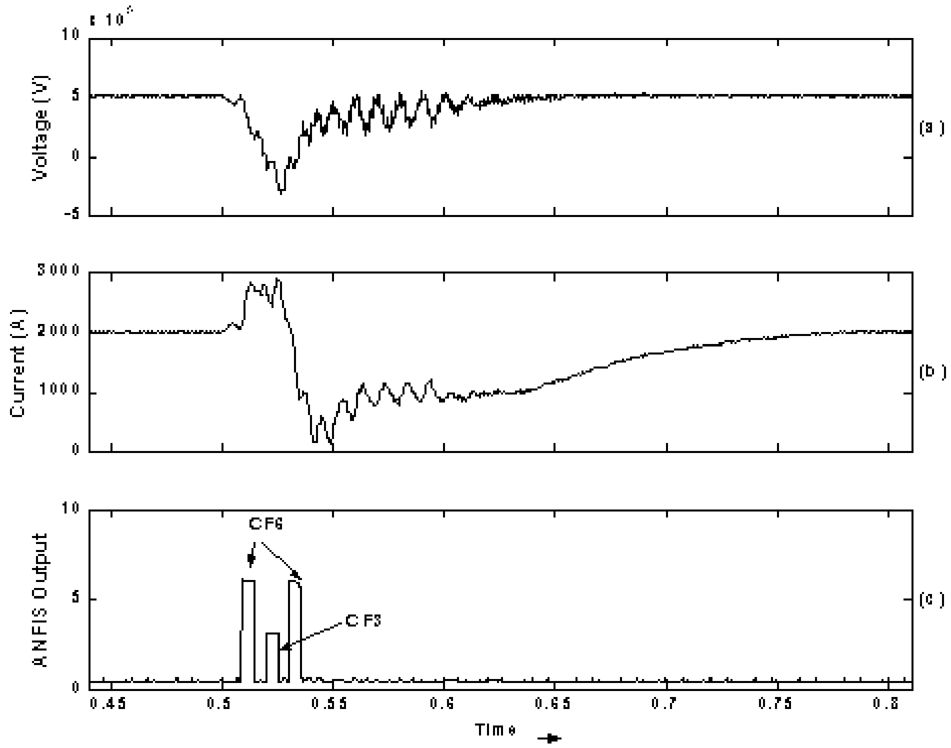

Figure 9: System response for 40 % dip in Ph. A: a) DC line voltage; b) DC current I_d; c) output from ANFIS-CF.

Fig. 9 shows performance of the identifier when the HVDC system is subjected to 1 phase, 40 dip in phase A during time 0.5-0.6 seconds. The fault identifier indicates a commutation failure of valves 6 and 3. In a similar fashion, the integrated fault identifier (ANFIS-AT) is also designed to detect fire through of valve. This identifier detects fire through of V_i valve if V_i conducts in $P_{(i-1)A}$ zone. Here subscript A indicates the first 60-degree part of $P_{(i-1)}$ Pulse zone. Thus the criterion used is

$$C_i \wedge P_{(i-1)A}. \tag{4}$$

One such identifier will be sufficient to detect firethrough of any valve within the bridge converter. The response of HVDC system and fault identifier ANFIS-AT, when the converter is subjected to firethrough of valve 6 is shown in Fig. 10.

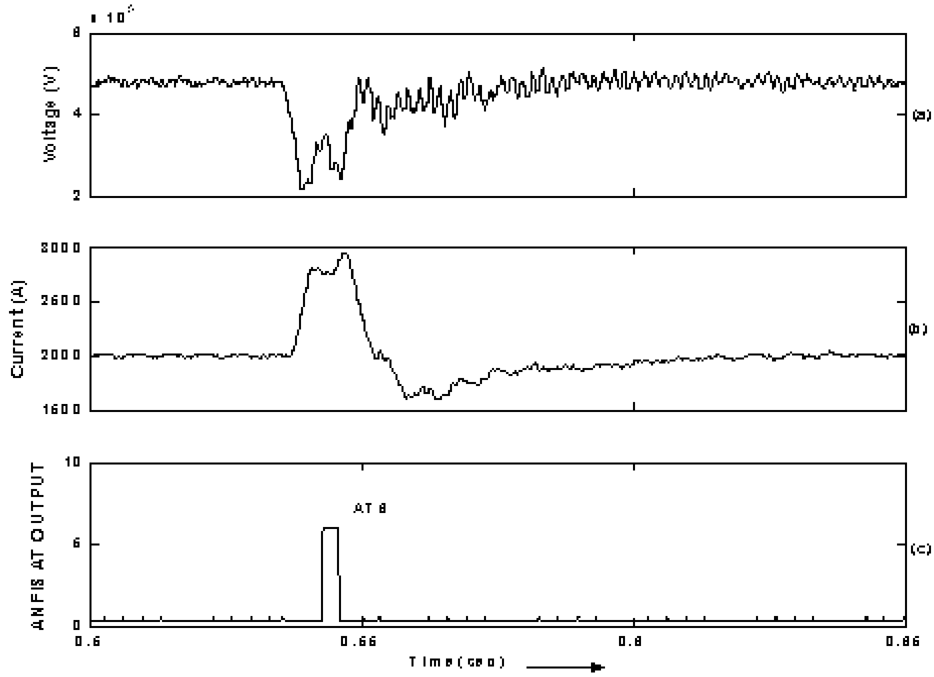

Figure 10: (a) V_{dcline}; (b) I_{dc}; (c) ANFIS-AT output.

6 Simulation and testing

Several digital simulations were carried out to validate different methods proposed in this paper for successful detection of converter faults and to demonstrate performance of ANFIS based current controller. The detailed HVDC system was developed in Simulink with MATLAB as computational engine. ANFIS based fault identifier and current controller were developed using Matlab fuzzy logic toolbox. Simulation results were also validated on CIGRE HVDC Benchmarking model.

7 Conclusions

Performance of FL based controller and ANFIS based current controller for HVDC system is compared. Simulation show the superior performance of ANFIS based current controller. Instead of using separate fault identifier for each valve, an integrated fault identifier is developed which is effective for the complete bridge converter. Fault identifier, which is developed, is able to provide discrete and unambiguous indication of converter faults such as commutation failure and arcthrough/firethrough of a valve within the converter. Fault identifiers are tested for HVDC with strong and weak ac side. Fault identification methods are applicable in both inversion and rectification mode.

Several digital simulation results are presented to verify the fault detection procedure outlined in the paper. ANFIS based control can be easily combined with the ANFIS based fault identifier to form integrated system, which can improve dynamic response of the HVDC system.

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