Chapter-1

INTRODUCTION

Electricity is the basic necessity for the economic development of a country. It is impossible to estimate the actual magnitude of benefit that electrical energy has contributed in building up of present day civilization. The survival of industrial undertakings and our social structure depends primarily upon low cost and uninterrupted supply of electrical energy. Indeed in this modern world, the dependence on electricity is so much that it has become a part of our life. Hence it can be stated that electric power system is backbone for the development of country in all aspects.

High Voltage Direct Current (HVDC) transmission system has become a mature and well accepted technology. Due largely to technical advances in high voltage converters and other high voltage apparatus, HVDC transmission has over the past three decades, become available means for transferring power in bulk over long distance. HVDC is today recognized as an effective and efficient means of transmitting bulk power over long distances through overhead lines. Advantages of HVDC over A.C. transmission include lower net cost for long distance, greater power per conductor, and possible use of ground as a return path, hence each
conductor can be operated as an independent circuit. It does not require any a charging current, no skin effect, hence the line does not require reactive compensation, elimination of system synchronization and stability problems, simpler transmission towers, may interconnect A.C. systems of different frequencies and elimination of intermediate switching stations. The prospects for the widespread use of HVDC transmission underlie a great deal of interest in the effects of D.C. corona discharge from the lines, including power loss, audible noise radio interference and television interference, chemical degradation of organic insulators from ozone and environmental impacts associated with it. HVDC is also being increasingly applied in undersea and underground cable links. The reliability of HVDC systems has always been of primary concern in the planning and operation of power systems. The total reliability of an HVDC system depends on the components in the line and at the stations.

HVDC transmission lines are mainly overhead transmission lines lay over long distances. The existence of fault on the transmission line may lead to the tripping of the transmission line. As the HVDC is a bulk power transmission system the short duration faults may lead to the total blackout of a region.

Among the various components and subsystems existing at an HVDC station, the HVDC transmission line and the converter
transformer are the major components which are having a significant impact on the total reliability of the HVDC system. Converter transformers are located on either ends of the HVDC transmission line. The transformers used in HVDC have different requirements due to superimposed DC voltage and current. Converter transformers designed for 12 pulse rectifiers have three windings. They are single phase 3 winding transformers. A bank of three transformers will be used for a 12 pulse converter. Out of the three windings of a converter transformer one of the winding is connected to the AC network and other two are connected to converter bridge i.e. one connected in delta and other in star. As an important component of HVDC system, the converter transformer is responsible for the stable and reliable power transmission. Incipient fault diagnosis of converter transformers is an important measure to prevent serious system outage incurred from deterioration of electrical insulation in transformers. Consequently transformers must strictly be periodically examined to find incipient fault and to protect them from further deterioration as early as possible. Failure in operation of converter transformers can be due to several reasons like the fault in the transmission line, switching and lightning surges, re-ignition in circuit breakers, over fluxing or resonance. The failure mode can also vary within the transformers depending on the phenomenon and insulation structure of winding. It is important to detect and identify the
type of fault in the transformer for proper operation of power transmission systems.

1.1 FAULTS IN HVDC TRANSMISSION SYSTEM

An HVDC transmission behaves differently compared to an AC transmission if there is a ground fault or short circuit. The fault current immediately following a fault is limited by the surge impedance and is of the order of 2.0 p.u. The current controller at the rectifier acts to limit this current to the pre-fault current. If the inverter current control is also active and power reversal in the inverter is permitted, the inverter current is maintained at a value which differs from the rectifier current by the current margin. This implies that the fault current in steady state is equal to the current margin (of the order of 0.1 p.u). Although this is much less than the currents in AC line faults, the clearing of the fault requires the current to be brought to zero and sufficient time given for the de-ionizing of the arc path.

For the fast clearing of the DC line faults it is necessary that inverter is not allowed to operate as a rectifier and the rectifier is put into the inverter mode by sudden increase in delay angle to its maximum limit. The converters at both terminals then help in discharging the energy stored in the DC circuit i.e. in capacitances and inductances and delivering it to the AC systems. The current and voltage in the DC line
fall to zero and help in de-ionizing the arc path. After some time has elapsed the line may be automatically energized by restarting the converters in the usual manner by ramping up the direct voltage and current. If the restart is unsuccessful, due to a persistent fault, the protection action will de-energize the line again. Normally three attempts are made to restart automatically with increasing dead time. The failure to restart even after three attempts implies a permanent fault and requires shutdown of the link until the fault is located and clear. Alternately, reduced voltage restart may be tried out if the insulation failure is due to heavy pollution on the line insulators and bad weather [1].

The automatic de-energization and restarting of the DC link is similar to the clearing of the fault and automatic re-closure in AC lines. The major difference in the two cases is that, while breakers are being used in AC lines, the clearing and restarting is performed in DC systems using converter control with the help of protective relays.

1.1.1 DC line faults

When a fault (flash-over) occurs on an AC line, there are circuit breakers that disconnect the line. It is then automatically re-connected again. There are no circuit breakers on the DC side in the HVDC converter stations, so when a fault occurs on a DC line the fault is
detected by the DC line fault protection. This protection orders the rectifier to operate in the inverter mode and thus it discharges the line effectively. After 80 - 100ms the line is charged again by the rectifier. If the fault is of intermittent in nature i.e. due to a lightning stroke, then after 200ms of duration from the instant of the fault, the line recovers and the line can support the voltage and the power to be transmitted continuously. But if the fault is due to its contaminated line insulators there is a risk that re-charging of the line results in a second fault. Many HVDC transmissions are designed such that after a number of failed restart attempts, the attempts will be made with reduced voltage i.e. 80% of the rated voltage.

As the DC line fault clearing does not involve any mechanical action and therefore it is faster than for an AC line. The DC fault current is also lower than the AC fault current and therefore the dead time before the restart is shorter than for an AC line. The reduced voltage restart is also unique for HVDC. The DC line faults on a bipolar line affect only one pole if fallen line tower is disregarded. The bipolar DC line is equivalent to a double circuit AC line.

HVDC transmission lines are prominent due to their unique capacity of transmitting power through under ground / under water cables. The faults associated with HVDC transmission using cables are very rare and they are due to mechanical damage. Therefore submarine
DC cables are often buried to prevent damage from anchors and trawls. The same protection action is implemented as for a DC line, but without the restart attempt.

1.1.2 AC network faults

When a temporary fault occurs on the AC system connected to the rectifier, the HVDC transmission may suffer a power loss. Even in the case of close single-phase faults, the link may transmit up to 30% of the pre-fault power. As soon as the fault is cleared, power will be restored to the pre-fault value.

When a fault occurs on the AC system connected to the inverter, commutation failure can occur and may interrupt power flow. Commutation failure is an unwanted, but natural process in a HVDC inverter that the system can handle. If the AC-fault is temporary the power is restored as soon as the fault is cleared. A distant fault with little effect on the converter station voltage (< 10 percent) does not normally lead to a commutation failure. A Capacitor Commutated Converter (CCC) in HVDC transmission can tolerate about twice that of the voltage drop, prior to that, there is a risk of commutation failure.
1.1.3 Converter station faults

HVDC converter stations are provided with an elaborate protection system that is designed for the detection of fault condition or other abnormal conditions that may cause hazard to the equipment or an unacceptable disturbance. The basic types of faults that can occur in converters are:

(i) Misfunction of valves and valve controls resulting in

(a) Arc through or fire through

(b) arcback

(c) misfire and

(d) current extinction

(ii) Commutation failure—most common with inverter operation

(iii) Short circuits inside the converter units

1.1.3.1 Misfire and arc through:

Misfire is the failure of the valve during conduction period, (i.e.) does not conduct when firing pulse are given and arc through or fire
through is the failure of the valve to block the conduction. These are mainly caused by improper or mis-function of the control circuits and firing circuits and are serious at the inverter end. On rectifier side voltage and current oscillation over the D.C. output will result in usually malfunction in gate pulse circuit or a spurious pulse introduced into the gating circuit will make the inverter conduct. Most of the time the inverter will have valve voltage positive and the unwanted pulse results in conduction resulting in a through conduction. Typical -fire through in valve V1 at instant ‘B’ is shown in Figure 1.1. The valve can fire through at any time after instant ‘A’ although it is scheduled to fixing at ‘F’. The wave forms shown are ideal, but in actual case both voltage and current wave forms will be highly-erratic.

Usually single arc through is self-clearing. But arc through may recover and the protection against this is taken care by the converter differential protection schemes. Misfire results in spurious pulse entering in gating circuits firing the valve at undesired instant and the next valve does not -fire properly. This is very rare.

Misfire can be either at rectifier or inverter end. At inverter point misfire will result in bridge average voltage becoming small or even going to zero. This will result in large voltage and current oscillations as A.C. voltage is injected into the D.C. side. D.C. current may extinguish and
large overvoltage may develop. Typical voltage and current waveforms due to misfire are shown in Figure 1.2.
Figure. 1.1 Single fix through of valve V₁ in typical inverter.
Figure 1.2 D.C. voltage and current for persistent misfire
1.1.3.2 **Commutation failure:**

Normally, the incoming valve has to takeover the conduction current before the commutating voltage reverses. The failure of such event results in the fault, the commutation failure. Strictly commutation failure is due to varying conditions of the inverter extinction angle due to either variations in D.C. or A.C. circuit conditions. A low A.C. voltage or a high D.C. current can cause incomplete commutation process in time for safe commutation. The D.C. current is shifted back to the previously conducting valve. Usually this occurs often at inverter end. Since $\gamma = (\pi - \alpha - \mu)$ and $\mu$ is a function of commutating voltage and Direct current, with either reduction of A.C. voltage or increase in current causes $\mu$ to increase and $\gamma < \gamma_{\text{min}}$. Hence commutation failure occurs. Typical commutation failure from valve $V_1$ to valve $V_3$ of a six pulse converter is shown in Figure 1.3(b) Commutation failure occurs at point ‘$t_2$’, the point of voltage crossing. Commutation reverses and valve $V_1$ of $V_2$ will continue to carry current. Consequently the voltage continues to fall as $V_{ca}$ of point $t_3$, $V_4$ turns on to take over from $V_2$ at which time $V_{ca}$ is shorted and D.C. voltage falls to zero. Assuming that the commutation from valve $V_2$ to $V_a$ is successful, the direct current will effectively pass through the leg of 1 and 4 valves, where as valve 5 does not have chance to takeover because its voltage is reverse biased. The D.C. short circuit ends at $t_4$ when valve 6 takes over from valve 4. D.C. voltage slightly goes negative and - comes back to normal. The one explained is single failure.
But sometimes multiple failures can also occur. This type of faults are normally set right after one complete cycle of operation by control circuits.

Figure. 1.3(a) Single commutation failure from valve V₃ to valve V₁
Figure. 1.3(b) Commutation failure in a thyristor-based line-commutated converter: (a) six-pulse thyristor converter; (b) inverter voltage during a single commutation failure; (c) inverter voltage during double commutation failure.
1.1.3.3 **Internal Short Circuits:**

Internal shorts are very rare in HVDC system. Internal shorts can occur at (i) ground fault at the converter terminals (ii) valve terminals (iii) D.C. bus, (iv) junction point of two valves (v) short across a non-conducting valve etc. These are mainly due to a flashover on the bushing or insulator supports. Most of these at the rectifier side of the converter will reflect as a 3 phase fault while shorting or flashover across a non-conducting valve. The worst case is when $\alpha$ is zero or near to zero. The peak short circuit current is equal to

\[ \frac{1}{2} \{ I_{do} + 3I_s \} \quad (1.1) \]

where \( I_s = \sqrt{3} V_{LL} / 2x_c \);

\( V_{LL} \) the true voltage on A.C. side

\( x_c \) equivalent transformer impedance and

\( i_{do} \) the D.C. current at the instant of firing of the valve.

The peak fault currents can be as high as 10 times the rated current and the valves (thyristors) must have this instantaneous short circuit capability. This fault is usually cleared by blocking of the valves. If the valve blocking is not done, the back up is given by tripping the circuit breakers on the A.C. side. The short circuit current is only limited by transformer short circuit impedance and the source impedance.
1.1.3.4 **Bridge Bypass and fault clearing action:**

Many temporary faults that occur in the valve can be cleared in about one cycle time by valve bypass action. In mercury arc rectifier schemes a bypass valve was used to divert the short circuit current. This valve was across the main converter bridge and kept blocked in normal operation. To make main bridge unit non-conducting and divert the current, the bypass valve was fired and other valves were blocked. The bypass valve can be blocked after first interrupting its current so that the grid gains its control. When the normal bridge valves are restarted after fault clearing the bypass valve cathode becomes positive with respect to anode and hence is automatically blocked.

In case of thyristor bridges no separate bypass valve is needed and a normal or healthy pair of valves in series of one leg of 6-pulse bridge can be used for this purpose (as shown in Figure 1.4). Blocking the converter using one leg is same as described earlier. The selection of blocking sequence to the bypass pair of valves is important to give the faulty valve the best possible time and chance to recover. The selection of the most suitable bypass pair for blocking depends on cause and type of fault. The fault detectors should be provided with good and sufficient discrimination. Restoration of normal operation requires the restoration of firing pulses and suppression of blocking pulses. Inverter deadlocking by these means is also much simpler.
Figure 1.4: Bypass pair (1,4) two series switches and a bypass switch for bypass action.

Figure 1.5(a): D.C. Line fault on the Rectifier Side: Rectifier voltage and current waveforms.
Fig. 1.5(b): Current and commutation voltage of value 1 for D.C. line fault.
1.2 FAULTS IN CONVERTER TRANSFORMER EQUIPMENT

In spite of the painstaking workman-ship in the design and construction of converter transformers, the most careful station and circuit design to ensure adequate lighting protection through maintenance and conservative loading practices, faults do occur in transformers, although they occur very seldom.

Faults can be classified into two classes:

- Faults in any auxiliary equipment, which is part of the transformers.
- Faults in the windings of the transformer.

**Auxiliary equipment failures:** The detection of faults in the auxiliary equipment is necessary to protect the transformer. These faults lead to the ultimate failure of the main transformer windings. By the extension of the meaning of auxiliary, the following may be considered as auxiliary equipment:

- Transformer Oil (at the proper level)
- Gas Cushion (inert atmosphere above the oil)
- Oil Pumps
- Forced-air fans.
**Faults in main transformer winding:** The most difficult problem of a converter transformer is detection of winding faults, which may be divided into three classes:

- Loose contacts (poor electrical connections)
- Faults between adjacent turns or part of coils
- Faults to ground or across complete windings

1.2.1 **Necessity of Fault Detection and Fault Diagnosis Techniques**

Converter transformers are amongst the most important components in a HVDC system. Avoiding damage to converter transformer is vital as continuity in power delivery may be seriously disrupted. Furthermore repair or replacement is expensive and time consuming. A converter transformer connected to an HVDC system is very likely to be subjected to steep fronted impulse voltages. A line surge of magnitude several times the rated system voltage will be concentrated on the end turns of the winding because of high equivalent frequency of the surge front. More clearly, under these surges, the voltage distribution across the winding is highly non-uniform.

The following are the methods adopted to analyze the fault generated signal for both the HVDC transmission line and the converter transformer.
Fast Fourier Transforms (FFT)
Artificial Neural Networks (ANN)
Wavelet Transforms (WT)

1.3 FAST FOURIER TRANSFORM (FFT)

Fourier theory is a classical tool to achieve different representations of a signal. This technique belongs to a class of algorithm used in digital signal processing that breaks the complex signal into elementary components. FFT is an efficient algorithm to compute the Discrete Fourier Transform (DFT) and its inverse. FFT’s are of great importance to a wide variety of applications from digital signal processing to solving partial differential equations to algorithm for quickly multiplying large integers.

Let \( x_0, \ldots, x_{n-1} \) be complex numbers. The DFT is defined by the formula,

\[
F_i = \sum_{k=0}^{n-1} X_k e^{\left(-\frac{2\pi i}{n}\right)^j} \quad i=0,1,\ldots,n-1
\]

Evaluating these sums directly would take \( O(n^2) \) arithmetical operations. An FFT is an algorithm to compute the same result in only \( O(n \log n) \) operations. In general, such algorithms depend upon the factorization of \( n \), but there are \( O(n \log n) \) FFT’s for all \( n \), even prime \( n \). since the inverse DFT is the same as the DFT, but with the opposite sign
in the exponent an a 1/n factor, any FFT algorithm can easily be adopted for it as well.

Consider the Discrete Fourier Transform

\[ X(n) = \sum_{k=0}^{N-1} X_0(k)e^{-j\frac{2\pi nk}{N}} \]

\( n = 0,1,\ldots\ldots\ldots\ldots N-1 \) (1.3)

if \( N = 4 \), we get

\[ W = e^{-j\frac{2\pi}{4}} \] (1.4)

The equation (1.2) can be written as

\( X(0) = x_0(0) W^0 + x_0(1) W^0 + x_0(2) W^0 + x_0(3) W^0 \)

\( X(1) = x_0(0) W^0 + x_0(1) W^1 + x_0(2) W^2 + x_0(3) W^3 \)

\( X(2) = x_0(0) W^0 + x_0(1) W^2 + x_0(2) W^4 + x_0(3) W^6 \)

\( X(3) = x_0(0) W^0 + x_0(1) W^3 + x_0(2) W^6 + x_0(3) W^9 \) (1.5)

Equation (1.5) can be more easily represented in matrix form

\[
\begin{bmatrix}
X(0) \\
X(1) \\
X(2) \\
X(3)
\end{bmatrix} =
\begin{bmatrix}
1 & 1 & 1 & 1 \\
1 & W^1 & W^2 & W^3 \\
1 & W^4 & W^6 & W^9 \\
1 & W^6 & W^9 & W^{12}
\end{bmatrix}
\begin{bmatrix}
X_0(0) \\
X_0(1) \\
X_0(2) \\
X_0(3)
\end{bmatrix}
\]

(1.6)

Or more compactly as

\[ X(n) = W^{nk} x_0(k) \] (1.7)

After the examination of above equation, it reveals that since \( W \) and possible \( X_0(K) \) are complex, then \( N^2 \) complex multiplication & \( N(N-1) \)
complex additions are necessary to perform the required matrix computation. The FFT owes it success to the fact that the algorithm reduces the number of multiplications from $N^2$ to $N \log_2 N$. For example if $N=1024 = 2^{10}$; $N^2=2^{20}$ operations of DFT and $N \log_2 N = 2^{10} \times 10$ operations of FFT. This amounts to a factor of 100 reduction in computer time and round-off errors are also reduced [2].

1.3.1 Weighting Functions

A weighting function, $w(n)$ is a sequence of numbers i.e. multiplied with input data prior to performing a discrete Fourier transform on the data. Weighting (also called window) functions reduce side lines of discrete Fourier transform filters and widen main lobes, while fortunately, not altering location of the centers of the filters. Weighting functions selection can be made early in the design process because the choice of FFT algorithm and weighting function are independent of each other. Choice of the weighting function to provide the specified side lobe level is done without concern for the FFT algorithm, which will be used because they work for any length FFT and they work same for any FFT algorithm. They do not alter the FFT’s ability to distinguish frequencies. Table 1.1 shows the weight functions used for FFT analysis.
Table 1.1 Types of the weight functions used for the FFT analysis

<table>
<thead>
<tr>
<th>S. No</th>
<th>Type</th>
<th>Function</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rectangular</td>
<td>n = 0 to N-1, W(n) = 1</td>
<td>Input data comes to zero abruptly</td>
</tr>
<tr>
<td>2</td>
<td>Exponential</td>
<td>n = 0 to N, w(n) = e^{-nΔt/T}</td>
<td>Spectrum is smooth</td>
</tr>
<tr>
<td>3</td>
<td>Triangular</td>
<td>n = 0 to N/2, w(n) = 2<em>n/N, n = N/2 to N-1, w(n)=2</em>(N-n)/N</td>
<td>Small number of slide lobes</td>
</tr>
<tr>
<td>4</td>
<td>Sine-lobe</td>
<td>n = 0 to N-1, w(n)=sin(n)</td>
<td>Performance is improved</td>
</tr>
<tr>
<td>5</td>
<td>Hanning</td>
<td>n=0 to N-1, w(n)=0.5*{1-cos(nΠ/2)}</td>
<td>Slide lobes fall of 50% faster</td>
</tr>
<tr>
<td>6</td>
<td>Sine – cubed</td>
<td>n = 0 to N-1, w(n) = sin^3*(nΠ/N)</td>
<td>-</td>
</tr>
<tr>
<td>7</td>
<td>Sine to the fourth</td>
<td>n = 0 to N-1, w(n) = sin^4*(nΠ/N)</td>
<td>-</td>
</tr>
<tr>
<td>8</td>
<td>Hamming</td>
<td>n=0 to N-1, w(n) = 0.54-0.46*cos(2Π/N)</td>
<td>-</td>
</tr>
<tr>
<td>9</td>
<td>Blackman</td>
<td>n=0 to N-1, w(n) = 0.54-0.46<em>cos(2Π/N)+0.08</em>cos(4Πn/N)</td>
<td>-</td>
</tr>
</tbody>
</table>
1.4 ARTIFICIAL NEURAL NETWORKS

Artificial Intelligence is a machine emulation of the human thinking process. The brain is the most complex machine on the earth some important functions of human brain are:

- Interfacing all the organs.
- Storing the information
- Processing the information & Decision making
- Controlling the activities based upon the decisions.

The brain not only retains a copy of pictures as a scanner would, but also stores it in the form of rules. The brain is able to constantly reprogram itself to represent and understand the world. The human brain is a source of natural intelligence and a truly remarkable parallel computer. At present the knowledge available about human brain is so inadequate and research on this complex organ of the body will dominate in next century to understand it better and its thinking process as well.

Artificial Intelligence tools such as neural networks and fuzzy logic are expected to user a new era in electrical engineering. These technologies have advanced significantly in recent years and have found wide applications in electrical engineering.

The current interest in neural networks is largely a result of their ability to mimic natural intelligence neural network have emerged as a
powerful technique for pattern classification, function approximation, optimization, Prediction and Automatic control.

1.4.1 Need for artificial neural networks

The interest in Artificial Neural Networks has grown rapidly over the past few years. Professional form such diverse fields has engineering, Philosophy and Psychology are puzzled by the potential offered by this technology and are searching applications with their description this raising of interest has been fired by both theoretical and applications successes. Suddenly, it appears to apply competition to ready previously restricted to human intelligence, To make machines that learn and remember in wage that bear a striking resemblance to human mental meaning to the term artificial intelligence. Neural networks, neurocomputing or “brain like” computational is based on the fact that can reproduce at least some of the flexibility and computational power of the human brain by artificial means. A neural network consists of many simple computing elements, generally simple non-linear summing junctions, connected together by means of varying strength. A gross abstract of the brain, which consists of very large number of far more complex neuron connected together with far more complex and far more structured couplings.
**Definition:** A neural network is a massive parallel–distributed processor that has natural propensity for storing experimental knowledge and making it available for use.

It resembles the brain in two respects:

a. Knowledge acquired by the network through a learning process.

b. Inter neuron connection strength is known as synaptic weights are used to store the knowledge.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. This highly connected, parallel interface forms the hardware of the Artificial Neural Network. One of the major advantages associated with the use of Neural Network is the parallel processing capability. The high degree of parallel connectivity of an Artificial Neural Network also brings about desirable properties such as noise rejection and fault tolerance. An Artificial Neural Network [3] derives its computing power through, first, its massively parallel distributed structure and second, its ability to learn and therefore generalize. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training.
(learning). These two information-processing capabilities make it possible for neural networks to solve complex problems that are currently intractable. In recent years, considerable progress has been achieved in the application of Artificial Neural Networks to power system problems such as load forecasting, unit commitment, economic dispatch, security assessment, fault diagnosis and alarm processing.

### 1.4.2 Characteristics of artificial neural networks:

The Neural networks an exhibit mapping capability i.e. they can map input patterns to their associated output patterns.

The Neural networks learn by examples. Thus, Neural networks architectures can be ‘trained’ with known examples of a problem before they are tested for their ‘inference’ capability on unknown instances of the problem. They can therefore, identify new objects previously untrained.

The Neural networks posses the capability to generalize. Thus, they can predict new outcomes from past trends.

The Neural networks are robust systems and are fault tolerant. They can, therefore, recall full patterns from incomplete, partial or noisy patterns.
The Neural networks can process information in parallel, at high speed, and in a distributed manner.

For example: they learn from experience, generalize from previous example to new one, and abstract characteristics from inputs containing irrelevant data.

1.4.3 Advantages of neural networks

- Neural Networks has the ability to learn and construct a complex nonlinear mapping through a set of input/output examples. The Network architecture allows for easy training without a need for structured model.

- Input variables can be easily added or deleted. Correlated or uncorrelated data can be utilized.

- Neural Network has superior noise rejection capability that can effectively deal with uncertainties of the actual process.

- Neural Network executes very fast. Most of the calculation overheads occur during the initial off-line training.

- Neural Network consists of a large number of parallel-processing units which can be implemented using general purpose Neural Network hardware. Hence it can relieve the burden of computation from the Energy Management Systems computers.
In this research work, a methodology for computing transfer capabilities based on ANN technique is described. Essentially, the development of the methodology comprises of two steps.

1. A suitably chosen ANN structure is to be trained first with a set of training data (input: loading pattern, output: optimal transfer capability pattern), with the help of a suitable training algorithm. The training data would be obtained from the proposed algorithm.

2. Once the ANN is trained, with sufficiently large number of training data, the ANN ‘learns’ the implicit correlation between the loading patterns and the transfer capability patterns. Next, new loading patterns (which have not been used to train the ANN) would be fed to the network and the network would provide the optimal transfer capability pattern at its output within a very short span.

1.4.4 Basic elements in neural network structure

As has been mentioned before, the ANN performs fundamentally like a human brain. The cell body in the human neuron as shown in Figure 1.6 receives incoming impulses via dendrites (receiver) by means of chemical processes. If the number of incoming impulses exceeds certain threshold value the neuron will discharge it off to other neurons through its synapses, which determines the impulse frequency to be fired off.
Each input signal coming along a dendrite passes through a synapse or synaptic junction, as shown. The junction is an infinitesimal gap in the dendrite which is filled with neurotransmitter fluid that either accelerates or retards the flow of electrical charges.

Therefore, processing units or neurons of an ANN consists of three main components; synaptic weights connecting the nodes, the summation function within the node and the transfer function. Synaptic weights characterize themselves with their strength (value), which corresponds to the importance of the information coming from each neuron. In other words, the information is encoded in these strength-weights. The summation function is used to calculate a total input signal by multiplying their synaptic weights and summing up all the products.
1.4.5 Artificial neuron model

A neuron is an information-processing unit that is fundamental to the operation of a neural network. The block diagram of Figure 1.4 shows the model of a neuron, which forms the basis for designing artificial neural networks. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained, for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the learning rule is used to determine the corresponding output.

Figure 1.7 Artificial Neuron Model

As shown in the Figure 1.7, each neuron could receive several inputs from neighboring neurons through interconnections. The net
input Net \( j \) of the neuron \( j' \) is the weighted sum of the inputs into the neuron \( j' \) and is given by

\[
U_k = Net(j) = \sum_{j=1}^{n} w_{kj} X_j
\]  

(1.8)

The neuron uses net input, together with information on its current activation state to determine its new state of activation, given by

\[
y_k = \varphi(U_k - \theta_k)
\]  

(1.9)

Where, 

\( X_1, X_2, \ldots X_n \) are the input signals, 

\( w_{k1}, w_{k2}, \ldots w_{kn} \) are the synaptic weights of neuron \( k \), 

\( \theta_k \) is threshold function, 

\( \varphi(.) \) is the activation function, 

\( U_k \) is the linear combiner output, and 

\( Y_k \) is the output signal of the neuron

The active function defines the output of neuron in terms of the activity level at its input. Most commonly used activation functions are Sigmoid, Tan-sigmoid and Linear.

1.4.6 Basic principles of neural networks

Two information-processing capabilities, its parallel distributed structure and its ability to learn and therefore generalize, make it
possible for neural networks to solve complex and large-scale problems. A neural network is characterized by three features: architecture, processing algorithm, and training algorithm [3].

The architecture of a neural network specifies the arrangement of the neural connection as well as the type of units characterized by an activation function. The processing algorithm specifies how the neuron calculates the output vector for any input vector and for a given set of weights. The training algorithm specifies how the Neural Network adapts its weights $w$ for all given input vectors $X$, called training vectors. Thus, the neural network can acquire knowledge through the training algorithm and store the knowledge in synaptic weights.

Generally speaking, two kinds of networks are commonly used as universal functional approximators, Radial Basis Function Network (RBFN) and Back-propagation feed-forward neural network (BPFN). Although they play very similar roles in that they both provide techniques for approximating arbitrary nonlinear functional mappings between multi-dimensional spaces. Distinct differences still exist between two kinds of networks. Radial basis function network (RBFN which has non-linear mapping capability) has become increasingly popular in recent years due to its structural simplicity and training efficiency. A potential advantage of RBFN is its ability to augment new training data without the need for retraining. Both RBFN and BPFN are nonlinear
layered feed forward neural networks, where a layer of neurons receives input only from neurons of a previous layer as shown in Figure 1.8. The flow of information for the processing of input vectors with fixed weight vectors is in one direction only. Input units feed the input values directly to the hidden neurons whereas hidden and output units process their input through a non-linear activation function.

Usually, BPFN may have one or more hidden layers. Thus, it can have many layers of weights and a complex pattern of connectivity, so that not all possible weights in any given layer are present. The hidden and output layers of BPFN can be non-linear or linear depending on the requirements of the application.

![Figure 1.8 Architecture of a layered feed-forward neural network](image)
However, RBFN consists of only three layers. The first layer is composed of input nodes whose number is equal to the dimension of the input vector. The second layer is a hidden layer, composed of non-linear radial basis neurons that are connected directly to all the nodes in the input layer. The output layer consists of single linear units, being fully connected to the hidden layer.

1.4.7 Activation Functions

1.4.7.1 The sigmoid function:

The sigmoid function more than one function goes by the name sigmoid function. They differ by their formulae and in ranges. They all have a graph similar to a stretched letter S.

There are two such functions:

- Hyperbolic tangent function with values in (-1,1)
- Logistic function has values between 0 and 1. So we can choose the one that fits the range we want.

i) Hyperbolic Tangent Functions: The Hyperbolic tangent function can be represented as

\[ F(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \]  

(1.10)
The graph of hyperbolic tangent function is as shown in Figure 1.9

**ii) Logistic Function:** It is the most interesting function in the sigmoid function as it provides a graded nonlinear response to the input signals. This sigmoid function can be represented as

\[ F(x) = \frac{1}{1 + e^{-x}} \]  

(1.11)

\[ F(x) = F(x) \times [1 - F(x)] \]  

(1.12)

Here, the squashing function is often chosen to be the logistic function or “sigmoid” as shown in Figure 1.10.

---

Figure. 1.9 Hyperbolic tangent function

Figure. 1.10 Sigmoid Function
1.4.7.2 **The step function:**

The step function is also frequently used as a threshold function. A jump to 1 occurs for the value of the function to the right of 0, and the function will remains at the level. It is interested in a step function that goes from 0 to 1 in one step as soon as the argument exceeds the threshold value 0. The graph of the step function is shown in the Figure 1.11.

1.4.7.3 **The ramp function:**

To describe the ramp function simply, first consider a step function that makes steps from 0 to 1 at some point. Instead of letting it take a sudden jump like that at 1 point, let it gradually gain in value, along a straight line (Looks like ramp), over a finite interval reaching from an initial 0 to final 1. We can use this function also as an activation function. The graph of the ramp function is shown in the Figure 1.12.
1.4.7.4 The Signum function:

It is also called as Quantizer function and Gaussian function as shown in figure 1.13. The function $\Phi$ is defined as

$$\Phi (l) = +1, \ I > \theta$$

$$-1, \ I \leq \theta$$

(1.13)

![Graph showing the Signum function or Gaussian function]

Figure 1.13 Signum function or Gaussian function

By analogy to analog electric systems, we may think of the activation function as defining a non-linear gain for the artificial neuron. The gain is calculated by finding the ratio of the change in OUT to a small change in NET. Thus, gain is the slope of the curve at a specific excitation level. It varies from a low value at large negative excitations (The curve is nearly horizontal), to a high value at zero excitation, and it drops back as excitations becomes very large and positive. Small input
signals require high gain through the network if they are to produce output; however, a large number of cascaded high gain stages can saturate the output with the amplified noise (random variations) that is resent in any realizable network. Also large input signals will saturate high-gain stages, again eliminating any usable output. The central high-gain region of the logistic function solves the problem of processing small signals, while its regions of the decreasing gain at positive and negative extremes are appropriate for large excitations. In this way a neuron performs with appropriate gain over a wide range of input levels.

This simple model of the artificial neuron ignores many of the characteristics of its biological counterpart for example: It does not take account time delay that affected the dynamics of the system, inputs procedure an immediate output. More important, it does not include the effect of synchronism or the frequency modulation function of the biological neuron characteristics that some researches feel to be crucial. Despite these limitations network formed of those neurons exhibits attributes that are strongly reminiscent of the biological system. Perhaps enough of the essential nature of the biological neuron has been captured to produce responses like the biological systems.
1.4.8 Types of artificial neural networks

Artificial neural network is massive interconnection of neurons. Basically the artificial neural networks can be of two types. They are


In a layered model the neurons are arranged in layers and the neurons receive information from the neurons of the previous layer and give the information to the neurons of the next layer. In this type of network the neurons of the same layer are not connected. The layers can be classified into three groups viz. Input layer, output layer and the hidden layer. The input layer receives external inputs while the output layer provides the output of the system. These layers are the interface of the network with external world.

In homogeneous model, the layer concept is forgotten. Every neuron is connected to every other neuron and inter faced with the external world. Hopfield network is an example of this kind. Artificial neural networks can again classified as

- Feed forward networks
- Feedback networks

Layered network is an example for feed forward network, while Hopfield network is an example of feedback network. In addition to these basic models a number of other models are also used in practice.
1.4.9 Training of artificial neural networks

**Objective:** A network is trained so that application of a set of inputs produces the desired (or at least consistent) set of outputs. Each such input (or output) set is referred to as a vector. Training is accomplished by sequentially applying input vectors, while adjusting network weights according to a predetermined procedure. During training, the network weight gradually converts to values such that each input vector produces the desired output vector.

Learning is a process of achieving the required network computation by determination of two types

- Supervised training
- Unsupervised training
- Reinforced training

1.4.9.1 Supervised training:

Every learning algorithm contains basically a learning rule. There are two main rules available for learning, Hebbian rule for supervised learning and Delta rule for unsupervised learning. Adaptation of these by simple modifications to suit a particular context generates in many other learning rules. Supervised learning requires the pairing of each input vector with the target vector representing the desired output, together these are called training pairs.
An input vector is applied the output of the network is calculated and compared to the corresponding target vector, the difference in feedback through the network and the weights are changed according to an algorithm that tends to minimize the error. The vector of the training set is applied sequentially, and errors are calculated and weights adjusted for each vector, until the error for entire training set is at an acceptably low level.

1.4.9.2 Unsupervised training:

It is difficult to conceive of a training mechanism in the brain that compares desired and actual outputs. The training set consists solely of input vectors. The training algorithm modifies network weights to produce output vectors that are consistent; that is, both application of one of the training vectors or application of a vector that is sufficiently similar to it will produce the same pattern of outputs. The training process, therefore, extracts the statistical properties of the training set and group’s similar vectors into classes. Applying a vector from a given class to the input will produce a specific output vector, but there is no way to determine prior to training which specific pattern will be produced by input vector class. Hence, the outputs of such a network must generally transformed into a comprehensible form subsequent to the training process. This does not represent a serious problem. It is usually a matter to identify the input–output relationships by the network.
1.4.9.3 Reinforced training:

In this method, a teacher though available, does not present the expected answer but only indicates if the computed output is correct or incorrect. The information provided helps the network in its learning process. A reward is given for a correct answer computed and a penalty for a wrong answer.

Whatever kind of learning process is used, an essential characteristic of any network is its learning rule, which specifies how weights adapt in response to a learning example. Often learning requires supplying a network with many examples for several thousand times.

1.5 WAVELET TRANSFORMS

A wavelet is a “small wave”, which has its energy concentrated in time. It gives a tool for the analysis of transient, non-stationary, or time-varying phenomena. It not only has an oscillating wave like characteristic but also has the ability to allow simultaneous time and frequency analysis with a flexible mathematical foundation [4].

Fourier transforms are useful mathematical tools for the analysis of signals whose statistical properties are constant over time or space. The reason being the Fourier transform represents the signal as the sum of sine and cosine functions which have infinite duration in time. Instead
of representing the signals with these functions, localized waves or wavelets can be used. Representing non stationary signals as the sum of basis functions which are localized in time leads to more compact representations and also provides better insight into the properties of the signals than what Fourier transform provides.

![Wavelet Transform](image)

**Figure. 1.14 Signal represented in time-amplitude is transformed into time-scale signal using wavelet transforms.**

In wavelet analysis, signals are represented using a set of basis functions. These are derived from a single prototype function called the “mother wavelet. These basis functions or wavelets are formed by translating and dilating the mother wavelet. This can also be stated as the basis functions formed by shifting and scaling the mother wavelet in time. Hence, the wavelet transform can be viewed as a decomposition of a signal in the time scale plane.

Traditional signal processing techniques such as Fourier transform and short time Fourier transform (STFT) are poorly suited for analyzing signals which have abrupt transitions superimposed on lower frequency
backgrounds such as speech, music and bioelectric signals. On the other hand, the wavelet transform, a new tool, provides a novel approach to the analysis of such signals. The wavelets transform has a multi resolution capability. The multi resolution signal processing used in computer vision, and wavelet series expansions developed in applied mathematics are recognized as different views of signal theory. The wavelet theory provides a unified frame work for a number of techniques which had been developed independently for various signal processing applications. The signal of time-amplitude representation transformed into time-scale signal using wavelet transforms is shown in Figure 1.14.

1.5.1 Time-Frequency representations

Stationary signals, whose spectral characteristics do not change with time, are represented as a function of time or frequency. Non stationary signals, which involve both time and frequency, especially the auditory and visual perceptions require the time frequency analysis. The time frequency analysis involves mapping a signal which is a one-dimensional function of time into an image which is a two-dimensional function of time and frequency, which displays the temporal localization of the spectral component of signal. The modification required in Fourier transform is localizing the analysis, so that it is not necessary to have the signal over \((-\infty, \infty)\) to perform the transform. Hence, this signal has to be mapped as a time-varying spectral representation.
The short time Fourier transform (STFT) can map a one-dimensional function \( f(t) \) into the two-dimensional function \( \text{STFT}(\tau, \tilde{f}) \). Here \( f(t) \) is assumed to be a stationary signal when viewed through a temporal window, \( w(t) \), which is a complex function. Hence, \( \text{STFT}(\tau, \tilde{f}) \) is defined as

\[
\text{STFT}(\tau, \tilde{f}) = \int_{-\infty}^{\infty} f(t) w^*(t - \tau) e^{-j2\pi\phi} dt
\]

(1.14)

Which is Fourier transform of the windowed signal \( f(t) w^*(t - \tau) \), where \( \tau \) is the centre position of window and the * represents complex conjugation. The Time-based, frequency-based, and STFT views of a signal is shown in Figure 1.15.

The STFT is based on windows of fixed duration. Since the window duration is fixed, the frequency resolution is also fixed, in conformity with the uncertainty principle. For many real word signals such as music and speech, the fixed resolution of the STFT in time and frequency entails a serious disadvantage. The wavelet transform circumvents the disadvantage of STFT and it is a form of mapping that has the ability to trade off time resolution for frequency resolution and vice-versa.

An advantage of the wavelet transform is that the size of window varies. In order to isolate signal discontinuities, it is better to have a very short basis function. At the same time, in order to obtain detailed
frequency analysis, a very long basis function is required. One way to achieve this is to have a short high frequency basis function and a long low frequency. The wavelet transform does not have single set of basis functions like the sine and cosine functions. Instead, it has an infinite set of possible basis functions.

Figure 1.15 Time-based, frequency-based, and STFT views of a signal
The wavelet transform is capable of providing the time and frequency information simultaneously, i.e. time frequency representation of the signal. The wavelet transform handles frequency logarithmically rather than linearly, resulting in a time-frequency analysis with the constant $\Delta f/f$, where $\Delta f$ is the band width and $f$ is the mid band frequency.

In wavelet analysis the time-domain signal is passed through various high pass and low pass filters, which filter out either high frequency or low frequency portions of the signal. This procedure is repeated every time a small portion of the signal corresponding to some frequency is removed from the signal.

Let consider a signal which has a frequency up to 1000Hz. The signal is split into two parts by passing the signal through a low pass (0-500Hz) and high-pass (500-1000Hz) filters. Either the low pass portion or the high pass portion or both are taken and the process is repeated again. This process is called decomposition.

When the low-pass portion is split again, there are three sets of signal, corresponding to the frequencies 0-250Hz, 250—500Hz and 500-1000Hz. If the low frequency signal is split and there are four sets of signal corresponding to 0-125Hz, 125-250Hz, 250-500Hz , 500-1000Hz. The process has to be continued until the decomposed signal corresponds to a certain predefined level. This group of signals actually
represents the same signal, but all correspond to different time on one axis, frequency in the second and amplitude in the third axis. This shows which frequency exists at a particular point of time.

The uncertainty principle states that it is not exactly known which frequency exists at that time instance, but it provides what frequency bands exist at what time intervals. The spectral components which exist at any given interval of time can be investigated. Wavelet transforms have this variable resolution when compared with STFT which has a fixed resolution at all times.

Higher frequencies are better resolved in time and lower frequencies are better resolved in frequency, i.e. a certain higher frequency component can be located better in time with less relative error and low frequency component can be located better in frequency.

The continuous wavelet transform grid is shown in Figure 1.16. The top row shows that at higher frequencies, there are more samples corresponding to smaller intervals of time, which implies, that higher frequencies can be resolved better in time. The bottom row corresponds to lower frequencies, which contains less number of points.
The discrete wavelet transform grid is shown in Figure 1.17. The top row shows that at higher frequencies, there are more samples corresponding to smaller intervals of time, which implies, that higher frequencies can be resolved better in time. The bottom row corresponds to lower frequencies, which contains less number of points and hence low frequencies are not resolved well in time-continuous case, but now, the frequency information has different resolutions at every stage too.
1.5.2 Continuous-Time Wavelet

A real or complex-valued continuous function \( \psi(t) \) is called a basic wavelet or mother wavelet if it satisfies the following two properties and one admissibility condition

(i) \[ \int_{-\infty}^{\infty} \psi(t) dt = 0 \] (1.15)

This means that the function integrates to zero. It also suggests that the function is oscillatory and hence there is no need to use sine and cosine waves as in Fourier analysis.

(ii) \[ \int_{-\infty}^{\infty} |\psi(t)|^2 dt = \infty \] (1.16)

It means that the function is square integral or equivalently has finite energy, i.e. most of the energy in \( \psi(t) \) is confined to a finite duration.

(iii) Admissibility condition is given by

\[ C \equiv \int_{-\infty}^{\infty} \frac{|\psi(w)|^2}{|w|} dw; 0 < C < \infty \] (1.17)

This admissibility condition is helpful in formulating a simple inverse wavelet transform.
1.5.3 Continuous- Wavelet Transform (CWT)

Consider \( f(t) \) to be a square integrable function i.e. \( L^2(\mathbb{R}) \) and \( \psi(t) \) be a wavelet satisfying the properties mention in equations. The continuous wavelet transform CWT of \( f(t) \) with respect to \( \psi(t) \) is defined as:

\[
W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^*\left(\frac{t-b}{a}\right)dt
\]

(1.18)

Where 'a' is a scale factor (dilation parameter) and \( b \) is the time delay (translation variable). The scale factor 'a' governs its frequency content, the delay parameter \( b \) gives the position of the wavelet \( \psi_{a,b}(t) \) and * denotes complex conjugation. It is important to note that both \( f(t) \) and \( \psi(t) \) belongs to \( L^2(\mathbb{R}) \), the set of square integrable functions. The above equation can be written in a more compact form by defining \( \psi_{a,b}(t) \) as

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right)dt
\]

(1.19)

Now,

\[
W(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}^*(t)dt
\]

(1.20)

Here the normalizing factor \( \frac{1}{\sqrt{|a|}} \) ensure that the energy is same for all \( a \) and \( b \), i.e.
\[ \int_{-\infty}^{\infty} |\Psi_{a,b}(t)|^2 dt = \int_{-\infty}^{\infty} |\Psi(t)|^2 dt \]  

(1.21)

From the above discussion, one can understand that the CWT operates on a function of one real variable and transforms it to be a function of two real variables. Thus, it can be seen as a mapping operator from a single variable set of function in \( L^2(\mathbb{R}) \) to two variable set of function i.e. \( W_\psi[f(t)] = W(a, b) \), where \( \psi \) in the subscript denotes that the transform depends not only on the function \( f(t) \) but also on the wavelet, i.e. CWT is with respect to \( \psi(t) \) on \( f(t) \).

### 1.5.3.1 Inverse CWT

Given \( W(a,b) \equiv W_\psi[f(t)] \) it is possible to obtain \( f(t) \) by applying the inverse CWT. The inverse continuous wavelet transform is given by

\[
f(t) = \frac{1}{C} \int_{a=-\infty}^{\infty} \int_{b=-\infty}^{\infty} \frac{1}{|a|} \Psi(a,b) W_{a,b}(t) da db
\]  

(1.22)

Where \( C = \int_{-\infty}^{\infty} \frac{|\Psi(w)|^2}{|w|} dw; 0 < C < \infty \) which is the admissibility condition.

The wavelet should satisfy this condition. Thus, the wavelet transform is providing a weighting function for synthesizing a given equation \( f(t) \) from translates and dilates of the wavelet much as the Fourier transform provides a weighting function for synthesizing from sine and cosine functions.
### 1.5.3.2 Properties of CWT

The various properties of the CWT are given below

**i. Linearity:** If \( f(t) \) and \( g(t) \) and \( L^2(\mathbb{R}) \) and \( \alpha \) and \( \beta \) are scalars, then

\[
W_\psi [\alpha f(t) + \beta g(t)] = \alpha W_\psi [f(t)] + \beta W_\psi [g(t)]
\]  
\[(1.23)\]

**ii. Translation:** The CWT of a translated function \( f(t-\tau) \) is given by

\[
W_\psi [f(t-\tau)] = W(a,b-\tau)
\]  
\[(1.24)\]

**iii. Scaling:** The CWT of a scaled function, i.e. \( \frac{1}{\sqrt{\alpha}} f \left( \frac{t}{\alpha} \right) \) is given by

\[
W_\psi \frac{1}{\sqrt{\alpha}} f \left( \frac{t}{\alpha} \right) = W \left[ \frac{a}{\alpha} \frac{b}{\alpha} \right]
\]  
\[(1.25)\]

**iv. Wavelet Shifting:** If \( \psi'(t) = \psi(t-\tau) \) then

\[
W_\psi [f(t)] = W(a,b+a\tau)
\]

Note that the translation property is the result of shifting of the signal \( f(t) \) while this is due to the shift of wavelet itself.

**v. Wavelet Scaling:**

\[
\psi'(t) = \frac{1}{\sqrt{\alpha}} \psi \left( \frac{t}{\alpha} \right)
\]

Let

\[
W_\psi [f(t)] = W(a\alpha,b)
\]

**vi. Linear Combination of wavelets:** Let \( \psi_1(t) \) and \( \psi_2(t) \) be two wavelets. If \( \alpha \) and \( \beta \) are scalars, then their linear combination,
aψ₁(t) + bψ₂(t) is also a wavelet. The CWT with respect to such linear combination of wavelet is given by

\[ W_{a\psi_1 + b\psi_2}(f(t)) = \alpha W_{\psi_1}(f(t)) + \beta W_{\psi_2}(f(t)) \]  

(1.26)

vii. **Energy Conservation:** The CWT has an energy conservation property, i.e. similar to Parseval’s formula of the Fourier transform.

Let \( f(t) \) and \( L^2(\mathbb{R}) \) have its continuous wavelet transform as \( W(a, b) \) then

\[ \int_{-\infty}^{\infty} |f(t)|^2 dt = \frac{1}{C} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |W(a, b)|^2 \frac{da db}{a^2} \]  

(1.27)

viii. **Localization Properties:** The continuous wavelet transform has some localization properties, in particular sharp time localization at high frequencies.

**Time localization:** Consider a Dirac pulse at time \( t_0 \), \( \delta(t-t_0) \) and a wavelet \( \psi(t) \). The CWT transform of the Dirac pulse is

\[ W(a, b) = \frac{1}{\sqrt{a}} \int \psi\left(\frac{t-b}{a}\right)\delta(t-t_0) dtm = \frac{1}{\sqrt{a}} \int \psi\left(\frac{t_0-b}{a}\right) \]  

(1.28)

For a given scale factor \( a_0 \), i.e. a horizontal line in the wavelet domain, the transform is equal to the scaled (and normalized) wavelet reversed in time and centered at the location of the
Dirac. For small 'a' the transform “zooms-in” to the Dirac with good localization for very small scales.

**Frequency localization:** Consider the sine wavelet, i.e. a perfect band pass filter. Its magnitude spectrum is 1 for between $\pi$ and $2\pi$. Consider a complex sinusoid of unit magnitude and at frequency $w_0$. The highest frequency wavelet that passes the sinusoid having a scale factor of $\pi/w_0$ (gain of $\sqrt{\pi}/w_0$) while the low frequency wavelet that passes the sinusoid having a scale factor of $2\pi/w_0$ (gain of $\sqrt{2\pi}/w_0$).

**ix. Reproducing Kernel:** The CWT is a very redundant representation since it is a 2D-expansion of a 1-D function. Consider the space $V$ of a square integrable function over the plane $(a,b)$ with respect to $da\,db/a^2$. Only a subspace $H$ of $V$ corresponds to wavelet transforms of functions from $L^2(\mathbb{R})$.

If a function $W(a, b)$ belongs to $H$, i.e. it is the wavelet transform of $f(t)$, then $W(a, b)$ satisfies

$$W(a_0, b_0) = \frac{1}{C} \iint K(a_0, b_0, a, b)W(a, b)\frac{da\,db}{a^2}$$

(1.29)

Where $K(a_0, b_0, a, b) = \Psi(a_0, b_0, \Psi_{a,b})$ is the reproducing Kernel.
1.5.4 Discrete Wavelet Transform

The discrete wavelet transform (DWT) corresponding to a CWT function \(W(a, b)\) can be obtained by sampling the co-ordinates \((a, b)\) on a grid as shown in the Figure 1.18. This process is called the dyadic sampling because the consecutive values of discrete scales as well as the corresponding sampling intervals differ by a factor of two. Then the dilation takes the values of the form \(a = 2^k\) and translation takes the values of the form \(b = 2^k l\) where \(k\) and \(l\) are integers. The values of \(d(k, l)\) represent the discretised values of \(CWT(a, b)\) at \(a = 2^k\) and \(b = 2^k l\). The two dimensional \(d(k, l)\) is commonly refereed as the discrete wavelet transform of \(f(t)\). The \(f(t)\) can be found using the following equation.

\[
f(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k, l) 2^{k/2} \Psi(2^k t - l)
\]

(1.30)

Figure 1.18 Time-Frequency Cells that Correspond to Dyadic Sampling
1.6 LITERATURE SURVEY:

The rapid development of power generated by increased demand for electric energy initially in industrialized countries and subsequently in developing countries led to different technical problems in the systems such as stability limitation and voltage problems. However breaking advances in semiconductor technology then enabled the manufacture of powerful thyristors and later other elements such as the gate turn off thyristors and insulted gate bipolar transistors. High voltage DC transmission (HVDC) technology which is being considered as an alternative to long distance AC transmission is based on this development.

During the latter part of the 19th century, electricity started to become increasingly important for society. In 1879, Edison invented the filament lamp and a few years later three phase alternating current was introduced simultaneously at several places across the world. One of these was Hellsjon near Ludvika in Sweden was one of the world’s first transmission links.

Since then, three-phase alternating current has been the dominant option for the transmission of electric power over long distances. Since the introduction of 765 kilovolts (KV) in 1968 there has been no further increase in the transmission voltage used for commercial systems. A
number of trial lines operating at 1,000 and 1,200KV have built, but up to now the decision has been to stay with 765KV as the highest voltage.

The amount of power transmitted over the alternating current systems increased accordingly. For AC systems, however, the transmitted power is limited by reliability and voltage stability requirements. Today, the normal capacity is 600MW for 400KV links and 2,000MW for 765KV systems [5].

A normal AC transmission system operating at 400KV and above generally has switchyards at sites where power needs to be drawn off or fed into the system. The equipment in such switchyards includes transformers to raise the voltage. On long transmission lines i.e. more than 300kM it is normal practice to install capacitors along the line to maintain the voltage and reduce losses.

The development of high-voltage direct-current (HVDC) for power transmission purposes began in the mid 1920s. The first commercial HVDC link, delivered by ASEA in 1954, carried power between the mainland of Sweden and the island of Gotland.

There are a number of differences between AC and DC:

Line losses are significantly lower for DC. For a 2,000 kM link, line losses for 800kV DC are about 5 %, while the corresponding losses for 765 kV AC are double, at about 10 percent.
For the transmission of comparable amounts of power, the cost of a power line is lower for DC. A 2,000kM HVDC transmission line rated at 6,000MW needs one power line with two suspended conductors. An equivalent AC link operating at 765kV requires three suspended conductors.

When DC is used, the power flow in the line can be controlled. This stabilizes the transmission network and prevents cascading outages.

HVDC requires converter stations at each end of the power line. This means that short power lines using DC are relatively expensive.

1.6.1 Artificial Neural Network Application to power system

The development of digital protection and control devices has increased the performance of many functions such as substation communication, fault recording, metering, supervisory control and data acquisition (SCADA) etc. Hence protection function itself is an adaptation for a microprocessor based device of conventional algorithm. Researchers designed and implemented a digital relay, which can be modified easily to accommodate the protection of different types of transformer by changing only the software algorithm [6]. The authors showed the experimental results for five selected algorithms. Discrete Fourier Transforms, Walsh
function, rectangular transforms, finite impulse response and least square have implemented using the designed digital relay.

Even though the method of protection has an advantage of using single relay for different transformers just by changing software, it also suffers from certain drawbacks like, need to define large set of data like differential current (as it is differential protection), threshold for normal loading, threshold for over excitation. Further it is understood that there is a need to define large set of data like different current (as it is differential protection), threshold for normal winding, over excitation and ground fault, 2\textsuperscript{nd} harmonic content in inrush current etc. Further, in the microprocessor based relays, sampling frequency is limited by economic constraints and such an adaptation could not result in considerably fast and accurate fault detection. Hence, it is time to make best possible use of new single processing techniques of single processing, neural network based analysis of power signal processing techniques to design fast and reliable digital/numerical relays. Among the new techniques of signal processing, neural network based analysis of power signals seem to be suitable, which overcomes the constraints required for digital relays.

Fault identification in transformer can be possible using neural network and fuzzy logic techniques. The necessary input data was obtained by chromatographic analysis of insulating oil to measure concentration (ppm by volume) of dissolved gases such as hydrogen,
methane, ethane, acetylene, carbon monoxide and carbon dioxide. Different operating conditions and structural peculiarities of transformers distort the chromatographic signatures for fault and this suggested consideration of DGA for different transformers as reference to obtain a reliable diagnosis.

1.6.2 Wavelet Transform applications to Power Systems

Wavelet transform (WT) has been introduced rather recently in mathematics, even though the essential ideas that lead to this development have been around for a longer period of time. It is a linear transformation much like the Fourier transform, however it allows time localization of differences frequency components of a given signal; windowed Fourier transform (STFT) also partially achieves the same goal, but the fixed width windowing function is a limitation. In the case of the wavelet transform, the analyzing functions called wavelets, will adjust the time width to the frequency in such a way that high frequency wavelets will be narrow and lower frequency ones will be broader. There are two main approaches to present wavelet theory: the integral transform approach (continuous time) and the multi resolution analysis (MRA)/filter bank approach (discrete time).

Several works have been developed in many areas with the aim of this tool, specially, in the last ten years have been met the potential
benefits of applying WT to power systems due to, among other, the interest in analyzing and processing the voltage-current signals in order to make a real time identification of transients in a fast and accurate way.

Wavelets were first applied to power system in 1994 by Robertson [7] and Ribeiro [8]. The main focus of application of WT in power systems is on identification and classification methods from the analysis of measured signals, however, few works use wavelet transform as an analysis technique for the solution of voltages and currents which propagate throughout the system due, for example, a transient disturbance.

The most popular wavelet transform applications in power systems are the following:

- Power system protection
- Power quality
- Power system transients
- Partial discharges
- Load forecasting
- Power system measurement

**Power quality:** In the area of power quality, several studies have been carried out to detect and locate disturbances using the wavelet
transform as an useful tool to analyze interferences, impulses, notches, glitches, interruptions, harmonics, flicker, etc. of non stationary signals.

There are two main approaches to the harmonics and flicker field. The first one, carries out a multi resolution analysis (MRA) using wavelet filter banks in a first step and the application of the continuous wavelet transform to the sub-bands in a second step; the second one, uses a complex wavelet transform analysis or continuous wavelet.

Accordingly to the first approach, in 1999 is presented a study [9] to evaluate harmonics, developing an algorithm to identify all of them, including integer, non integer and sub-harmonics. In the first step of this approach, the frequency spectrum of the waveform is decomposed in two sub-bands using discrete wavelet packet transform filter banks with orthogonal high order Daubechies function. In the second step, a continuous wavelet transform is applied to nonzero sub-bands, achieving satisfactory results from a real test system. In later works [10,11], is presented an improvement to eliminate the effect of imperfect frequency respond of the filters in WT filter banks, and to better analyze sub-harmonics. A similar approach for harmonics and flicker analysis is discussed by many researchers [12,13]. Other similar work using different mother wavelets is presented in [13]. Second approach [14], describes a harmonic analysis with a trapezoid complex wavelet function.
and the associated trapezoid WT [15,16], show a flicker analysis using the Morlet and Gaussian continuous WT.

However, the effectiveness of wavelet transform for voltage disturbances studies is questioned in [11], pointing out that the STFT is more appropriate for this analysis with a properly chosen window size.

In power system disturbances field, the first works make use of WT to detect and locate various types of power quality disturbances, decomposing a disturbance into its wavelet coefficients using a MRA analysis technique. Santoso et al.[17] set up an investigation line on this area with the work, then the authors in [18] make the proposal that, based on uniqueness of squared WT coefficients at each scale of the power quality disturbance, a classification tool such as neural networks may be employed for the classification of disturbances [19,20]. Moreover, in [21] develop an application to compress power quality disturbances.

However, the application of WT is not always adequate for the analysis of all types of disturbances, such as the case of voltage sag, as [22] points out, because the wavelet filter does not detect the voltage sag depth.

**Partial discharges:** The partial discharges are difficult to detect due to their short duration, high frequency and low amplitude signals, but the capacity of the wavelet transform to zoom in time the signals with
discontinuities unlike the Fourier transform which allows identifying local variations of the signal. [23-27] applies these principles to detect partial discharges in transformers winding, cables and GIS (gas insulated substations).

**Load forecasting:** Demand forecasting is a key to the efficient management of electrical power systems. The works have been developed for short term electrical load forecasting by combining the wavelet transform and neural networks. As electrical load at any particular time is usually assumed to be a linear combination of different components, from the signal analysis point of view, load can be also considered as a linear combination of different frequencies. Every component of load can be represented by one or several frequencies. The process decomposes the historical load into an approximate part associated with low frequencies and several detailed parts associated with high frequencies through the wavelet transform. Then, the forecast of the part of future load is develop by means of a neural approximation [28,29] or adjusting the load by a regression method [30].

**Power system measurements:** The advantage of using the wavelet transform for the application of power/energy and rms measurements is that it provides the distribution of the power and energy with respect to the individual frequency bands associated with each level of the wavelet analysis. There has not been much work on applying wavelet transform
for rms voltage and power measurements. The discrete wavelet transform (DWT) algorithm for rms value of voltage or current and active power measurements is first introduced in the literature to achieve frequency separation into the various wavelet levels using IIR filters, [31,32], however provides non-uniform frequency bands which cannot be used to measure the rms value of voltage or current and power of individual harmonic components. In [33] this problem is solved developing a wavelet packet that can decompose a waveform into uniform frequency bands, so that this WPT algorithm has a capability to measure the rms value of voltage or current and power of individual harmonic components.

**Power system protection:** The potential benefits of applying wavelet transform for improving the performance of protection relays has been recognized in recent years [34-65]. In 1996, Chaari et al.[56] introduce wavelets for the power distribution relaying domain to analyze transient earth faults signals in a 20 kV resonant grounded network as generated by EMTP; Magnago and Abur [50] set up the development of a new investigation line in the area of fault location using wavelets, for this purpose, the fault generated travelling wave is processed by the wavelet transform to reveal their travel times between the fault and the relay locations; EMTP simulations are used to test and validate the proposed fault location. In 1999 the same authors extended the method to the identification of the faulted lateral in a radial distribution system and in
2000 presented an improved method for their earlier papers [51]. Similar methods for fault location can be found in [52,53].

High impedance fault identification [57,58,60] is other application area of wavelet transform, for example, in [60] Charytoniuk presents a comparative analysis for arc fault time location, frequency and time-frequency (wavelet) domain, the author demonstrates that the wavelet approach is strongly affected by the choice of a wavelet family, decomposition level, sample rate and arcing fault behavior.

The application of wavelets to autoreclosure schemes [61,62] is developed to accelerate trip of power transmission lines, wavelet transform is adopted to analyze the fault transients generated by the secondary arc and permanent faults and the results reveal that certain wavelet components can effectively be used to detect and identify the fault relevant characteristics in transmission systems and then to distinguish between transients and permanent fault.

The wavelet transform is also applied for the bus-bars [34], motors [39-42], generators [37,38] and transformer protection [43-48], in most of this cases, the spectrum of signals is analyzed with the wavelet transform to develop online detection algorithm to detect insulation degradation, inrush and to carry out the precise discrimination between internal and external faults.
**Power system transients:** In the mainstream literature, wavelets are first applied to power system transients in 1994 [7]. In this paper, the authors present a methodology for the development of software for classifying power disturbances by type from the transient waveform signature. The waveform signature is derived from the wavelet transform of the transient signal. In 1996, Robertson, et al. [66] apply wavelet for the analysis of capacitor switching transients. The authors give a digital implementation of the wavelet transform via filter bank analysis and make clear that any valid wavelet can be used in this implementation.

Up to this point, the focus in the literature has been on identification methods. That is, identifying a transient disturbance and perhaps classifying it according to its wavelet spectrum. In [67-69], Heydt and Galli propose the use of the Morlet wavelet as an analysis technique for power systems transients. The term analysis denotes the solution of voltages and currents which propagate throughout the system due to a transient disturbance.

In 2000, Meliopoulos [70], presents an alternative method for transient analysis of power systems, the method is based on the wavelet series expansion and reconstruction. The system matrix is developed by applying wavelet series expansion on the integro-differential equations of the power system. The procedure results in a set of algebraic equations for the entire network. The solution is in terms of the wavelet expansion
coefficients of the voltages at the nodes of the network. The actual voltages can be reconstructed via the wavelet series reconstruction.

The transformer inrush identification based on wavelet [71,72] have the advantages that different kinds of inrush of the transformers can be correctly identified from different types of internal transformer faults; external transformer faults can be also distinguished from the internal fault.

Apart from, the application of wavelets to introduce new identification, classification and analysis methods such as those presented previously, at the moment is also studied for the application of wavelets to develop new components models; for example in 2001, Abur et al.[73] extend the results of previous works [74] and describe a transmission line model which is based on wavelet transform taking into account frequency dependence of modal transformation matrices into the transients simulation. A different approach to the simulation of frequency dependence, un-transposed transmission line transients is introduced. The effect of strong frequency dependence of modal transformation matrices on the transmission line transients is accounted for the time domain simulations via the use of the wavelet transform applied to the signals. This allows the use of accurate modal transformation matrices that vary with frequency and yet still remain in the time domain during the simulations.
1.6.3 Literature Survey on HVDC system analysis

HVDC transmission system are mainly overhead transmission lines lay over long distances with the converter stations located on both the ends of the transmission line. Few faults in the HVDC system such as faults on the transmission line, faults in the converter transformers which are located in the converter stations, faults on the ac side of inverter and rectifier may lead to the failure of the HVDC system. Thus, to ensure greater reliability the detection and fast clearance of faults in HVDC lines are indispensable. The major faults associated with HVDC transmission system are dc line to ground fault, faults on the ac side of the inverter, commutation failure at the inverter.

A HVDC link modeled within the harmonic domain using a full Newton method for solution has been described by Bathurst, G.N. et al. [75]. The solution is rapid and robust for a variety of cases and shows excellent agreement with time domain simulation. The HVDC link is also modeled with an extended control system for realistic specification of the steady-state operating point.

A method for accurate calculation of the harmonics generated by a bipolar HVDC link has been described by Bathurst, G.N et al. [76]. This method illustrates the importance of including detailed representation of the mutual coupling effects of DC transmission lines, even when
smoothing reactors are included. The overall solution is achieved by means of a unified Newton algorithm in the harmonic domain.

Using the Symmetrical Space Phasor Components, the harmonics of a periodical signal are decomposed into several groups (components). Within each group the harmonics show a similar behavior. The advantages of the Symmetrical Space Phasor Components become apparent in describing networks with time variant elements with a cyclic behavior like converters. Strobl B, et al. [77] proposed that the equivalent networks can be derived which show certain relationships between the components. Because of the fact that these components are sets of certain harmonics, the relationships between these groups correspond to a relationship between the harmonics in these groups. This allows for general conclusions without any assumption concerning the switching behavior or the time function of the voltage or the current. Generalized formulas describing the harmonic transfer in a converter are derived analytically. Hereby the behavior of the harmonics under special conditions is also included.

A back to back (BTB) HVDC interconnector consisting of multilevel current re-injection (MLCR) converters has been described, based on the parallel converter configuration by Yong He Liu et al. [78]. Since the MLCR creates a zero current region during the commutations, the proposed BTB configuration permits the continued use of thyristor
valves, without losing the control flexibility of the self-commutating process. Extensive EMTDC simulation is used to demonstrate the satisfactory response of the proposed BTB HVDC interconnector control structure to varying active and reactive power operating conditions.

Based on analysis of the development, technology characteristics and application scope of conventional HVDC and voltage source converter based HVDC (VSC-HVDC), an alternative form of HVDC transmission, named hybrid HVDC, has been explained by Li Guangkai et al. [79]. At first the fundamental principle and technology characteristics of hybrid HVDC are analyzed, and then the simulation model is founded based on simulation software PSCAD/EMTDC. Simulation results show that the proposed hybrid HVDC system can be operated steadily. Further more when two AC sides have single phase to ground or three phases short circuit fault in short time it has the capability to restore steadily and rapidly. At last the advantages and disadvantages of the hybrid HVDC and its application foreground are evaluated.

A review of the ability of present protection systems to provide adequate protection for proposed future HVDC systems has been proposed by Naidoo, D et al. [80]. This initial study reviews current protection systems used for DC line protection and highlights both the advantages and disadvantages of these systems including the factors
that adversely influence their performance. The paper stresses the importance of local fault detection and suggests that telecommunication should, as far as possible, only be used to enhance and optimize the systems. The paper also highlights the major advantages of using the system transients to detect DC line faults in terms of security, reliability, speed of fault clearance and fault recovery as well as the drawbacks and current limitations and possible solutions. The authors finally evaluate the current protection systems and propose ways of enhancing some of the existing protection systems with local supervision and other techniques to improve their performance and capability.

For the third project of the Hokkaido-Honshu HVDC Link in Japan, called the HVDC Link III project (rated at 250 kVDC-1200 A-300 MW), a HVDC transmission line protection method based on a new working principle that allows high-speed and highly sensitive detection of faults, enhancing reliability in the supply of electric power has been developed by Takeda, H et al. [81]. In general, increasing the sensitivity of relays will lead to an increased likelihood of undesired operation whereas lowering the sensitivity will impair the responsiveness of the relays. The proposed method meets these apparently incompatible requirements very well. Basically classified as a differential scheme, the HVDC transmission line protection method compensates for a charging and discharging current that flows through the line-to-ground capacitance at times of voltage variations caused by a line fault or by the
operation of DC power systems. The developed protection method is also characterized in that it uses current changes induced by voltage variations to restrain the operation of a relay. This configuration has made the proposed method far superior in responsiveness and sensitivity to the conventional protection method. A simulation using an EMTP (Electro-Magnetic Transients Program) was conducted on this method. Developed relay equipment embodying the new protection method was subjected to various verification tests, where this equipment was connected to a power system simulator, before being delivered to the HVDC Link III facility.

Kato, Y. et al. [82] described the principle of fault detection and its simulator study, principal circuitry, field test results and field performance records on the neutral line protection system for an HVDC transmission system. In the protection system, 125Hz AC current injected to the neutral line is utilized as a pilot current to detect the neutral line faults. The pilot current injection is made through the neutral line surge capacitor without detracting its capability. Combined with a metallic return protecting breaker, this protection system has demonstrated a satisfactory performance on the grounding fault clearance without interrupting the power transmission.

Senthil, J. et al. [83] presents the simulator study of a two terminal HVDC system. The various AC system faults to which the study system
is subjected are a) remote-three-phase ground fault, b) single-phase-ground fault and c) three phase ground faults. These faults are applied both at the rectifier and inverter ends. The results of the simulator study are presented to demonstrate the controller performance in the recovery of HVDC link following AC system faults.

An evaluation study of the behavior of the over current and differential relays of the HVDC converter during common internal faults has been presented by Darwish H.A et al. [84]. The study is conducted via simulation of an HVDC converter using the electromagnetic transient program (EMTP). Rectifier misfires and backfires in addition to the inverter fire-through and different types of commutation failure are considered. Under these faults, the converter over current and differential relay performances have been computed. In addition, the computed results are corroborated using a laboratory scaled down model in conjunction with a DSP board-based over current and differential relays. Delayed detection or complete blindness of these relays in detecting typical converter internal faults has been recorded. Modification of the principle of the converter differential and over current relays is a must.

The mono polar grounding fault in bipolar HVDC system with phase-modal transformation method has been analyzed by Hua Li et al. [85]. Initial jumping voltage and maximum voltage on health pole with
different kinds of termination are deduced by establishing the modal circuit under the fault. Simulation results show a grounding fault in the middle of the line exhibiting maximum voltage with value of 1.54 p.u., which agrees well with the theoretical value. And the maximum voltage decreases with the increasing grounding resistance. The inductance of the reactor influences the maximum voltage on health line a little.

Support Vector Machine (SVM), which based on Statistical Learning Theory, is a universal machine learning method. The fault diagnosis of nonlinear and high-controllable High Voltage Direct Current (HVDC) system based on SVM method is proposed by Xi-mei Liu et al. [86], which can take full advantage of effective ability and superiority of SVM in dealing with small samples, and solve many familiar problems in fault diagnosis of HVDC system. In this work a simulation model of HVDC system is set up, and performance of SVM models under different parameters using polynomial kernel function and RBF kernel function respectively are compared. Results show the superiority of SVM method, also the validity and feasibility of the proposed method.

A simple model for the commutation margin control of inverters for the digital simulation of transients is described. A commutation margin control representation for digital simulations has been proposed by Bhattacharya, S et al. [87]. That is based on a recursive fault detection
method. The results of simulations with the proposed inverter control representation agree reasonably well with HVDC simulator outputs.

Lidong Zhang et al. [88] have been given a method to mitigate commutation failures in HVDC systems due to voltage dips from AC systems. The abc-$\alpha\beta$ transformation is used for three-phase fault detection, and the zero-sequence voltage, which is obtained by the addition of the three-phase voltages, is used for single-phase fault detection. Both detection methods are based on instantaneous values, which ensure fast reaction of the control system when AC faults occur. After detecting the fault, an additional angle is deducted from the firing order at the inverter station, which in practice enlarges the commutation margin. The test results show that this method is very effective in reducing the risk of commutation failures.

The study of commutation failures requires more detailed and accurate simulation of HVDC systems. Hypresim is an integrated digital simulator, which could provide reliable, extensible and high-speed electromagnetic transient simulation for power systems. Its special characteristics are introduced by Lingxue Lin et al. [89]. A HVDC system is established based on Hypersim. Modeling details of the ac system, dc lines, dc converters and their control systems are presented. Commutation failures are triggered by external disturbances on the ac bus and internal faults on the thyristor valve; the dynamic behavior of
the HVDC system is demonstrated; detailed analysis is also given. A protection method against commutation failures is proposed. Simulation result indicates that the probability of failure could be reduced.

A method to mitigate commutation failures in HVDC systems due to voltage dips from AC systems has been analyzed by Ludvika et al. [90]. The abc - αβ transformation is used for three-phase fault detection, and the zero-sequence voltage, which is obtained by the addition of the three-phase voltages, is used for single-phase fault detection. Both detection methods are based on instantaneous values, which ensure fast reaction of the control system when AC faults occur. After detecting the fault, an additional angle is deducted from the firing order at the inverter station, which in practice enlarges the commutation margin. The test results show that this method is very effective in reducing the risk of commutation failures.

The 200 MW back-to-back Sidney (Nebraska) Converter Station (SCS) provides an asynchronous tie between the east and west AC power networks. In order to maintain electromechanical stability of the east network under worst-case line outage conditions, a remedial action scheme (RAS) was integrated in the HVDC (high-voltage direct-current) control. Basic components of the SCS RAS are frequency-dependent power modulation combined with an effective voltage control in the western network by Johnson, R.K. et al. [91] presented. The authors
present the conceptual development of the RAS, as well as details on the
RAS control hardware and software. Studies and live system tests have
demonstrated the ability of the relatively fast HVDC controls to change
the power in feed from the DC station quickly. These rapid changes in
power transfer properly coordinated with speed deviation of a nearby
generation unit, help maintain, and in some cases improve, the
electromechanical stability of the AC system.

The KII channel HVDC transmission system (1400 MW in the first
stage) was commissioned in the year 2000 and transmits power
generated in Shikoku Island to the AC 500 kV system on Honshu Island.
The transmission line of approximately 100 kM between the converter
stations consists of two sections-undersea cable and overhead line
sections. The transmission lines consist of 2 main lines and 2 return
lines. The fault protection function was verified by making artificial
grounding faults both for the main lines and return lines during a series
of commissioning tests has been explained by Hara, S. et al.[92] . The
characteristics of the protection system of the return circuit including
the metallic return transfer breakers (MRTBs) were evaluated from the
tests. At some of the points along the line, the grounding arc
extinguishes itself before closing MRTB and at other points; the,
grounding arc is cleared by closing MRTB. It was confirmed that the
clearing time of the grounding arc was consistent with the system design
parameters.
Previous studies have shown that many types of system disturbances will lead to commutation failure at HVDC inverter stations. The problem is further aggravated if the inverter is connected to a weak (low short-circuit ratio) AC system. Kristmundsson, G.M et al. [93] analyzed the problem in terms of the frequency spectrum of the AC network and its relation to the transient disturbance which causes the failure. Methods are discussed for modifying the frequency spectrum in order to decrease the probability of commutation failure. A sample simulation study was performed to illustrate the effectiveness of one particular type of filter. Results indicate that in some cases the probability of failure can be reduced dramatically.

The use of wavelet transforms for analyzing power system fault transients in order to determine the fault location has been described by Magnago, F.H.et al. [94]. Travelling wave theory is utilized in capturing the travel time of the transients along the monitored lines between the fault point and the relay. Time resolution for the high frequency components of the fault transients, is provided by the wavelet transform. This information is related to the travel time of the signals which are already decomposed into their modal components. The aerial mode is used for all fault types, whereas the ground mode is used to resolve problems associated with certain special cases. The wavelet transform is found to be an excellent discriminantor for identifying the travelling wave reflections from the fault, irrespective of the fault type and impedance.
EMTP simulations are used to test and validate the proposed fault location approach for typical power system faults.

User feedback has proven very successful to query large multimedia databases. Due to the nature of the data representation and the mismatch between mathematical models and human perception, the query techniques benefit substantially from interactively modifying a query. Typical examples are generalized ellipsoid queries where optimal ratios and orientations of the half-axes are determined by relevance feedback. However, no information about the outcome of a feedback process is stored whatsoever once the process is terminated. Accordingly, the entire feedback loop has to be repeated---starting out with default parameters---if the same query is posed again. Ilaria Bartolini et al. [95] presented preliminary results on how to preserve feedback results in a space efficient way and learn from user feedback. The cornerstone of our system is multidimensional unbalanced wavelets that are used to store the parameters determined during the feedback process. Using wavelets lets us not only store parameter combinations but also enables us to predict parameter settings for queries similar to earlier ones by interpolation: the feedback process for an entirely new query can be started with a parameter setting, usually much closer to the optimal than the default parameters. As a result, after an initial learning phase, feedback is needed for fine tuning only, increasing effectiveness and response time of multimedia databases.
The application of wavelet based multi-resolution signal decomposition in monitoring different disturbances in HVDC systems has been described by Gaouda A.M. et al.[96]. The features extracted from the proposed technique are generated from signals monitored on both DC and AC sides of the HVDC system. These monitored signals show promising features that can classify different disturbances that may occur anywhere in the HVDC system.

A disturbance classification technique based on wavelet multi-resolution analysis has been proposed by Gaouda, A. M.et al. [97]. The wavelet multi-resolution transform is introduced as a tool for providing discriminative, translation-invariant features with small dimensions to classify different disturbances in an HVDC transmission system. The proposed method extracts features from signals monitored on both dc and ac sides of the HVDC system. It is shown that monitored signals show promising features that can classify different disturbances that may occur anywhere in the HVDC system.

A new high-speed HVDC line protection using wavelet technique has been proposed by Shang L.et al. [98]. Based on the representation of the travelling waves through wavelet modulus maxima, the protection criteria for HVDC fine are proposed. Simulations are carried out for testing the criteria. The influences of similar faults are discussed. The protection can detect the HVDC line fault well and identify the HVDC line
fault clearly from the similar transients, such as commutation failure and AC single phase fault.

Different HVDC system faults are analyzed and the rationing criteria based on wavelet modulus maxima for the identification of the HVDC system faults are proposed by Shang L. et al. [99]. The simulation results are discussed. The results show that the application of wavelet technique leads to a proper and more reliable solution for fault identification. The results also provide a good basis for the new high-speed protection of HVDC lines.

The problem of useful electrical power quantification in environments with power quality problem has been discussed by Johan Driesen et al. [100]. As it is difficult to correctly apply a Fourier-based approach, alternative power quantifications in the time-frequency domain, based on a complex wavelet transform, are presented. Using the property that instantaneous amplitudes of voltages and currents as well as instantaneous phase differences can be obtained, power definitions with time and frequency localization properties are derived. The physical interpretation is given and a comparison with traditional formulae is made. Examples, with typical power quality problems, illustrating this methodology are given.

Automation of power system fault identification using information conveyed by the wavelet analysis of power system transients has been
proposed by K.Harish Kasyap et al. [101]. The Probabilistic Neural Network (PNN) for detecting the type of fault is used. The work presented in this paper is focused on identification of simple power system faults. Wavelet Transform (WT) of the transient disturbance caused as a result of the occurrence of a fault is performed. The detail coefficient for each type of simple fault is characteristic in nature. PNN is used for distinguishing the detail coefficients and hence the faults.

The S-transform (ST) is an extension of wavelet transforms which possess’ superior property over the latter as the moving functions are fixed with respect to time axis while the localizing scalable Gaussian window dilates and translates. Phase spectrum obtained in this transform is always with respect to fixed reference point and the real and imaginary spectrum can be localized independently. Such a transform with moving and scalable localizing Gaussian window, therefore, provides excellent time localization property for different non-stationary signals. In this paper the ST of fault current signal is analyzed for an advanced series compensated transmission system by Chilukuri M.V. et al. [102]. The time-frequency analysis of the current signals at different fault conditions of the system clearly classifies the faulty sections and phases.

The technique using the current travelling waves to detect the fault position in the transmission lines has been proposed by Dong Xinzhou et al. [103]. How to identify the incident travelling waves and reflected ones
from the fault point when noises exist is discussed and resolved. A fault position relay based on current travelling waves and wavelets theory is designed. The relay's principle is mainly on wavelet theory and modulus maxima of the wavelet transform. By analyzing the distribution of the modulus maxima, different components in the current travelling waves can be distinguished and then the incident and reflected travelling waves are identified and finally useless components are filtered. The incident and reflected travelling wave's time difference arrival time difference indicates the fault position. An EMTP simulation example is illustrated. The relay is been proved correct and effective.

The modern travelling wave based fault location principles for transmission lines are analyzed by Ping Chen et al. [104]. In order to apply the travelling wave principles to HVDC transmission lines, the special technical problems are studied. Based on this, a fault locating system for HVDC transmission lines is developed. The system can support the type D and type A modern travelling wave principle simultaneously, and it is composed of three different parts: travelling wave data acquisition and processing system, communication network and PC based master station. In the system, the fault generated transients are induced from the ground leads of the over-voltage suppression capacitors of a HVDC line through special developed travelling wave couplers. The system was applied to 500 kV Ge Zhouba-Nanqiao (Shanghai) HVDC transmission line in China. Some field
operation experiences are summarized, showing that the system has very high reliability and accuracy, and the maximum location error is about 3kM (not more than 0.3% of the total line length). Obviously, the application of the system is very successful, and the fault location problem since the line operation has finally been solved completely.

A wavelet based commutation failure (CF) detection technique in HVDC system, and selects the suitable mother wavelets has been proposed by Wang Yuhong et al. [105]. The different properties of wavelets are analyzed in detail. It is shown that the orthogonality, regularity, moments, and symmetry of a wavelet function may affect the CF detection to some extent, and the critical factor is the moments of the mother wavelet. Discrete wavelet transform (DWT) has executed respectively on normal sinusoidal voltage signal and alternative voltage record with CF in Tianguang HVDC project. The transform result shows that DWT by Daubechies wavelet function with high vanishing moments is a cogent tool for CF detection in HVDC system.

Travelling waves recorders (TWR) are used to accurately find the location of different faults in transmission networks. These recorders are installed at few substation buses where current travelling waves can be extracted. The recorded signals' time delay of the initial wave is receded at each TWR has been proposed by Elhaffar A et al. [106]. The minimum travel time of the travelling wave has been calculated considering
Dijkstra algorithm to select the nearest TWR to the faulted line. The wavelet transform is used to find the highest spectral energy of the frequency band of the travelling wave signals. Thus, the Wavelet Transform enhances the travelling wave fault location. The current transformers (CT) are modeled and experimentally verified to represent the travelling wave interaction with the CT. The secondary wiring from the CT secondary winding to TWR has also some effect on the measured travelling wave signal which motivates practical issues associated with measuring the arrival times. Correction factors are derived to monitor high frequency current travelling wave signals. Validation of fault location is examined by ATP/EMTP simulations for typical 400 kV power system faults.

Commutation failure (CF) is a serious malfunction in HVDC systems. Fast detection and identification is important to avoid HVDC system block or even further deterioration of the whole system. Yuhong Wang et al. [107] proposed a novel approach of CF recognition using wavelet transform and Shannon entropy technique. Only phase a voltage signal at inverter is used as the input of the new method. AC voltage is decomposed by discrete wavelet transform to get details and approximations on all scales. High frequency details are used to locate the fault time. A fault entropy feature matrix T is formed for fault classification. CF can be identified by comparing the Euclidean distances of its feature vector to those of the known fault types in matrix T. The
proposed approach is verified by fault signals simulated in a complete 12-pulse HVDC transmission system in Matlab/Simulink. The results have approved its feasibility and preciseness.

A fault location procedure for distribution networks based on the wavelet analysis of the fault-generated travelling waves has been proposed by A.Borgnetti et al. [108]. In particular, the proposed procedure implements the continuous wavelet analysis applied to the voltage waveforms recorded during the fault in correspondence of a network bus. In order to improve the wavelet analysis, an algorithm is proposed to build specific mother wavelets inferred from the fault-originated transient waveforms. The performance of the proposed algorithm are analyzed for the case of the IEEE 34-bus test distribution network and compared with those achieved by using the more traditional Morlet mother wavelet.

Fault identification and classification is very important for the secure and optimal exploitation of electric power systems. The Wavelet Analysis can be used as a tool for providing discriminative features with small dimensions to classify different disturbances in HVDC transmission system. The application of wavelet based multi-resolution analysis (MRA) for signal decomposition to monitor some of the faults (e.g.- L-G Fault, DC line fault, Commutation failure) in the HVDC system has been described by Rashmi Aspi Keswani et al. [109]. The faults in
HVDC System can be classified by monitoring the signals both on AC and DC sides of the HVDC System like Inverter side AC phase currents, DC voltage, DC current, Valve currents. The fault classifier can be developed from these monitored signals which show promising features to classify different disturbances in the HVDC System. The simulation results are also presented to verify the performance of the proposed method. The method has been used to classify different faults as well as to identify faulted phase(s) and valve(s) in case of AC faults and Commutation failure respectively.

A investigates travelling wave based protection schemes developed for high voltage transmission systems and their adaptation to medium voltage distribution networks in order to enable ultra high speed relaying (within a quarter of a cycle of the power frequency) on a medium voltage level has been proposed by Magnus Ohrstrom et al.[110]. After different travelling wave algorithms are evaluated using simple test systems, they are applied to an industrial power system where fault detection within one millisecond is required. Difficulties that arise from typical characteristics of medium voltage distribution systems are outlined and requirements to measurement and signal processing systems are discussed.

Neural network and its simulation results for fault diagnosis in HVDC systems has been described by Lai, L.L et al. [111]. Fault
diagnosis is carried out by mapping input data patterns, which represent the behavior of the system, to one or more fault conditions. The behavior of the converters has been described in terms of the time varying patterns of conducting thyristors and AC and DC fault characteristics. A three-layer neural network consisting of 20 input nodes, 12 hidden nodes and 4 output nodes has been used. 16 different faults have been considered and dynamic characteristics of networks for different configurations were also studied. The time performance of the network has been included. Neural networks provide an effective way for fault diagnosis.

The use of artificial neural networks to classify power system faults has been described by Lai, LL et al. [112]. Examples are used to demonstrate this approach for applications such as faults occurring in high voltage transmission systems, or those stored with a digital recorder. The paper proposes an adaptive scheme employing neural networks for developing digital distance relay protection schemes. High impedance faults and variable source impedance are also considered. An example, based on a three-terminal line configuration is used to illustrate the effectiveness of the method. Secondly, a discussion on the future use of NN in protection applications is given. In conclusion, the author believes that neural networks should be integrated with different computational techniques to enhance their application to fault classification and protection.
The application of a Radial Basis Function (RBF) Neural Network (NN) for fault diagnosis in a HVDC system has been presented by Narendra K.G et al. [113]. To provide a reliable preprocessed input to the RBF NN, a new pre-classifier is proposed. This pre-classifier consists of an adaptive filter (to track the proportional values of the fundamental and average components of the sensed system variables), and a signal conditioner which uses an expert Knowledge Base (KB) to aid the pre-classification of the signal. The proposed method of fault diagnosis is evaluated using simulations performed with the EMTP package.

1.6.4 Literature Survey on Converter Transformer analysis

Fault location can provide critical information for converter transformer maintenance, failure investigation and restoration. According to the knowledge of possible faulty areas, a plan of detailed fault investigation can be made long before the scheduled shutdown or the necessary spare part or equipment or resource can be prepared adequately in case of an unavoidable failure. The resultant could be, considerably reduced transformer downtime and restoration effort, which is essential in today’s competitive electric power market.

Fault investigation is a major issue of transformer maintenance. The results are the basis of a trade off decision to continue operation, re-
energize the protection of tripped transformer after treatment, partially fully repair or replace the failed transformer.

The digital recording instrumentation and signal processing techniques developed for transformer impulse tests were described by Malewski R et al. [114]. This work focuses on the sensitivity and accuracy limits of the transfer function method, which were evaluated by analyzing a large number of tests on power transformer and reactors as well as real scale winding model, where the fault was applied at different locations on the coil. The analysis led to an evaluation of the quantization error of the recorder and also of the signal processing routines required by the Fast Fourier Transform as the accuracy of the transfer function method is essential for detecting winding displacement in power transformer in service.

E. Hanique [115] reported that for comparison of the transfer function, it is necessary to recognize the valid range of the frequency spectrum. This depends upon the type of wave form. A normal 1.2/50 µs waveform has a frequency spectrum up to 500 kHz, while chopped waveform has a frequency spectrum up to 1 MHz. Due to the chopping, the tail of the waveform is normally much steeper than the front of the waveform. In order to obtain additional diagnostic information, while comparing the transfer function of normal wave form and a chopped waveform, the author felt that this comparison shall be limited up to
500Hz frequency only. This is verified by experimenting on 300MVA, 3-phase winding transformer with rated voltage of 245/44/13.1kV. Based on the results the author suggested that the transformer specifications/design play a significant role in the transfer function evaluation of a fault.

j. Back – Jensen et al. [116] experimented on single phase potential transformer of 20kV/110V, 30VA. Two test series are carried out on transformers, which are a sensitivity test series and an aging test series. The purpose of the sensitivity test series is to determine how close the identified transformer model is connected to the physical condition of the modeled transformer. The purpose of aging test series is to identify development in the transfer function method of the transformer towards breakdown. Based on the two test series proposed, it is concluded that the detection of failures and aging phenomena in transformers by transfer function is dependent on detectable changes in few characteristic transformer parameters basically lumped winding capacitances, total losses and core reluctances.

E. Rahim Pour et al. [117] developed a detailed model for the detection of axial displacement, radial deformation of windings and in this model their mathematical descriptions in the frequency domain are evaluated as well as correlated with experimental results on two test transformers. It shows that there is a good matching between the
measured and calculated results in the frequency range of a few kHz to about a few MHz. The model predicts the essential frequency range characteristics accurately. The correlation between the changes of the transfer function and corresponding axial displacements as well as radial deformation is given by the model correctly. These results have proven that the mechanical displacements in transformer windings could be explained with the help of the above detailed model. All transfer functions show that the radial deformation changes the transfer function characteristic in entire frequency range whereas axial displacement changes beyond 200 kHz only. It is also noted that the terminal condition cannot change the resonance behavior significantly.

Three different ways of using the transfer function method for detecting mechanical winding displacements in power transformers has been proposed by J. Christian et al. [118]. The authors adopted time, construction and type based comparison. All these comparisons are well suited for transfer function evaluation. However time based comparison provides better sensitivity. The results of separately tested legs can be applied as reference only for Y and D coupled windings. Construction-based comparison method is applicable for three phase assemblies as well as multi leg single phase transformers. The similarity of the transfer function behavior of zigzag coupled winding is not sufficient for performing any diagnosis. Usually, a type based evaluation leads to distributed transfer function results. A statistical evaluation method is
presented for separating the effects of manufacturing process from the effects of defects and change in core coil assemblies for sets including more than ten test objects.

A quantitative method to determine a winding fault of a transformer by a transfer function model via system identification techniques has been proposed by Chan Ding Zhang et al. [119]. A fault model is developed and is used to determine winding fault in transformers. Theoretical and the experimental results are also compared.

James J Dukaram [120] suggested few methods of transformer oil diagnosis using fuzzy logic expert system and these can identify abnormalities like over heated oil, over heated cellulose, partial discharge, arcing etc.

A two step Artificial Neural Network (ANN) method to detect faults with or without cellulose based on dissolved gas in oil analysis has been proposed by y. Zhang et al. [121]. Characteristic key gases have been used to identify particular type of faults [122]. Result of the study showed that the two steps ANN approach in promising but for complicated diagnosis, relationship is more complex and hence more training data is required. A similar fault diagnosis with the use of gas sensors having different characteristics by using NN has been suggested by Takeki Nogami et al. [123].
transformer faults by NN proved to be available for methane and ethylene. The performance or earlier detection of fault is dependent on detection sensitivity of the gas sensors.

An improved and different method of fault identification using NN depending on the gas analysis was given by S. Birlasekaran et al. [124]. The authors used both FFT and ANN signal processing techniques. The author use membrane and forced diffusion techniques to extract the dissolved gases in oil and senses gases by two thin film semi conducting gas sensors. The FFT analysis resolves the frequency components of the sensor response up to third harmonic and the data has been used to train a back propagation ANN network. All the above described methods needed the support of gas analysis, gas sensors and membranes, etc for fault identification using ANN.

Luis G. Perez et al. [125] reported a feed – forward NN to discriminate between inrush magnetizing current and internal faults in power transformers. The sample data for NN is obtained by sampling conventional methods. Similar method was developed by M.R.Zaman et al. [126] and also experimentally tested.

Hong Tzer Yang [127] proposed a new NN diagnostic system for a line fault section estimation using information of relays and circuit breakers. This system has similar profile of an expert system but can be constructed much more easily from elemental samples. These samples
associate fault section with its primary, local and or remote protective relays and breakers. The diagnostic system can be applicable to the power system control center for single or multiple fault estimation, even in the case of failure operation of relay and breaker or error existent data transmission. The proposed approach was practically verified by testing on a model power system and proved to be efficient. This achievement confirmed that ANN technique proves to be very efficient for protection of transformers, if used in right manner. Fulfilling basic necessity of NN i.e. providing large amount of sample data, it is possible to get very good results. As stated before, this point was also considered by the researchers who designed NN using DGA.

A unique method was presented by H. Wang et al. [128], which used finite elements analysis models to generate data for training and testing of NN. The results were compared with that obtained by using the data from field experiment to train NN of transformers; it showed that well trained NN can be used to simulate the terminal behavior and their internal faults. They also proposed two kinds of neural networks, back propagation feed forward network and radial basis function network. Simulation results of the two kinds of networks were compared and discussed in terms of training and generation performance.

Alves da Silva et al. [129] proposed an approach to the fault location problem. It is in operation at the 500 KV GIS of the Itaipu
system. The author discussed about the advantages and disadvantages of ANN over expert system. A. Z. Mazon et al. [130] developed ANN automatic selection system using a MATLAB package. The inputs to the neural network are the current and voltage magnitudes in fault and pre-fault situation. Further, the voltage and the current magnitudes needed for the training phase and for the test afterwards are given by a fault simulator. For this purpose, MATLAB software has been used. Hence from above discussion it is clear that NN can give wonderful results based on the quantity of training. Thus the challenges in fault identification of transformer are to generate the training data by using exact simulation methods.

Ghendy Cardoso et al. [131] described a tool applied to real bulk power systems and are able to deal with topological changes without having to retrain the neural network. ANN is used as pattern classifier [131]. ANN relay can as well provide fast and precise operations, keeping the reach accuracy, when faced with different fault conditions as well as network changes. David C Yu et al. [132] presented that ANN could be used to correct current transformer secondary waveform distortions to avoid mal operation or prevent tripping. Neural network approach is also used in online identification of multiple failures of protection systems [133,134]. A.J.Mazon et al. [131] used ANN to detect the faults in a transmission line. The authors practically applied this on several transmission lines of Spanish electric power systems.
P. Werley et al. [135] discussed partial discharge localization in power transformer using neural networks. Li Yongli et al. [136] proposed a neural network method to identify the different operating states of transformers. An expert knowledge and artificial neural network based transformer stat detector overcomes the drawbacks of the traditional different protective relays of the transformers. Zadgaonkar [137] discussed applications of neural network for detection of some transformer faults over the conventional techniques.

McDermid, W. Glodjo, A. Bromley, J.C. Manitoba Hydro et al [138] observed that in spite of periodic off-line electrical tests and on-line gas-in-oil analysis, three HVDC converter transformers have failed within a 12-month period. The possible causes of failure are reviewed together with changes in maintenance, monitoring and system operation that might prolong the life of similar transformers are proposed.

W. McDermid D.H. Grant A. Glodjo et al [139] examined a group of eight 3-phase core form HVDC converter transformers, six have now failed in service for the analysis of converter transformer failures and application of periodic on-line partial discharge measurements. The final failure mechanism has consisted of a turn-to-turn fault, usually in the valve winding. All the windings were produced using continuously transposed conductors. Thermal aging of the insulating materials was evident. The authors summarized the results of the various tests and
inspections that were made in an attempt to better understand the circumstances that may have contributed to these failures. On-line partial discharge measurements using an electrical detection method are being made on a periodic basis on a number of large power transformers, primarily those used in HVDC conversion. The authors described the measuring system and methods of noise deletion. An example of the test results has been provided describing a significant failure hazard that was detected.

Grant, D.H. McDermid, W. Manitoba Hydro et al [140] proposed a method for the assessment of thermal aging of HVDC converter transformer insulation. An HVDC converter transformer was removed from service and salvaged after 24 years of service. It had not experienced an in-service failure, although others from the same family had failed as a result of overheating. The salvage of the transformer provided an opportunity to observe signs of overheated cellulose, to take paper samples for DP measurements, and to assess the mechanical strength of the bonded CTC.

R. Leelaruji, J. Setréus, and G. Olguin [141] proposed a reliability assessment technique of the HVDC converter transformer system (CTS) comparing different component models and configurations. The CTS model is based on the Markov modeling approach, which is shown to be well suited for these relatively small systems. The failure rate data in the
models is based on statistical surveys by CIGRÈ. A number of scenarios are calculated in order to evaluate the impact of the availability of the CTS given different conditions. The result presented on the benefit in availability using a spare transformer, particularly at a close location of the HVDC station.

LI, Yong, NAKAMURA, Kazuo, LUO, Longfu et al [142] proposed a new topology circuit of a new converter transformer’s wiring mode and a corresponding inductive filtering system for HVDC transmission system. Compared with the traditional converter transformer and AC passive filtering system, it analyzes the degree of the action of harmonic and reactive power for converter transformer and the degree of the difficulty of short-circuit impedance’s design. Based on this, the characteristic parameters of the new converter transformer have been theoretically analyzed, simulation calculated and tested certified. Through deducing the voltage relation, the constraint condition of turn-ratio has been obtained, which can satisfies the demand of the twelve-pulse converter in HVDC transmission system. Through deducing the current relation, the fundamental and harmonic wave characteristics of the winding currents has been obtained. The authors adopted a systematic analysis method to systematically analyze and calculate the structure type and characteristic parameters of the new converter transformer. The detailed simulation calculation and tested results certified the correctness of the above theoretical analysis and calculation.
An HVDC transmission system has a converter transformer as one of its main components. The failure of the converter transformer is one of the major concerns for electric power utilities all over the world. Invariably, the top portions of the secondary windings of the converter transformers fail whereas the primaries are left unaffected. An effort has been made to analyze the causes for these failures by means of modeling a practical HVDC system existing in India which ties up Talcher and Kolar and has a length of 1368 km by G. Bhuvaneswari and B. C. Mahanta [143]. The modeling and analysis have been carried out in the MATLAB/SIMULINK environment. Based on the analysis, possible solutions for this problem have been suggested, such as providing passive filters on the secondary windings of the converter transformer, connecting a parallel capacitor on the dc side of the converter and R-C snubbers across the secondary windings. The suggested solutions have been compared to bring out their relative merits and demerits.

In this thesis, the focus is on the analysis and identification of faults in the HVDC system using wavelet transform technique. In the HVDC system, HVDC transmission line and the converter transformer were chosen for the analysis, classification and location of faults. A 1000 MW (500 kV, 2 kA) DC interconnection is used to transmit power from a 500 kV, 5000 MVA, 60 Hz network to a 345 kV, 10000 MVA, 50 Hz network has been used for the transmission line fault analysis.
A 315 MVA, single phase, $\frac{400}{\sqrt{3}}/\frac{206}{\sqrt{3}}$ KV, three winding, converter transformer, is used for the analysis of the transformer. The neutral current signals are analyzed using different techniques. The test data has been analyzed using FFT, ANN and wavelet analysis techniques. Finally it has been identified that wavelet transform approach of identification and location of faults most efficient and accurate method of analysis.

1.7 CONCLUSIONS

The HVDC system HVDC transmission system is one of the most popular and available means for transferring power in bulk over long distances. In this chapter various faults on the HVDC transmission line and converter transformer research work done by several authors has been discussed. Various testing methods of the converter transformer are also presented. The neutral currents obtained during the impulse test can be analyzed for the classification of faults in the converter transformer have been presented by researchers are also discussed.

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The artificial neural networks are mainly used for the classification problems and hence it is most suitable method for the classification of faults in power systems. Various
rules for training the ANN are also presented. In this chapter the HVDC transmission system fault analysis has been also presented. The literature on the application of wavelets for the power system protection, power quality measurement, power system transients, and partial discharge has been discussed. The wavelet transform is seems to be one of the best method for the relaying and protection system, since it has the capability in analyzing the transients.