

Artificial Neural Network Fault Detection For Transmission Line Protection

استخدام الشبكات العصبية الصناعية في التعرف على الأعطال و مكانها لخطوط نقل الكهرباء

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الملخص:

تعتبر الشبكات العصبية الصناعية أداة فعالة للتعرف على الأخطاء التي تحدث على خطوط نقل الكهرباء و ذلك لقدرتها هذه الشبكات على التمييز بين الأشكال المختلفة للموجات. يتم في هذا البحث تمثيل منظومة القوى في الحالات الطبيعية و كذلك في حالات الاعطال المختلفة باستخدام برنامج EMTP. يتم تسجيل موجات التيار و الفولت المتوقع وصولها الى المرحل في حالات التشغيل الطبيعي و ظروف الأعطال و يتم تحليلها من أجل الوصول الى أشكال يسهل على الشبكات العصبية الصناعية التعرف عليها. تم تقسيم الشبكات الصناعية المستخدمة الى ثلاث مراحل أولها لتحديد وجود العطل من عدمه وثانيها لتحديد الوجه المعطل و ثالثها لتحديد مكان العطل. تمت تجربة هذا الأسلوب على شبكات قوى مختلفة و أثبتت فاعليته في تحديد نوع و مكان العطل.

Abstract-- The artificial neural network is a powerful tool for the detection of the transmission line faults due to its ability to differentiate between various patterns. In this paper, simulation of power system under normal and faulty conditions are carried out using electromagnetic transient program. The voltage and current waveforms at the relay location for normal and fault conditions are extracted. The waveforms obtained are preprocessed in order to improve the performance of the neural network used. Three neural networks are built one for fault detection, one for fault type and a third for fault location. The proposed technique is tested with different types of faults and successive decision was reached.

I. INTRODUCTION

The analysis of voltages and currents at the relay location is essential for the correct decision of the relay tripping action. During the fault, transients arise in both voltage and current waveforms. The past techniques used to analyze the symmetrical components of these waveforms.[1] Recently artificial intelligent techniques are used for the waveforms analysis. The artificial neural network are widely used in fault detection and classification.[2-6] Various applications of neural networks were used in the past to improve recognition of the faults on transmission lines. Wherever input patterns with large dimensionality are present, training of these networks are slow and needs much more training sets.

In this paper simulation of the used power system is performed using PSCAD which is an electromagnetic transient program with CAD user interface. Simulation outputs of large number of scenarios including various faults and locations were used as database for the analysis procedure. The voltage and current waveforms obtained from the simulation were analyzed using artificial neural network. In order to minimize the size and time for training of the neural network, pre processing of these waveforms was performed initially.

The next sections include presentation of the procedure used, pre processing techniques of the data and finally results obtained.

II. PROPOSED DETECTION TECHNIQUE

The power system used for the algorithm is 220 kV generator connected to a transmission line of length 360 km extended to an infinite bus with the relay located at the beginning of the line. The model is implemented using PSCAD. The implementation includes 11 types of faults (AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC, & ABCG) and the simulation has been conducted at different locations of the transmission line from 10% - 100% as seen by the relay at the beginning of the line. For each of these locations there are 11 data sets, and each set contains the instantaneous phase voltages and currents corresponding to each fault type. The normal operating case is taken as a reference for the faulted cases.

The proposed topology is composed of three levels of neural networks. In level-1 a neural network (ANN_F) is used to detect the fault, while level-2, contains neural networks (ANN_T) used to identify fault type & faulted phases, and i level-3 a neural network (ANN_L) is used to detect the fault location. The output of the first level (ANN_F) activates both the second and third level (ANN_T & ANN_L) if there is a fault.

Therefore the proposed topology determines both fault type and the fault location. Based on the fault type and fault location which occurs on the system, output neurons should be 0 or 1. The proposed scheme is shown in Fig. 1.

Where O_F , O_T and O_L are the output corresponding to presence of fault, fault type and fault location respectively.

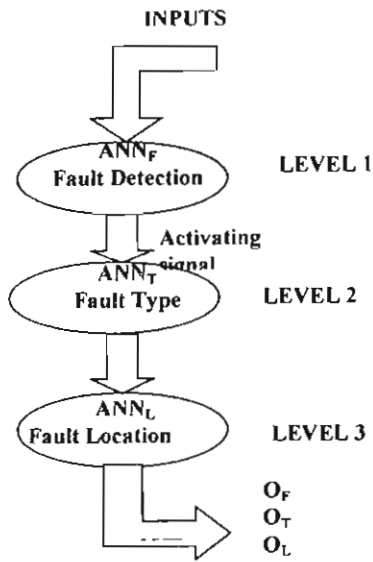


Fig. 1 The proposed scheme

III. DATA PROCESSING

The Figs.2 & 3 represent a line to line fault voltage and current waveforms. The Figures illustrate that the voltages reduce towards zero and the currents increase after fault. It is also observed that the voltage signal contains more harmonics than the current signal. It is obvious that the difference between the current and voltage remains constant before fault and increases after fault.

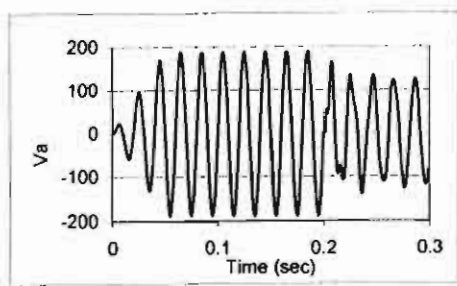


Fig.2 Voltage waveform for ab fault

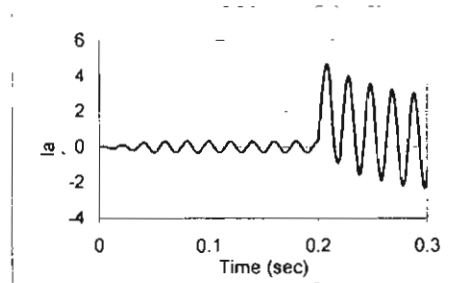


Fig. 3 Current waveform for ab fault

It was noticed that the (V-I) difference increases significantly after the fault with many oscillations in the signal (each phase is represented in one signal instead of two signals). The signal is similar to the voltage signal but the oscillation is magnified due to the difference signal. But the (V-I) difference does not significantly differentiate the fault signal from the normal signal, it merely magnifies the variation. The (V-I) signal before the fault occurrence is nearly sinusoidal which means the rate of change of magnitude is steady. Post-fault V-I difference signal exhibits strong oscillations signal exhibits degrading toward zero.

For each fault set we choose the maximum (V-I) value which is considered as the base value of the whole set (fault type). The normalized (V-I) to the base value is shown in Fig. 4. By this we obtain data set with value in between -1 & 1 which facilitates the neural computing.

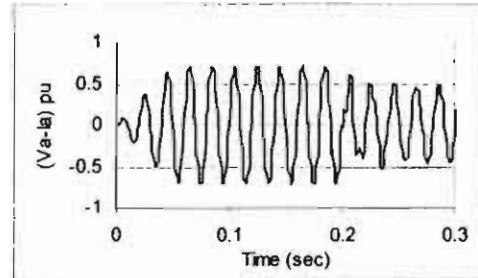
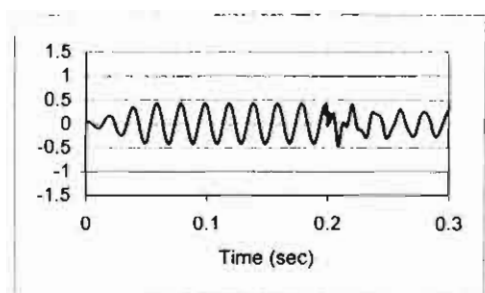


Fig.4 Normalised (Va-ia) for ab fault

An averaged difference on the V-I would result in a waveform that differentiates the part with oscillations, namely the post-fault signal, from the normal signal. The function that was used is

$$Y = (X_{i+1} - X_i) + (X_{i+2} - X_{i+3}) \quad (1)$$

Where Y is the ith value of the resultant signal as shown in Fig. 5 and X_i is the ith value of the input signal, the V-I difference. The artificial neural network would be able to

Fig.5 Y_a for ab fault

learn this differentiation very quickly when compared to the original raw signal.

The transformed signal still has a region of conflict which could be solved by accumulating points together, as it would eliminate the spurious points. The accumulated function is called SADI (Sum of Averaged Differences), and is derived as given

$$F_i = \sum_{j=i-5}^{i+5} abs(Y_j) \quad (2)$$

Where F_i is the i th value of the SADI filtered signal. The SADI filtered signal is illustrated in Fig. 6.

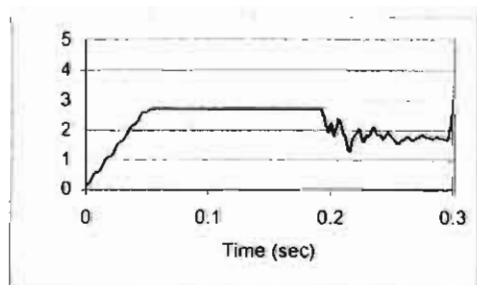


Fig. 6 SADI filtered signal for phase a for ab fault

For different fault locations the SADI values could be seen in Fig. 7.

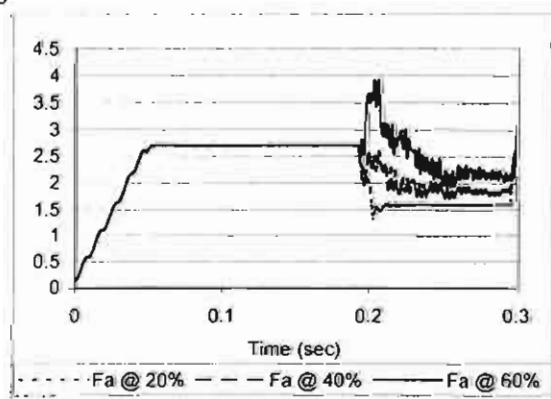


Fig. 7 SADI for phase a for ab fault at different locations

IV. RESULTS AND DISCUSSION

The principle of variation of voltage and current signals before and after the fault incidence is used and a fast and reliable ANN-based fault detector/classifier module is designed to detect the fault and classify the fault type.

From the above analysis the SADI filtered signal (F_i) is chosen as the appropriate input for the neural network because of the fault signals are clearly distinguished from each other and the number of inputs is reduced to three inputs instead of six inputs.

Input into the neural network is in the form of the moving data window containing samples of SADI filtered signals of the V-I difference signals.

Multilayer feedforward networks were chosen to process the prepared input data. A few different networks were selected initially. For designing the fault selector based neural network, different networks with 3 inputs and 4 outputs were considered. Four different A, B, C and G outputs were considered to determine whether each of the three phases A, B, C and/or ground G are present in the fault loop.

The networks' architectures were decided empirically, which involved training and testing different number of networks. Three layer networks were found to be appropriate for the fault selector application.

Once trained, the networks performance was tested using a validation data set. The suitable network which showed satisfactory results was finally selected. The network has 3 SADI filtered signals and 4 outputs.

For all the networks, hyperbolic tangent function was used as the activation function of the hidden layer neurons. Saturated linear function was used for the output layer.

The neural network ANN_T composed of 38 inputs, 10 hidden neurons and 4 outputs. Neural network desired outputs for different types of faults are shown in Table 1.

As mentioned previously, the output of ANN_F activates ANN_T and respectively the output of ANN_T activates ANN_L. ANN_L is activated once the fault type is known. Neural network (ANN_L), as shown in Fig. 8, has four outputs, which indicates the fault location in binary digits which can be converted to decimal values. The output for ANN_L could be summarized in Table 2

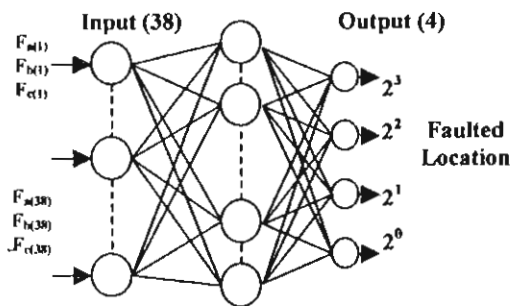
V. CONCLUSION

The neural network performance of the proposed scheme is evaluated using various fault types. It was shown that the network was able to perform fast and correctly for different combinations of fault conditions, e.g. fault type and fault location. The fault is identified just in a few milliseconds which prove that the network is able to detect and classify the fault quite fast. The network outputs remain stable after identifying the fault.

The network was subjected to another power systems with different parameters. The same sequence and procedure of data extraction and signal conditioning of the first power system was applied to the second one. It was observed that the network was able to identify the faults and their different types in a few milliseconds with the same network structure and training functions.

Table 1 Neural network desired ANN_T outputs

Fault Type		A	B	C	G
L-G	AG	1	0	0	1
	BG	0	1	0	1
	CG	0	0	1	1
L-L	AB	1	1	0	0
	BC	0	1	1	0
	CA	1	0	1	0
L-L-G	ABG	1	1	0	1
	BCG	0	1	1	1
	CAG	1	0	1	1
3-Ph	ABC	1	1	1	0
	ABCG	1	1	1	1

Fig. 8 Architecture of ANN_LTable 2 Neural network desired ANN_L outputs

Fault Location	2^3	2^2	2^1	2^0
10 %	0	0	0	1
20 %	0	0	1	0
30 %	0	0	1	1
40 %	0	1	0	0
50 %	0	1	0	1
60 %	0	1	1	0
70 %	0	1	1	1
80 %	1	0	0	0
90 %	1	0	0	1
100 %	1	0	1	0

VI. REFERENCES

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