Recurrent Neural Networks Based Differential Protection of Power Transformers

الحماية التفاضلية للمحولات الكهربية باستخدام الشبكات العصبية ذات التغذية الخلفية

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Abstract

Power transformers are important electrical equipments that need fast protection, because of their essential role in power system operation and their expensive cost. The most common technique used to protect the transformer is the differential relay, but it doesn't provide discrimination between internal fault and inrush currents. This paper presents an algorithm based on recurrent neural network (RNN) as a differential protection for three phase two windings transformer. The algorithm uses both the primary and secondary currents and second order harmonics of currents to discriminate between internal fault and inrush currents. A comparison among the performance of three neural networks based classifiers is presented. These networks are: FFBPNN (feed forward back propagation), cascade-forward back propagation network (CFBPNN), and proposed recurrent network (RNN). The transformer fault conditions are simulated using PSCAD/EMTDC in order to obtain the primary and secondary current signals. These current signals are used to train and test the neural networks which implemented by Matlab/Simulink. The test results prove that the RNN is stable and give good behaviors for different fault conditions. It is more reliable for recognition of transformer inrush and internal fault currents.

تعتبرمحولات القدرة من أهم المعدات الكهربيه التى تحتاج لحماية سريعة وذلك يرجع الى ارتفاع أسعارها، والى كونها جزء ضرورى لتشغيل منظومة القوى الكهربية، كما أن خروجها من الخدمة يؤدى الى انقطاع التغذية. ويعتبر المرحل التفاضلى هو التقنيه الاكثر استخداما فى حمايه المحول ولكنه لايحقق التمييز بين الخطأ الداخلى للمحول والتيارات العشوائية. هذا البحث يقدم خوارزمية تعتمد على الشبكات العصبية ذات التغذية الخلفية RNN للحمايه التفاضليه لمحول ثلاثى الاوجه ذو ملفين، وهذه الطريقة تستخدم تيارات الملف الابتدائى والثانوى والتوافقيات الثانية للتمييز بين الخطا الداخلى للمحول والتيار العشوائى. وقد تم مقارنة الشبكة المقترحة مع عدد من الشبكات العصبية الاخرى مثل FFBPNN , CFBPNN. كما تم عمل محاكاه لاخطاء المحول باستخدام برنامج PSCAD/EMTDC للحصول على تيارات ملف الابتدائى والثانوى، ثم استخدمت هذه التيارات لتدريب واختبار الشبكات العصبية باستخدام برنامج Matlab/Simulink. واوضحت نتائج الاختبار أن أداء الشبكة العصبية المقترحة RNN جيد وأنها شبكة مستقره ولها اعتماديه أعلى من الشبكات العصبية الاخرى فى التمييز بين التيار العشوائى والخطأ الداخلى فى ملفات المحول .

***Keywords*:** Neural network, Recurrent Neural Network, Feed Forward Network, Cascade-forward back propagation, transformer fault, differential protection.

1. Introduction

Power transformer is an important and expensive component of power systems. Occurrence of faults can cause damage to the transformer, so detecting winding faults with high sensitivity, speed and reliability is necessary to clear faults to avoid the transformer damage [1].

The differential protective system establishes the main protection against internal faults on transformer windings [2]. It is based on the comparison of the measured currents on both power transformer sides. The differential relay trips whenever the difference of the currents in both sides exceeds a predetermined threshold. This technique is accurate for transformer internal faults. However, there are some factors that can cause mal-operation of differential relay such as over excitation, saturation of current transformer, transformer tap changer operation and inrush currents [3].

Inrush currents are generated by transients in transformer magnetic flux. The magnetizing inrush current, which occurs during energizing of the transformer, generally results in several times full load current and therefore can cause mal-operation of the relays [4]. When the transformer tap changer is moved up and down with respect to the middle point at which the relay is adjusted to, the differential relays may be in mal-operation. Such mal-operation of differential relays can affect both the reliability and stability of the whole power system. Inter-turn (turn-to-turn) fault is one of the most important failures which could occur in power transformer [5]. Such faults are extremely difficult to detect since they induce negligible increase of the currents at the transformer terminals, although the currents flowing at the fault place are very high and dangerous for the transformer [6].

To enhance the reliability of differential protection, signals other than current have also been utilized. The use of voltage signals was proposed in [7]. A method based on differential power has been proposed in [8], to recognize fault conditions from inrush current conditions. In [9] a proposed method based on modal transform of voltage and current waveforms was presented. The disadvantages of these methods include the need to use voltage transformers and the increased cost of the protection system. Another class of methods identifies fault conditions based on using the second order harmonic component as a discriminator factor between inrush and internal fault current [10-13]. The main drawback of this method is the possibility of generation of the second order harmonic component during faults due to CT saturation [13]. Another technique uses the waveform fluctuations of differential current. The method based on measuring the time between the respective peaks of differential current. The method depends on the fact that the time interval between two respective peaks in case of inrush current is smaller than the time interval in the fault current. The length of time that the current waveform stays close to zero is the main idea in [14]. Delayed fault detection is the main disadvantage of that algorithm.

Early methods were based on desensitizing or delaying the relay to overcome the transients [15]. These methods are unsatisfactory nevertheless, since the transformer was exposed to long unprotected times. Ref. [10,16] use the wave shaped recognition technique, this technique depends on fixed threshold index (either in time domain or in frequency domain) and these may require large computational burden. In [17], a wavelet-based method has been presented. The drawback of this method is that it requires the measurement of both voltage and current which increases the cost of hardware implementation.

Recently various Artificial Intelligence (AI) based algorithms are introduced to power transformer protection. Among of these techniques, the artificial neural networks (ANN) are considered as a powerful tool for solving the problems of transformer protection. ANN possesses excellent features such as generalization capability, noise immunity, robustness, and fault tolerance. Consequently, in most cases the decision made by an ANN based relay would not be seriously affected by variations in system parameters. In particular, ANNs have been applied to protective relaying to improve power transformer protection [18-25].

This paper presents an algorithm based on recurrent neural network (RNN) as a differential protection scheme for three phase two windings transformer. The algorithm uses the primary and secondary currents and second order harmonics to discriminate between internal fault and inrush currents. The paper compares the proposed method with other neural networks such as the feed forward back propagation neural network (FFBPNN) and cascade-forward back propagation neural network (CFBPNN).

2. Power system modeling and simulation

The studied power system consists of a three phase source connected to a load through a three phase power transformer 110/10.5 kV, 100 MVA, as shown in Figure 1. The transformer has a star-star-to-ground connection. The data required for training and testing the neural networks are developed by modeling and simulating the studied power system using the PSCAD/EMTDC software package. Figure 2 shows the PSCAD test model. The necessary information required to generalize the problem are obtained from simulation results. Different types of internal winding faults are simulated at different, percentage of windings, and inception time. For the secondary and primary sides of the transformer, the CT ratios are chosen as 1257:1 and 120:1 respectively. The transformer operating conditions tested in this paper include:

- Normal,
- Magnetizing inrush current,
- Over excitation,
- Internal fault.
- External fault

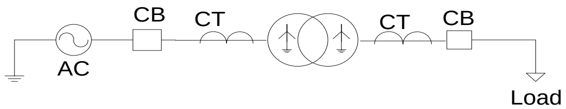

Figure 1: Single line diagram of the test system

In this study, many cases have been simulated and implemented for different transformer conditions. Figure 3 shows the current waveforms of the two sides of transformer at normal operation. The connected load is 100 MVA at lagging 0.9 p.f**.** The three phase primary currents are illustrated in Fig. 3-a, and the three phase secondary currents are shown in Fig. 3-b. The peak value of the currents in the two sides equal to 1.3 p.u.

Figure 4 shows the currents in case of internal fault condition. An internal single phase to ground fault occurred at 0.22 sec, fault occurred at 50% of primary winding of phase A with a fault resistance of 1 Ω. The value of the primary current in phase A increases to 30 p.u during the fault duration. On other hand, the value of the secondary current in phase A decreases to 0.5 p.u.

In case of external fault condition, a three phase to ground fault is applied at the secondary side (out the transformer protection zone). The fault starts at time of 0.22 sec. The results show that the primary and secondary currents are raised to 8 p.u during the fault. Figure 5 shows the transformer currents in this case.

Figure 6 illustrates the current waveforms in case of inrush condition with no-load (due to transformer energization). The inrush current increases to 4.5 p.u but still less than the current in case of internal fault explained by Fig. 4.

The final case study is the over excitation condition. In this case the transformed is overexcited by 150% of rated voltage. The primary currents increase to 5 p.u (see Fig. 7-a), while the secondary side currents decrease to about 0.08 p.u. (see Fig .7-b).

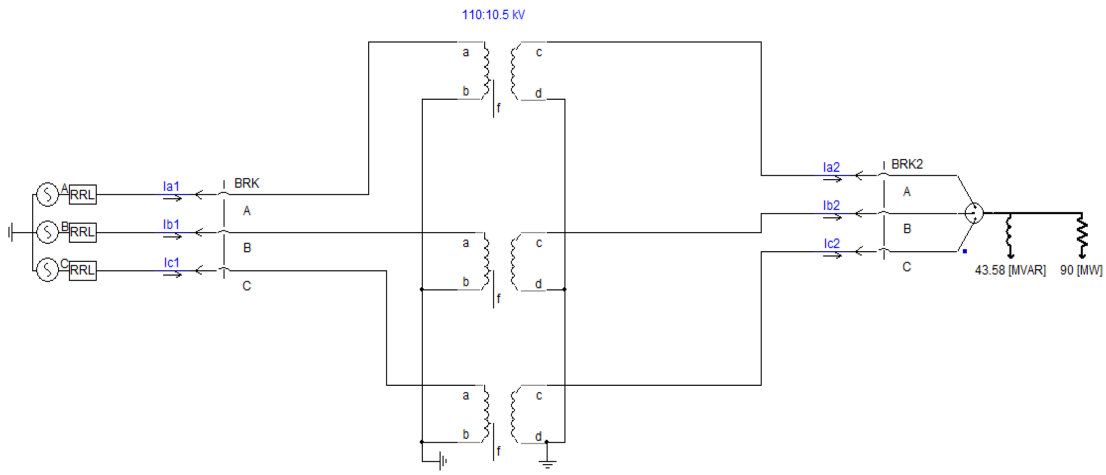

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Figure 2: PSCAD Power system model

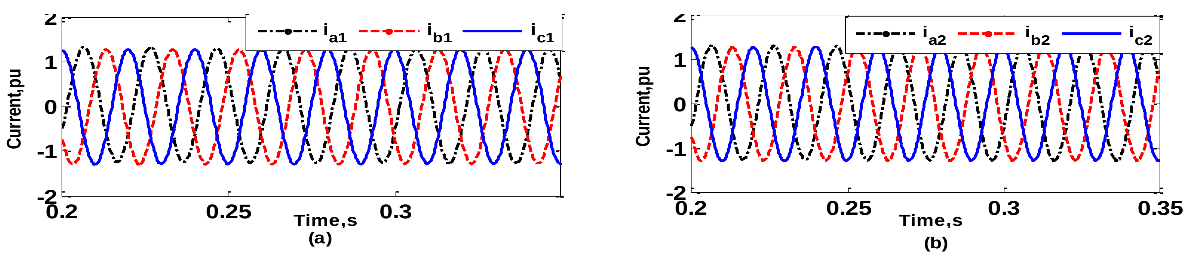

Figure 3: Current waveforms for normal operation condition.

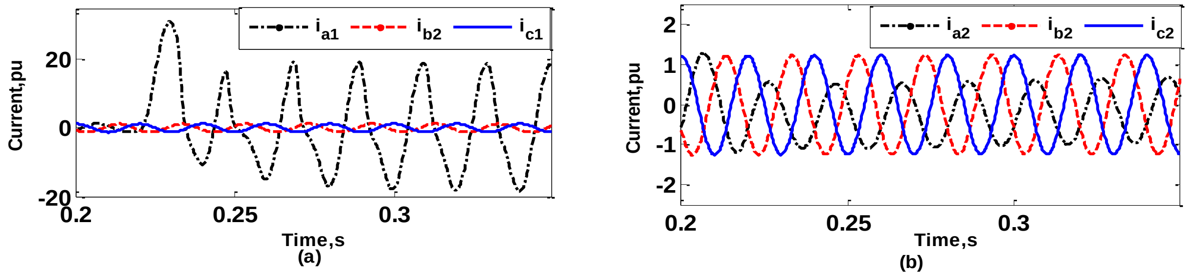

Figure 4: Current waveforms in case of internal fault condition

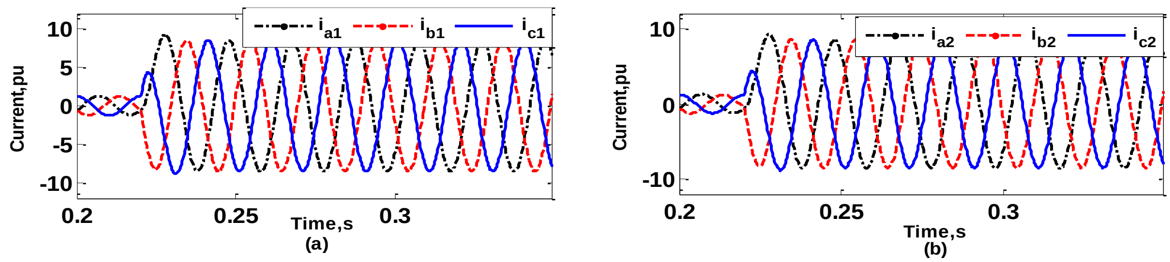

Figure 5: Current waveforms in case of external fault condition

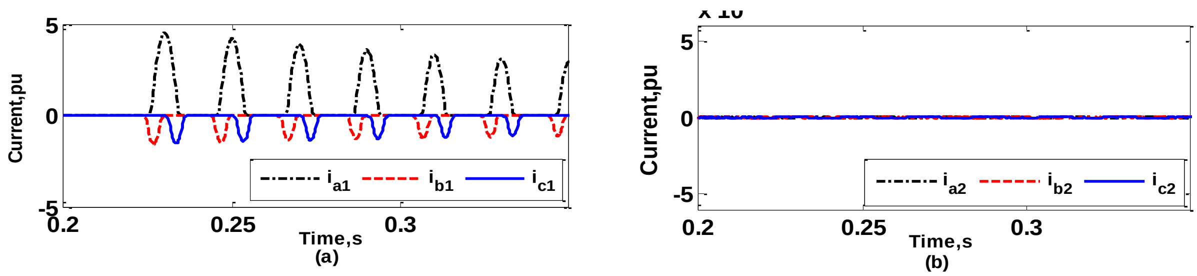

Figure 6: Current waveforms under inrush condition

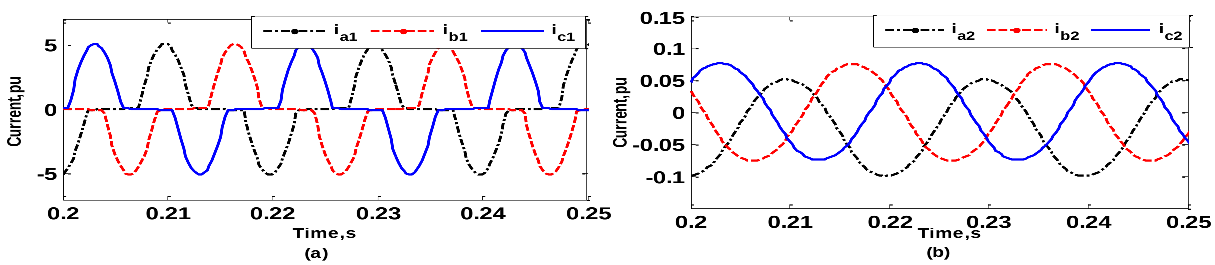

Figure 7: Current waveforms in case of over excitation condition

3. Harmonics Restrain

Harmonics restrain is based on the fact that the inrush current second-harmonic component is larger than that of internal fault current. Figure 8 shows the simulation of second harmonic components of magnetizing inrush and internal fault currents occurred at 0.1 sec. These harmonics can be used to restrain the relay from tripping during inrush current condition. They can be used to obtain better discrimination between inrush and internal fault currents.

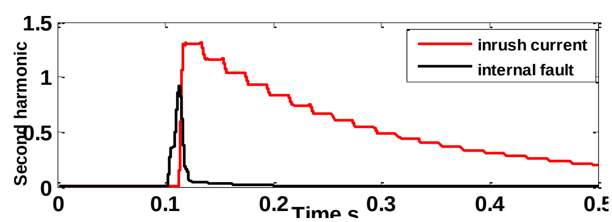

Figure 8: Second harmonic components of magnetizing inrush and internal fault

4. Artificial Neural Network (ANN)

Artificial neural networks (ANN) are computational models inspired by the human brain. They are composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. Each neuron has an activation function and many inputs and outputs. Neural networks with hidden units are universal approximations, which theoretically mean that they are capable of learning an arbitrarily accurate approximation to any unknown function. Their complexity is increased at a rate approximately proportional to the size of the training data. Neural networks can be applied to time series modeling without assuming a priori function forms of models [13].

Using different time-lagged input variables is the simplest way to include temporal information into a multilayer feed forward network. For a target series s(t), series {s(t−1),s(t−2), .. , s(t −τ) } can be used as input variables. Selecting the proper time lags and the informative set of input variables are critical to the solution of any time series prediction problems.

A dynamic neural network requires a given memory. There are two techniques to accomplish this requirement. The first one is the Time Delay Neural Networks (TDNNs). These networks are multilayer feed forward neural networks. They provide simple forms of dynamics by buffering lagged input variables at the input layer and/or lagged hidden unit outputs at the hidden layer. The standard back-propagation algorithm is used for training these networks [10,14].

The second technique is the recurrent networks which have feedback connections from neurons in one layer to neurons in a previous layer. A typical recurrent network has concepts bound to the nodes whose output values feed back as inputs to the network. So the next state of a network depends not only on the connection weights and the currently presented input signals but also on the previous states of the network. The network leaves a trace of its behavior; and keeps a memory of its previous states. Depending on the architecture of the feedback connections, there are two general models of recurrent networks: (1) partially recurrent, and (2) fully recurrent.

The back-propagation-through-time algorithm for training a recurrent network is an extension of the standard back-propagation algorithm. It may be derived by unfolding the temporal operation of the network into a layered feed forward network, the topology of which grows by one layer at every time step. The recurrent neural network (RNN) has some advantages over feed-forward neural network FFNN such as faster convergence, more accurate mapping ability, etc., but it is difficult to apply the gradient-descent method to update the neural network weights in RNN [15].

5. The Proposed NN

The ANNs which used in transformer protection are the FFBPNN and CFBPNN. The CFBPNN is just a FFBPNN that has time delay inputs in order to adapt the architecture to manage time variable signals. Compared to other existing approaches to deal with temporal data, recurrent networks have generated interest mostly because of their capability of implementing adaptive long-term memories. They have feedback connections from neurons in one layer to neurons in a previous layer. This kind of NNs has proven good performance in time series prediction; it can be a good choice for power transformer protection. In this study an RNN is proposed to diagnosis the different conditions in transformer as explained by Fig. 9.

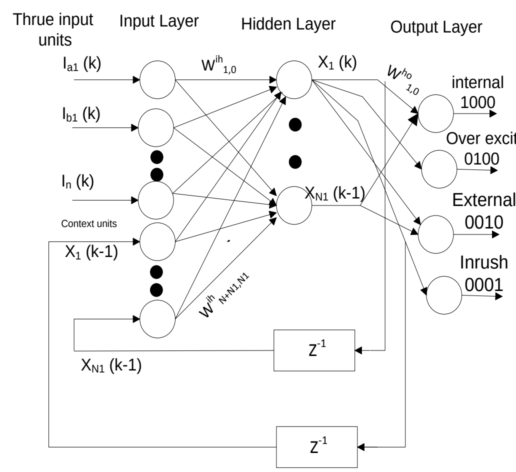

Figure 9: The proposed recurrent neural network

5.1 Training data generation

The simulated cases are divided into three groups. The first is the training group and its patterns are selected randomly and normally distributed in order to generalize ANN and prevent skew learning. The second group is used to validate the ANN during the training process and the last one is the test group. In this study the training sets consist of 1152 patterns obtained from simulating the transformer states at different conditions which can be classified as shown in Table 1.

Table 1 Training patterns of NN

Transformer condition	No_ pattern
Normal operation	108
Internal fault	756
Over excitation	108
External fault	63
Inrush current	117

5.2 Inputs and outputs selection of RNN

The input data is collected by measuring the three-phase currents at the two sides of the transformer and the second harmonics current. Long data window of inputs enables protective algorithms to get more information and in turn resulting in stable performance. On the other hand, long data window leads to slow decisions. After analyzing the simulation results and having acceptable NN performance, a length of data window of 5 samples is selected at a sample rate of 1 kHz for a 50 Hz power frequency. Each of the measured currents is represented by 5 samples and a second harmonic, making a total of 36 inputs. Hence, the network's input consists of:

$i_{as}(n)T$, $i_{as}(n-1)T$, $i_{as}(n-2)T$, $i_{as}(n-3)T$, $i_{bs}(n)T$, $i_{bs}(n-1)T$, $i_{bs}(n-2)T$, $i_{bs}(n-3)T$, $i_{cs}(n)T$, $i_{cs}(n-1)T$, $i_{cs}(n-2)T$, $i_{cs}(n-3)T$, $i_{ap}(n)T$, $i_{ap}(n-1)T$, $i_{ap}(n-2)T$, $i_{ap}(n-3)T$, $i_{bp}(n)T$, $i_{bp}(n-1)T$, $i_{bp}(n-2)T$, $i_{bp}(n-3)T$, $i_{cp}(n)T$, $i_{cp}(n-1)T$, $i_{cp}(n-2)T$, $i_{cp}(n-3)T$, $i_{hrms}(1)$, $i_{hrms}(2)$, $i_{hrms}(3)$, $i_{hrms}(4)$, $i_{hrms}(5)$, $i_{hrms}(6)$.

The patterns normalize the output to be within [0, 1] range. To represent different transformer conditions; the network needs 4 neurons in output layer. Table 2 illustrates the output of the proposed network.

Table 2 Output of the proposed NN.

Transformer condition	Output
Normal operation	0 0 0 0
Internal fault	1 0 0 0
Over excitation	0 1 0 0
External fault	0 0 1 0
Inrush current	0 0 0 1

5.3 Design procedure of the RNN

The design process of the proposed NN follows the following steps:

1. Prepare a suitable training data set that represents the cases required for learning the NN, and apply the input vector to the input layer.
2. Select a suitable NN structure.
3. Select training pair from the training set and calculate the output of the NN.
4. Calculate the error between the network output and the desired output.
5. Adjust the weights of the network in a way that minimizes the error
6. Repeat steps from 1–4 for each vector in the training set until its performance is satisfactory.

It is important to understand that the design process is iterative. It is possible that a particular NN structure selected in step 2 may not train to designer's satisfaction. In this situation, the structure and parameters must be changed and the network retrained. Figure 10 shows the flow chart of the proposed protection algorithm.

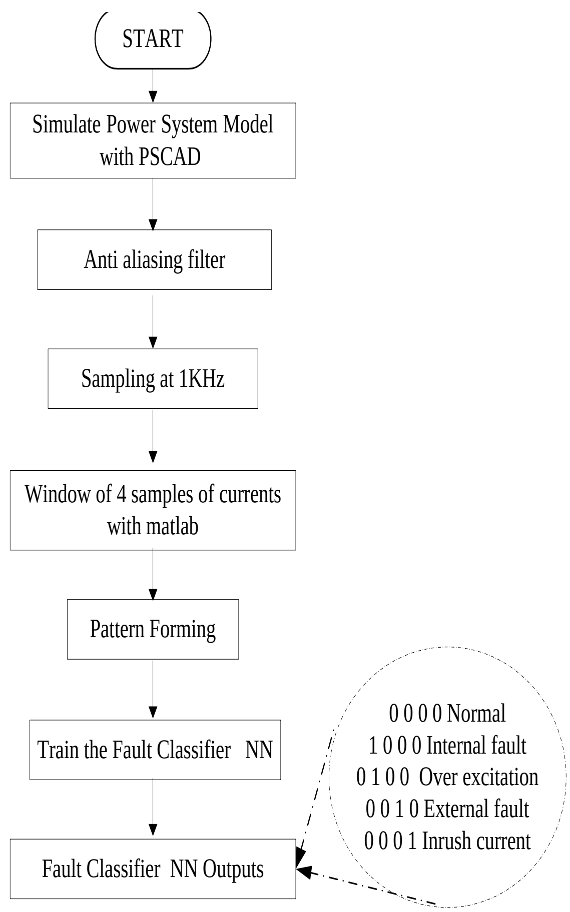

Figure 10: Flow chart of the proposed algorithm.

5.4 Architecture of the proposed NN

The number of neurons in each hidden layer, and the number of time delay have been selected by trial and error method. Different RNN structures, with different considered number of neurons in their hidden layers are consider and trained. Training and testing patterns are generated by simulating different types of faults on different locations and phases regions of the simulated system. The proposed network is a small sized and gives satisfactory results. It consists of 20 neurons in the first hidden layer, 18 neurons in the second hidden layer and 4 neurons in the output layer. The number of time delay units is two for the output layer. The RNN structure of the fault classifier is (36-20-18(2)-4). The used activation function is a log sigmoid function. The RNN-based algorithm is tested to evaluate the performance of the proposed method in terms of accuracy, robustness and speed.

6. Test and Results

The simulated power system model was tested by subjecting it to different types of internal fault, external fault, over excitation and magnetization inrush conditions. After training the proposed RNN fault classifier, a test was carried out for many case studies include different fault conditions and different power system data for each type of fault. The classification accuracy was calculated by using the follows equations [26]:

$$\%\,\text{Classification error} = \frac{\text{no . of false positive} + \text{no . of false negative}}{\text{total nomber of test cases}} * 100$$

$$\%\,\text{Classification accuracy} = 100 - \%\,\text{classification error} \quad (1)$$

The three types of ANN FFBPNN, CFBPNN, proposed recurrent network (RNN) are tested and simulated for the same tanning and tested data in this paper. Table 3 shows a comparison between the three types of ANN.

7. Case studies

The proposed RNN is applied to many case studies. In this section we will present four cases to illustrate the diagnosis ability of proposed method. The results indicate that the proposed network is able to classify faults very fast and reliably. The network performance is shown in Figure 11 to Figure 14 for the studied conditions. The following items discuss the results of each case study.

Table 3 Classification accuracy for FFNN, CFNN and RNN

Network Type	Structure	No. of pattern for Test case					error%	accuracy %
		Normal	Internal	External	Inrush	Over excit.		
FFBPNN	**36-20-18-4**	**30**	**20**	**15**	**20**	**15**	**7**	**93**
CFBPNN	**36-20-18-4**	**30**	**20**	**15**	**20**	**15**	**5**	**95**
RNN	**36-20-18-4**	**30**	**20**	**15**	**20**	**15**	**2**	**98**

7.1 RNN response to external faults

Figure 11 shows the condition of external fault of double phase to ground (A-B-g) starts at 0.205 sec. Figure 11-a and 11-b show the three phases primary and secondary currents respectively. Figures 11-c to 11-f illustrate the output of the RNN as a function of the time (sec). These results simulate the output of [0 0 1 0] for a fault occurrence and represent the external fault state.

7.2 RNN response to magnetizing inrush case

This case represents the condition of inrush current occurring at 0.1 second. Figure 12 illustrates the current wave-forms and the RNN outputs for this case study. The results simulate the output of [0 0 0 1] when the transformer is energized and represent the inrush current state.

7.3 RNN response to internal faults

This case represents the condition of an internal fault state. The fault is a three phase to ground fault starts at 0.3 sec, and is applied at 65% of primary winding turns. Figure 13 illustrates the results for this case study. These results simulate the output of [1 0 0 0] for a fault occurrence and represent the internal fault state.

7.4 RNN response to over excitation

The tested over excitation condition occurs at 0.1 sec. Figure 14-a and 14-b show the three phase primary and secondary currents respectively. Figures 14-c to 14-f show the outputs of the RNN. These results simulate the output of [0 1 0 0] when the transformer is over excited and occurs to represent the over excitation state.

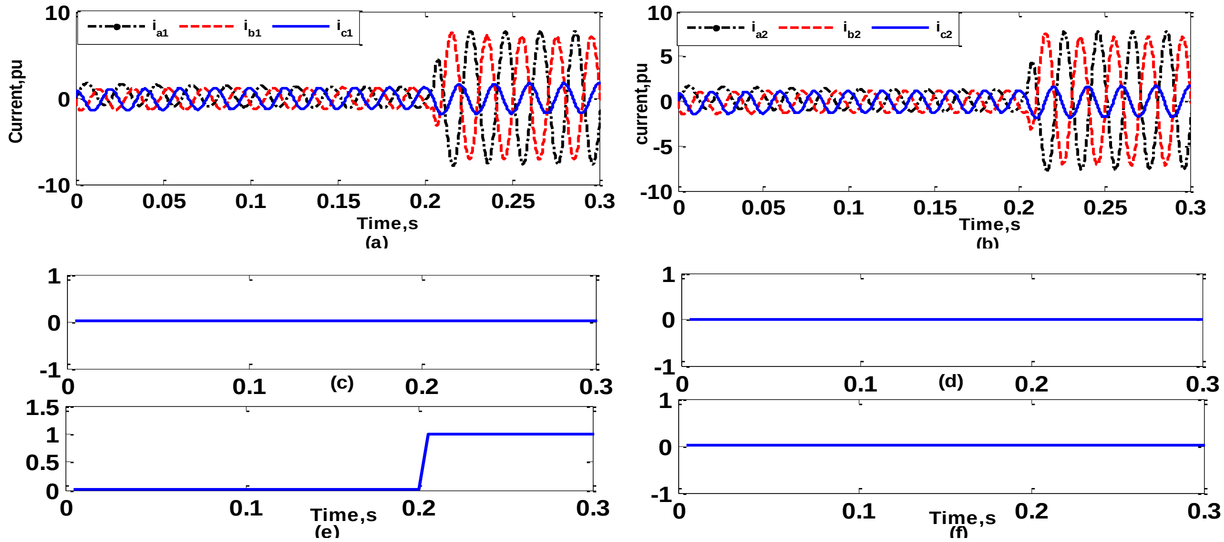

Figure 11: Results for external fault state

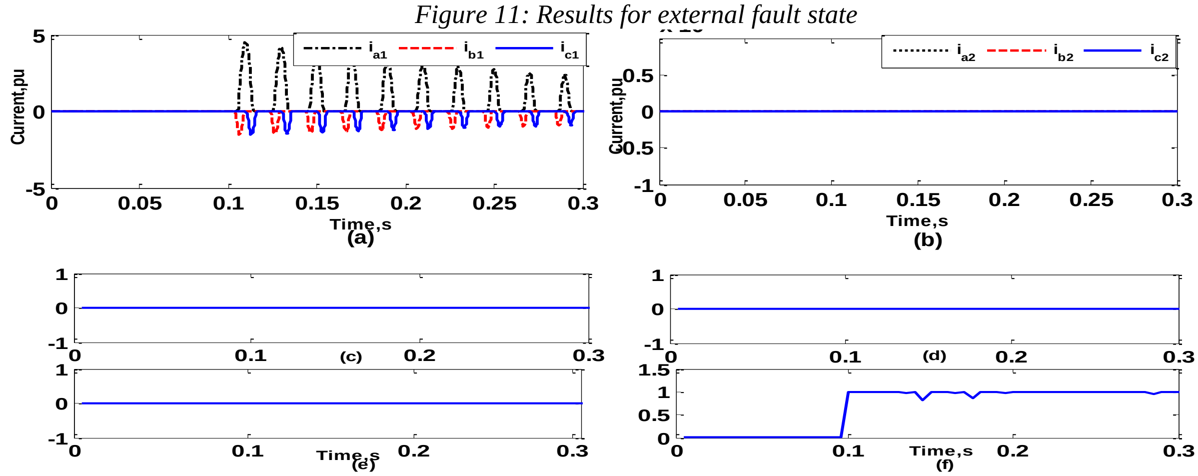

Figure 12: Results for inrush current state

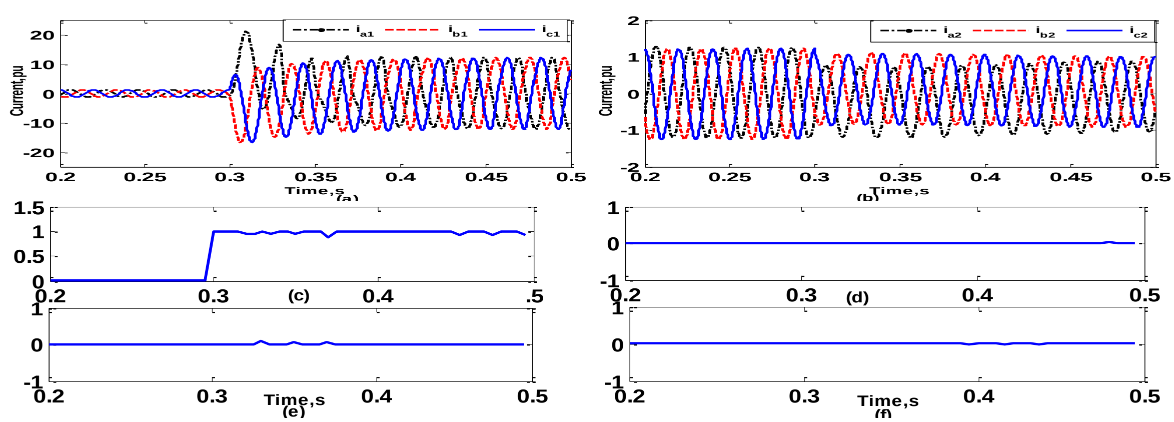

Figure 13: Results for internal fault state

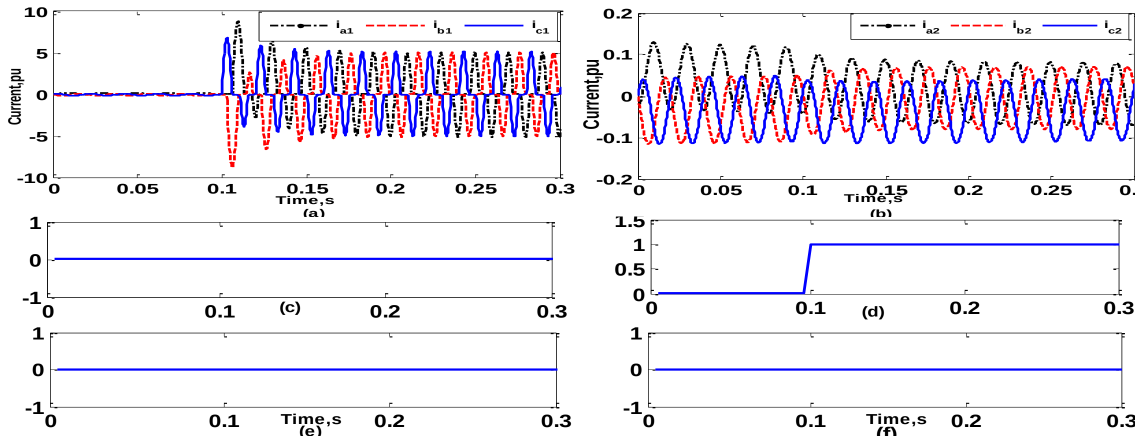

Figure 14: Results for over excitation state

8. Conclusion

This paper described a protection technique which can successfully discriminate between normal, inrush, over excitation, internal and external faults in power transformers. The RNN makes their decision based on a quarter cycle information of the 3-phases currents at both primary and secondary sides. The proposed RNN was compared with other two neural networks: FFBPNN and CFBPNN. The comparison proves that, the RNN is stable and more reliable than the other two networks. The RNN-based algorithm was applied to many case studies to evaluate the performance of the proposed method. Test results show that the proposed RNN classification technique is highly reliable and very fast in detecting and classifying different transformer conditions with classification accuracy of 98 %.

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