An Artificial Neural Network Based Digital Differential Protection Scheme for Synchronous Generator Stator Winding Protection

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Abstract—This paper describes a new Artificial Neural Network (ANN) based digital differential protection scheme for generator stator winding protection. The scheme includes two Feedforward Neural Networks (FNNs). One ANN is used for fault detection and the other is used for internal fault classification. This design uses current samples from the line-side and the neutral-end in addition to samples from the field current. Fundamental and/or second harmonic present in the field current during a fault help the ANN, used for fault detection, to differentiate between generator states (normal, external fault and internal fault states). Results showing the performance of the protection scheme are presented and indicate that it is fast and reliable.

Keywords—Synchronous Generators, Differential Protection, Digital Relays, Neural Networks.

I. INTRODUCTION

Differential protection, using electromechanical and solid state relays, is the most common method used by electric utilities for stator winding protection. However, the rapid advances in digital technology enabled researchers and designers to make significant progress in developing microprocessor based protection algorithms [1], [2]. Several microprocessor based algorithms for detecting stator winding faults have been proposed. An algorithm that uses instantaneous differences between line-side and neutral-end currents for detecting phase faults is described in [3]. The sum of the instantaneous currents was used to provide a restraint. Cross-correlation was used to compute fundamental frequency phasors of the line-side and neutral-end currents in [4]. The sums and products of these currents were used in the fault detection algorithm. A method which monitored the presence of the second harmonic in the field winding to detect faults is described in [5]. The direction of negative-sequence power flow at the generator terminals was used to differentiate between internal and external faults. A digital technique that uses the positive and negative sequence models of the generator, and voltages and currents measured at the generator terminals to differentiate between internal and external faults is given in [6]. The use of multifunctional digital relays for generator protection has also been investigated [7], [8]. These relays use digital filters to compute the phasors of voltages and currents, and apply appropriate digital algorithms for providing a variety of protection functions including stator winding protection. The majority of the previously proposed algorithms take one cycle to issue a trip signal. Moreover, fault detection computations involve a number of signal pre-processing requirements.

The ability of Artificial Neural Networks (ANNs), in particular Feedforward Neural Networks (FNNs), to learn by training any complex input/output mapping makes their use as pattern classifiers successful [9]. Subsequently, researchers have applied ANNs to solve relaying problems in a number of different areas [2]. In transmission line protection, FNNs have been proposed for fault direction discrimination [10], fault classification [11] and adaptive reclosing [12]. ANNs are also helpful in recognizing magnetizing inrush current waveforms, hence assisting in transformer protection [13]. An ANN has also been proposed to detect incipient faults, in the form of turn-to-turn stator insulation fault and bearing wear, in single phase induction motors [14]. The use of ANNs in predicting the field current of an alternator and then detecting the field winding interturn fault is described in [15].

Design of a new ANN based digital differential protection scheme for generator stator winding protection is presented in this paper. The scheme has two FNNs: one FNN is used by the fault detector module and the other by the fault classifier module. The FNN based fault detector module is used to discriminate between three generator states, namely the normal operation state, external fault state and internal fault state. In the event of an internal fault the trip logic module issues a trip signal and activates the FNN based fault classifier module, which identifies the faulted phase(s). Current patterns used to train the FNNs were obtained by simulating normal operation state for the generator at different loading conditions and different types of internal and external faults. Simulations were performed using an electromagnetic transient program built for simulating the three states of the generator. The performance of the proposed protection scheme was tested using a set of independent test patterns.
II. SIMULATION OF GENERATOR STATES

To adequately train the ANNs to detect faults and classify internal faults, an accurate model for simulating normal operation state, external fault state and internal fault state in a synchronous generator should be available. For the purpose of this project an electromagnetic transient program for simulating generator states was built. Figure 1 shows the simulated model. It consists of a multi-parallel path synchronous generator connected to an infinite bus through a short transmission line (TL), having a resistance \( R_{TL} \) and an inductance \( L_{TL} \). Both the generator and the infinite bus neutrals are grounded through resistances \( R_{g1} \) and \( R_{g2} \) respectively.

Normal operation at different power levels and power factors can be simulated using this model. Simulation of the external faults is based on the algorithm presented in [16], by which it is possible to simulate all types of external faults that can occur along the TL.

An algorithm for simulating internal faults in the synchronous generator of Fig. 1, using the direct phase quantities, was developed. This algorithm follows the same basic lines followed in [16], for the simulation of external faults. The method for calculating the self and mutual inductances of the faulted winding of the synchronous machine is based on the analysis presented in [17],[18],[19]. The internal faults algorithm is able to simulate different types of internal faults at different percentages of the stator winding. A full description of that algorithm is available in [20].

Hence, the developed model is able to simulate all three states. The model gives the instantaneous values of the rotor currents and of the currents in the stator paths, in per unit (pu).

III. DESIGN OF THE PROTECTION SCHEME

The structure of the proposed ANN based differential protection scheme, used for detecting faults and classifying internal faults, is shown in Fig. 2. The modules shown in Fig. 2 are not the complete modules of a digital relay, but rather the important modules needed for the proposed scheme. In this section the operation of the protection scheme as a stand alone relay is described. However, the ANN modules used in the scheme can be used to support existing algorithms used for generator protection, hence increasing the reliability of the protection operation.

A. Inputs

The inputs to the relay are the generator three phase currents from both the line-side (\( i_{aTL}, i_{bTL}, i_{cTL} \)) and the neutral-end (\( i_{an}, i_{bn}, i_{cn} \)) in addition to the field current (\( i_f \)). The second harmonic present in the field current, during a fault, has been used previously in a generator digital protection algorithm to indicate the existence of an abnormality [5]. Although fundamental and/or second harmonic (depending on the type of fault) appear in both internal and external faults, the simulation results showed that their amplitudes in external and internal faults are different. Hence, samples of the field current are used to help the ANN based fault detector module to differentiate between the three states.

B. Analog Input Subsystem

In an actual hardware implementation the inputs to these modules would be the low level signals provided by the current transformers (CT) [1]. However, in this project the inputs to the analog input subsystem are the instantaneous pu current values provided by the simulation model described in section II. A sampling frequency of 1200 \( Hz \) (20 samples/cycle) is used in this relaying scheme. Hence, to avoid aliasing problems, an antialiasing low pass filter, with a cut-off frequency of 570 \( Hz \), is used at the analog input subsystem.

C. Analog Interface

This module performs two functions, i.e. sampling the currents at a sampling rate of 1200 \( Hz \) and scaling the
current values such that they have a maximum value of +1 and a minimum value of -1.

D. Memory

The memory is used to store the most recent samples of the 7 inputs, in addition to four previous samples of each input. The stored samples are later used by the fault detector module and the fault classifier module.

E. Fault Detector Module

The ANN based fault detector module is the main part of the differential protection scheme. Its function is to differentiate between three generator states, namely the normal operation state (NOS), external fault state (EFS) and internal fault state (IFS). The following sections describe the structure of the ANN used for fault detection and its training process.

E.1. Artificial Neural Network Structure

One of the characteristic features of ANNs is the ability to learn by training any required input/output mapping, and subsequently respond to new inputs in the most appropriate manner [9]. The model of the ANN is determined according to network architecture, transfer function and learning rule. One layer FNNs are used for simple cases of pattern classification, two layer FNNs can be used to classify inside, convex and open or closed fields, but three layer FNNs can generate arbitrary complex decision regions. In this project three layer FNNs were used. The structure of the FNN based fault detector module is shown in Fig. 3. The inputs to the FNN are 7 currents, each current being represented by five consecutive samples, making a total of 35 inputs. The index n in Fig. 3 is used to indicate the most recent sample of each current. The FNN has three layers, with 18 tan-sigmoid neurons in the first hidden layer, 10 tan-sigmoid neurons in the second hidden layer and 3 log-sigmoid neurons in the output layer. Each neuron in the output layer is responsible for one fault type, except the first one that signals the 'normal state'. Therefore depending on the state of the generator one output is mapped to a value greater than 0.9 while the two others are less than 0.1.

E.2. Training Process

The training algorithm used is the back propagation algorithm with momentum and adaptive learning rate [9]. The training set consisted of about 30000 patterns representing different cases of the three generator states. About 10000 patterns were used for each state. The normal operation state was represented by three phase balanced operation at different loads and power factors. Patterns from different types of external faults at various percentages of the stator winding, about 10000 patterns were used for each state. The external fault state was represented by three phase balanced operation at different loads and power factors. Patterns from different types of external faults at various percentages of the stator winding, about 10000 patterns were used for each state. The fault classifier module averages six consecutive outputs of each of the three output neurons. The generator is considered to be operating at its normal state if (1) below is valid. A trip decision is taken in the case of an internal fault if the conditions specified in (2) exist for 3 consecutive samples.

\[
AVNS > 0.7 \& AVEF < 0.23 \& AVIF < 0.15
\] (1)

\[
AVNS < 0.4 \& AVEF < 0.4 \& AVIF > 0.8
\] (2)

where AVNS, AVEF and AVIF are the averaged outputs of normal state, external fault and internal fault neurons respectively. When the trip logic module issues a trip signal based on the detection of an internal fault it also activates the fault classifier module. In the event of an external fault, this relay is used as a back-up relay, in case the responsible relay failed to trip. A delayed trip decision is taken in the case of an external fault if the conditions specified in (3) are sustained for a prespecified number of cycles, X, and no other relay has tripped. The setting, X, is chosen based on the expected operating time of the responsible relay.

\[
AVNS < 0.4 \& AVEF > 0.8 \& AVIF < 0.4
\] (3)

G. Fault Classifier Module

Analysis of the internal faults in the armature winding of a generator is essential to the proper performance of
G.1. Feedforward Neural Network Fault Classifier

The structure of the FNN is shown in Fig. 4. The inputs to the FNN are 6 currents, each current being represented by four consecutive samples, making a total of 24 inputs. Samples of the field current are not used in this module as they do not help in classifying the phases. The FNN has three layers, with 14 tan-sigmoid neurons in the first hidden layer, 7 tan-sigmoid neurons in the second hidden layer and 3 log-sigmoid neurons in the output layer. Each neuron in the output layer is responsible for a fault in one of the phases. As an example, suppose there is an internal fault in phase a, then the output of phase a neuron will be mapped to a value greater than 0.95, indicating that this phase is faulty, while the outputs of the two other neurons will be less than 0.1, indicating that these two phases are healthy.

The training algorithm used is the back propagation algorithm with momentum and adaptive learning rate. The training set consisted of about 10000 patterns representing different types of internal faults. These patterns were the internal fault patterns used previously for training the fault detector module. As this module is activated during internal faults only, there was no need to expose it to patterns from other states.

G.2. Fault classifier logic

The fault classifier logic does not indicate that a certain phase is faulty except after confirming the output of the FNN fault classifier. The classifier confirms the presence of an internal fault in one of the phases by averaging five consecutive outputs of each of the three output neurons. So, for the fault classifier logic to indicate that there is an internal fault in phase a, the conditions specified in (4) should exist for 3 consecutive samples. For a two phase fault, for example in phases b and c, the relay would not indicate that these two phases are faulty unless the boundary conditions of (5) exist for 3 consecutive samples.

\[
\begin{align*}
AVFA &> 0.8 & AVFB &< 0.3 & AVFC &< 0.3 & (4) \\
AVFA &< 0.15 & AVFB &> 0.8 & AVFC &> 0.8 & (5)
\end{align*}
\]

where AVFA, AVFB, AVFC are the averaged outputs of phase a, phase b and phase c neurons.

IV. TEST RESULTS

ANNs are difficult to account for and explain their results. The only means of verifying the performance of a trained network is to perform extensive testing. For that reason the proposed protection scheme was tested using a large set of independent test patterns. In addition to using the three machine parameters previously used for training to generate new faults for testing, two more machine parameters were also used. One of these parameters was for a 100MVA cylindrical type machine and the other was for a 40MVA salient pole type machine. The results of the different modules are presented in the following sections.

A. Results Of The Fault Detector Module

Figures 5,6 show the results of the FNN based fault detector module. The internal fault percentages mentioned in Figs. 5,6 are measured from the neutral-end of the generator. The results shown in Fig. 5 indicate that the fault detector module is not affected by different loading conditions, fault types, fault locations and fault inception times. It takes the FNN 2 to 5 samples (1.7-4.2ms) to change its output, as a change from one state to another occurs.

In protection it is more important to ensure proper relay operation during transients and light faults. In Fig. 6 the response of the fault detector module to some of these cases is presented. Figure 6-a shows the success of the FNN in detecting a normal operation state, even though there was a 2% unbalance in the phase currents. The response of the FNN to a step change of 0.15 pu in power is shown in Fig. 6-b. Each neuron in the output layer had a constant value during transient. Percentage differential protection is mainly used to compensate for current transformers (CT) mismatches [21]. CT errors are apparent in the event of high currents associated with severe external fault conditions, and could cause the relay to falsely identify the fault as an internal fault and maloperate. The outputs of the FNN during a 3 phase fault at
Fig. 5. Results of the FNN based fault detector module (a) NOS, P=0.8, pf=0.9, (b) NOS, P=0.4, pf=0.8, (c) EFS, pp b, c, at machine terminals, P=0.93, pf=0.9, FI=6, (d) EFS, pg at middle of TL, P=0.9, pf=0.9, FI=18, (e) IFS, ppg at 50% of a & 50% of c, P=0.92, pf=0.9, FI=12, (f) IFS, pg at 37% of c, P=0.88, pf=0.8, FI=2, where NOS = normal operation state, EFS = external fault state, IFS = internal fault state, pp = phase to phase fault, pg = single phase to ground fault, ppg = two phase to ground fault, FI = fault inception time in samples and P, pf = Power in pu and power factor before fault occurrence.

Fig. 6. Results of the FNN based fault detector module (a) NOS with 2% unbalance, P=0.5, pf=0.9, (b) Step change of 0.15 pu in power at sample number 22, P=0.8, pf=0.9, (c) EFS, 3 phase, at machine terminals with a CT mismatch of 15%, P=0.8, pf=0.9, FI=16, (d) EFS, pg at end of TL, P=0.45, pf=0.83, FI=12, (e) IFS, pg at 20% of a, P=0.75, pf=0.8, FI=8, (f) IFS, ppg at 25% of a & 25% of c, P=0.63, pf=0.9, FI=19.

C. Results Of The Fault Classifier Module

The FNN part of the fault classifier module was subjected to different types of internal faults at different percentages of the windings, to check its performance. The results shown in Figs. 8-a,b,c,d indicate that the FNN accurately classified the phases. It takes the fault classifier module (FNN+logic) 6-7 samples after its activation to identify the faulty phase(s), as shown in Figs 8-e,f.

V. CONCLUSIONS

A new multi-neural network based digital differential protection scheme for stator winding protection is presented. The protection scheme has two main tasks. The
The second task is classifying the stator phases as faulty. The first task is to differentiate between normal operation and external fault state. The output of the FNN based fault detector module is used by the trip logic module to issue a trip signal in the event of an internal fault or a prolonged external fault. The second task is classifying the stator phases as faulty or healthy in the event of an internal fault. The obtained results are encouraging and indicate that the presented FNN based modules can be used to support existing protection algorithms, hence increasing the reliability of the protection operation. It can also be used as a part of a new generation of very high speed digital relays.

REFERENCES


BIographies

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DISCUSSION

B. Kasztenny (Texas A&M University, College Station, TX). This discussor would like to congratulate the authors on their interesting paper and finds the following issues worth to be further addressed:

1. In section IV.B the authors point out the influence of saturation of the CTs on the behavior of the protection scheme. Have the authors modeled the CTs when creating both their training and testing patterns? If positive, what was the model used and what was the proportion of the cases with saturation of the CTs in the overall population of cases?

2. The presented fault detecting ANN is fed by five consecutive samples of the selected signals. With the used sampling frequency, those samples cover $\frac{3}{4}$ of a cycle. If the generator's frequency changes considerably (for example during the synchronizing routine), the pattern composed from a fixed number of samples also changes what will apparently affect the quality of recognition. Have the authors considered the frequency deviations during both training and testing? If positive, what were the results?

3. The authors decided to feed the ANN with the currents in the natural coordinates. Have they consider using the differential—restraining coordinates? Certainly, the ANN is supposed to reconstruct internally the coordinate transformation if needed, but the experiences with transformer protection using ANNs show that feeding the ANN with the differential—restraining currents speeds-up the training and improves the quality of recognition.

4. During the training phase, have the authors exposed the ANNs to the patterns consisting of both pre-fault and fault samples? If positive, what was the response requested from the ANN for such patterns?

5. In the paper, only the examples of the operation of the protective scheme are presented. Have the authors tested the classifiers in the statistical way? If positive, what was the size of the testing data base, the percentage of maloperations and the average tripping time?

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Dr. Kasztenny first asked about the modeling of the saturation of the CTs and its effect on the protection scheme. During the computer simulation studies, which are presented in this paper and include both the training and testing phases, only the mismatches of the CTs were considered and the saturation was not modeled. However, in the laboratory implementation phase of that project, several faults accompanied by severe CT saturation were presented to the protection scheme. In all the cases the FNNs clearly indicated the type of the fault despite the saturation of the CTs. The results of the cases with the CT saturation are available in [1] and are going to be presented in a coming paper. It should be noted that the FNNs did not require any further training to detect a case with CT saturation. In other words the weights and biases of the FNNs used in the relay implementation are the same ones obtained from the off-line training process described in this paper.

The second question dealt with the change in the frequency of the generator and its effect on the FNNs. The authors would like to thank the discussor for raising such an important issue. As mentioned in Sections III.E and IV, several generator sizes were used during both training and testing. During different faults, including the step change in power shown in Fig. 6.b, a change in frequency occurred. This frequency change differs from one generator to another depending on its inertia constant and size, but this did not affect the accuracy of classification of the FNNs as shown in all the results presented in this paper. Hence, it can be said that slight changes in frequency will not affect the performance of the FNNs. The real time test results also confirm this claim [1]. However, the authors believe that considerable changes in frequency (as in the synchronizing routine) can have an effect on the protection scheme. In that case a technique which fixes the inputs to the time interval of quarter of a cycle, regardless of the frequency of the generator, can be used. Such techniques are available in the literature as in [2].

In that project the phase currents were used to train the FNNs to detect and classify the faults. As their usage resulted in accurate and fast detection and classification, there was no need to pursue other alternatives such as the usage of the differential-restraining coordinates. Other methods might be equally accurate or even they could produce better results. However, further research is needed to assess or deny such a claim.

Regarding question number four, the FNN used for fault detection was exposed during training
to both pre-fault and fault samples. In that case the response requested from the FNN was the fault type, i.e. either an external fault or an internal fault. The FNN used for fault classification was not exposed to pre-fault and fault samples as it is only activated after confirming that an internal fault already exists as described in detail in Section III.G.

While assessing the performance of the FNNs, each FNN was tested individually. The testing of each FNN was not conducted in a strict statistical way as described in [3] for example. Initially training started with a smaller training set, around 20000, for the FNN fault detector, but during validation tests it was found that the FNN response to boundary patterns was poor. Those boundary patterns represent normal operation at low power, external single phase to ground faults at the end of the TL and internal single phase to ground faults involving small winding percentages. Hence, more boundary patterns were generated and included in the training set, which finally reached about 30000 patterns. A similar test was done for the FNN fault classifier. In view of the validation tests carried out before the finalization of training, it can be said that maloperation was occurring for those boundary patterns. However, after the completion of training, the FNNs were able to accurately detect and classify those boundary patterns as shown in Figs. 6 and 8. The average detection and classification times were the same as those reported in the paper.

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