# APPLICATION OF ARTIFICIAL INTELLIGENCE IN POWER SYSTEM PROTECTION

**BY**

**J. KATENDE**
Department of Electrical and Information Engineering
Covenant University, Otta, Ogun State
sempa54@yahoo.com

AND

**M. S. HARUNA**
Department of Electrical Engineering
College of Engineering, Kaduna Polytechnic, Kaduna.
msharuna@gmail.com

## ABSTRACT

The main artificial intelligence techniques found in power systems applications are those utilizing the logic and knowledge representatives of expert systems, fuzzy systems artificial neural networks and, more recently evolutionary computing. This paper deals with the design and application of intelligent relay using the first three areas. It describes in some detail the important attribute that these branches have, which make them particularly well suited for solving protection problems where traditional methods have limitations/difficulties. It also deals with some of the fundamental issues relating to AI technology that needs to be addressed in order to maximize the benefits/advantages that can be attained from these branches of AI, particularly when applied to protection; the aforementioned are supplemented by specific applications.

**SIGNIFICANCE:** The paper has clearly shown that artificial intelligence methods and approach is effective in automating the relay setting, coordinating and monitoring of protection process which would otherwise be time consuming and error prone and heavily dependent upon the skills of protection engineers.

**KEYWORDS:** Expert systems, neural networks architecture, phase selection, test pattern, rule based logic.

## 1. INTRODUCTION

Since the early to mid 1980s much of the effort in power systems analysis and protection has turned away from the methodology of formal mathematical modeling which came from the fields of operations research, control theory and numerical analysis to the less rigorous techniques of artificial intelligence.

The reliable operation of large power systems with small stability margins is highly dependent on control systems and protection devices. Progress in the field of microprocessor systems and demanding requirements in respect of the performance of protective relays are the reason for digital device applications to power system protection. The superiority of numeric protection over its analogue alternatives is attributed to such factors as accurate extraction of the fundamental voltage and current components through filtering, functional benefits resulting from multi-processor design and extensive self-monitoring, etc. However, all these reasons have not led to a major impact on speed, sensitivity and selectivity of primary protective relays, and the gains are only marginal; this is so because conventional digital relays still rely on deterministic signal models and a heuristic approach for decision making, so that only a fraction of the information contained within voltage and current signals as well as knowledge about the plant to be protected is used.

The performance of digital relays may be substantially improved if the decision-making is based on elements of artificial intelligence (AI). Relays capable of that ought to have the following properties:

- tripping decisions ought to be based on several criteria with adaptable weighting factors
- uncertainty with regard to the signals and setting ought to be modelled qualitatively

- the consequence of a wrong decision ought to be considered, making the relays more inclined to trip or more inclined not to trip, depending upon actual conditions.
- delay of the final decision ought to depend on the inflow of information related to the critical quantities.

The mathematical tools, which lend themselves very well to the design of the intelligent relay, are: (i) expert systems, (ii) fuzzy logic and (iii) artificial neural networks. This paper deals with these three main areas of AI as applied to protection.

## 2. AN EXPERT SYSTEM (ES) FOR PROTECTIVE RELAY SETTINGS

### 2.1 Explanation

Protective relays are hardware devices responsible for sensing the over-currents and tripping the circuit breakers to isolate transmission line faults as soon as possible. The effect of faults can be minimized by proper coordination of the protective relays. Setting the operating parameters of such relays is a knowledge-intensive problem that very often requires the experience of senior relay engineers. It also involves comprehensive and repetitive routine work dealing with a large database; this is a tedious and time consuming task. The complexity of this problem is compounded when various relay types from different manufacturers are involved, and this is typical in almost all power systems. Moreover, the increasing complexity of modern power systems adds an extra burden to the relay setting process. However, since major parts of the setting knowledge are available in a rule style, an ES lends itself naturally to the purposes of facilitating/optimizing relay settings.

Application of ES to power system protection has been investigated for several years, but very few applications have been implemented owing to the stringent time response requirements of relaying functions. It is mostly applied to problems for which time response requirement is not critical [4,10], in this respect, distance relays are the most difficult to set in that they employ non-unit measurements and require a multiplicity of settings; the application chosen in this paper therefore concentrates on outlining the development of an ES for setting and coordinating the very widely employed distance protective relays.

### 2.2 Problem Description

Figure 1 shows the principal sub-problems in the relay setting process. The distance protection comprises five distance zones and seven time steps as indicated in Table 1. The study presented herein focuses on the normal distance stages and the overreach resetting stages. The normal zones $Z_1$, $Z_2$ and $Z_3$ operate independently from one another and also independently from the overreach zones $Z_{OB}$ and $Z_{OL}$.

For the first zone, $Z_1$, instantaneous tripping (typically $T_1$ = 0.02s-0.03s) is normally selected for the first 85% of the line length. For each of the subsequent stages, the delay time is increased by one grading time unit; normally 0.3s-0.4s is used. In this respect, reach is selected so that it covers up to 80% of the equal time stage for the next line section. Figure 2 gives an example of the grading plan for a typical transmission system.

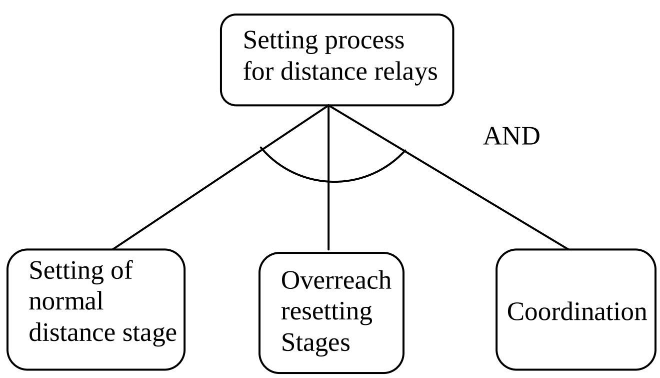



**Figure 1. Decomposition of the initial problem**

**Table 1 Different zones and time delays for distance protection**

| Setting | Zone | Time delay |
|---|---|---|
| Normal | $Z_1$ | $T_1$ |
| Distance | $Z_2$ | $T_2$ |
| Stages | $Z_3$ | $T_3$ |
| Over-reach | $Z_{OB}$ | $T_{OB}$ |
| Resetting stages | $Z_{OL}$ | $T_{OL}$ |
| Fault | | $T_4$ (directional delay) |
| Detection | | $T_4$ (non-directional delay) |

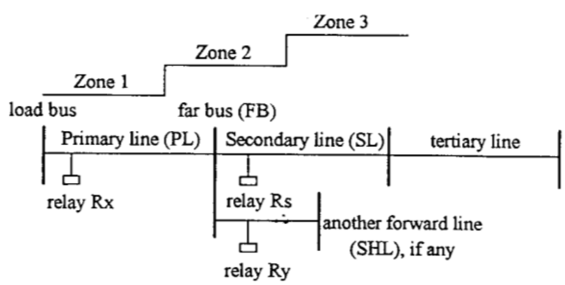



**Figure 2 A model for reach setting of distance relays**

In this case, the setting values for, say, relay Rx, would be as follows:

$$X_1 = 0.85X_P \quad \ldots(1)$$

$$X_2 = 0.8[X_P + 0.85X_S] \quad \ldots(2)$$

$$X_3 = -0.8[X_P+0.8(X_S+0.85X_t)] \quad \ldots(3)$$

Where $X_1$, $X_2$, $X_3$ are the reach setting for the normal distance stages and $X_p$, $X_S$, and $X_t$ are the reactances for primary, secondary and tertiary lines, respectively. The problem is to be able to properly identify both the secondary and tertiary lines for every relay in a given network; this would of course depend in general on the network configuration and the reactances of the transmission lines. The knowledge of protection engineer in selecting relay for both secondary and tertiary lines is rule-based as specified below. In these rules, the set of forward lines for a given relay is defined as those lines connected to the far end bus, excluding the primary line and any other line that runs in parallel to it. The secondary line is considered to be the longest forward line during the preliminary calculation of the second zone setting $X_2$. However, the settings obtained are checked during the coordination process, and readjusted if necessary, to avoid improper relay operation due to the possible existence of forward lines, which are too short.

The rule structure is as follows:

Rule L1: **if** the set of forward lines is empty, **then** it is an end-line case.

Rule L2: **if** a secondary line is needed for the relay setting model, **AND** end-line is proved, **then** the primary line is used as a fictitious secondary.

Rule L3: **if** a secondary line is needed for the relay setting model, **AND** it is not an end-line case, **then** the secondary line is the longest line in the set of forward lines connected at the far end bus.

Rule L4: **if** a tertiary line is needed for the relay setting model, **AND** an end-line case is proved, **then** the primary line is used as a fictitious tertiary.

Rule L5: **if** a tertiary line is needed for the relay setting model, **AND** it is an end line case, **AND** the secondary line is known (say line SL), **AND** the bus at the far end of the primary line is known (say bus FB),**then** the tertiary line is the secondary line for the next relay Rs (at the bus FB and line SL).

The overreach setting stages $Z_{OB}$ and $Z_{OL}$ for zones 2 and 3, respectively, may be obtained following similar procedures. Considering zone 2 it is necessary to stimulate a fault on the longest forward line at the end of zone 2. A short-circuit analysis software module may be used to simulate the fault and find the relevant short-circuit currents. Next, the overreach resetting is calculated from:

$$X_B = X_1 + X_b[1 + (I_1/I_a)] \quad \ldots(4)$$

Where $X_B$ is the over-reach resetting for zone 2, $X_b$ the reactance of the faulty line at the end of zone 2, $I_a$ the short-circuit current of the primary line, and $I_1$ the sum of the injected fault current for all lines at the far end bus except the primary and the longest forward (faulty) line.
For every relay, the expert system (as described in the next section) is required to identify the relevant lines, run the proper fault simulation, and obtain the relevant short-circuit results to be substituted in eqn 4.
Referring to the model of figure 2, if any forward line at the far bus (FB) is too short, for instance line (SHL), then the Zone 2 reach for relay $R_X$ extended beyond the Zone 1 reach of the next relay $R_y$; and hence it will overlap the zone 2 reach of the latter. If the zone 2 time delay for both relays is equal, then erroneous operation would occur, losing the selectivity. In this case, the zone 2 reach should be reduced or the backup time delay should be increased to avoid undesirable relay operation. A similar argument holds for zone 3. Zone 2 coordination rules are summarized in the following, and similar rules apply for zone 3:
Rule C1: **if** the zone 2 reach of the backup relay ($R_x$) extends beyond the zone 1 reach of the primary relay, ($R_y$) **AND** then zone 2 time delay of the backup relay is less than or equal to that of the primary relay, **then** zone 2 miscoordination exists for the relay pair ($R_x$,$R_y$).
Rule C2: **if** Zone 2 miscoordination exists for the relay pair ($R_x$ $R_y$), **AND** the zone 2 setting to reach 80% of the backup line (SHL) is greater than 120% of the primary line (PL) reactance, **then** set zone 2 to reach 80% of the backup line.
Rule C3: **if** zone 2 miscoordination exists for the relay pair ($R_x$,$R_y$), **AND** the zone 2 setting to reach 80% of the backup line (SHL) is less than or equal to 120% of the primary line reactance, **then** increase the time delay of zone 2 by 0.2 s.

**2.3 Expert system approach**

ESs are computer programs that perform sophisticated tasks. The expert program is built from explicit pieces of knowledge extracted from human experts using AI programming techniques such as symbolic representation, inference and heuristic search. Knowledge-based systems can be distinguished from other branches of AI by their emphasis on domain-specific knowledge rather than from more general problem solving strategies. Because their strength is derived from the former rather than the latter, ESs are often called knowledge-based systems. An ES typically consists of four main components [14,15] as illustrated in figure 3:

- A knowledge base with highly specialized information on the problem area as provided by the expert.
- An inference engine which is modeled after the expert's reasoning. The engine works with available information on a given problem, coupled with the knowledge stored in the knowledge base, in order to draw conclusion and make recommendations.
- A knowledge-acquisition interface that assists experts in expressing knowledge in a form suitable for incorporation into knowledge base.
- A user interface that assists users in consulting the ES, prompting them for information required to solve their problem, displaying the program's conclusions and explaining the reasoning. Generally, these interfaces attempt to provide the users with most of the capabilities they would have had if they were interacting with a human expert.

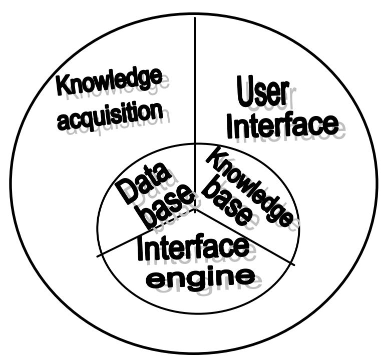



**Figure 3 General structure of an expert system**

engine interacts with the user interface to accept network description input from the user and supply the relay setting results. A software module is included to perform short-circuit analysis upon request from the inference engine. The network description and calculated short-circuit currents are exchanged via magnetic disk buffers (database) as shown in figure 4.

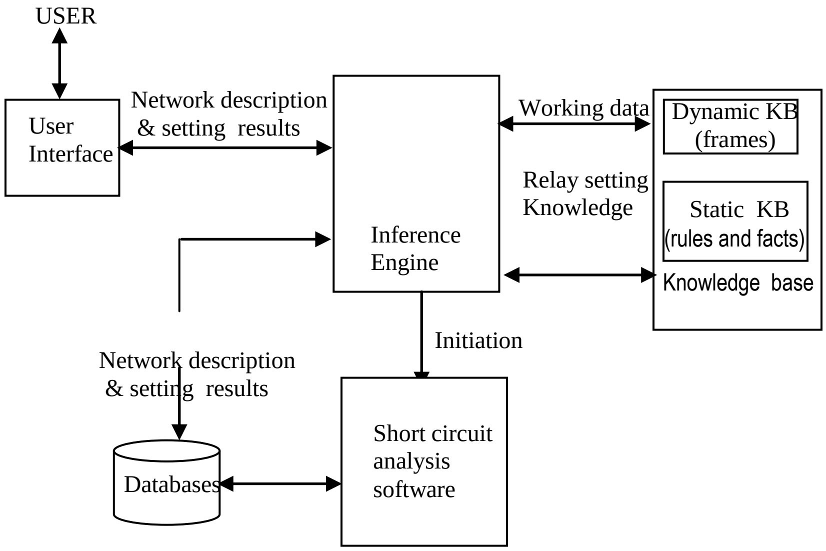



**Figure 4 Structure of the relay setting expert system**

The input data involved in the application includes the network configuration, electrical and physical properties of the HV transmission lines, lay locations, etc. Such data should be stored in a well-organized and packaged form in order to allow efficient access and reasoning.

The frame-based approach satisfies the above-mentioned need and permits modular and efficient knowledge representation. Consequently, knowledge about every relevant network element (buses, transmission lines, and relays) would be packaged in a separate frame named after that element. The system output data, i.e. relay setting values, can be incorporated easily into the same frames that contain the input data.

Knowledge about the network configuration may be described in two alternative ways. One method is to store the names of terminal buses for every line in the network. However, this representation would be inefficient when there is a need to examine all lines connected to a given bus. Alternatively, the network configuration may be represented by storing lists of lines connected to every bus in the network. This representation, however, would be inefficient when there is a need to know the buses at both ends of a given line.

Consequently, to obtain efficient access to the configuration knowledge, both mechanisms should be implemented simultaneously. Consistency of the redundant knowledge can be tightly controlled through the data entry mechanism.

**2.4. A typical application**

A prototype for the developed ES is implemented using Prolog on a powerful PC. The prototype can accept any network configuration and produce the relay setting parameters. The network, shown in figure 5, is selected as an example to illustrate the performance of the developed system. Table 2 typifies the generated results for the normal distance stages as well as the coordination adjustments for the second zone.

With reference to the previous sections, the setting results obtained using the grading plan of eqns 1-3, together with rules *L*1 *L*-5. Zone 2 miscoordination, for the relay pairs (dp, cq) and (eq, cp) have been proved according to rules C1-C3. The ES has provided the necessary coordination adjustments by reducing the second zone settings for the indicated backup relays, as shown in Table 3.

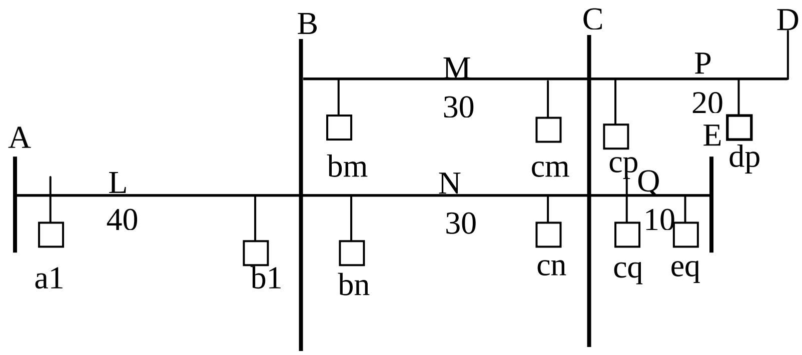



**Figure 5 Network studied (line reactances are shown in ohms)**

**Table 2 Generated relay setting results for the network studied**

| Relay | Pri | Sec | Ter | X1 | T1 | X2 | T2 | X3 | T3 |
|---|---|---|---|---|---|---|---|---|---|
| a1 | L | M | P | 34.0 | 0.02 | 52.4 | 0.49 | 62.08 | 0.9 |
| b1 | L | L | L | 34.0 | 0.02 | 59.2 | 0.49 | 79.36 | 0.9 |
| bm | M | P | P | 25.5 | 0.02 | 37.6 | 0.49 | 47.68 | 0.9 |
| cm | M | L | L | 25.5 | 0.02 | 51.2 | 0.49 | 71.36 | 0.9 |
| bn | N | P | P | 25.5 | 0.02 | 37.6 | 0.49 | 47.68 | 0.9 |
| cn | N | L | L | 25.5 | 0.02 | 51.2 | 0.49 | 71.36 | 0.9 |
| cp | P | P | P | 17.0 | 0.02 | 29.6 | 0.49 | 39.68 | 0.9 |
| dp | P | M | L | 17.0 | 0.02 | 36.4 | 0.49 | 56.96 | 0.9 |
| cq | Q | Q | Q | 8.5 | 0.02 | 14.8 | 0.49 | 19.84 | 0.9 |
| eq | Q | N | L | 8.5 | 0.02 | 28.4 | 0.49 | 48.96 | 0.9 |

**Table 3 Zone co-ordination results**

| Backup relay | Primary relay | initial setting | adjusted setting |
|---|---|---|---|
| dp | cq | 36.4 | 22.8 |
| eq | cp | 28.4 | 21.6 |

## 3. FUZZY LOGIC (FL) FOR POWER SYSTEM PROTECTION

### 3.1 Motivation

Because of environmental and regulatory concerns, the growth of electrical power transmission facilities is restricted and as a result, many utilities worldwide are investigating novel ways of better utilization and control of existing transmission systems. This in turn has posed new challenges for protection engineers to develop improved protection techniques that will meet the complex and onerous requirements; this will lead to increased system reliability, stability and maintenance of the quality of supply at high levels, and at the same time constrain costs

. **Problem description**

To a large extent, the majority of conventional protection techniques are involved in defining the equipment states by identifying the patterns of the associated voltage and/or current waveforms, albeit of the power frequency components. However, for the reasons stated below, there exists a large element of uncertainty and vagueness due to the complex relationships between the vast number of system variables and this poses a significant difficulty when applying conventional techniques:

- changing power system operating conditions such as changes in load or generation and changes to the topology of power systems.
- Various power system configurations such as untransposed/transpose, horizontal/vertical, single/double circuit lines, etc
- Many different fault conditions, including fault inception, fault location, fault types and fault resistance
- Inaccuracies caused by voltage and current transducers or noise introduced by electromagnetic interference.

The aforementioned problems are compounded by their random nature. In this respect, FL, as one of the AI branches, has been investigated as a powerful tool in the development of novel protective relays for transmission systems [15]; this is particularly so by virtue of the fact that FL is much closer in spirit to human thinking and natural language than traditional logical systems [14] . It is a method of easily representing human expert knowledge on a digital computer where mathematical or rule-based expert systems experience difficulty.

**3.3. Fuzzy logic approach**

Faults on a power system always result in abnormal currents and voltages. Figure 6 illustrates typical voltage and current waveforms. Fault included high frequency components, reduced magnitudes of the power frequency component in the voltage Waveform [11] and a sharp increase in the current are clearly evident. To a large extent, the majority of protection techniques are based on defining equipment states through identifying the associated voltage and current waveforms. Some schemes are discriminative to fault location and involved several parameters, for example, time, direction, current, impedance (voltage/ current), current balance and phase comparison. Others discriminate according to the type of fault, e.g negative -sequences relays. Due to changing power system conditions and many causes of faults, there always exist difficulties in the setting of relays. As a result, the protection system may maloperate (for example, over-reach or under-reach in a distance relay) under certain conditions. [1,11].

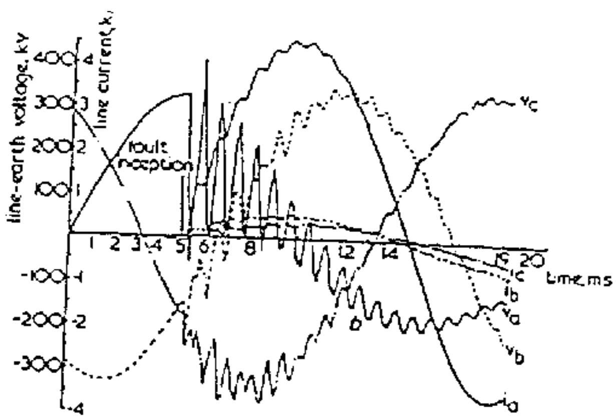



**Figure 6 Typical faulted voltage and current waveforms**

**3.3.1 General structure of a fuzzy relay**

A schematic of a fuzzy protection relay is shown in figure 7. It is essentially similar to a fuzzy controller, which comprises four principal components: a fuzzification interface, a knowledge base, an inference engine and a defuzzification interface.

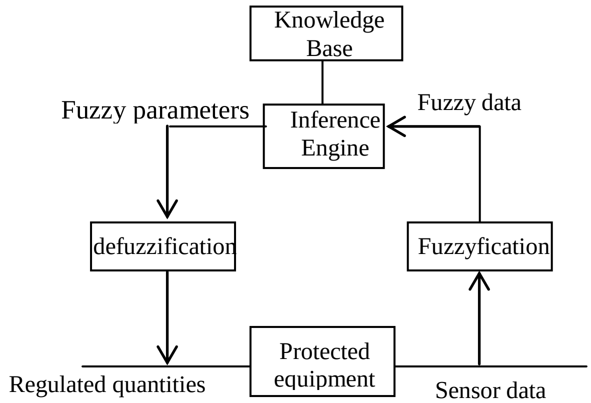



**Figure 7 Structure of a fuzzy relay**

(1) The fuzzification interface performs the following functions:
(a) measures the values of input variables
(b) performs a scale mapping that transfers the range of values of input variables into corresponding universes of discourse
(c) performs the function of fuzzification that converts input data into suitable linguistic values which may be viewed as labels of fuzzy sets.
(2) The knowledge base comprises a knowledge of the application domain and the attendant control goals. It consists of a 'data base' and a 'rule base' as follows:
(a) the data base provides the necessary definitions which are used to define linguistic control rules and fuzzy data manipulation
(b) generally the design of fuzzy controllers is based on the operator's understanding of the behavior of the process instead of its detailed mathematical model. The main advantage of this approach is that it is easy to implement the 'rule of thumb' experiences and heuristics. These rules are often expressed using a syntax of the form: if <fuzzy proposition>, then <fuzzy proposition>, where the fuzzy propositions are of the form, 'x is Y' or x' is not Y', x being a scalar variable and Y being a fuzzy set associated with that variable.
(3) The decision making logic is the kernel; it has the capability of simulating human decision making based on fuzzy concepts and of inferring fuzzy control actions employing fuzzy implication and the rules of inference is in fuzzy logic.
(4) The defuzzification interface performs the following functions:
(a) a scale mapping, which converts the range of values of output variables into corresponding universes of discourse.
(b) Defuzzification, which yields a nonfuzzy control action from an inferred fuzzy control action.

### 3.3.2 Fuzzy logic approach for transmission line protection

According to the general structure introduced in section 3.3.1, the steps to design a fuzzy relay include: (1) choosing appropriate variables as the inputs; (2) converting the inputs to fuzzy sets (fuzzifier); (3) determining the fuzzy matrix (knowledge base); (4) designing the fuzzy inference (decision making); and (5) devising an appropriate transformation of fuzzy trip actions into crisp trip actions (defuzzifier) [1,6]

From the conventional protection technique, normally current *I*, voltage V and their transients DI, DV can be chosen as the input signals to the fuzzy relays for a transmission line. Choosing transients which correspond to the superimposed value has distinctive advantages. In terms of the normal and abnormal operation of a power system, the inputs, I,V can be expressed in linguistic variables as very large value (VL) large value (LV), normal value (NV), small value (SV) and very small value (VS), and the inputs DI,DV can be expressed by large positive (LP), medium positive (MP), small positive (SP), small negative (SN), medium negative (MN) and large negative (LN). They can be normalized, based on the rating current and voltage respectively, and then described by membership functions, one of which is shown in figure 8. The output of the fuzzy logic is absolute trip (AT) possible trip (PT), possible no trip (PN) and no trip (NT).

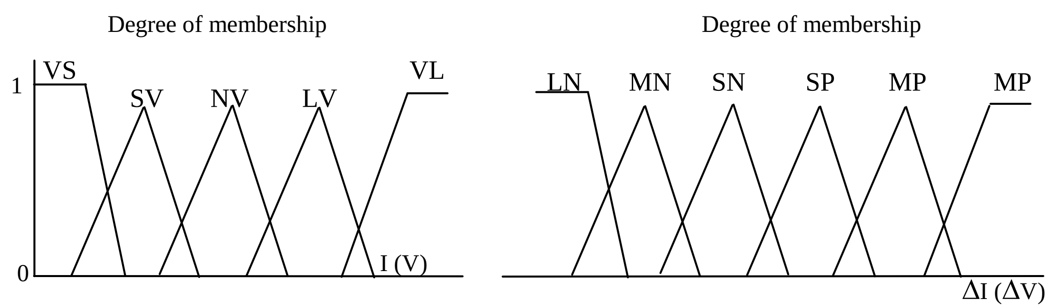



**Figure 8 Membership functions for current and voltage**

The rules that are used for fault identification can be expressed in a linguistic manner. This problem solving approach is similar to that of human experts, where they solve problems by using particular rules based on their experience and knowledge [3] There are several ways to drive the rules, including methods based on: (1) the expert's experience and / or knowledge; (2) the fuzzy model of the process; (3) learning algorithms, especially using neural networks which have the ability to learn from examples. Through the combination of the four inputs, there will be 900 decision rules (5 elements of I x 5 elements of V x 6 elements of DI x6 elements of DV) in all, for example:

Rule 1: **IF** I is VL, DI is LP, V is VS **AND** DV is LN **THEN** the output is AT

Rule 2: **IF** I is NV, DI is SP, V is NV **AND** DV is SN **THEN** the output is NT

Based on the decision rules, the membership function of the output can be determined using the composition rule. To illustrate this process, an example is shown in figure 9.

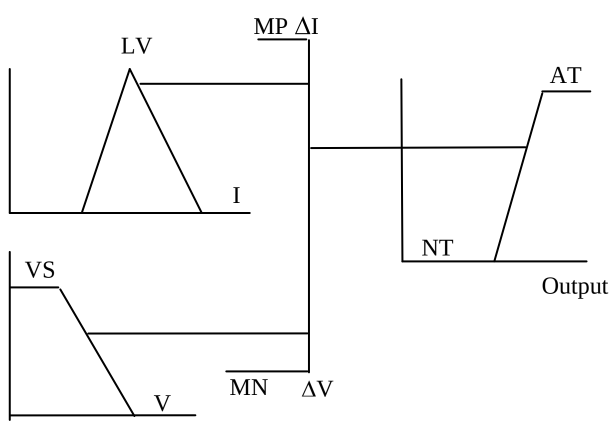



**Figure 9 Decision inference of a fuzzy relay**

Once the membership function of the output has been obtained, a suitable algorithm must be used to determine the output signal. The 'maximum algorithm' in which the signal with the largest memberships value, or the 'centre of gravity method; can be then employed to derive the output [12].

## 4 ARTIFICIAL NEURAL NETWORKS (ANNS) METHOD

### 4.1 Overview

Single-pole autoreclosure (SPAR) has been recognized as an effective means of improving system security and reliability [7]. The benefits of SPAR are particularly apparent in applications where economic and or/ stability considerations prelude the use of three-phase autoreclosure. The benefits are even greater in long line applications where the use of shunt compensation arrangements together with improved design methods is leading to more widespread use of SPAR [5,7].

SPAR applications involve tripping only the faulted phase under single-phase-earth fault conditions and initiate three-phase autoreclosure for other types of fault. Reliable phase selection of the faulted phase is thus vitally important in order to avoid either tripping of the incorrect phase or unnecessary three-phase tripping, thereby minimizing system insecurity and instability. Moreover, apart from correct phase selection, a concomitant requirement of phase selectors is high-speed operation since the selection process must be completed in the immediate postfault period so as to avoid any serious potential problems.

**4.2 Problem description**

Conventional phase selectors, primarily based on power, frequency, voltage and current measurands, suffer from a degradation in performance as a result of their accuracy being dependent upon such factors as remote-end infeed , fault resistance, mutual coupling from adjacent parallel lines, etc. In this respect, artificial neural networks (ANNs), with their ability to map complex and highly non-linear input/output patterns, provide an attractive solution to the long-standing problem of accurate phase selection. This section describes the design of a novel technique for phase selection using neural networks. A recent technique, which has been successfully used for developing a new non-unit protection scheme [4,10], is employed for measurement of fault generated by high frequency noise on faulted EHV transmission lines. It is essentially based on a specially designed stack tuner (tuned to a particular frequency bandwidth), which is connected to the coupling capacitor of the capacitor voltage transformer (CVT). A neural network associated with necessary digital processing is then developed to identify the faulted phase in accordance with the captured information. The section concludes by presenting results based on extensive simulation studies carried out on a typical 330 KV line.

**4.3 Measurement of fault generated high frequency components**

**4.3.1 Basic Principle**

A fault on a power line produces wideband noise and/or travelling waves. Much of this noise is outside the reception bandwidth of the present generation of protection. However, a recent and new measurement technique that can detect high frequency components of system voltage under fault by means of a stack-tuner circuit, which is connected to a transmission line via the high voltage coupling capacitor of a typical CVT, has been proposed [11]. Figure 10 shows the basic arrangement in which each stack-tuner and coupling capacitor combination is arranged to behave as a very high impedance over a pre-defined range of frequencies.

A series of studies has shown that a bandwidth of around 20 kHz centered on a frequency of 100 kHz is suitable for the majority of practically encountered system and fault conditions [2].

**4.3.2 Fault simulation**

A series of simulation studies has been carried out to obtain the fault generated high frequency noise for subsequent analysis through the ANN based phase selector. The system considered is a typical 330 kV single circuit vertical construction line of the type widely used on the UK supergrid system. The source parameters, line length, etc are as shown in figure 10. The simulation of the power system has been carried out using the well known EMTP software. Within the simulation has also been embodied a realistic model of the non-linear fault arc. [2,13].

Figure 11 typifies the faulted response attained for an ‘a’-earth fault at the midpoint. First of all considering the primary system voltage waveforms, it is evident from figure 11a that the faulted phase experiences a high degree of frequency distortion.

As expected, distortion also appears on the healthy phases due to the mutual coupling effects between the faulted and healthy phases. However, the magnitude of the transients in the latter case is relatively small. When comparing the outputs of the stack tuner for the three phases, figure 11b quite clearly shows that the wave shapes are very similar and more importantly, the magnitude of the peak transients are comparable for the three phases. This is so by virtue of the fact that the stack tuner only captures the in-band high frequency components. This phenomenon can be clearly seen by examining the frequency spectra of the stack tuner (figure 11c), from which it is difficult to discern which of the three phases is the faulted phase.

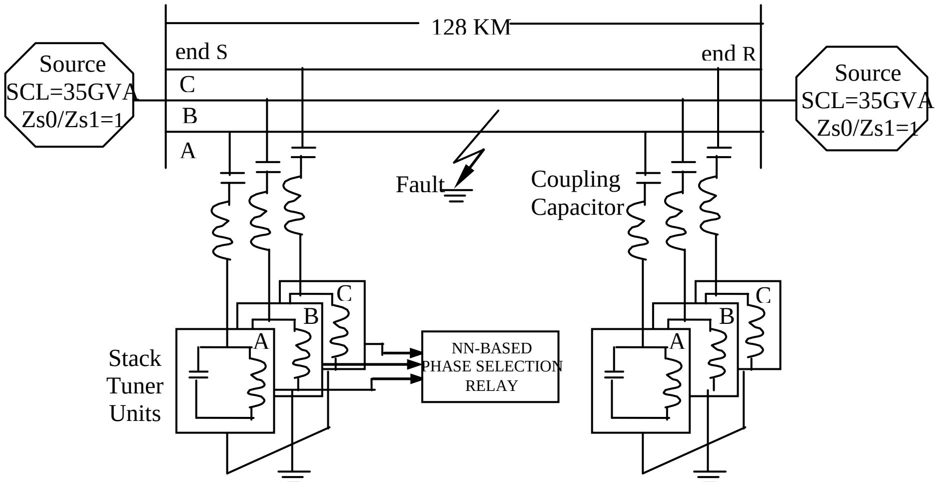
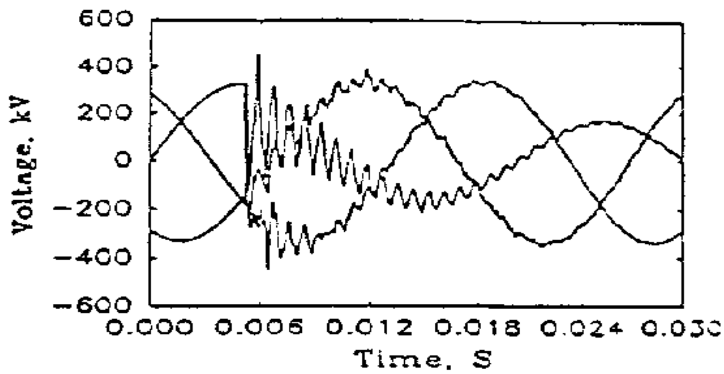
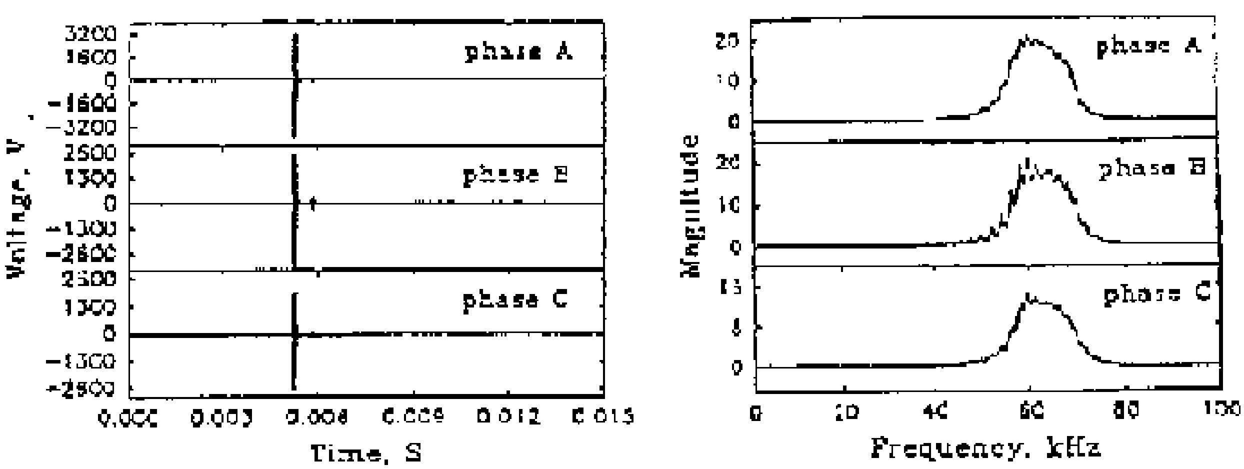



**Figure 10 System arrangement for detecting fault-induced high frequency noise**




**(a) Primary system voltage waveform**




**(b) Stack tuner output** **(c) Spectrum of stack-tuner output**

**Figure 11 Typical fault transient response**

### 4.4 Artificial neural network (ANN) approach

From the foregoing discussion, it is evident that the differences between the captured high frequency information on the faulted and healthy phases following a fault are very subtle. It is obviously difficult to design a phase selection scheme using conventional techniques, such as statistical-based pattern recognition. In this respect, NNs have gained renewed reputation in solving long-standing problems [2]. In particular, they have demonstrated the special capability of mapping the very complicated relationships between the inputs and the outputs and of revealing the stubble differences in features between ill defined patterns particularly of the forementioned types associated with wideband fault generated noise. Figure 12 illustrates the basic configuration of the NN-based phase selection techniques. The key elements are feature extraction and the NN itself, which are discussed in the next section.

#### 4.4.1 Feature selection and training/ test patterns

As a first step in any pattern recognition technique, feature extraction is used to reduce the dimension of the raw data and extract the useful information in a concise form. For the NN considered here, this process leads to a significant reduction in the size of the network. Thus the performance and speed of the training process can be significantly improved. Although a number of feature selection algorithms are already in existence, an extensive series of studies has shown that none of them is suitable for the practical problem addressed here. Hence a more empirical method based on frequency decomposition is adopted.

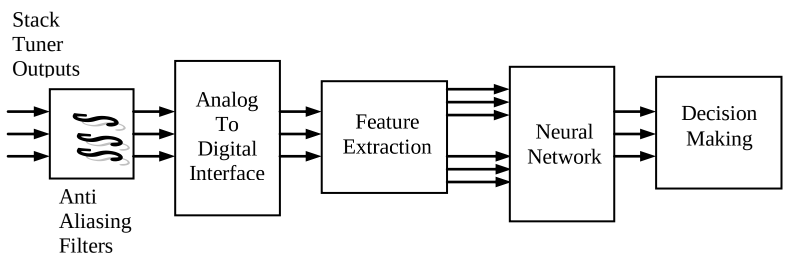



**Figure 12 NN-based phase selection relay arrangements**

Although there are no obvious discernible characteristic in the overall spectra of the faulted and healthy phases, it can be clearly seen from the detailed spectral shown in figure 13 (this is for an ‘a’-earth fault 90 km from end S) that the frequency components in different ranges within the in-band vary significantly in the faulted and healthy phases. It is the presence of such relationship that is used to split the whole in-band frequency components into several ranges of interest. An acceptable simple criterion used here for selecting a variable, as a feature is that it should provide more information for classification than those not selected. After a series of studies employing the frequency spectra approach, the following six parameters were chosen for each phase: (1) below 16.6 kHz (2) over the range 16.7-33.3 kHz; (3) over the range 33.4-49.9 kHz (4) over the range 50-66.6 kHz; (5) over the range 66.7-83.3 kHz; (6) over the range 84-100 kHz.

After the appropriate features have been selected, a large number of simulations are performed off-line to generate a good representative data set for training and testing the NNs, which cover wide system and fault conditions, e.g (1) prefault loading; (2) fault instant; (3) fault location; and (4) faulted phase. There are 18 inputs to the NN, corresponding to the 18 features associated with the three phases and three desired outputs corresponding to the state of the three phases, respectively. The desired output for the NNs is ‘1’ for the faulted phase and ‘0’ for the healthy phases. The data obtained is split into sets, one for training and one for testing.

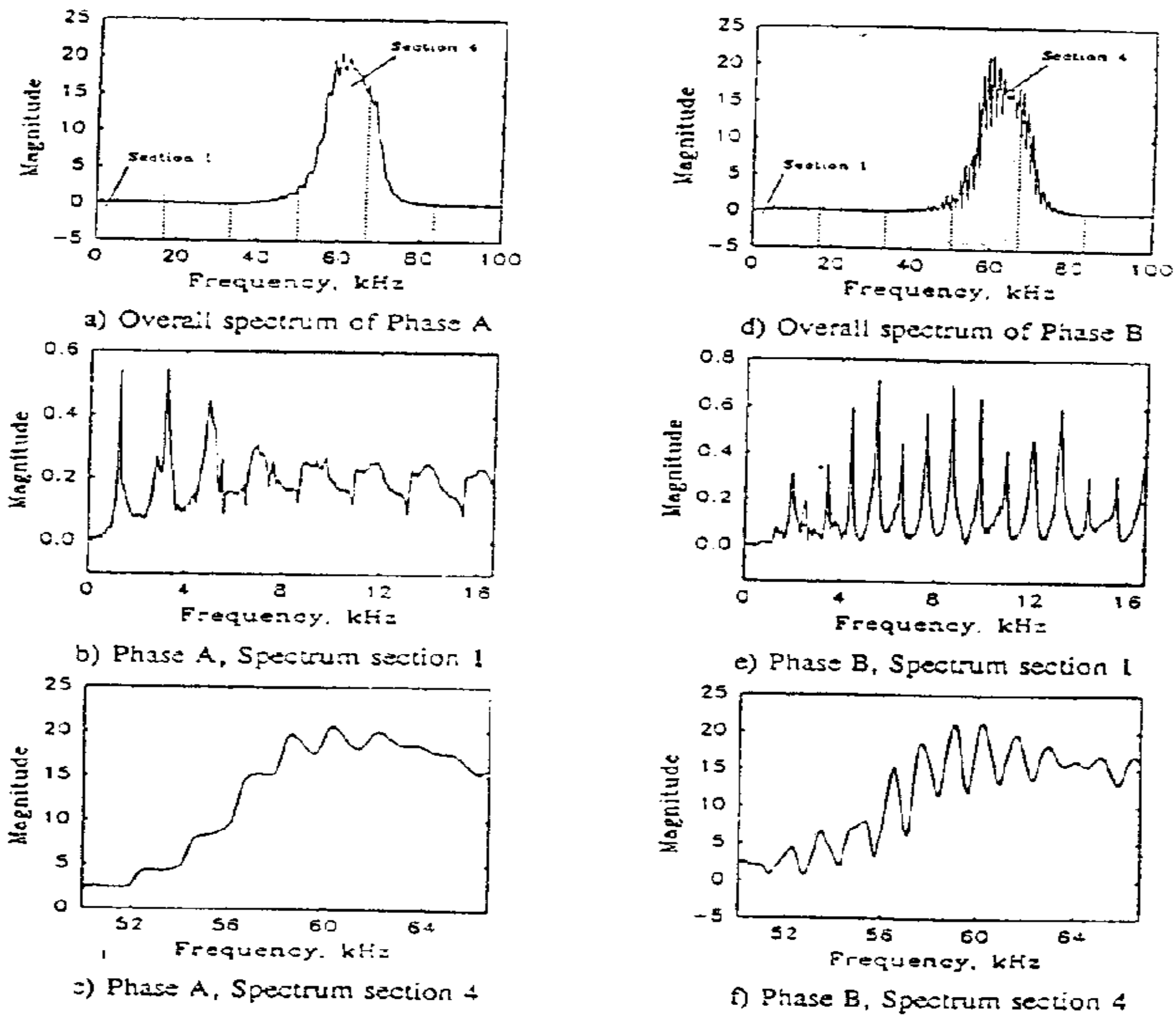



**Figure 13 Typical spectra of stack tuner output**

### 4.4.2 Neural network architecture and the training

Once sets of training/testing patterns have been generated, appropriate NN architecture and associated parameters must be chosen for the particular application. The task of NNs is to learn to capture these common underlying characteristics to select the faulted phase. The feed forward multilayer perception [8] is chosen for this study, as they are known to be well suited for pattern classification. Deciding upon an optimal NN architecture for a classification task is still an open issue. Through a series of tests and modifications, it has been found that the network shown in figure 14 provides the best performance for this particular application. It is a three-layered network which consists of 18 inputs in the input layer, 12 nodes in the hidden layer and three outputs in the output layer. The transfer function used is hyperbolic tangent. After the training data have been scaled to the neurodynamic range, they are presented to the neural network randomly; otherwise the sequenced presentation may make the network oscillate as a result of the NN forgetting what it had learnt previously. The commonly used back-propagation training technique is employed, which basically adjusts the weights in all connecting links and thresholds in the nodes of the NN so that the differences between the actual output and the desired output are minimized for all patterns.. After the RMS error converges to the predefined value, in this case 0.01, the network is assumed to be well trained

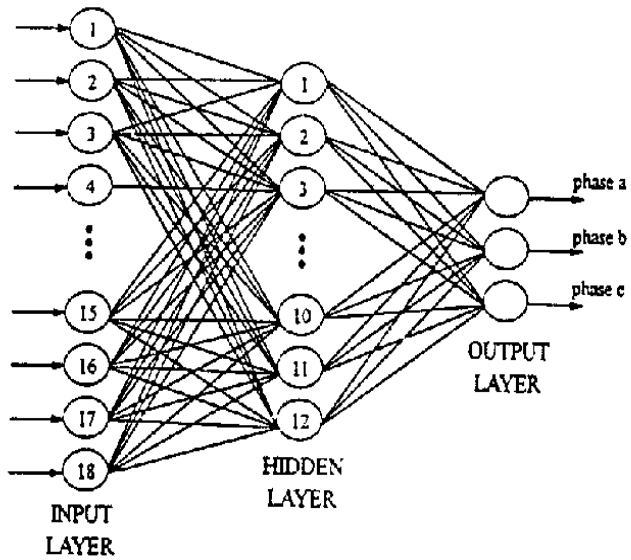



**Figure 14 ANN Topology**

### 4.5 Test results

After the NN has been trained, a separate set of test matters is supplied as input to the NN and its performance is evaluated. Table 4 gives some samples of the test results. The left three columns of the table are the desired outputs, ideally '1' or '0' and the right three columns are actual outputs, of the NN. It is clearly evident that the result is very promising.

**Table 4 Example of the test results**

| Desired output | | | | Actual output | | |
|---|---|---|---|---|---|---|
| Case | A | B | C | A | B | C |
| 1 | 1.000 | 0.000 | 0.000 | 0.998761 | 0.000035 | 0.000656 |
| 2 | 1.000 | 0.000 | 0.000 | 0.998832 | 0.0001213 | 0.001075 |
| 3 | 1.000 | 0.000 | 0.000 | 0.998080 | -0.001303 | 0.001145 |
| 4 | 1.000 | 0.000 | 0.000 | 1.001626 | -0.000071 | 0.001805 |
| 5. | 1.000 | 0.000 | 0.000 | 0.998446 | 0.001981 | -0.000263 |
| 6. | 0.000 | 1.000 | 0.000 | 0.001459 | 1.005280 | -0.005372 |
| 7. | 0.000 | 1.000 | 0.000 | 0.005188 | 0.998601 | -0.000525 |
| 8. | 0.000 | 1.000 | 0.000 | -0.000877 | 0.992729 | 0.008233 |
| 9. | 0.000 | 1.000 | 0.000 | 0.003361 | 1.000853 | -0.004372 |
| 10 | 0.000 | 1.000 | 0.000 | - 0.000748 | 1.001863 | -0.003162 |
| 11. | 0.000 | 1.000 | 0.000 | - 0.005815 | 1.000912 | 0.005864 |
| 12. | 0.000 | 0.000 | 1.000 | - 0.003921 | 0.002568 | 1.009315 |
| 13. | 0.000 | 0.000 | 1.000 | 0.000470 | -0.000830 | 0.99.7005 |
| 14. | 0.000 | 0.000 | 1.000 | 0.002511 | -0.002845 | 1.001085 |
| 15. | 0.000 | 0.000 | 1.000 | -0.002810 | 0.003420 | 0.999195 |
| 16. | 0.000 | 0.000 | 1.000 | 0.008578 | -0.006805 | 0.993810 |
| 17 | 0.000 | 0.000 | 1.000 | -0.005714 | 0.004839 | 0.996618 |

## 5 FUTURE DEVELOPMENTS

From the foregoing discussion, it is apparent that AI provides a very effective and, therefore an attractive alternative to traditional techniques for solving many complex protection problems. However, more recent research has indicated that the performance of Al-based protection techniques can be significantly enhance by the integration of different AI branches rather than the employment of only one particular type. For example, a combined structure of FL and NN to form a fizzy neural network (FNN) will give an insight into the cause and effect of the problem, because an FNN has a higher level inference function than an NN on its own. Another advantage of the former lies in the fact that it is capable of additional learning which the latter is incapable of handling, this is so because any additional data changes the weights of NN as a whole whereas an FNN influences only some of the rules. Another example is a neural-network-experts system which can be used to extract rules from complex data where explicit knowledge is not available. Integration of AI techniques thus provides a very important way forward in the next generation of intelligent protection system design.

## Conclusion

This paper illustrates the use of knowledge –based techniques in the process of setting and coordinating protective relays for complex HV transmission networks. Fuzzy logic theory for power system protection and potential area of application has been discussed. Finally, artificial neural network technology and its ability to solve some of the long standing pattern recognition problems in power system protection, in particular those associated with phase selection in EHV transmission systems was illustrated. Exploitation of these techniques will ensure full benefits of the superiority of Artificial Intelligence in system control and protection.

## 7. References


1. **AGGARWAL, R.K JOHNS, A.T. SONG, Y.H., DUNN, R.W., and FITTON, D.S. (1994);** "Neural network technique based adaptive single pole autoreclosure for EHV transmission systems" IEE Proc., Gener. Transmission Distribution. **141**, (3).

2. **BARRUNCHO, L.M,. LIU C.** *Et al* **(2000),** "Application of a knowledge based system for voltage monitoring and control on the NGC system". Proc. of the IEE conference on control, N16, PP. 146-153.

3. **CHEBBO, A.M, and IRVING, M.R. (2000)**; "Combine active and reactive dispatch, part I" Problem formulation and Solution algorithm, IEE Proc. C. 142 (4), PP. 393-400.

4. **DILLON, T.J., and LAUGHTON**, **M.A**. **(1990);** "Expert system application in power systems" Prentice Hall, London, United Kingdom.

5. **HAIDAT, T., and AKIMOTO, Y. (2003);** "Voltage optimization using generic algorithms" http://www.system-protection.com

6. **HERTZ, J., KROGH, A., and PALMER R. G. (1991);** "Introduction to the theory of neural computing". Addison Wesley, California, USA.

7. **HOLLAND, J. H. (2003);** "Adaptation in natural and artificial systems," http://www.powerquality international.

8. **HUI, K.C. and SHORT M.J. (2002);** "A neural network approach to voltage security monitoring and control". IEE Proceedings on Artificial Intelligence Vol.9, PP.89-93.

9. **IEEE, (2003);** "Standard Guide for Electric Power System Indices", IEEE standard 1366.

10. **IEE WORKING GROUP D10 REPORT (2004);** "Application of expert system to power system protection'. IEEE PES summer meeting, paper 93, SM 384-8 PWRD.

11. **JOHNS, A.T., BO, Z.Q., and AGGARWAL, R.K. (1993); "**A novel non-unit protection scheme based on fault generated high frequency noise on transmission lines". Proc. IEE 5$^{th}$ International Conference on Developments in Power System Protection, No. 368.

12. **LAMOREE , J., SMITH, J.C. (1998);** "The impact of voltage sags on industrial loads", First International Conference on Power Quality, PQA, 91' Paris, France.

13. **RANDALL A. (2004);** "Protecting sub-distribution circuits; Transmission and distribution world on line http://www.tdw.com

14. **ROSS, T.J. (1995); "**Fuzzy logic with engineering applications", McGraw-Hill, New York, USA.

15. **URASAWA, K., KANOH, H., KANEMANI, K., and SUGIYAMA, K. (1991);** "Fault location system for electric power transmission lines based on fuzzy knowledge", Proc. Electrical Engineering Applications, **111**, (4), Tokyo, Japan.