Application of Cascade Correlation Neural Network in Modelling of Overcurrent Relay Characteristics

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Abstract — Modelling of Overcurrent (OC) relays with inverse time relay characteristics is a vital job for coordination of these relays. There are many publications in which the OC relay characteristics have been modelled. In this paper a new model based on cascade correlation neural network is proposed. The cascade correlation neural network is used to calculate operating times of OC relays for various Time Dial Settings (TDS) or Time Multiplier Settings (TMS). This method can cover nonlinearity of the characteristic and its accuracy is much higher than the polynomial and the other neural networks models such as perceptron and backpropagation neural networks models.

The method is tested on three types of OC relays and the results obtained shows, the accuracy of the new method is higher and therefore it is more useful than the others. The model is validated by comparing the results obtained from the new method with nonlinear analytical, perceptron and backpropagation neural networks models.

Index Terms — Overcurrent Relay, Relay Coordination, Relay Modelling, Neural Network, Cascade Correlation

I. Introduction

Many attempts have been used in the past to coordination different types of OC relays with inverse time-current characteristics [1, 2, 3]. To coordinate OC relays in a network, time-current (TC) curves are modelled and stored in the computer [4, 5]. If the relays characteristics are not modelled well, the settings of the relevant relays may not be accurate. Therefore maloperation of protection system may occur during fault appearance.

Each OC relay posses many Time-Current (TC) curves which must be represented in a computer [6]. The simplest method for modelling OC relay is based on specify points of characteristic's curve for different TDS/TMS and store in the memory of the computer. If the operating point does not match with one set of the stored values, then an interpolation is necessary to determine the corresponding time or TDS/TMS. Therefore, the problems with this method are due to large space memory of the computer [7]. For the midpoints, interpolation is necessary otherwise, the accuracy is disturbed.

Another way is software models. Software models of OC relay characteristics play a major role in coordinating protection schemes of power systems [8].

In other methods, the relay characteristics are modelled mathematically by polynomial form. In these methods the variation of t versus TDS is assumed linear. Reference [9] shows that Sachdev models are simple and have useful polynomials for modelling OC relays for coordination purposes.

Recently a method based on fuzzy logic and perceptron neural network has been presented [10].

In this paper a new model, which is more accurate than analytical models and other neural networks models and does not have difficulties of look up table method, based on cascade correlation artificial neural networks for OC relays is proposed.

The new model has accurate estimation for operation times of the OC relays when the operating times of an OC relay lay over a vast area. Cascade correlation neural network has simpler training rules, minimum topology (because of its dynamical training algorithm) and high accuracy than the other neural networks.

The proposed model is tested on three types of OC relays. The results are compared with nonlinear analytical, perceptron and backpropagation neural networks models and from them it will be shown that the results of the new method are much accurate than the others.

II. CASCADE CORRELATION NEURAL NETWORK

Cascade correlation neural network is a network in witch the modification is made in training algorithm [11]. The most significant difficulty with current learning algorithms for neural networks such as backpropagation, is their slow rate of convergence. This is due to the fact that all of the weights are being adjusted at each stage of training. A further complication is the rigidity of the network architecture throughout training [11, 12, 13, 14].

In other word, overcurrent relay characteristics modeling using perceptron and backpropagetion neural networks needs two nodes in the input layer, 108 nodes in the hidden layers and one node in the output layer [10]. Therefore, their topologies are very complicated and their training is too difficult. To solve this problems, cascade correlation neural network for relay modeling is used and described below.

Cascade Correlation network addresses both of these issues by dynamically adding hidden units to the architecture, but only up to the minimum number necessary to achieve the specified error tolerance for the training set. Furthermore, a two-step weight-training process admits that only one layer of weights is being trained at any time. This allows the use of simpler training rules (the delta rule, perceptron etc.) than for multi layer training. In practice, a modification of back propagation algorithm known as Quick Propagation is usually used [11, 15].

A cascade correlation net consists of input units, hidden units, and output units [12]. At first, input units are connected directly to output units with adjustable weighted connections. Connections from inputs to a hidden unit are trained when the hidden unit is added to the net and are then frozen. Connections from the hidden units to the output units are adjustable consequently.

Cascade correlation network starts with a minimum topology, consisting only of the required input and output units and a bias input that is always equals to 1. This net is trained until no further improvement is obtained. The error for each output is then computed by summing over all training patterns.

Next, one hidden unit is added to the net in a two steps process. In the first step, a candidate unit is connected to each of the input units, but is not connected to the output units. The weights on the connections from the input units to the candidate unit are adjusted to maximize the correlation between the candidate's output and the residual error at the output units. The residual error is the difference between the target and the computed output, multiplied by the derivative of the output unit's activation function, i.e., the quantity that would be propagated back from the output units in the backpropagation algorithm. When this training is completed, the weights are frozen and the candidate unit becomes a hidden unit in the net.

The second step in which the new unit is added to the net now begins. The new hidden unit is then connected to

The output units and the weights on the connections are adjusted. Now all the connections to the output units are trained. Here the connections from the input units are trained again, and the new connections from the hidden unit are trained for the first time.

After that, a second hidden unit is added using the same process. However, this unit receives an input signal from the both input units and the previous hidden unit. All weights on these connections are adjusted and then frozen. The connections to the output units are then established and trained. The process of adding a new unit, training its weights from the input units and the previously added hidden units, and then freezing the weights, followed by training all connections to the output units, is continued until the error reaches an acceptable level or the maximum number of epochs (or hidden units) is reached.

This process is shown in figures 1 to 5.

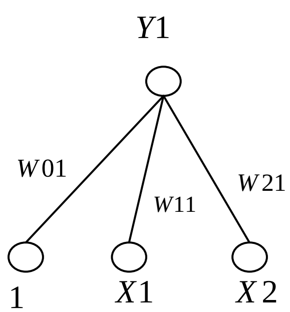


Fig. 1. Stage 0, no hidden units

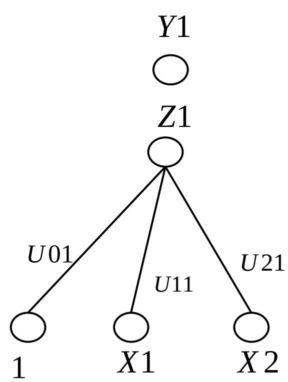


Fig. 2. Stage 1, one candidate unit (z1)

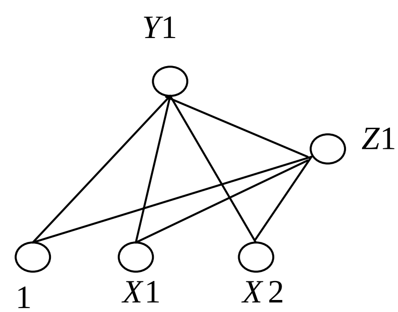


Fig. 3. Stage 1, one hidden unit (z1)

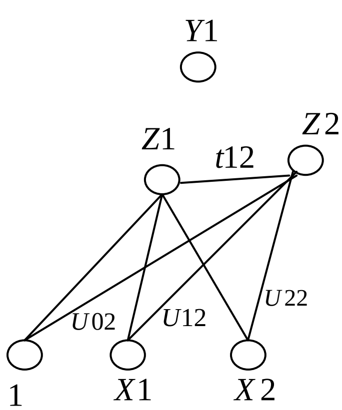


Fig. 4. Stage 2, new candidate unit (z2)

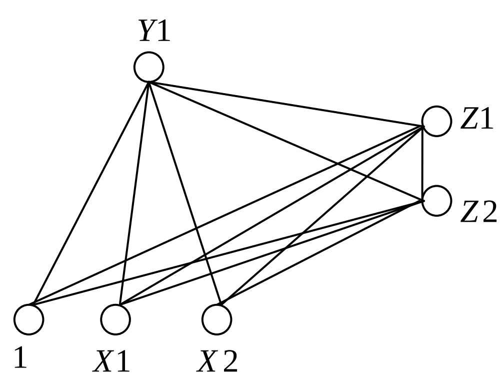


Fig. 5. Stage 2, hidden unit (z2)

As mentioned in introduction and the reasons described the beginning of this section, cascade correlation shown in figures 1 to 5 is used for considering nonlinearity relationship between operating times and their TDS/TMS in OC relay modelling.

The cascade correlation neural network has two nodes in the input layer, two nodes in the hidden layer and one node in the output layer. The current multiplier setting and TDS/TMS are selected as input data. These are shown in figures 1 to 5 as X1 and X2. The output of the neural network is operating times and shows as Y1. It should be noted that Z1 and Z2 are hidden nodes and W, U and t are weights between input-output, hidden-output and hidden nodes respectively. The ways of calculating the weights have been described before in this section. The input data are normalized before applying to the neural network, because normalizing improves the learning process of neural network.

The output layer's activation function is linear and the hidden layer's activation function is sigmoid. The random values of initial weights are between -0.5 and 0.5.

As described in this section, cascade correlation neural network has simpler training rules, minimum topology because of its dynamical training algorithm and in the next section it will be shown that it possess high accuracy than the other neural networks.

III. Case study

Three types of OC relays were used for testing the new method. These are RSA20, CRP9D and SIEMENS 75K88. Relay RSA20 is inverse electromechanical OC relay. Relay CRP9D is very inverse relay and the third one is an inverse static OC relay. TDS of first two relays varies from 4 to 20 and TMS of the third one varies from 0.05 to 0.5. The sampled data of the relay are illustrated in Fig. 6, Fig. 7 and Fig. 8 for relays modelling, however, additional sampled data shown in Fig. 9 and 10 are used for testing and comparing between the analytical, backpropagation, perceptron neural networks with proposed model. For SIEMENS 75K88, data in Fig. 8 are used for training and testing the cascade correlation, perceptron and backpropagagtion neural networks.

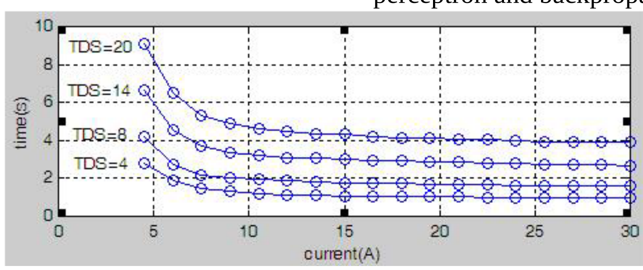


Fig. 6. time-current curve of RSA20 OC relay when TDS=4, 8, 14 and 20

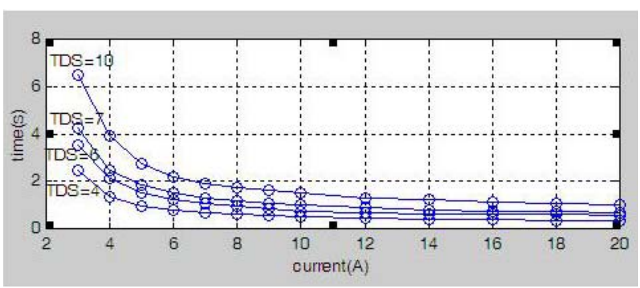


Fig. 7. time-current of CRP9D OC relay when TDS=4, 6, 7 and 10

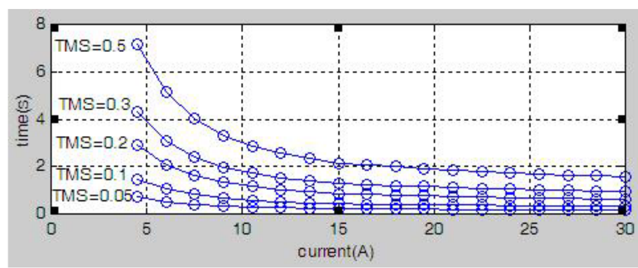


Fig. 8. time-current of SIEMENS 75K88 OC relay when TMS=0.05,0.1,0.2,0.3 and 0.5

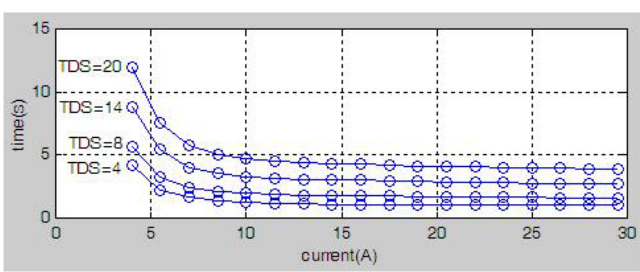


Fig. 9. Test time-current of RSA20 OC relay when TDS=4, 8, 14 and 20

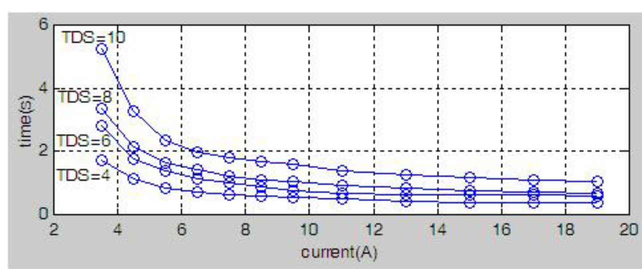


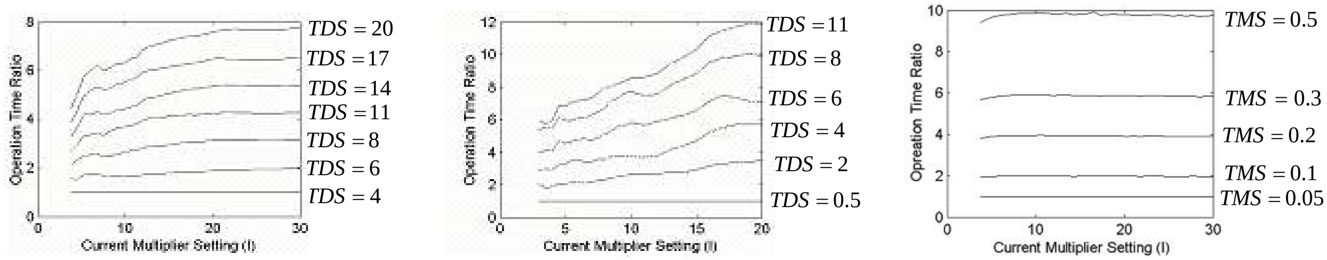
Fig. 10. Test time-current of CRP9D OC relay when TDS=4, 6, 8 and 10

The sampled data are obtained by performing experimental tests five times using an accurate computerised relay tester for RSA20, CRP9D and SIEMENS 75K88 relays, to make sure the measurements results are correct.

The relationship between the operating times of an OC relay and its TDS/TMS is not usually linear. As an example in Fig. 11-a, when TDS is 20, the operating time of the relay RSA20 is not five times the relevant time for TDS=4 for the same current multiplier setting. This is also true for the relay CRP9D, which is shown in Fig. 11-b.

However, for static relay the relationship between operating times and its TDS/TMS are linear than the electromechanical relay then the curves convert to horizontal direct lines. It has been shown for SIEMENS 75K88 in fig 11-c.

But for both type of static and electromechanical relays the effect of nonlinearity in low current settings are higher than the other points.



a) The operation time ratio of RSA20 when the operating times for TDS=4 are referenced

b) The operation time of CRP9 when the operating times for TDS=0.5 are referenced

c) The operation time of SIEMENS 75K88 when the operating times for TMS=0.05 are referenced

Fig. 11. The operating time relation of different time multiplier setting

The new method is compared with the nonlinear analytical and neural network combined with fuzzy model published in reference [10].

The analytical equation model is illustrated as Eq. (1)[9].

$$g(x) = b_0 + b_1.x + b_2.x^2 + ... + b_6.x^6 \qquad (1)$$

Where, x is TDS or TMS.

The coefficients of Eq. (1) are obtained by curve fitting techniques and the number of the coefficients is limited to six. This is because of ill-structure matrices and poor outputs for the coefficients number higher than six. The input data for curve fitting are the sampled operating times of different TDS/TMS of an OC relay for a given current multiplier settings shown in table 1.

Hence, for each current multiplier setting there is a different set of data and different coefficients. For example if for I=6, the coefficients of analytical model for a TDS/TMS relay curve is computed, for other currents, let say I=4, different coefficients will be obtained. Therefore different error percentages will be for the same TDS/TMS curve. It means that for each value of current multiplier setting, there is a specific equation. But for the mathematical nonlinear model of OC relay, only one equation must be selected. It is not straightforward, because in the protection of power systems, OC relays are set and operates under a wide range of current multiplier setting. Therefore, each equation produces some errors when a relay operates in a section, which is different from the section for which data is sampled. This is the problem of nonlinear analytical model, which neural network model does not have.

The coefficients of Eq. (1) are shown in Table 1 for RSA20, CRP9D and SIEMENS 75K88 respectively. For each relay, the current multiplier setting (I) has different values, which vary from 6 to 18.

Table 1. Analytical polynomial coefficients for three type OC relay when I=6, 12 and 18

Relay type	RSA20 OC			CRP9D			SIEMENS 75K88		
Coefficient	Poly1, I=6	Poly2, I=12	Poly3, I=18	Poly1, I=6	Poly2, I=12	Poly3, I=18	Poly1, I=6	Poly2, I=12	Poly3, I=18
b_0	1.1908	1.0249	1.0611	0.0506	1.0249	1.0611	0.0151	0.0110	0.0178
b_1	-5.1414	-1.8461	-1.8543	-0.0415	0.0481	0.0512	19.7707	19.8323	19.6986
b_2	79.6322	55.4136	50.6364	8.2619	-0.2763	0.5123	-1.6610	-1.4216	-1.3449
b_3	-188.3968	-110.2849	-79.6902	-42.5388	8.6108	-3.5950	2.1520	2.1292	2.1110
b_4	230.5395	108.2454	36.1614	102.0402	-39.2359	15.2354	-0.1059	-0.1053	-0.1046
b_5	-140.4977	-48.5280	24.4574	-06.9288	89.8343	-14.5460	--	--	--
b_6	33.6731	6.9750	-19.8040	40.1574	34.3761	-1.4435	--	--	--

For each relays, RSA20, CRP9D OC and SIEMENS 75K88 relays, comparisons are made between the result of the cascade correlation neural network model and those of the analytical, perceptron and backpropagation neural networks models. All of the models calculate the operating time of OC relay for different current multiplier settings, i.e., when TDS=14 for RSA20, TMS=0.4 for SIEMENS 75K88 and TDS=7 for CRP9. The results are shown in Table 2, Table 3, Table 4 and table 5.

The results of the new method developed in this paper are shown in column 2 of the tables 2, 3 and 4. In the other columns the results of back propagation and perceptron neural networks and analytical method which has been published in reference [10] are again shown for comparison with column 2. To show its flexibility and accuracy of the new method the results of cascade correlation neural network and the existing methods for relay SIEMENS 75K88 which have not been shown before even for the previous methods are illustrated in table 4. The first column of Table 2, Table 3 or Table 4 gives different values of current multiplier settings (I). Columns poly1 to poly3 refer to the obtained results by

Eq. (1) for the three columns of Table 1, as coefficients for RSA20, CRP9D or SIEMENS 75K88 relays.

Table 2. Error percentages of calculated operating time of RSA20 OC relay for TDS=14 when I=6, 12 and 18

I	CC Neural	BP Neural	Perceptron Neural	Poly 1	Poly 2	Poly 3
6	1.9870	2.1940	2.1941	0.3335	16.4352	19.1328
12	0.2109	0.4173	4.0419	12.4598	2.2686	4.6380
18	0.0406	0.8463	0.0511	20.6734	7.3268	5.1798

Table 3. Error percentages of calculated operating time of CRP9D OC relay for TDS=7 when I=6, 12 and 18

I	CC Neural	BP Neural	Perceptron Neural	Poly 1	Poly 2	Poly 3
6	1.0139	1.5477	2.7357	8.8928	19.1230	6.2242
12	1.2061	1.7469	6.3199	2.1858	7.0036	4.5828
18	0.4218	2.5527	0.7215	16.5961	27.5499	13.7387

Table 4. Error percentages of calculated operating time of SIEMENS 75K88 OC relay for TMS=0.4 when I=6, 12, 18 and 24

I	CC Neural	BP Neural	Perceptron Neural	Poly 1	Poly 2	Poly 3
6	0.0772	0.0967	0.0972	0.2009	0.5345	0.0777
12	0.0224	0.0204	0.0244	0.8345	0.1038	0.5576
18	0.0633	0.0869	0.0945	0.3207	0.4138	0.0424

Table 5. error percentage average of each method of three types of OC relays

Average of error percentage	RSA20	CRP9D	SIEMENS 75K88
CC neural net	0.7462	0.8806	0.0543
BP neural net	1.1525	1.9491	0.0680
Perceptron neural net	2.0957	3.2590	0.0720
Poly 1	11.1556	9.2249	0.4520
Poly 2	8.6769	17.8922	0.3507
Poly 3	9.6502	8.1819	0.2259

The results of RSA20 OC relay in Table 2 show that the error percentage of the cascade correlation neural network model for I=6 is 1.9870 percent, while for backpropagation and perceptron neural networks and analytical nonlinear model showing in columns Ploy 1, 2 and 3 are 2.1940, 2.1941, 0.3335, 16.4352, 19.1328 respectively. Even for most cases, the error of the cascade correlation neural network method is less than for the backpropagation, perceptron neural networks and Poly 1, which is the analytical model with smallest error. The comparison shows the error percentage of poly 1 changes from 0.3335 to 20.6734 percent, the error percentage of backpropagation neural network is from 0.8463 to 2.1940 and the percentage error of perceptron neural network is from 0.0511 to 2.1941. However for the cascade correlation neural network column is from 0.0406 to 1.9870. In other words, the average and variation error is much lower for the cascade correlation neural network model.

The results in Table 3 show that the proposed model has a good performance. Again, it can be seen from Table 3, that the error percentage of the cascade correlation neural network model changes from 0.4218 to 1.0139 percent, but for the better cases of the analytical model, i.e. ploy 1 and poly 3, they vary from 2.1858 to 16.5961 and 4.5828 to 13.7387 percent, respectively and for the backpropagation and perceptron neural networks model the error percentages vary from 0.5539 to 1.1247 and from 0.7215 to 6.3199 percent

The obtained results from table 4 again show that the error percentage of the new method is lower than the others.

The error percentage average for each method of three types of OC relays are shown in table 5. As it is seen from this table the error percentage averages for RSA20 OC relay in the new method, percepteron and backpropagation neural networks, poly1, poly2 and poly3 are 0.7462, 2.0957, 1.1525 11.1556, 8.6769 and 9.6502 respectively. In other word the accuracy of the new method compared to two others neural networks and three kinds of polynomial methods are 1.5, 2.8, 14.9, 11.6 and 12.9 times. It means that the accuracy of the new method is at least 1.5 times to other methods neural networks. To compare the accuracy of the new method with polynomial method, it can be seen that it's accurate at least 11.6 times to polynomial method. For other types of OC relays i.e. CRP9D and SIEMENS 75K88, table 5 shows that the error percentage average for the new method is again lower than the others.

IV. Conclusion

If the relay characteristics not modelled suitably, error would appear with settings of relays and maloperation of protection system may occur. In the traditional analytical methods the relationship between operating times and their TDS/TMS have been considered linearity while in reality this is not true and therefore the accuracy of the relay settings are disturbed. To increase accuracy, the neural networks may be used. In this paper a new model for OC relays, based on cascade correlation neural network is presented. The validity of the proposed model is achieved by testing of the methods on three types of OC relays. The results show that the error percentages of cascade correlation neural network model for the relays are lower than analytical and backpropagation and perceptron neural networks models. In comparing the results of the new method with the backpropagation and perceptron neural networks models, it is evident that the new model has simpler training rules, minimum topology as well as its high accuracy. This is due to its algorithm ability to train dynamically. It has been shown that the method is flexible and can take into account different relay characteristics with linear and nonlinear features.

V. References

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