[[1]](#footnote-1)

Wavelet Based Neural Network for High Speed Transmission Line Transient Classification

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*Abstract*--The most reliable fault detection schemes using travelling waves require information from the two ends of the protected line to make a correct decision. Communications are increasingly threatening the cyber security of Smart Grids. In this paper we show that high frequency content of the signal not only can be used to detect faults but also can classify transients and faults on adjacent lines. A scheme will be presented that uses only one end data for transients’ classification on adjacent lines. Modal transformation is used to transform phase quantities to modal quantities. Wavelets are used to extract high frequency components of modal voltages or/and currents at relay location. A vector consisting of voltages or/and currents modes stacked in one column is used to train a neural network. Results show that not only can this scheme detect faults but can also classify transient on adjacent lines. The method is very robust against bus capacitance and surge arrester operation. Simulations are presented and results are discussed.

*Index Terms*--ART neural networks, Classification algorithms, Discrete wavelet transforms, Wavelet coefficients, Modal analysis, .Power system faults, Power system measurements, Current transformers, lightning.

# Introduction

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ourier transform requires that the signal be stationary in the wide sense for the calculation of coefficients to be accurate, i.e. the signal can’t have any temporal variations for the calculation of coefficients to be correct and accurate. Short Window Fourier Transform can solve some of the problems with FFT but it introduces other issues. However most signals encountered in practice are not stationary but have their characteristics change with time. Multiresolution analysis (MRA) is signal processing tool that has been introduced in the nineties [1] to solve some of the problems inherent in Fourier transform analysis methods. Wavelets [2] are usually used along with MRA to solve this very exact problem. Wavelets have a strong localization property that enables studying changes not only in time but also in frequency feasible. It is known, from the uncertainty principle, that if the signal spans a small portion of the time domain then its Fourier transform will span a large portion frequency band. Wavelets on the other hand don’t suffer from such a limitation. On the contrary, the signal is approximated at various levels –frequency bands- and changes in time manifest themselves at the coefficients of the wavelets only around the time which the event occurred. Such property makes it ideal to detect disturbances and study power system transients [3]. In [4], [5] and [6] wavelets had been used to detect and classify power quality disturbances. In [7] wavelets have been used to decompose the signal of transient events into two signals: a detailed version and a smoothed version to assess power quality issues. The authors in [8] used the localization property of wavelets to detect the moment of arrival of the travelling waves initiated by faults and their reflections to locate faults on transmission lines. The idea behind [9] is to define a threshold for the summation of the coefficients of wavelets that determines fault and non-fault conditions. The main principle in paper [10] is the use of modulus maximum principle to detect faults from single ended data. In [10] a surge impedance relay is introduced by using the modulus maximum principle which is another manifestation of the time localization property. The transient energy method is also used to detect faults in [11]. A detailed look at the literature associated with the use of wavelets in power systems will immediately reveal that wavelets have been used almost exclusively for localization property without much regard to their other characteristics. In this paper, we use wavelets in a different way. For this paper, we use wavelet decomposition to extract useful oscillatory information about the signal. We argue that any transient event on transmission line causes the voltages and currents to oscillate in a unique way. Power engineers are accustomed to treating traveling waves as if they were pulses travelling down the line with no regard to the oscillatory components they carry. We call the traveling wave and the associated oscillatory components the transient signature of the event. The transients we study in this paper are lightning, line energisation and faults. At a certain terminal of the line which is typical a relay location, we argue that those signatures are unique to the event and to the line which initiated those events. Those oscillatory components are a function of the line parameters, the network topology and the instance of the event. In essence, the signature of the fault occurring on a certain line will be different form the signature of the fault on adjacent lines. Also, line energisation will cause the voltages and current to oscillate in a manner that’s different from the faults and lightening and those oscillatory components are different to different lines. A relay not only can detect and classify faults on a line but also can detect and classify faults and transient on adjacent lines. We use neural network classification to show that indeed this is the case. The paper is organized as follows: A review is given about wavelets and classification using neural networks in the background in part II. The statement of the problem and the solution methodology are given in part III. Analysis of transposed and twin lines is given in part IV. Conclusions are provided at the end of the paper.

# Background

In this Section we provide an overview of both wavelets and neural networks as used in this paper.

## Wavelets

In this paper we use the dyadic wavelet transform [12]. The transform takes the signal and applies low and high pass filter to it. The transform convert the original signal into an independent set of signals spanning certain frequency bands. The frequency bands are determined by the number of levels we want to analyze the signal. The word independent means that we can’t derive one level from another, i.e., level 2 can’t be derived from level 1. The frequency of each level depends on the sampling frequency. Nyquist theory still holds here. The high frequency we see in the signal will be at most equal to half of the sampling frequency. Given a certain sampling frequency the dyadic transform will first apply a high and low pass filter to the signal resulting in two signals. The signal corresponding to the output of the high pass filter is called level 1 and the other signal is called approximation 1. Both of those signals are independent so you can’t derive anyone from the other. We can stop at this step or we can apply another low and high pass filter to the first approximation to get level 2 and approximation 2. Again level 2 will span a frequency band corresponding to the upper half of the frequency band of approximation 1 while approximation 2 will occupy the lower frequency band. Continuing this manner by applying successive low and high pass filters we obtain a set of levels also called details and one last approximation. In theory the last approximation should correspond to a pure sine wave assuming the high frequency components imposed on the power frequency have high frequency not to be included in the frequency band of the last approximation. Taking numerical example, if we use a 100 kHz frequency then we have: level 1 will occupy the frequency band from 50 kHz to 25 kHz, level 2 will occupy the frequency band from 25 kHz to 12.5 kHz, level 3 will occupy the frequency band from 12.5 kHz to 7.25 kHz and approximation 3 will correspond to 7.25 kHz to zero hertz. The equation used for the transform is given below where φ(t) is the wavelet is used, a causes scaling (which is level determination) and b causes shift in time. In practice it is not needed to apply the transform all over the infinite line. Since wavelets have a strong localization property then it is only needed to apply the transform to the time period under study. The equation for the details coefficients are given below in equation (1) [12]

(1)

## Classification with Neural Networks

Neural networks are very well known tool for classification. The classification done in this paper is not probabilistic but rather deterministic. The inputs are vectors in the n-dimensional space, the size of an input vector, that need to be mapped to another vector space the size of which is determined by the number of output classes we want to map to. In simple terms this classification can be shown to be carried out by a neural network [13]. All neural networks in this paper consist of three layers: an input layer, a hidden layer and output layer. Each layer consists of a certain number of neurons. The connections between those neurons are called synapses. The input layer consists of junctions that represent the input. The number of junctions must equal to n which is the dimension of the input vector. The hidden layer can consist of any number of neurons. The classification is greatly affected by the number of neurons in the hidden layer. The output layer consists of neurons that are activated by a function the input of which comes from the hidden layer. Classes or more specifically output classes are the patterns we want to maps the input to. The main idea behind classification in the n-dimensional space is that if the inputs belong to subspaces of the n-dimensional space then using neural networks we can draw planes in that space so that the space between those plane contain only one subspace and each subspace is then mapped to one of the output classes using the activation function in the output neuron. The weights or more specifically synaptic weights of the synapsis are adjusted during the training phase such that the vector space is divided to subspaces each of which corresponds to certain class. Any output neuron receives the input vector through synaptic weights. The input is then applied to the function of the neuron which has the form g(x)=0 which is an equation of the plane in the n-dimensional space. The neuron is activated only if the output is positive. In this paper we use the widely known and used backward propagation algorithm for the calculation of weights. Knowledge is stored in the network through those weights. We only do supervised learning in this paper. The algorithm of the steepest gradient is used throughout the paper [13].

# Statement of the problem

In this paper we argue and show that the information preset in the transient signal caused by sudden network conditions contain sufficient information for classification not only between transients on the same line but also transients on adjacent lines. Any change of configuration on the line causes a traveling wave to be generated travelling from the point of change towards the ends of the line. In the simplest case this wave will be just a pulse- a step- but in reality will have a lot of oscillating components. Fourier analysis is not suitable for such waveforms because the oscillations will be distorted and attenuated as they arrive at the line terminals. However, applying discrete wavelet transform will enable us to see both the spectral and temporal variations. We extract the information from the traveling waves using the DWT at various levels. Fourier transform is not suitable for this purpose since the signals frequency content of the signal changes with time. Any level can be used but we choose level 5 or level 3 since they are less expensive computationally. Before we apply wavelets we decouple phase currents and voltages from each other using modal analysis [14]. Voltages or/and currents can be used for this purpose. Current is preferable because of the cut of frequency of the current transformer is much larger than the potential transformer or CVT [15]. Since current transformer has bandwidth of 100 kHz we choose a sampling rate of 200 kHz for our ATP simulations. After that DWT is applied to the currents to convert the signals to a series of coefficients that will be used for training of the neural networks. The time window is only one eight of a post-event power cycle. We then stack the coefficients of the modes of currents or/and voltages on top of each other to build one vector that will be used to train the network. A neural network of an appropriate size is selected for classification. The neural network is then trained using various scenarios for transients on lines. We show that using only local information at one end of the line- corresponding to a relay- we can distinguish various transient on different lines. We can tell that a specific waveform is dues to a fault and another is due to a transmission switching on a certain adjacent line. We start by showing that a fault on an adjacent line can be distinguished from a fault on the line under study. We also show that the same is true for lightning and line energisation. This means using local information we can see what is happening on adjacent lines without communications and undermining the cyber security of the grid. The creation of those scenarios has been automated. The main script will be release with a github repo and the paper is currently under review [16]. The paper builds on a paper we published in 2012 in IPST [17]. We use IEEE 118 bus as a test system with emphasis on line connection bus 23 and bus 25 [18].

# Simulation Results

We present the simulation results for two cases. A transposed line case in given in part A and a twin line case is given in part B.

## Transposed line

We present the topology of the system under study in figure [1]. Measurement devices are located at bus 23. We first apply the algorithm with no surge arrester. Arrester can damage the information contained the signal in theory especially in a lighting surge when the arrester works. The line under study is a transposed line connecting bus 23 to bus 25 and we measure the current and voltage at bus 23. Bus 23 is connected to three lines and a load. The lines are as follows: a line from bus 23 to bus 32; a line from bus 23 for bus 24; a line from bus 23 to 22. The other terminal of line which is terminal 25 is connected to a transformer and a line. The transformer connects a generator as bus 26 through a step up transformer and a line from bus 26 to bus 30. The line that is adjacent to the line under study is the line connection bus 25 and 27. In this section all lines are transposed. Surge arrester and bus capacitance are not shown in the figure but they do exist in simulations. Surge Arrester is selected according to [19]. In our simulations we haven’t seen any effect for bus capacitance on classification so we choose not to report on it. On the contrary we have seen that surge arrester have small effect on classification. We do the classification in three steps. First, we create faults on the line under study and then we create faults on adjacent lines. We create all types of faults at varying fault resistances and different incipient angles. A total of 8066 fault cases per line have been generated. Those faults span all types of faults at all distances from 5% to 95% of line length and with fault resistances up to 1000 Ohms. We do as descripted in the methodology and show the classification output. For this transposed line we only use ground and aerial mode. We show results when using currents alone and voltages alone. A standard way of showing the output of the neural classification is showing the confusion matrix. We choose not to show the confusion matrix unless the classification is not 100%. In the next patch of simulations, we stop creating fault cases and generate lightning cases. We strike the line under study and adjacent line by a lightning strike with different amplitudes and at different instants of times fixing the waveform rise and tail times. We use an ATP Heidler type lightning with rising time equal to 4 μs and a τ equal to 10 μs. Amplitudes ranging from 5000 A to 30000 A with at distances up to 95% have been simulated. We again use ground and serial modes, apply DWT then train the neural network. Finally we energize the line under study and adjacent lines at different instants of time and do the classification as descripted in the methodology. We repeat all simulations for faults, line energisation and lighting for the case when surge arrester exists. We should point out that transients behind the transformer were so much attenuated to the point that no real transient can be observed at relay location. Also transients that are two lines away from the relay were very weak to be detected by the current mythology. Results are summarized in the following paragraphs and tables.

The reader will need to bear in mind the following for understanding and interpreting the results. A 100% classification means all cases have been classified correctly. To read the tables correctly one need to illustrate the following: each output class corresponds to a line; class (1) corresponds to the line under consideration; class (2) corresponds to line 23-22; class (3) corresponds to line 23-24; class (4) corresponds to line 23-32; class (5) corresponds to line 25-27.

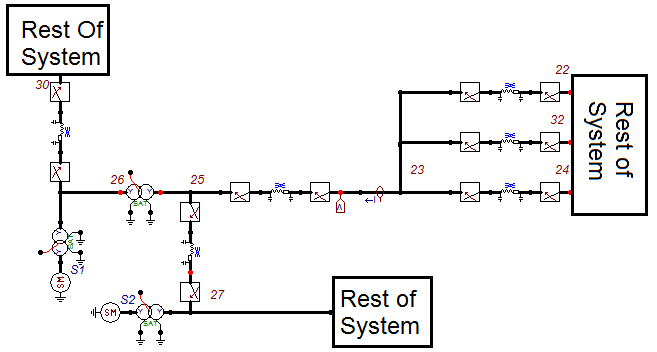


Fig. 1. System Configuration

For line energisation and irrespective of surge arrester connected or not, we found that a neural network such as the one described in previously in the background with 25 neurons in the hidden layer makes a near to 100% classification when used with level 5 coefficients, the confusion matrix is shown in table (1). Another neural network with 25 neurons in the hidden layer is needed when level 3 coefficients are used; the confusion matrix is shown in table (2). The previous results are obtained when used in conjunction with voltages. When used with currents only, classification becomes less precise; the confusion matrix is shown in table (3) for a neural network with 25 neurons in the hidden layer and level 3 coefficients. A neural network with 25 neurons using current and voltage coefficients at levels 3 gives a 100% classification.

Table 1

Confusion matrix for transposed line energisation at level 5 voltage coefficients and a neural network of 25 neurons

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Input Class | | | | |  |
| 1 | 2 | 3 | 4 | 5 |
| Output Class | 1 | 362 /20% | 0/0% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 2 | 0/0% | 362 /20% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 3 | 0/0% | 0/0% | 362 /20% | 0/0% | 0/0% | 100%/0% |
| 4 | 0/0% | 0/0% | 0/0% | 354 /19.6% | 9/0.5% | 97.5%/2.5% |
| 5 | 0/0% | 0/0% | 0/0% | 8/0.4% | 353 /19.5% | 97.8%/2.2% |
|  | | 100%/0% | 100%/0% | 100%/0% | 97.5%/2.5% | 97.8%/2.2% | 99.1%/0.9% |

Table 2

Confusion matrix for transposed line energisation at level 3 voltage coefficients and a neural network of 25 neurons

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Input Class | | | | |  |
| 1 | 2 | 3 | 4 | 5 |
| Output Class | 1 | 358/19.8% | 1/0.1% | 1/0.1% | 1/0.1% | 0/0% | 99.2%/0.8% |
| 2 | 0/0% | 361/19.9% | 1/0.1% | 1/0.1% | 0/0% | 99.4%/0.6% |
| 3 | 3/0.2% | 0/0% | 348/19.2% | 1/0.1% | 16/0.9% | 94.6%/5.4% |
| 4 | 0/0% | 0/0% | 1/0.1% | 347/19.2% | 9/0.5% | 97.2%/2.8% |
| 5 | 1/0.1% | 0/0% | 11/0.6% | 12/0.7% | 337/18.6% | 93.4%/6.6% |
|  | | 98.9%/1.1% | 99.7%/0.3% | 96.1%/3.9% | 95.9%/4.1% | 93.1%/6.9% | 96.7%/3.3% |

For lightning, we found that, irrespective of the surge arrester, with only 25 neurons we can achieve a 100% classification with level 3 or 5 voltage coefficients are used.

A close examination of faults will now be given. A hidden layer with 90 neurons was found to be the best size to give good classification with level 5 voltage coefficients. The confusion matrix is shown in table (4). However, using voltage level 3 coefficients for training gives a 100% classification but only using 60 hidden neurons. If we use level 3 coefficients of currents, we still get a close to a 100% classification; the confusion matrix is shown in table (5).

We now turn our attention to classification between different transients; we inquire whether it is possible for a neural network to classify line energisation, faults and lightning correctly. For this we find that the best classification was achieved with a hidden layer of 60 and the confusion matrix in shown in Table (6) where class (1) denotes faults, class (2) denotes line energisation and class (3) denotes lightning.

Table 3

Confusion matrix for transposed line energisation at level 3 current coefficients and a neural network of 25 neurons

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Input Class | | | | |  |
| 1 | 2 | 3 | 4 | 5 |
| Output Class | 1 | 362 /20% | 0/0% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 2 | 0/0% | 362 /20% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 3 | 0/0% | 0/0% | 362 /20% | 0/0% | 0/0% | 100%/0% |
| 4 | 0/0% | 0/0% | 0/0% | 140/7.7% | 140/7.7% | 50%/50% |
| 5 | 0/0% | 0/0% | 0/0% | 222/12.3% | 222/12.3% | 50%/50% |
|  | | 100%/0% | 100%/0% | 100%/0% | 38.7%/61.3% | 61.3%/38.7% | 80%/20% |

Table 5

Confusion matrix for twin line energisation at level 5 currents coefficients and a neural network of 15 neurons

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Input Class | | | | |  |
| 1 | 2 | 3 | 4 | 5 |
| Output Class | 1 | 7560/20% | 0/0% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 2 | 0/0% | 7560/20% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 3 | 0/0% | 0/0% | 7560/20% | 0/0% | 0/0% | 100%/0% |
| 4 | 0/0% | 0/0% | 0/0% | 3510/9.3% | 3510/9.3% | 50%/50% |
| 5 | 0/0% | 0/0% | 0/0% | 4050/10.7% | 4050/10.7% | 50%/50% |
|  | | 100%/0% | 100%/0% | 100%/0% | 46.4%/53.6% | 46.4%/53.6% | 80%/20% |

Table 4

Confusion matrix for transposed line faults at level 5 voltage coefficients and a neural network of 90 neurons

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Input Class | | | | |  |
| 1 | 2 | 3 | 4 | 5 |
| Output Class | 1 | 7553/20% | 0/0% | 1/0% | 3/0% | 0/0% | 99.9%/0.1% |
| 2 | 2/0% | 75560/20% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 3 | 2/0% | 0/0% | 7558/20% | 0/0% | 0/0% | 100%/0% |
| 4 | 1/0% | 0/0% | 1/0% | 7555/20% | 0/0% | 100%/0% |
| 5 | 2/0% | 0/0% | 0/0% | 2/0% | 7560/20% | 99.9%/0.1% |
|  | | 99.9%/0.1% | 100%/0% | 100%/0% | 99.9%/0.1% | 100%/0% | 100%/0% |

## Twin Lines

We replace the line connecting bus 23 to bus 25 by twin lines and only measure the current going through of the lines. We use two lines with the parameters given in [20] and the distance between both lines is 82 meters. For this training we have found that any two modes of the lines perform well in any classification. Creation of fault cases, line energisation and lightning follows the procedures done in transposed line case. In this case instead of having 5 output classes we have 6 output classes the extra output class is for the twin line.

For line energisation, we found that a neural network with 15 neurons gives a 100% classification irrespective of the surge arrester status and when using voltage coefficients of level 3. When coefficients of level 3 currents are used, we still get near to a 100% classification. The confusion matrix in this case is given in table (7).

For lightening we find that a hidden layer with 15 neurons was enough for a 100% classification when we used level 3 voltage coefficients. Currents still give a 100% classification.

For faults, a hidden layer of 20 neurons was enough for a 100% classification using level 3 voltage coefficients. We know ask if a neural network can classify different transients originating from each line one at a time. We use all the six modes for classification. The confusion matrix is shown in Table (8). Classification using currents gives less accurate results and we choose not to show them.

# Conclusions

This paper presented and showed by examples an argument that high frequency signals can be used for high speed power system transient classification. We envision that in a smart grid setting relaying as a by-product of the classification. Speed doesn’t exceed one eights of a cycle in all cases.

1. The effect of surge arrester has been examined and shown that in all cases it has negligible effect although it actually attenuates travelling waves.
2. For line energisation, lower levels are generally needed to do correct classification. This stems from the fact line energisation doesn’t cause a lot of high frequency signals but signals in the medium frequency range.
3. Lightning can be classified with any level coefficients. This is due to the fact that the oscillations caused by lightning are very high due to the high amplitude of the surge.
4. Currents generally don’t have all information necessary for classification. However they do give satisfactory results when the line under study is targeted with no respect for other lines.

Table 7

Confusion matrix for transposed line transients at level 5 voltage coefficients and a neural network of 120 neurons

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Input Class | | | | | |  |
| 1 | 2 | 3 | 4 | 5 | 6 |
| Output Class | 1 | 362/16.7% | 0/0% | 0/0% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 2 | 0/0% | 362/16.7% | 0/0% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 3 | 0/0% | 0/0% | 362/16.7% | 0/0% | 0/0% | 0/0% | 100%/0% |
| 4 | 0/0% | 0/0% | 0/0% | 183/8.4% | 183/8.4% | 0/0% | 50%/0% |
| 5 | 0/0% | 0/0% | 0/0% | 179/8.2% | 179/8.2% | 0/0% | 50%/0% |
| 6 | 0/0% | 0/0% | 0/0% | 0/0% | 0/0% | 362/16.7% | 100%/0% |
|  | | 100%/0% | 100%/0% | 100%/0% | 50.6%/49.4% | 49.4%/50.6% | 100%/0% | 83%/17% |

Table 6

Confusion matrix for transposed line transients at level 5 voltage coefficients and a neural network of 120 neurons

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | | Input Class | | |  |
| 1 | 2 | 3 |
| Output Class | 1 | 37797/88.4% | 241/0.6% | 15/0% | 99.3%/0.7% |
| 2 | 0/0% | 1537/3.6% | 0% | 100%/0% |
| 3 | 3/0% | 32/0.1% | 3135/7.3% | 98.9%/1.1% |
|  | | 100%/0% | 84.9%/15.1% | 99.5%/0.5% | 99.3%/0.7% |

1. Line energisation will be always confused with faults. We still are researching the cause of this phenomenon. A reason would be because the fact that we have included a 1000 Ω in fault simulations which is very likely to be confused with line energisation. Although not shown in the results, we achieved a 98% classification accuracy with line energisation when we used just one eights of a cycle of approximation 5. Still, we need to look further into the issues preventing a 100% classification.

Table 8

Confusion matrix for twin line transients at level 5 voltage coefficients and a neural network of 80 neurons

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | | Input Class | | |  |
| 1 | 2 | 3 |
| Output Class | 1 | 48384/89.0% | 284/0.5% | 2/0% | 99.4%/0.6% |
| 2 | 0/0% | 1880/3.5% | 0/0% | 100%/0.0% |
| 3 | 0/0% | 8/0% | 3778/7% | 99.8%/0.2% |
|  | | 100/0% | 86.6%/13.4% | 99.9%/0.1% | 99.5%/0.5% |

1. For fault classification, higher levels give better classification results. . However this doesn’t come at a free price, going high up in the levels requires more nodes in the neural network which means the need for a high computing facility; a situation not present in most utilities or consulting firms.

The shown algorithm can be readily used as an online monitoring tool for detection of relay misoperation or to supervise impedance elements in impedance relays.

The next step in this analysis is to show how the ideas shown here can be used for relaying and achieving a 100% classification. To show this we need to show how a fault can be detected when a lightning surge evolves to a fault. There is a positive correlation between the number of faults and lightning surges striking a line. The neural network architecture given in this paper can’t be used to detect such phenomena. Research is still needed to apply the current method for relaying. The authors are currently researching this issue further and will publish a paper when the results are ready.

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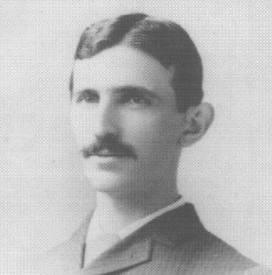
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# Biographies

**Nikola Tesla** (M’1888, F’17) was born in Smiljan in the Austro-Hungarian Empire, on July 9, 1856. He graduated from the Austrian Polytechnic School, Graz, and studied at the University of Prague.

His employment experience included the American Telephone Company, Budapest, the Edison Machine Works, Westinghouse Electric Company, and Nikola Tesla Laboratories. His special fields of interest included high frequency.

Tesla received honorary degrees from institutions of higher learning including Columbia University, Yale University, University of Belgrade, and the University of Zagreb. He received the Elliott Cresson Medal of the Franklin Institute and the Edison Medal of the IEEE. In 1956, the term "tesla" (T) was adopted as the unit of magnetic flux density in the MKSA system. In 1975, the Power Engineering Society established the Nikola Tesla Award in his honor. Tesla died on January 7, 1943.

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