ARTIFICIAL NEURAL NETWORKS APPLICATIONS IN DYNAMIC SECURITY ASSESSMENT OF POWER SYSTEMS

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In the dynamic security assessment of power systems, the critical clearing time – CCT is one of the parameter of paramount importance. It constitutes a complex function of the pre-fault system operations conditions, fault type and location and post fault conditions that themselves are dependent on the protective relaying strategy employed. The evaluation of CCT involves elaborate computations that often include time-consuming solutions of non-linear algebraic and differential equations. From the point of view of on-line implementation of CCT assessment, this presents a major difficulty. Application of artificial neural networks – ANNs is a promising alternative. High adaptation capabilities of ANNS enable them to readily synthesize the complex mappings that transform input attributes or features into the single valued space of CCTs. In this paper we examine the generalization capabilities of layered feedforward neural network – LFNN, focusing on their ability to deal with a large range of operation regimes in power system. For CCT assessment, each generator is represented by three features, which can be derived from the measurable parameters of power system. The effectiveness of the proposed neural network based approach is demonstrated on the Test2 system with 13 buses, 5 generators, 15 lines and 8 loads.

Keywords: dynamic security, critical clearing time, artificial neural networks.

1. Introduction

One of the main responsibilities of system operators from control and command centers is to ensure the functioning of the power systems close to predetermined security and quality parameters. The assessment of power systems security is an extremely complex task. To this purpose numerous studies are performed in order to identify the vulnerability level of the power systems in normal operating conditions (static security), as well as in emergency conditions (dynamic security), e.g. subject to a contingency or a fault.

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The fault critical clearing time (CCT) plays an important role when evaluating the dynamic security. The CCT is a complex function of operating conditions before the fault (loading, network topology etc.), fault type and location, and operating conditions after the fault. Furthermore, the latter depend on the system protective relaying strategy. Therefore, the computation of the CCT is an elaborate and time consuming task, as it needs to numerically solve the set of nonlinear algebraic-differential equations describing the dynamic behavior of power systems [1,2].

In practice, there are different methods used to compute the CCT value [2,3]:

- ***Dichotomy search method***: numerical integration of the algebraic-differential equations combined with an dichotomy search process;
- ***Energy function (second Lyapunov function) method***: using the integration of the algebraic-differential equations corresponding to the fault period, the value of an energy function is computed and compared to the previously determined critical value;
- ***Hybrid methods***: combines the numerical integration of the algebraic-differential equations with the equal area method, usually used to determine the fault CCT for a generator connected to an infinite bus scheme.

As can be seen, the numerical integration of the algebraic-differential equations describing the system behavior is part of each one of these methods. This represents a major drawback for on-line applications.

Another promising method to estimate the fault CCT on-line is to use artificial intelligence techniques, particularly Artificial Neuronal Networks (ANN). The main advantage of using ANN to estimate the CCT is represented by the capability to determine, as a result of the learning process, the complex relations that can be used to translate the parameters describing the power system behavior, subject to a specific fault, into an one-dimensional space corresponding to the CCT.

This paper analyses the capacity of a multi-layer perceptron ANN to determine the actual relationship between the power system operating point and the CCT corresponding to a severe fault, e.g. three-phase short circuit.

The ANN input set contains the following parameters describing the generators behaviour at the instant of fault initiation [2,3]:

- *rotor angles* measured with respect to the centre of angle (COA);
- *generators acceleration*;
- *a parameter proportional with the kinetic energy stored in each generator during the fault period.*

All these parameters are determined from the electric state at the fault initiation. Therefore, is not necessary to solve the set of differential equations.

The proposed method was tested on a test system. The obtained results show that the use of LFNN to assess the CCT represents a potential solution for on-line applications.

2. Power system model

In our study, the transient behaviour of a multi-machine power system is described by the classical model in the form of a set of non-linear algebraic-differential equations [1,4]:

- the differential equations describing the rotor dynamics (*swing equation*) of each machines;

$$\begin{aligned} M_i \frac{d\omega_i}{dt} &= P_{m,i} - P_{e,i} - D_i \omega_i \\ \frac{d\delta_i}{dt} &= \omega_0 \omega_i \end{aligned} \qquad i = 1,2,...,m \tag{1}$$

- the algebraic equation of electrical power output of each machine;

$$P_{e,i} = \sum_{k=1}^{m} E_i^{'} E_k^{'} \left[G_{ik}^{red} \cos(\delta_i - \delta_k) + B_{ik}^{red} \sin(\delta_i - \delta_k) \right], i = 1,2,...,m \tag{2}$$

- the complex algebraic equation of electromotive force behind transient reactance of each machine (Fig. 1.);

$$\underline{E}_i^{'} = \underline{U}_i + jX_{d,i}^{'} \underline{I}_{g,i} = E_i^{'} e^{j\delta_i} \qquad i = 1,2,...,m \tag{3}$$

where:

M_i, D_i	are	the inertia and dumping constants;
ω_i	–	the angular velocity of the rotor generator relative to the synchronous reference;
δ_i	–	rotor angle;
$P_{m,i}$, $P_{e,i}$	–	mechanical and electrical active powers;
$E_i^{'}$	–	electromotive force behind transient reactance $X_{d,i}^{'}$;
m	–	number of generators in system.

Bus loads are modeled by constant admittances (Fig. 1.)

$$\underline{Y}_{c,i} = \frac{P_{c,i} - jQ_{c,i}}{\underline{U}_i^*} \qquad i = 1,2,...,n \tag{4}$$

and included in the diagonal terms of the extended network bus admittances matrix, so that the network equations becomes:

$$\left[\begin{array}{c|c} \underline{\mathbf{Y}}_{CC}^{'} & \underline{\mathbf{Y}}_{CG} \\ \hline \underline{\mathbf{Y}}_{GC} & \underline{\mathbf{Y}}_{GG} \end{array}\right] \left[\begin{array}{c} \underline{\mathbf{U}}_{C} \\ \hline \underline{\mathbf{E}}_{G}^{'} \end{array}\right] = \left[\begin{array}{c} 0 \\ \hline \underline{\mathbf{I}}_{G} \end{array}\right] \tag{5}$$

from which we eliminate $\underline{\mathbf{U}}_C$, to find:

$$\underline{\mathbf{Y}}_{nn}^{red}\,\underline{\mathbf{E}}_{G}^{'} = \underline{\mathbf{I}}_{G} \tag{6}$$

where

$$\underline{\mathbf{Y}}_{nn}^{red} = \underline{\mathbf{Y}}_{GG} - \underline{\mathbf{Y}}_{GC}(\underline{\mathbf{Y}}_{CC}^{'})^{-1}\underline{\mathbf{Y}}_{CG} \tag{7}$$

is the reduced bus admittance matrix. The elements $Y_{ik}^{red} = G_{ik}^{red} + jB_{ik}^{red}$ of this matrix are used to compute electrical power output of each generator with (2).

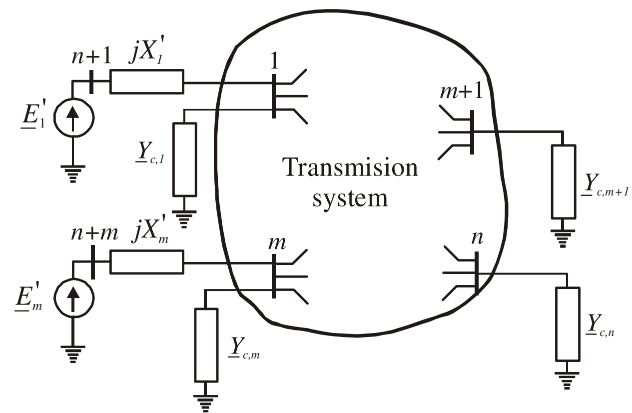


Fig. 1. Multi-machine power system representation (classical model).

3. Neural network and learning algorithms

The Layered Feedforward Neural Network – LFNN, one of the most popular and successful neural network architectures, comprises a number of identical units organized in layers. The units of one layer are connected to those of the next layer so that the outputs of one layer are fed-forward as inputs to the next layer (Fig. 2) [5,6,7,8].

Typically LFNNs are trained using a supervised training algorithm known as “backpropagation”. The learning process in a backpropagation has two steps. In the first step each pattern is presented to the network and propagated forward to the output. In the second one the obtained errors are back propagated and the weights and biases are changed.

There are many variations of the backpropagation algorithm [9]. All of these algorithms are using a gradient method to determine how to adjust the weights in order to minimize a certain performance function. The default performance function for feedforward networks is the average squared error between the network outputs and the target or desired outputs:

$$E = \frac{1}{2}\sum_{k}\left(d_k - o_k\right)^2 \tag{8}$$

where d_k is the desired output for the x_k pattern;

o_k – output of neural network corresponding to the same x_k pattern.

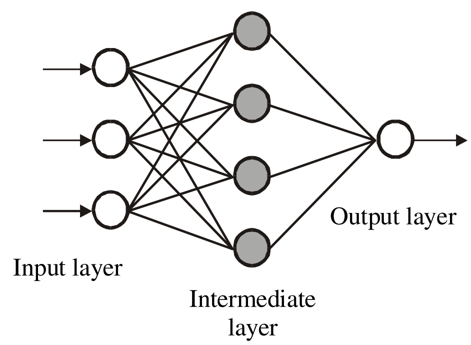


Fig. 2. Structure of a LFNN with a single intermediate layer and a single output

The simplest implementation of backpropagation learning algorithm updates the network weights and biases in the direction in which the performance function decreases most rapidly, i.e. the negative of the gradient. One iteration of this algorithm can be written:

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta \mathbf{G}_k \tag{9}$$

where $\mathbf{w}_k$ is a vector of current weights and biases;

η – the learning rate;

$\mathbf{G}_k$ – the gradient corresponding to step *k*.

There are two different ways in which this gradient descent algorithm can be implemented: incremental mode and batch mode. In the incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In the batch mode all of the inputs are applied to the network before the weights are updated.

The standard backpropagation training algorithms are often too slow for practical problems. Several high performance algorithms that can converge from ten to one hundred times faster were developed. All of these algorithms operate in the batch mode and fall into two main categories. The first category uses heuristic techniques such as variable learning rate backpropagation and resilient backpropagation. The second category of fast algorithms uses numerical optimization techniques: conjugate gradient, quasi-Newton and Levenberg-Marquardt methods.

4. Neural network based critical clearing time assessment. Test results

In this section a LFNN-based approach is suggested for assessing the critical clearing time. The artificial neural network used consists of three layers (Fig. 2): the input layer with $3m$ inputs, one hidden layer with as many units as necessary and a single unit in the output layer.

Input patterns, provided from the dynamic power system model are defined as follow:

- inputs 1 to m are the rotor angles of each generator relative to the inertial center of angle measured at the instant of fault initiation, $t_0 = 0$;

$$I_i = \delta_i(t_0) - \delta_{COA}(t_0) \quad i = 1, 2, ..., m \tag{11}$$

where

$$\delta_{COA} = \frac{\sum_{i=1}^{m} M_i \delta_i}{\sum_{i=1}^{m} M_i} \tag{12}$$

- input $m+1$ to $2m$ are the acceleration of each generator calculated at the moment t_0

$$I_{n_g+i} = \frac{P_{m,i} - P_{e,i}(t_0)}{M_i} \quad i = 1, 2, ..., n_g \tag{13}$$

- input $2m+1$ to $3m$, calculated at the moment t_0 are defined as:

$$I_{2m+i} = \frac{\left(P_{m,i} - P_{e,i}(t_0)\right)^2}{M_i} \quad i = 1, 2, ..., m \tag{14}$$

With the assumption of constant mechanical power $P_{m,i}$ and almost constant generator output power $P_{e,i}$ during fault period, the features defined in Eq. (13) give a measure of rotor angle deviations at the instant of fault clearing relative to their pre-fault values. Under the same assumption the features defined in Eq. (14) provide information about the individual kinetic energy of system generators accumulated throughout the fault period [3].

The effectiveness of the proposed approach has been tested on the TEST2 system with 13 buses, 5 generators, 15 lines and 8 loads (Fig. 2). Network parameters, machines data and nominal operating point are provided in reference [1].

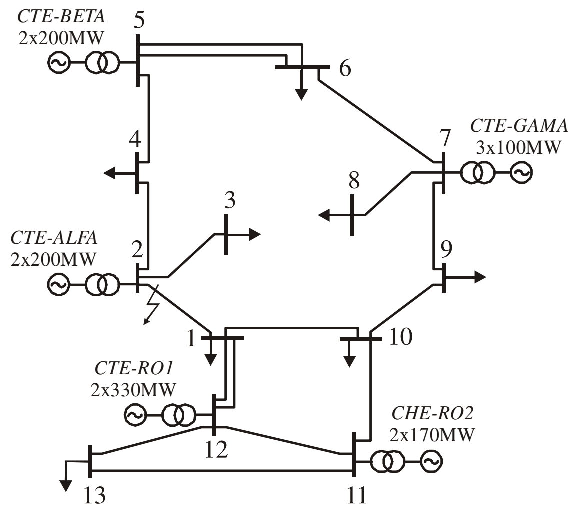


Fig. 2. On-line diagram of the TEST2 System

In this work our goal is to examine the synthesize capabilities of the neural network in the scope of being able to deal with a large range of operating conditions. In this respect, for the basic configuration we considered random variations of the nodes consumed power between –15% and 25%. In this way a number of 5000 operation conditions were generated.

For each generated regime the attributes defined above (Eqs. (12-14)) were calculated. Also the CCT value, representing desired neural network output for each pattern, was calculated using a dichotomy search method. The requested database for training and testing the neuronal network was generated off-line with the support of the EDSA program. A three-phase short-circuit is simulated at the line 1-2 near the bus 2 and the fault clearing policy is to restore pre-fault system configuration.

Out of the 5000 input-output patterns, 3500 were used in the training process and the rest of 1500 in the validation one. Using different fast backpropagation training algorithms from MATLAB Neural Network Toolbox, the 3500 input-output patterns selected for training and a performance goal of 10^{-6}, after many tests, we found out that the optimum LFNN configuration has 6 neurons in the hidden layer.

In order to validate the obtained neuronal network, the 1500 patterns of the testing set were delivered as inputs, and the outputs were compared with the known values.

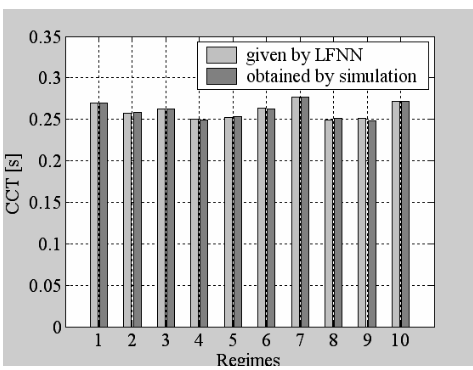
The performances of the chosen training algorithms in terms of number of epochs, as well as those of the corresponding neuronal networks in terms of average and maximum validation errors are presented in Table 1. As can be seen, the fastest training method is Levenberg–Marquardt, the average minimum error is obtained with Quasi–Newton method, and the absolute maximum errors of these two methods are comparable. Considering the value of the average error as main performance parameter, we have chosen the LFNN obtained with the Quasi–Newton method to be used to evaluate new operating conditions (different than those used in the training and validation processes).

Table 1

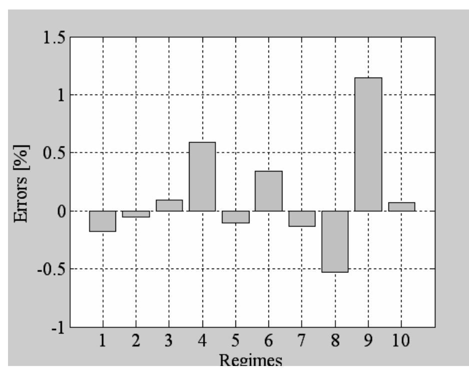
Average and maximum errors

Training algorithm	Number of epochs	Errors [%]	
		Average	Maximum
Conjugate Gradient	190	-0.0491	-1.3642
Quasi–Newton	75	**0.0170**	**-1.2869**
Levenberg–Marquardt	**16**	0.0672	**1.2821**

Fig. 3.a. shows the CCT values obtained with the LFNN in comparison with the values obtained with the EDSA program, for a set of 10 new regimes. As can be seen in Fig. 3.b. the maximum error of the CCT estimation with LFNN is slightly greater than 1%.



a)



b)

Fig. 3. CCT values and errors

6. Conclusions

The critical clearing time is an important parameter when evaluating the dynamic security of power systems. The CCT is a complex function of multiple parameters (pre-fault operating conditions and network topology, fault type and location), making the computation of his value an elaborate and time-consuming task. In this paper we analyzed the possibility to use ANN to estimate the CCT value for on-line applications.

The results obtained on small test system taking into account only changes in the operating conditions, suggest that the CCT values estimated with the chosen

LFNN are accurate and comparable with the ones obtained with classical methods. Despite the fact that the design process of an ANN requires an extensive computation effort, when employing it the necessary time to estimate the CCT value is compatible with that of on-line applications.

The use of such techniques in an efficient dynamic security assessment system necessitate further studies meant to analyze the ANN capability to estimate the CCT value for cases including network topology changes and different fault locations.

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