# A STUDY ON RELIABILITY OF INSULATORS USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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**Abstract:**
The reliability of DC lines is critical for the reliability of Ultra High Voltage (UHV) DC system operation. Being the main factor in determining the reliability of DC lines, the external insulation is designed mainly with the consideration of the pollution performance of DC insulators at the operating voltage in contaminated areas. In order to use the statistical method with reasonable confidence for (U)HVDC projects, the influences of various potential inputs on the dimensioning results with statistical principles are studied and evaluated in a cooperative project between ABB and China EPRI.The results demonstrate that the interpretation from the natural conditions to artificial conditions or vice versa is most important for the reliability of the insulator dimensioning in the statistical method because it affects the insulator performance and consequently the dimensioning results significantly. The maximum vertical jump height, horizontal swing of conductor line and unbalanced tension of suspension insulator string, known as the dynamic response parameters, of transmission lines after ice-shedding are key parameters determining the electric insulation clearance and strength of the tower-line system in the ice zone. Numerical studies on the dynamic responses of lines with various structural, ice and wind parameters are carried out, and from the dynamic responses the s jump height, horizontal swing and unbalanced tension are extracted to create a dataset. Based on the dataset and the back-propagation neural network and the extra-trees algorithm, two prediction models for the three parameters, i.e. the jump height, horizontal swing and unbalanced tension, are constructed. With eight input variables, the three dynamic response parameters can be predicted quickly and effectively by the two models. These prediction models are suitable for transmission lines with a wide range of structural parameters such as long span and large elevation difference, and provide an efficient means for electric insulation clearance and strength design of transmission lines in ice zone.
**Key words:** UHV, Algorithms, HVDC.

## 1. INTRODUCTION

The exposure of insulator surface to various conditions of environmental and pollution depositions is inevitable in almost all energy systems. Flashover on outdoor insula-tor occurs due to increase of electrical stresses on the transmission line combined with the high pollution level. Critical voltage of flashover on polluted outdoor insulator surface is one of the important parameters for accessing reliability of a power system. Flashover prediction especially using numerical approaches have been always become a topic of interest among researchers. Artificial intelligence for example can be used to analyses degree of pollution level, tracking / erosion and also for estimation of the flashover voltage. In this work, data from the experimental works of uniform and non-uniformly polluted insulators combined with the proposed mathematical model are uti-lized to develop an enhanced flashover parameters prediction algorithm via Artificial Neural Network (ANN) and Adaptive Neuro-fuzzy Inference System (ANFIS). Flash-over voltages of polluted insulator for 1:1, 1:5, 1/10 and 1:15 ratios of T/B surface ESDD on cup-pin insulators (porcelain and glass) are investigated.

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## 2. METHODOLOGY:

### 2.1. Fuzzy learning

Fuzzy logic is used in natural language processing and various intensive applications in artificial intelligence. Fuzzy logic mimics how a person would make decisions, only much faster. Thus, you can use it with neutral networks. The approach of fuzzy learning imitates the way of decision making in humans that involves all intermediate possibilities between digital values YES and NO. The conventional logic block that a computer can understand takes precise input and produces a definite output as TRUE or FALSE, which is equivalent to human's YES or NO. The inventor of fuzzy logic, Lotfi Zadeh, observed that unlike computers, the human decision making includes a range of possibilities between YES and NO, such as In the boolean system truth value, 1.0 represents the absolute truth value and 0.0 represents the absolute false value. But in the fuzzy system, there is no logic for the absolute truth and absolute false value. But in fuzzy logic, there is an intermediate value too present which is partially true and partially false.

 

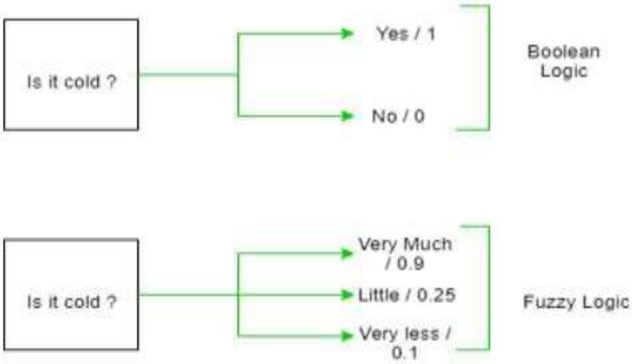


Fig 1.1 Boolean vs Fuzzy logic

**2.2 Architecture of fuzzy method:**

Its Architecture contains four parts :

1. RULE BASE: It contains the set of rules and the IF-THEN conditions provided by the experts to govern the decision-making system, on the basis of linguistic information. Recent developments in fuzzy theory offer several effective methods for the design and tuning of fuzzy controllers. Most of these developments reduce the number of fuzzy rules.
2. FUZZIFICATION: It is used to convert inputs i.e. crisp numbers into fuzzy sets. Crisp inputs are basically the exact inputs measured by sensors and passed into the control system for processing, such as temperature, pressure, rpm's, etc.
3. INFERENCE ENGINE: It determines the matching degree of the current fuzzy input with respect to each rule and decides which rules are to be fired according to the input field. Next, the fired rules are combined to form the control actions.
4. DEFUZZIFICATION: It is used to convert the fuzzy sets obtained by th inference engine

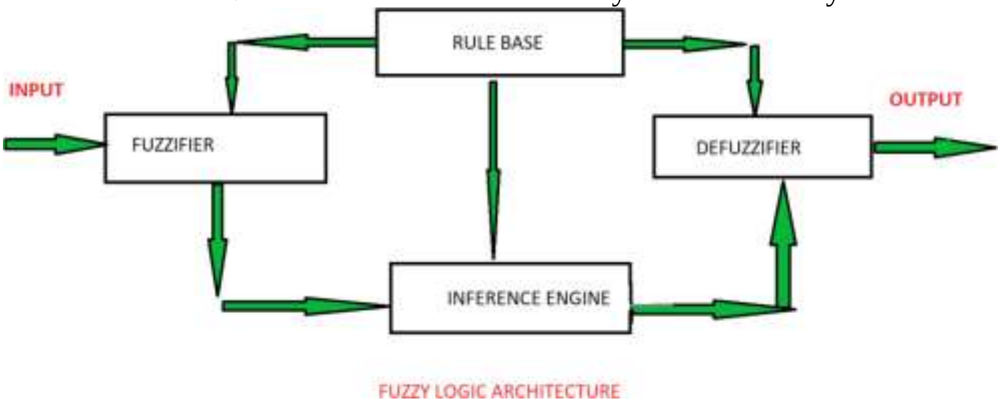


Fig 1.2 Fuzzy logic architecture

Although Fuzzy Logic in artificial intelligence helps to mimic human reasoning, these systems need expert guidance to be built. This lets you rely on the experience of experts who have a better understanding of the system. Fuzzy Logic can also be used for enhancing the execution of algorithms. IBM Watson uses Fuzzy Logic and fuzzy semantics. Fuzzy logic in this narrow sense deals in a natural way with the representation and inference from such vaguely formulated or uncertain knowledge, similarly to classical logic which deals with crisp knowledge where statements can only be either true or false. In recent years, however, it has become increasingly common to employ the term fuzzy logic in a much broader sense, making the difference between the notions of fuzzy set theory and fuzzy logic vanish. To avoid confusion, we follow the trend to use fuzzy logic in its general sense.

**3. Neutral Networks:**

Neutral networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons

signal to one another. Artificial neural networks (ANNs) are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.
Neutral networks rely on training data to learn and improve their accuracy over time. However, once these learning algorithms are fine-tuned for accuracy, they are powerful tools in computer science and artificial intelligence, allowing us to classify and cluster data at a high velocity. Tasks in speech recognition or image recognition can take minutes versus hours when compared to the manual identification by human experts. One of the most well-known neural networks is Google's search algorithm.
A neutral network is a method in artificial intelligence that teaches computers to process data in a way that is inspired by the human brain. It is a type of machine learning process, called deep learning that uses interconnected nodes or neurons in a layered structure that resembles the human brain. It creates an adaptive system that computers use to learn from their mistakes and improve continuously. Thus, artificial neural networks attempt to solve complicated problems, like summarizing documents or recognizing faces, with greater accuracy.

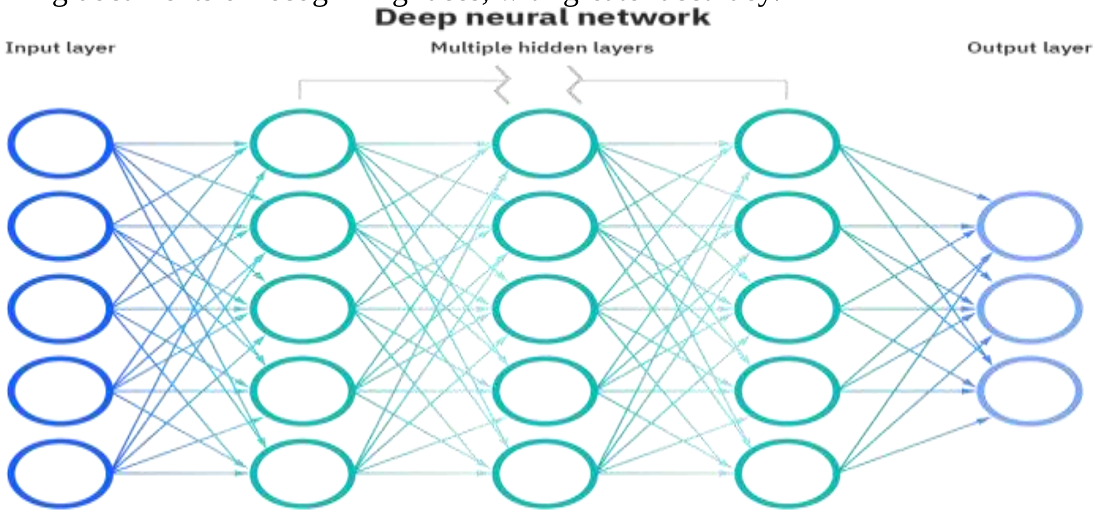


Fig 2.1 Neutral Network

### 3.1. The Architecture of a Neural Network

Let's take a closer look and see how the virtual assistant accomplishes this feat of speech recognition. There are five recognized types of neural networks

- Single layer feed- forward network.
- Multilayer feed-forword netework.
- Single node with its own feedback.
- Single-layer recurrent network.
- Multilayer recurrent network.

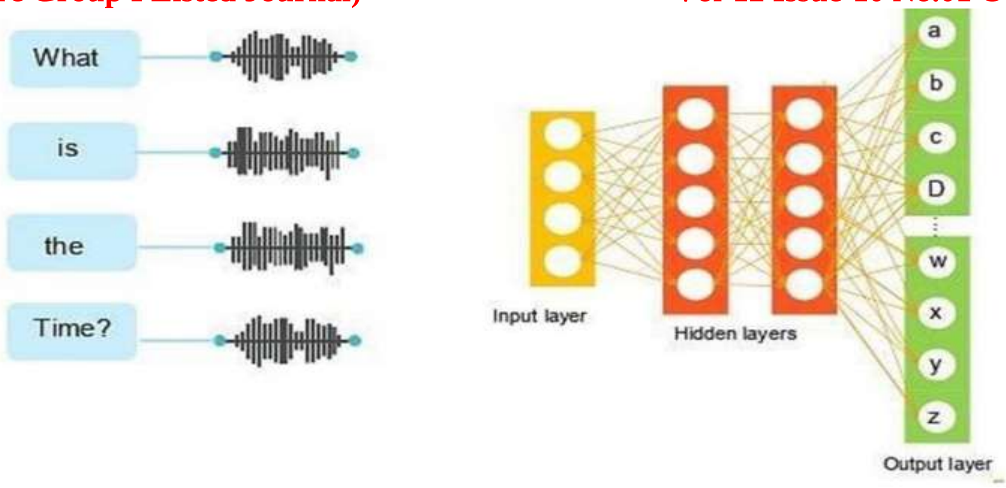


Fig 2.2 Architecture of a Neutral Network

## 4. MACHINE LEARNING:

Machinelearningisafieldofinquirydevotedtounderstandingandbuilding methods that 'learn', that is, methods that leverage data to improve performance on some set of tasks . It is seen as a part of artificial intelligence.Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtiring,speech recognition andcomputer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

Asubsetofmachinelearningiscloselyrelatedto computational statistics.which focuses on making predictions using computers, but not all machine learning is statistical learning. The study of mathematical optimization ,delivers methods, theory andapplication domains to thefield of machine learning.Data mining is a related field of study,focusingone exploratory data analysis through unsupervised learning .Some implementations of machine learning use data and neutral networks in a way that mimics the working of a biological brain. In its application across business problems, machine learning is also referred to as predictive analytics.

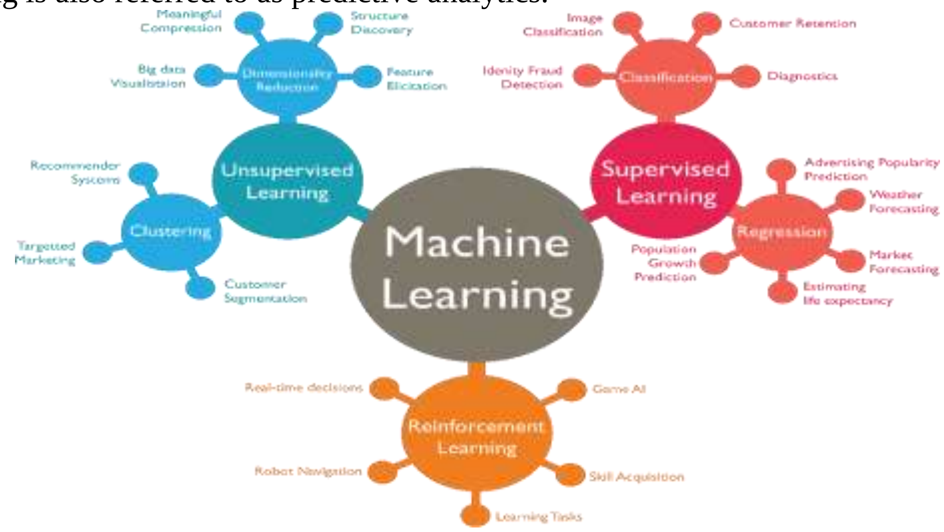


Fig 3.1 Machine Learning

**Working process:**

1. A Decision Process: In general, machine learning algorithms are used to make a prediction or classification. Based on some input data, which can be labelled or unlabeled, your algorithm will produce an estimate about a pattern in the data.

 

2. An Error Function: An error function serves to evaluate the prediction of the model. If there are known examples, an error function can make a comparison to assess the accuracy of the model.
3. AnModelOptimizationProcess:Ifthemodelcanfitbettertothedatapoints inthetrainingset,thenweightsareadjustedtoreducethediscrepancybetween the known example and the model estimate. The algorithm will repeat this evaluate and optimize process, updating weights autonomously until a threshold of accuracy has been met.

**5. Digital Image Processing (DIP) based Algorithm.**

**5.1 Finite modeling technique:**

The finite element (FE) method has been used to investigate the dynamic responses of transmission lines after ice-shedding, such as the works of Jamaleddine et al. Fekr and McClure Kalm an Kollar and Farzaneh Yang et al. Mirshafiei et al. Yan et al.and Ji et al.In these works, parameter study and qualitative analysis on jump height and tension variation of conductors after ice- shedding were studied It has been demonstrated that the deformation of tower has little influence on the dynamic response of transmission line after ice shedding , so the towers in the numerical models are ignored. As mentioned by Fekr and McClure it is not necessary to consider unequal adjacent spans for design purpose of transmission lines. Our previous research demonstrated that the maximum jump height occurs when ice-shedding takes place on the central span of a line with odd number of spans . Therefore, the continuous span line with odd number of spans and equal span length are considered, and the dynamic responses of typical transmission lines with 3, 5, 7, 9 spans after ice-shedding are firstly investigated. The FE software ABAQUS is used to set up the models and simulate the dynamic responses of the transmission lines after ice-shedding, and the simulation method and process are discussed in detail by Yan et al. A five- span transmission line with quad bundle conductor is shown in the FE model, each sub-conductor is modeled with cable elements. The suspension insulator.

strings are modeled with spatial two-node beam elements, and only three translation degrees of freedom of their upper ends are constrained, which allows them to swing freely whenever an unbalanced load exists as shown in The dead-end insulator strings are also modeled with beam elements. Moreover, the clamps and the spacers are simulated as frames, whose weights are set to be the same as those of real clamps and spacers. Because the deformations of the insulator strings, clamps and spacers are smaller and theirinfluence on the dynamic responses of conductor lines are negligible, their Young's modulus and Poission ratio are set to be 2.0 *10^5 MPa and 0.3. Moreover, the mechanical properties of the conductors.

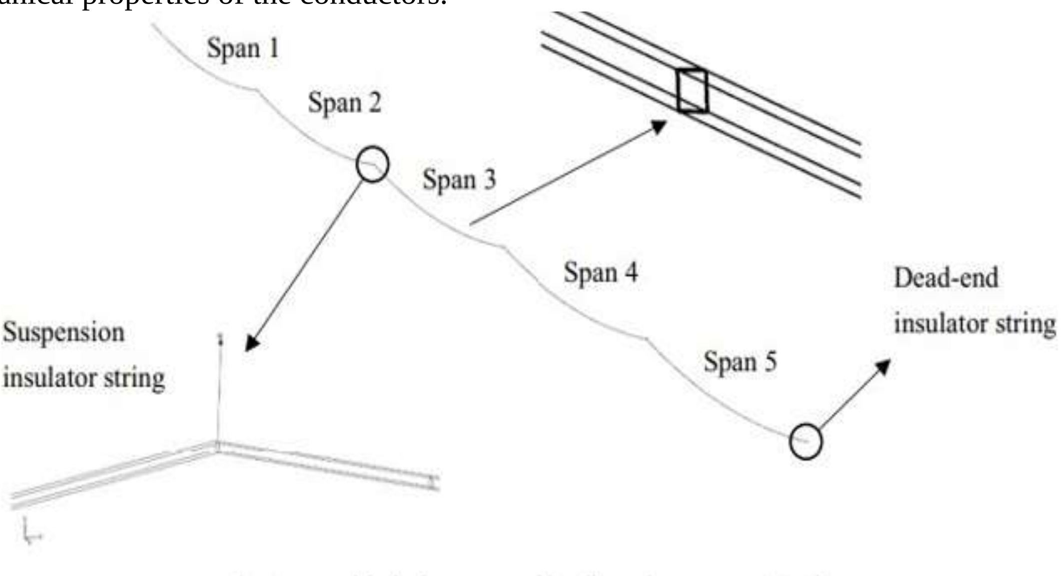


Fig: 5.1 FE model of a five span Quad Bundle conductor Transmission line.

**Table 1**

Parameters of conductors and insulator strings.

| Conductor type | $A(mm^2)$ | $W$(kg/km) | $T$(kN) | $E$(GPa) | $\alpha(\times 10^{-6}/°C)$ | $l$(m) | $w$(kg) |
|---|---|---|---|---|---|---|---|
| JL/G1A-300/40 | 339 | 1132 | 92.36 | 70.5 | 19.4 | 3.1 | 90 |
| JL/G1A-300/50 | 348 | 1208.6 | 103.6 | 73.9 | 18.9 | 3.1 | 500 |
| JL/G1A-500/45 | 532 | 1687 | 127.3 | 65.9 | 20.3 | 5.2 | 240 |
| JL/G1A-500/65 | 564 | 1885.5 | 153.5 | 70.5 | 19.4 | 5.2 | 1180 |
| JL/G1A-630/45 | 673 | 2078.4 | 150.2 | 63.7 | 20.8 | 10.5 | 750 |
| JL1/G2A-1250/100 | 1350 | 4252.3 | 299.8 | 65.2 | 20.5 | 10.5 | 1100 |

Note: *A*: Cross-section area of conductor; *W*: conductor mass per unit length; *T*: tensile strength of conductor; *E*: Young's modulus of conductor; *α*: expansion coefficient of conductor; *l*: insulator string length; *w*: insulator string weight.

**Table 2**

Parameters of transmission lines for case study.

| $N$ | Conductor type | $L$ (m) | $h/L$ | $t$ (mm) | $\beta$ (%) | $v$ (m/s) |
|---|---|---|---|---|---|---|
| 2 | JL/G1A-300/40<br>JL/G1A-300/50 | 300,400,500,600,<br>700,800 | 0,0.1,0.15,0.2,0.3,0.5 | 5,10,15,20,30 | 20,30,40,<br>50,60,70,<br>80,90,100 | 0,5,10,20,30 |
| 4 | JL/G1A-500/45<br>JL/G1A-500/65 | | | | | |
| 6 | JL/G1A-630/45 | 300,400,500,600, | | | | |
| 8 | JL1/G2A-1250/100 | 700,800,900,1000,1100,1200 | | | | |

Note: *N*: number of sub-conductors; *L*: span length; *h* (m): elevation difference; *t*: ice thickness; *β*: ice-shedding rate; *v*: wind speed.

Dynamic responces of Quad bundle lines after Ice shedding under different windspeed

a) Displacment time histories at mid point of middle span.

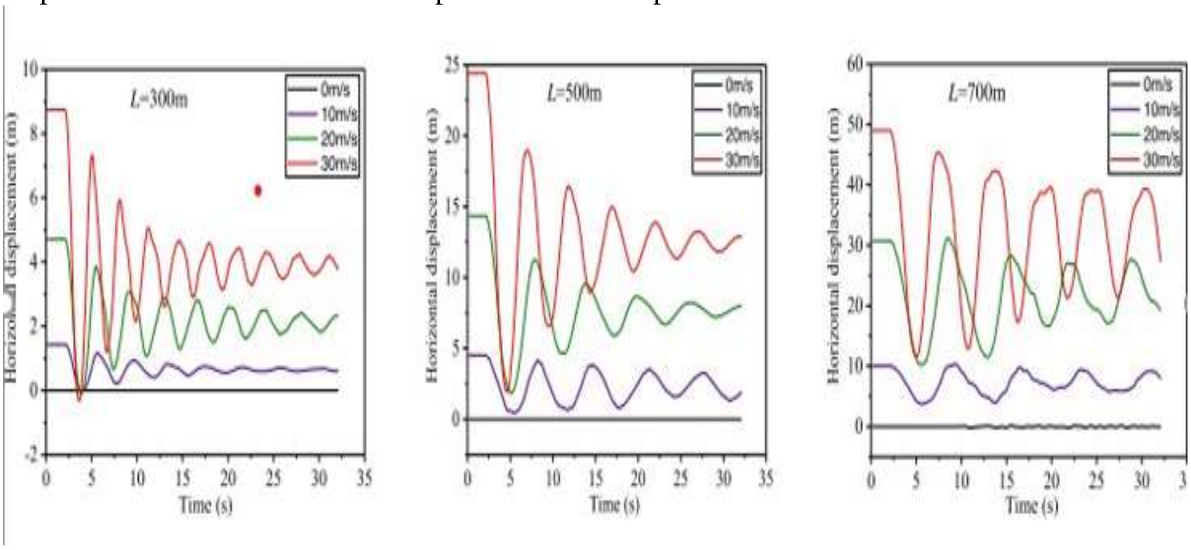


Fig : 5.2 horizontal displacements vs time

b) Unbalanced tension time histories at suspension points of insulator string close to middle span

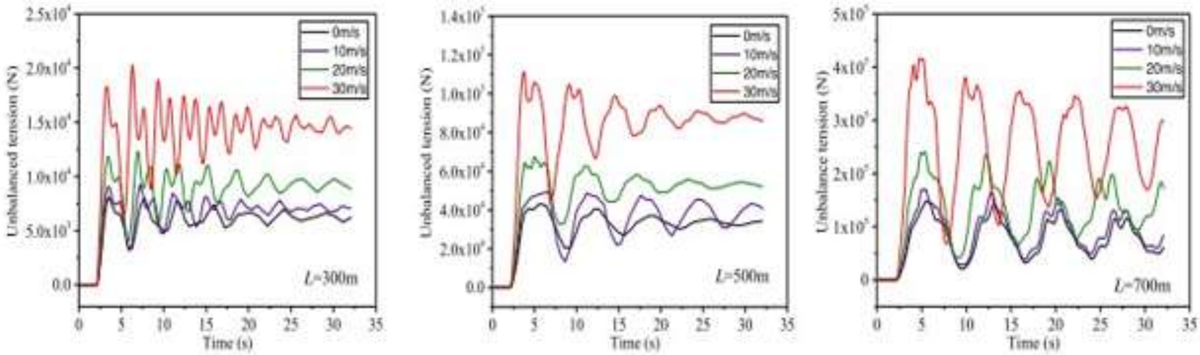


Fig : 5.3 Unbalanced tension vs Time

## 6. FUZZY LEARNING TECHNIQUE:

### 6.1 Extra trees algorithm:

The extra-trees algorithm by Geurts et al. and random forests algorithm by Breiman et al. have attracted more attention of researchers and engineers in recent years. The basic principle of these two algorithms, which is called bagging algorithm, is combing many diverse CART decision trees developed by Breiman et al.to construct a strong ensemble model. Generally, individual decision tree typically exhibits high variance and tends to be overfitting. However, the variance is reduced significantly in the ensemble model by taking an average value of predicted results by all of the decision trees. The difference between extra-trees algorithm and random forests algorithm is mainly represented in two aspects, i.e., all of the samples in the training dataset participate in the growth of tree and the splitting threshold is selected at random in the extra-trees algorithm. With the same number of samples, the prediction performance by the extra-trees algorithm is better than that by the random forests algorithm. Moreover, compared with the BP neural network, the extra-trees algorithm has the advantages of swarm intelligence, resistance against overfitting, convenience to realize and high efficiency. By means of the extra-trees algorithm, the prediction model, known as the ET model, for dynamic response parameters of transmission lines after ice- shedding is created. In the prediction model, the eight input variables, i.e. the number of bundle, conductor type, span length, elevation difference, initial stress in sub-conductors, ice thickness, iceshedding rate and wind speed, areset as the input variables, and the maximum jump height, horizontal swing and unbalanced tension are the output variables. The dataset is also divided into training dataset and testing data. The number of parallel CART decision trees is an important parameter of the ensemble model. By means of trial- and-error method and training effect, the optimal number of trees is set to 200 finally. Due to the parallelization capability of the algorithm, the prediction model is trained quickly

**Performance indices of ET model by testing dataset.**

| Prediction parameter | *MAE* | *MSE* | $r^2$ |
|---|---|---|---|
| *H* | 0.3217 | 0.3477 | 0.9984 |
| *S* | 0.3485 | 0.4410 | 0.9972 |
| *F* | 2.6770 | 38.4206 | 0.9994 |

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Structural and load parameters of transmission lines in typical cases.

| Case No. | Number of bundle | Conductor type | Span length (m) | Elevation difference (m) | Initial tensile stress (MPa) | Ice thickness (mm) | Ice-shedding rate (%) | Wind speed (m/s) |
|---|---|---|---|---|---|---|---|---|
| 1 | 4 | JL/G1A-500/45 | 800 | 0 | 59.05 | 5 | 100 | 30 |
| 2 | 2 | JL/G1A-300/50 | 500 | 75 | 32.24 | 20 | 40 | 5 |
| 3 | 2 | JL/G1A-300/50 | 500 | 100 | 62.09 | 10 | 100 | 25 |
| 4 | 2 | JL/G1A-300/50 | 400 | 200 | 35.31 | 20 | 100 | 20 |
| 5 | 4 | JL/G1A-500/45 | 400 | 60 | 35.31 | 20 | 100 | 5 |
| 6 | 2 | JL/G1A-300/40 | 500 | 75 | 32.24 | 30 | 80 | 5 |
| 7 | 8 | JL1/G2A-1250/100 | 1200 | 120 | 44.88 | 20 | 100 | 20 |
| 8 | 4 | JL/G1A-500/45 | 600 | 90 | 35.98 | 30 | 100 | 20 |
| 9 | 4 | JL/G1A-500/45 | 700 | 0 | 35.98 | 30 | 100 | 20 |
| 10 | 6 | JL/G1A-630/4 | 900 | 135 | 35.03 | 30 | 100 | 20 |

## 7. NEUTRAL NETWORK TECHNIQUE:

### 7.1 Back Propagation Neutral network:

The BP neural network proposed by Rumelhart et al. is the most widely used artificial neural network, which is particularly suitable for nonlinear problems that are affected by many factors. It is known that a BP neural network is a multi-layer network composed of an input layer, an output layer, and at least one hidden layer. There are a lot of nodes in the network structure, and the node numbers of input and output layers respectively equal to the numbers of input and output variables. The structure of the BP neural network model predicting the dynamic response parameters, known as the BP model in this paper.The output of the prediction model consists of the maximum jump height (H), horizontal swing (S) and unbalanced tension (F), so there are three nodes in the output layer corresponding to the three predicted parameters. On the other hand, all the structural, ice and wind parameters, which include the number of bundle, conductor type, span length, elevation difference, initial stress in sub-conductors, ice thickness, ice- shedding rate and wind speed, are set as the input variables of the model. There is no strict theoretical method to determine the number of hidden layers and the number of nodes in the hidden layers. Due to the development of computer hardware and the efficiency of algorithm, more nodes in the hidden layers can be set to obtain better learning ability. In order to acquire better model performance, two hidden layers and 32 nodes for each hidden layer are set in the BP neural network model for predicting dynamic response parameters of transmission lines after ice-shedding. The signal forward-propagation from input to output and the error back propagation from output to input, which adjusts the weights and thresholds of nodes continually. The error between output (predicted) value yi and the actual data Yi is defined as the loss function, which can be written as where n is the number of samples E(i) is the error ofa single sample. the values of different input variables may be much different. For example, the values of the span length are in range of 300~1200, but the ice thickness in the range of 0~30. Thelarge differences between the values of the input variables may lead to lower convergence speed, saturation of neuron output and other problems during training process, so normalization to all the input variables is necessary. To normalize the data to vary in the range of [0, 1],

The data are normalized with the following transformation. where x0 denotes the original data, Xmax and Xmin are respectively the maximum and minimum values of the original data, and Xis the normalized data. After the transformation, all the input variables vary in the range of [0, 1].

Variations of dynamic response parameters with number of bundle and conductor type

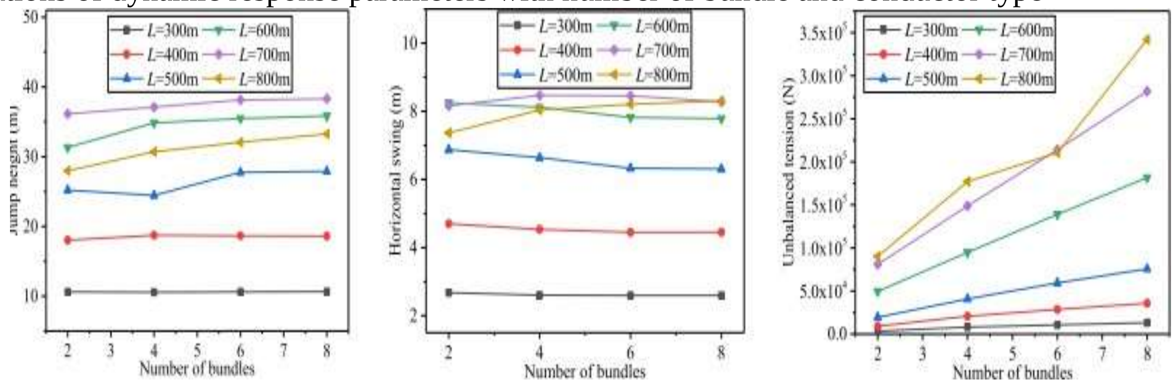

Fig : 7.1 Effect of number of bundles

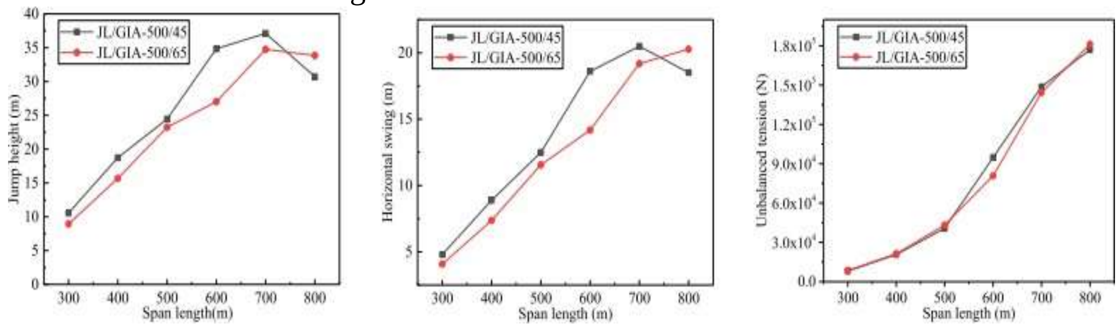

Fig : 7.2 Effect of conductor type

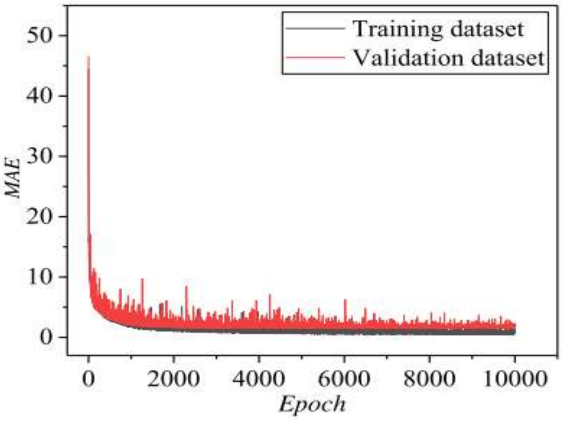

Fig :7.3 Convergence of BP neutral network model for dynamic response parameter of transmission lines after ice-shedding during traini

## 8.RELIABILITY OF INSULATOR:

**Insulator:**

An insulator is a material which does not easily allow heat and/or electricity to pass through it. Plastic, wood, rubber and glass are examples of good insulators.

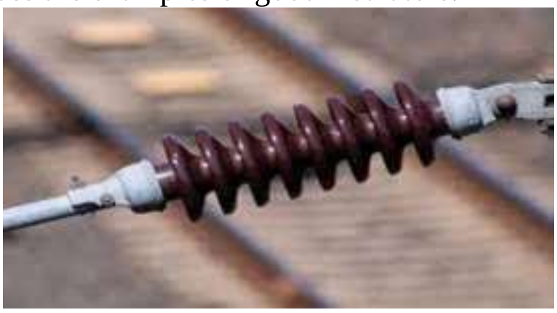
Fig :8.1 Insulator

 

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**Causes of failures:**

Examples of failures include flashovers and leakage currents along insulators, as well as wear and tear on mechanical suspension clamps resulting from corrosion. Inspections of pole tops can reveal deterioration of an insulator's properties, such as corrosion deposits on cross bars.

**Hazardous corrosion deposits:**


Fig :8.2 Corrosion of insulator

Detailed inspection is necessary to reveal smaller deteriorations. On the insulator shells, see image below, traces of iron oxide is revealed. Iron oxide, together with other conductive contaminations sources such as salt and water, provide ideal creep current pathways.

**Reduced lifetime:**

On the power line's steel core, corrosion is revealed in exposed areas, such as under the steel wire lashings. Rust is formed because of rupture in the anti-corrosion zinc sheath. Rupture of the zinc sheath means that the steel core has entered a critical phase in which deterioration of mechanical strength may be aggravated, and shortening of lifetime accelerated, as a result of corrosion.

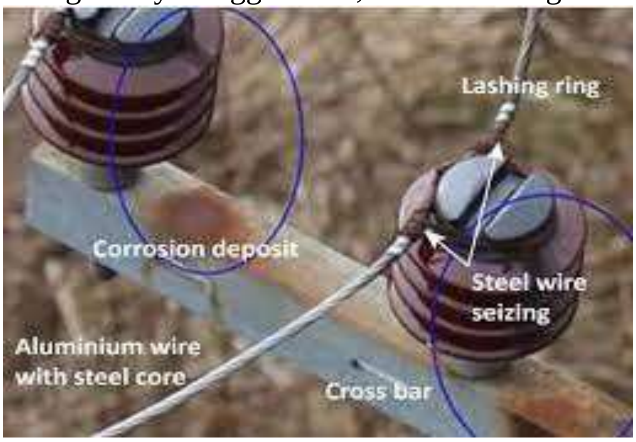


Fig :8.3 Fault insulator

**Good and inadequate insulators:**

It is not easy to distinguish between a good and an inadequate insulator. Suppliers tend to refer to approved tests based on established standards. However, this is no guarantee that an insulator will stand up to the actual operating conditions.

Fig:8.4 Good insulator

**9. CONCLUSION:**

This paper has proposed a Digital image processing based algorithm using AI Techniques.The results obtained from experimental test was used to achive the suitable vlaues of agening of insulators in general the identification of faults in insulators of over head transmission lines is very difficult. Due to this, by using digital image processing we find faults of insulators easily. And hence we recognitize the agening of insulators. AI techniques were designed for the estimation of critical current and flashover voltage in uniform insulator. The mathematical model based to the Algorithms of insulators,ESDD and constant of arc was applied and validated using experimental flashover voltage results.And By using this AI techniques we find dynamic response parameters also.

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