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Adaptive load blinder for distance protection

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ABSTRACT

This paper proposes a novel adaptive load blinder for distance protection. A distance relay can provide remote backup protection by zones 2 and 3, but it may mal-operate under heavy loading conditions and cause cascading trips in the network, which could further lead to a widespread blackout. To prevent cascading outages, load blinders or load encroachment elements are generally used to block the distance relay when there is heavy load in the system. However, these elements are not always able to discriminate heavy loading conditions from fault conditions, especially for heavy loads with low power factors or faults with fault resistance. This paper presents a novel load blinder scheme for distance protection by using artificial neural network (ANN). Test results show that the proposed ANN-based load blinder scheme is able to discriminate between different heavy loads with a wide range of power factors and different faults with fault resistance.

1. Introduction

Transmission line protection is the most elaborate and challenging function in power system protection. About two thirds of faults in power systems occur on the transmission line network. Consequently, it has received extensive attention from the researchers and designers in the area of power system protection.

Distance protection is the most common transmission line protection. Zone 1 of a distance relay is used to provide primary high-speed protection of a significant portion of a transmission line. Zone 2 is used to cover the rest of the protected line and provide some backup for the remote end bus. Zone 3 is the backup protection for all the lines connected to the remote end. The impedance of loads can be actually less than the impedance of some faults in very long and heavily loaded transmission line applications. This phenomenon may cause distance relays to mal-operate.

Studies of several large blackouts during the past decades indicate that backup zones of distance relays are involved in most of the major blackout incidences, such as the Northeast Blackout on November 9, 1965 [2], the New York City Blackout on July 13, 1977 [3], the West Coast Blackout on July 2, 1996 [4], the West Coast Blackout on August 10, 1996 [4], and the Northeast Blackout on August 14, 2003 [5].

Many of the operations of zone 3 of distance relays, during major disturbances, were caused by line overloading conditions [1]. The undesired operation of zone 3 distance relays caused by line overloads is the most obvious distance relay characteristics that have been widely discussed after the August 14, 2003 blackout [6–8]. Because zone 3 distance relay operations (or other over-reaching zone operations) have contributed to the severity of blackouts, a lot of efforts have been placed into reviewing their settings and developing loadability requirements and standards. The protection relays must be made selective enough to discriminate between load and fault conditions. Difference between loads and unsymmetrical faults can be detected by unbalance conditions. However, it is more difficult to discriminate between heavy loads and three-phase faults. One solution is to use lenticular or elliptical shape characteristics for load rejection. Unfortunately, these characteristics reduce the fault-resistance coverage [9]. Another solution is to use additional comparators to make blinders parallel to the transmission line characteristics. However, it will limit the impedance plane coverage thus exclude load from the tripping characteristics [10]. All traditional solutions are based on the same idea: to shape the operating characteristics of the relay to avoid or minimize load encroachment. The traditional solutions have some disadvantages:

- Reducing the size of the relay characteristics desensitizes the relay to faults with resistance [11]. Notice that some symmetrical faults as shown in Fig. 1 with fault resistance can affect the impedance measured by distance relay.
- Avoiding a small area of load encroachment often requires the sacrifice of much larger areas of fault coverage [11].

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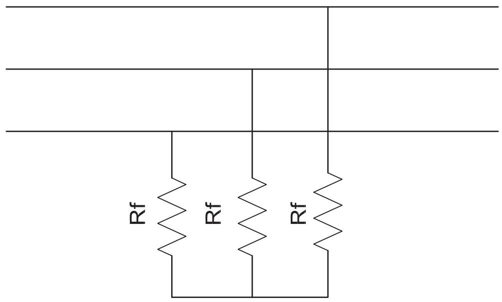

Fig. 1. Symmetrical fault with fault resistance.

- Power factor may not always be a sure indicator that a load rather than a fault exists on the line [1] if significant amounts of VARs are being transmitted under unusual system conditions.

Protection relaying is just as much a candidate for the application of pattern recognition techniques. The majority of power system protection techniques involve the definition of system states through identifying the pattern of the associated voltage and current waveforms measured at the relay location. This means that the development of adaptive protection can be essentially treated as a problem of pattern recognition or classification, for which artificial intelligence (AI) based techniques are powerful. AI possesses excellent features such as generalization capability, noise immunity, robustness, and fault tolerance. Consequently, the decision made by an AI-based relay will not be seriously affected by variations in system parameters. AI-based techniques have been used in power system protection and encouraging results have been obtained [12–15].

In this paper, a new scheme is proposed for designing an accurate and reliable load blinder. The proposed scheme is based on artificial neural network (ANN). Various power system scenarios are modeled and an ANN based algorithm is used for the recognition of these patterns. Performance of the proposed scheme is evaluated under various conditions and encouraging results are obtained. It is shown that the algorithm is able to perform correctly for different combinations of conditions, e.g., fault resistances, fault locations, pre-fault power flow directions, source impedance ratios, and load power factors.

The rest of the paper is organized as follows. Section 2 presents the structure of the proposed ANN-based load blinder. Test results of the proposed scheme are demonstrated in Section 3. Section 4 concludes the paper.

2. The proposed neural network based load blinder

The structure of a distance relay with the proposed load blinder is shown in Fig. 2. In this scheme, a conventional three-zone distance relay is used to detect faults. To prevent the second and the third zones from undesired trip due to heavy load, an ANN-based load blinder is used. Load blinder will be activated only when the condition is balanced. By using suitable functions of voltage and current as inputs, the load blinder is able to discriminate between faults and heavy loads and accordingly block distance relay operation during heavy loads [16].

2.1. Balancing condition check

A heavy load can be considered as a balancing condition. Therefore there is no loadability concern if a condition is unbalanced, such as an unbalance fault (single phase, phase to phase). To detect balancing conditions, the negative-sequence current is compared

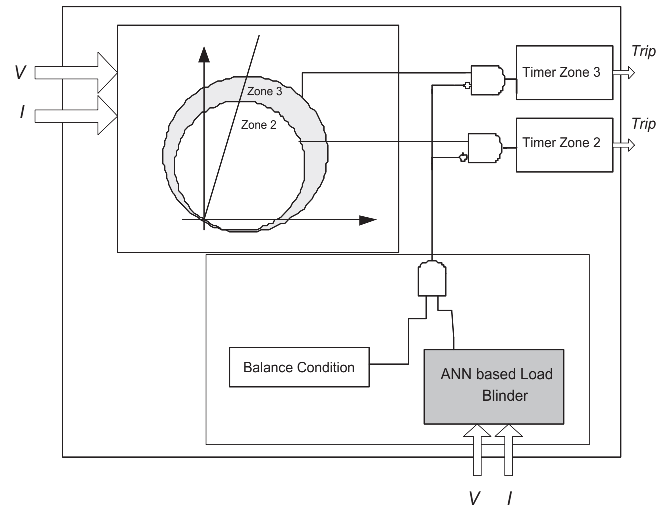

Fig. 2. The structure of the proposed scheme.

with a threshold (0.1 p.u. on a base of 1500 A in this paper). A condition is detected as a balancing condition if the negative-sequence current is less than the threshold.

2.2. ANN-based load blinder

The block diagram of the proposed ANN-based load blinder scheme is shown in Fig. 3. The details are discussed as follows.

2.2.1. Preprocessing

The input current and voltage signals to the preprocessing module are sampled at 1 kHz. A 2-sample FIR digital filter removes the dc component, which enhances the training capabilities of the ANN. Next the full cycle discrete Fourier transform (DFT) algorithm is applied to obtain the phasors (including magnitudes and angles) of voltage and current signals. The preprocessing stage can significantly reduce the size of the neural networks based classifiers, which in turn improves the performance and speed of the training process [17].

2.2.2. ANN inputs

One of the keys to the success of any ANN application is the choice of input signals. After analyzing different factors such as current and voltage magnitudes, impedance, change rate of voltage, current, and power, we have chosen active power, reactive power, voltage, the change rate of phase A voltage, and the change rate of phase A current as input signals to ANN. The change rate of voltage and current are defined as follows:

$$\Delta I_A = I_A(n) - I_A^*(p) \quad (1)$$

$$\Delta V_A = V_A(n) - V_A^*(p) \quad (2)$$

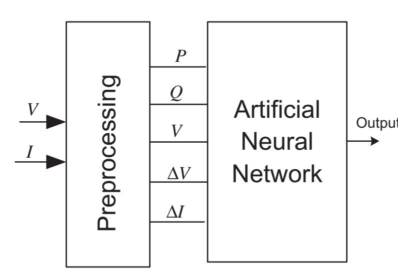

Fig. 3. The structure of ANN-based load blinder.

$$n = kN + p \quad 0 \le p < N$$

where n is the sample index and N is the number of samples per cycle; I_A and V_A correspond to phase A current and phase A voltage at the current cycle; I_A^* and V_A^* correspond to phase A current and phase A voltage at one cycle before the fault occurrence, respectively. For better performance, inputs are scaled to have a maximum value of 1 and a minimum value of −1. As shall be seen, the ANN with the proposed inputs is able to discriminate between different loads and different faults.

2.2.3. ANN output

The ANN has one node in the output layer with output ranging from 0 to 1. For the purpose of classification, any case with an output less than the pre-specified threshold value of 0.5 is classified as a fault case, thus no blocking signal is produced. Otherwise, the case is recognized as a heavy-load case and a blocking signal is produced.

3. Test of the proposed ANN-based load blinder

The proposed ANN-based load blinder scheme is extensively tested under various conditions. For the studies performed, the proposed load blinder scheme is able to correctly classify different kinds of conditions and discriminate between faults and heavy loads. The simulation of power system conditions, and the training and testing of the ANN-based load blinder scheme are discussed as follows.

3.1. Power system simulation and pattern generation

Using an electro-magnetic transient program EMTDC [18], a multi-machine three-phase 345-kV power system has been simulated for the study of transmission line protection. The one-line diagram of the system in study is shown in Fig. 4. In this paper, we consider a distance relay installed on the bus A end of line AB, the length of which is 150 miles. This distance relay operates as the backup protection for line BC by using zone 3. The length of line BC is also 150 miles. Table 1 shows the parameters of line AB. Table 2 shows the ratios of the current transformer (CT) and the capacitive voltage transformer (CVT) installed at bus A.

As shown in Table 3, different system conditions are simulated to generate training patterns for the load blinder. These conditions include heavy loads, faults at different locations with different power angles, three-phase faults with various fault resistance, and three-phase faults during heavy loads.

The training data sets are generated using EMTDC software and then converted to a format that can be used by the training algorithms in MATLAB. The ANN training continues until the error reaches an acceptable level.

3.1.1. Distance relay model

Fig. 5 shows the block diagram of the distance relay used for evaluating the load blinder. Three-phase voltage and current input signals are processed by 2nd-order low-pass Butterworth filters and a 2-sample Finite Impulse Response (FIR) digital filter is used to remove the dc component. After the preprocessing, the voltage and current phasors are input to the three zones. Each zone has six impedance measuring units, a logic unit, and a phase selector. The logic unit issues suitable order based on the results obtained from the phase selection and impedance measuring units. Table 4 shows the settings of distance relay's three zones at secondary side. In Table 4, Zr represents reach impedance and MTA represents the maximum torque angle of the MHO characteristics.

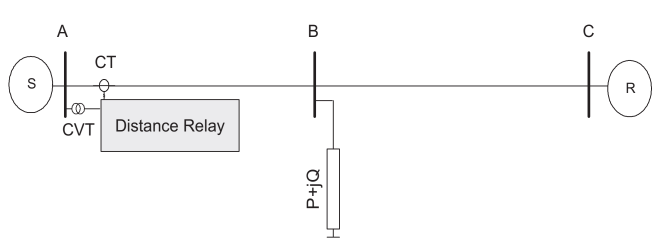

Fig. 4. Model of the simulated power system.

Table 1
Parameters of the simulated transmission lines.

$R1$ (ohm/mile)	$X1$ (ohm/mile)	Emergency power rating	Emergency power rating for 15 min
0.01650	0.5133	717 MVA (1200 A)	956 MVA (1600 A)

Table 2
CT and CVT ratio.

CT ratio	1500:5
CVT ratio	345000:110$\sqrt{3}$

Table 3
Training patterns.

Fault location (mile)	10, 30, 60, 80, 120, 140, 170, 200, 225, 250, 275, 300
Fault inception angle (°)	Different values between (0–360) with a step of 45
Fault resistance (ohm)	0, 4, 8, 12, 16, 20
Load (MVA)	100–950
Load angle (°)	Different values between (−60 to 60) with a step of 15
Source impedance ratio (SIR)	0.5, 5, 10, 15

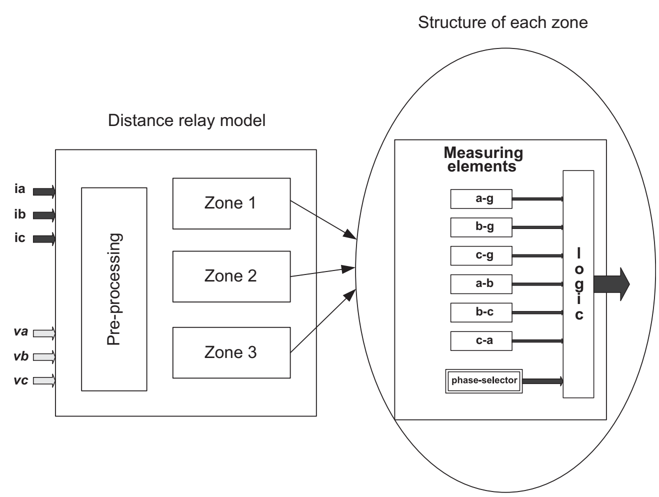

Fig. 5. The block diagram of the distance relay.

3.2. ANN training

Multilayer feedforward networks were chosen to process the input data. The architecture of the neural network is determined empirically, involving training and testing a different number of layers and neurons. To choose the neural network, a few different

Table 4
Distance relay zone settings.

Zone	Zr (ohm)	MTA (degree)	Time delay (ms)
1	10.8648	85	–
2	15.3385	85	200
3	28.1206	85	800

network structures with appropriate number of neurons in their hidden layers were considered. Different networks with one and two hidden layers were considered and trained. It was found that the networks with reasonable number of neurons in their only hidden layers can not cover some of the extreme cases. On the other hand, networks with two hidden layers provided better results without having to have high number of neurons in their only hidden layers. The number of neurons for the two hidden layers is 10 and 5, respectively. As explained in Sections 2.2.2 and 2.2.3, there are 5 neurons in the input layer and 1 neuron in the output layer. A tan-sigmoid function is used as the activation function for the hidden layer. A sigmoid function is used for the output layer.

Various networks with different number of neurons in their hidden layer were trained with both conventional Back-Propagation (BP) and Marquardt–Levenberg (ML) algorithms [17,19]. While BP is a steepest descent algorithm, ML algorithm is an approximation to the Newton's method. The ML algorithm is a nonlinear least square algorithm applied to learning of the multilayer perceptrons. The Marquardt–Levnberg update rule is:

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \tag{3}$$

where J is the Jacobian matrix of derivatives of each error to each weight, μ is a scalar and e is an error vector. If the scalar μ is very large, the above expression approximates gradient descent, while if it is small then it becomes the Gauss–Newton method.

The comparison between learning rate of BP and ML algorithms for the selected network is presented in Fig. 6. As shown in this figure, the ML algorithm training is faster. It is also found that the networks trained with the ML algorithm provide better results compared with the results of the networks trained with the BP algorithm. Therefore, it was decided to use the ML training algorithm for this application.

3.3. Initial tests

A validation data set consisting of different fault scenarios is generated using the power system model shown in Fig. 4. Patterns of the validation data set are different from those used to train the neural network. In the validation set, system operating conditions, fault locations, fault inception angles, SIRs, pre-fault power flow directions, and loads with different power factors are changed to investigate their impacts on the performance of the proposed algorithm. Table 5 shows different conditions for generating the testing pattern data. The major differences between the training patterns in Table 3 and the testing patterns in Table 5 include different load conditions (e.g., MVA load and load angle), different system conditions (e.g., SIR), and different fault conditions (e.g., fault location, fault inception angle, and fault resistance).

The performance of the proposed ANN-based load blinder scheme is compared to a conventional load blinder modeled and a load encroachment method.

3.3.1. Conventional load blinder

Fig. 7 shows the characteristics of a conventional load blinder. The blinder restrains the operation of the distance element for load impedance that appears to the right of the blinder. If the impedance seen by the relay is within the Mho characteristic and to the left of the blinder, it is allowed to operate and trip the breaker. Based on Fig. 6, some areas of zones 2 and 3 will be lost.

The NERC recommendation [5,20] is used to set this conventional blinder. As per NERC Task Force requirements, phase distance settings and other applicable phase and ground distance zone settings must permit loading of the line, without trip, up to 150% of emergency line ampere rating and 115% of short duration (15 min) emergency line ampere rating, with 0.85 per unit bus voltage and a load angle of 30°. Considering the above guidelines, the load blinder element is set to prevent the tripping of the distance protection element on load.

The settings of the load blinder based on NERC recommendation can be calculated as follow:

Table 5
Testing patterns.

Fault location (mile)	5, 40, 75, 100, 125, 140, 175, 210, 220, 250, 280, 300
Fault inception angle (°)	Different values between (0–360) with a step of 25
Fault resistance (ohm)	0, 1, 5, 10, 15, 20
Load (MVA)	100–950
Load angle (°)	Different values between (−60 to 60) with a step of 5
Source impedance ratio (SIR)	0.5, 5, 10, 12.5, 15

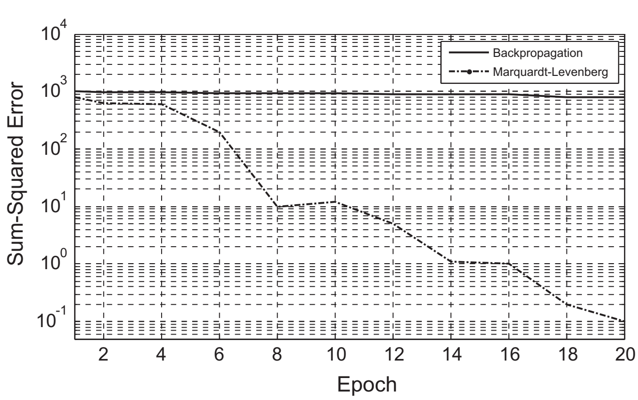

Fig. 6. Variation of error during the training process.

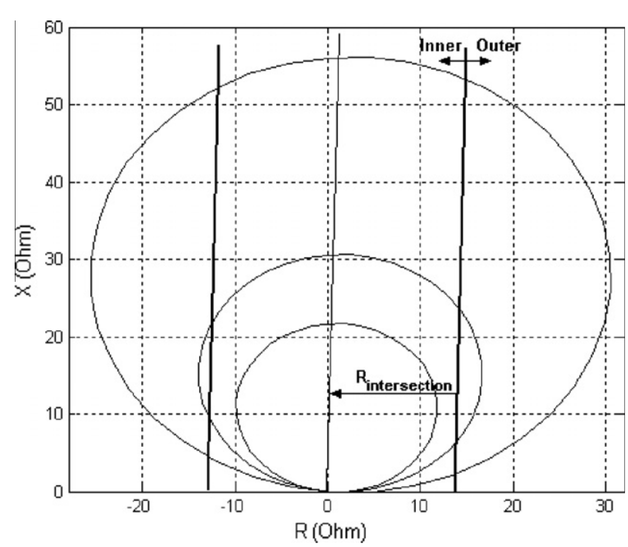

Fig. 7. Load blinder characteristics.

$$Z_{1relay-30} = \frac{0.85 * V_{L-L}}{\sqrt{3} \times 1.5 \times I_{emergency}} \times \frac{CTR}{VTR} = \frac{0.85 * 345,000}{\sqrt{3} \times 1.5 \times 1600} \times \frac{1500/5}{345/(0.110\sqrt{3})} = 15.58 \quad (4)$$

$$Z_{2relay-30} = \frac{0.85^* V_{L-L}}{\sqrt{3} \times 1.15 \times I_{emergency\_15\_minute}} \times \frac{CTR}{VTR} = \frac{0.85^* 345,000}{\sqrt{3} \times 1.15 \times 1600} \times \frac{1500/5}{345/(0.110\sqrt{3})} = 15.24 \quad (5)$$

$$Z_{relay-30} = \min\{Z_{1relay-30}, Z_{2relay-30}\} = 15.24 \quad (6)$$

where $Z_{1relay\text{-}30}$ is the relay reach in secondary Ohms at a 30° power factor angle for emergency current rating, $Z_{2relay\text{-}30}$ is the relay reach in secondary Ohms at a 30° power factor angle for 15-min emergency rating, $V_{L\text{–}L}$: is the rated line to line voltage, $I_{emergency}$: is the emergency current rating, $I_{emergency\_15\_minute}$: is the 15-min emergency rating current, CTR is the current transformer ratio, VTR is the voltage transformer ratio.

The intersection resistance for load blinder can be calculated using the following equation.

$$R_{intersection} = \mathrm{Re}(Z_{relay-30}) - \mathrm{Im}(Z_{relay-30}) / \tan(Angle_{line}) = 12.96 \quad (7)$$

3.3.2. Conventional load encroachment method

Load encroachment method is another conventional scheme used to block distance relay for heavy load conditions. In this method, the load encroachment regions are defined in the impedance plane, and the operation of the three-phase distance elements is blocked if the positive sequence impedance lies within the defined regions. Fig. 8 shows the characteristics of a load encroachment. The blinder is basically formed from an under-impedance circle, with radius set by the user and two blinder lines crossing through the origin of the impedance plane. It cuts the area of the impedance characteristic that may result in an operation under maximum dynamic load conditions.

The load encroachment element has to be set to prevent the tripping of the distance protection element on load based on NERC recommendation. The radius of the circle should be less than the $Z_{relay\text{-}30}$ and the blinder angle could be set to 35°.

3.3.3. Performance analysis

The performance of the conventional load blinder, the conventional load encroachment method, and the proposed ANN-based load blinder scheme has been checked for two cases: a heavy load condition and a three-phase fault with fault resistance.

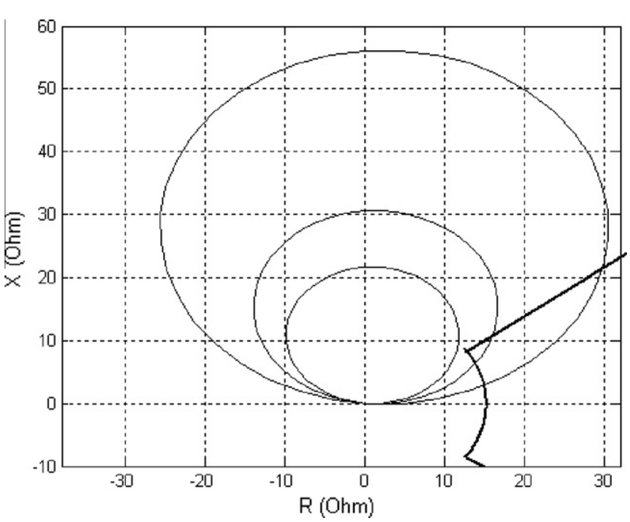

Fig. 8. Load encroachment characteristics.

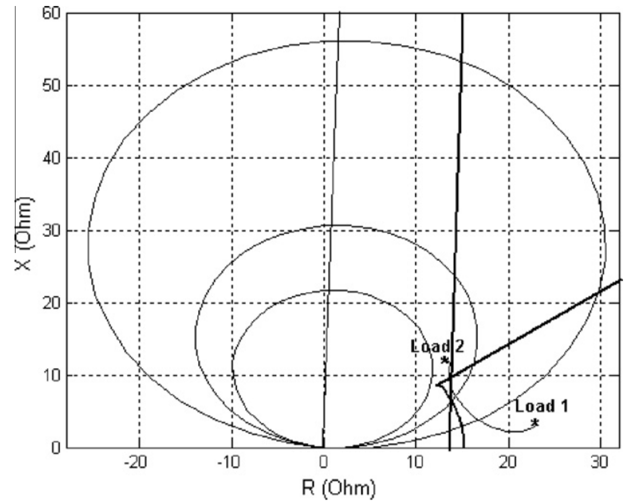

Fig. 9. Impedance loci for a heavy load.

Fig. 9 shows the change of the impedance seen by distance relay from a normal load with S = 660 MVA, pf = 0.988, V = 0.90 p.u. (Load 1) to a heavy load with S = 813 MVA, pf = 0.755, V = 0.85 p.u. (Load 2). The power factor of 0.755 in this case in not usual. However, it is possible under unusual system conditions where significant amounts of reactive power are being transmitted [1]. In Fig. 9, the high load impedance (Load 2) seen by the distance relay is in the second zone. The distance relay will operate with the conventional load blinder or load encroachment method. Fig. 10 shows the R and X seen by the distance relay, the output of the ANN-based scheme, and the output of the conventional scheme. In this case, the load changes from the normal load (Load 1) to the high load (Load 2) at 0.4 s. It can be seen that the ANN-based load blinder keeps blocking for this un-faulty case while the conventional load blinder resets the blocking signal after sometime and lets the relay operate for this un-faulty case.

The impedance loci for a three-phase fault at 200 miles from bus A and with 20 ohms fault resistance are shown in Fig. 11. The conventional load blinder blocks the relay's operation for this fault since the impedance is to the right of the blinder. Fig. 12 shows this mal-operation. It can be seen from Fig. 11 that the ANN-based scheme and load encroachment method release the

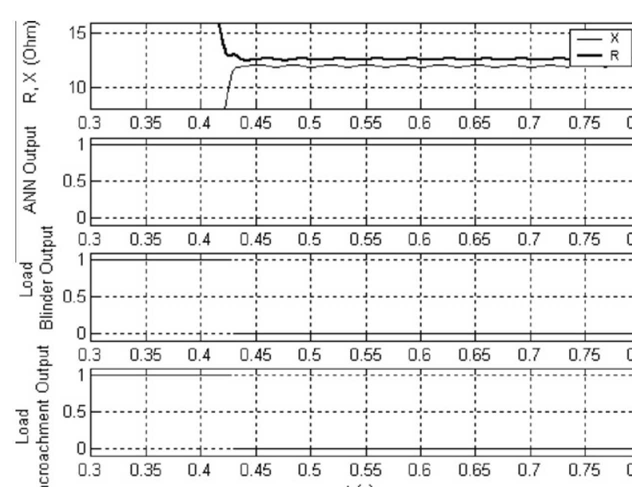

Fig. 10. The performance of the ANN-based and conventional load blinder schemes for a heavy load.

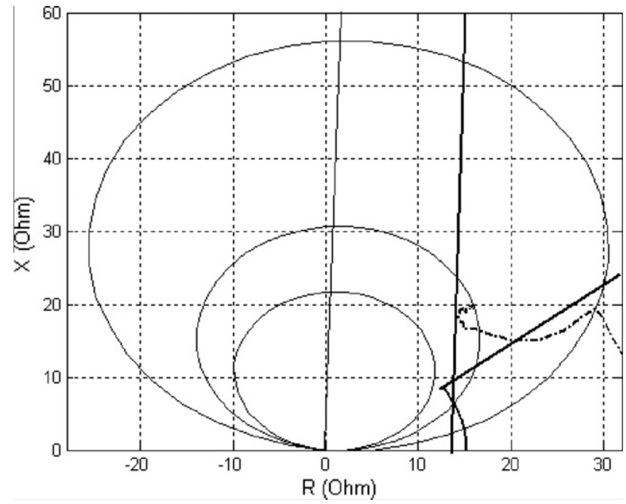

Fig. 11. Impedance loci for a three-phase fault.

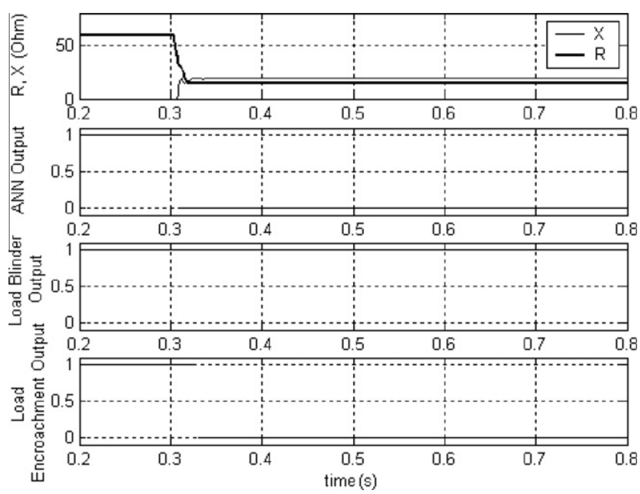

Fig. 12. The performance of ANN-based and conventional load blinder schemes for a three-phase fault.

blocking signal after a while and let the distance relay at bus A serve as remote backup protection for the distance relay at bus B. It can also be seen from Fig. 12 that the ANN-based scheme operates faster than load encroachment.

3.4. Additional test

Table 6 shows the performance of the proposed load blinder, the conventional load blinder, and the load encroachment method for different loads. It can be seen that the conventional load blinder and load encroachment method do not operate correctly for some heavy loads with load power angle more than 30°. But the ANN-based scheme is able to block distance relays for all cases, even for loads with very low power factor (large load power angle).

The performance of the proposed load blinder has also been checked for faults with different fault resistances. The results are shown in Table 7. It can be seen that the conventional load blinder and load encroachment method block the relay for some faults with fault resistance, especially when the sending source is weak and receiving source is strong. In comparison, the ANN-based scheme is always robust and does not block distance relay for all faulty conditions.

Table 6
Load blinder performance for different loads.

Load power (MVA)	Δ (°)	VB (p.u.)	ANN-based load blinder	Load enc.	Conventional load blinder
950	35	0.90	Block	Block	–
900	40	0.90	Block	–	–
770	45	0.85	Block	–	–
800	40	0.85	Block	–	–
920	35	0.85	Block	Block	–
700	30	0.85	Block	Block	Block
850	0	0.90	Block	–	Block
700	55	0.95	Block	–	–
720	60	1.00	Block	–	–

δ: load angle; VB: bus voltage; Load enc.: load encroachment.

Table 7
Load blinder performance for different faults.

Zs/Zr	δ (°)	Rf (Ω)	Lf (mile)	ANN-based load blinder	Load enc.	Conventional load blinder
5	30	10	140	–	–	–
10	−30	20	160	–	Block	Block
10	15	12	220	–	–	Block
10	−30	25	190	–	Block	Block
5	30	9	250	–	–	Block
10	−10	15	200	–	–	Block
10	30	20	185	–	–	Block

Rf: fault resistance; Lf: fault location.

4. Conclusions

Cascading trips caused by backup relays due to transmission line overload are a severe threat to power system stability and security. In this paper a new load blinder scheme is presented and its effectiveness is demonstrated. The proposed approach is based on the use of neuro-computing technology and implementation of pattern recognition concepts. A comprehensive set of simulation results has shown that a distance relay employing the proposed method has no problems of mal-operations caused by heavy loading associated with conventional distance relays. The proposed scheme is able to prevent distance relay from operation for different usual and unusual heavy loads and does not block distance relay for three-phase fault with fault resistance. The performance of the proposed scheme has been evaluated by comparing its results with the results obtained from a conventional load blinder and a load encroachment method. Test results indicate that in general the proposed relay performs more reliably. Thus, this paper presents an approach to improving the performance of conventional load blinders.

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