# ANN BASED DETECTION OF OS CONDITIONS IN POWER SYSTEM

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***ABSTRACT*** - *In the paper a new neural network based out-of-step protection scheme is presented. Numerous ANNs have been trained and tested with input patterns calculated from voltage and current signals generated with use of EMTP/ATP programme. Optimal selection of decision signals for ANN feeding has been done with help of proposed statistical PDF distance indices. The OS detection/prediction efficiency was assessed for various ANN sizes and data window lengths. The impact of measurement rate on the classification results has been analysed. Wide robustness checking of developed solutions has been done against different fault types and synchronous machine ratings.*

## INTRODUCTION

Reliable operation of contemporary power systems depends highly on control and protection devices applied there. Proper analysis of disturbances that may occur in power networks are necessary conditions to assure uninterrupted delivery of electrical energy to customers and to minimise losses caused by these disturbances. The modern protection and control devices perform their functions in digital technique. Despite a number of advantages which have arrived with this technique, numerous drawbacks may still be found when traditional protection principles are applied.

It has been proved that considerable improvement of operation as well as quite simple achievement of adaptive features of protection functions may be obtained with use of various AI techniques [1]. In this paper the results of investigations on possibility of ANN application to protection of synchronous machines are presented. The main efforts have been focused on development of new ANN based protection techniques which should ensure better (faster and more secure) detection of generator loss of synchronism. The latter may occur in the aftermath of loss of excitation or pole slipping. Both the mentioned effects may on the one hand threaten power system stability and on the other hand cause severe mechanical and thermal stresses to the generator itself.

The loss of excitation protection guards against the consequences for the generator of a partial or complete failure of the excitation. A parameter which is usually used to detect asynchronous operation resulting from loss of excitation is the ratio of the generator terminal voltage to the excitation current absorbed from the system. An underimpedance relay is used to recognise this event. In case of small generating units other protection schemes including power factor relays or reverse power relays are often recommended [2].

The pole slipping protection also detects loss of synchronism, but with the excitation intact. This condition can arise after a long power system fault or when a tie line between two systems is opened. This kind of loss of synchronism or out-of-step is accompanied by oscillations of real and apparent power in the system. The parameter supervised to detect generator pole slipping and out-of-step is the impedance vector measured at the generator terminals. Crossing of the impedance vector trajectory with properly set characteristic on the impedance plane is checked to detect the pole slipping [2]. The other methods used for OS protection are based on the equal area criterion [3], direct method of Liapunov [4] or rate of change of apparent resistance augmentation [5]. If a communication channel is available, an OS protection system may use observations of the phase differences between substations [6].

Since the commonly used methods of loss of excitation and pole slipping protection are not always precise enough and secure, it is justified to search for new solutions applying AI approach. Hence, appropriate relaying procedures have been considered and adequate ANN based solutions have been developed and tested.

## NEURAL NETWORKS AS A TOOL FOR PROBLEM SOLVING IN POWER SYSTEMS

Artificial Neural Networks (ANN) represent a modern and sophisticated approach to problem solving widely explored also for power system protection and control applications. The ANNs perform actions similar to human reasoning which relies upon experience gathered during so called training. Advantages of ANNs computing methodologies over conventional approaches include faster computation, learning ability, adaptive features, robustness and noise rejection. A few attempts to AI methods application for generator protection have recently been reported. The papers [7, 8] present some ideas of using neural networks to improve such protection tasks as localisation of winding shorts, fault detection and recognition in generator-transformer units, etc. The ANN technique was also used for machine stability assessment or control purposes [9, 10].

### ANN common design issues

While preparing useful and efficient ANN-based classification/recognition unit, one has to take into consideration at least the following design issues:

- ANN choice (ANN structure type, number of layers and neurones in particular layers, neurone activation functions),
- ANN training (training algorithm, initial values of synapse weights and biases), etc.

For an application at hand a representative set of patterns together with a set of desired ANN outputs should be prepared. The ANN input signals are usually obtained in simulative way since appropriate number of real-world cases are mostly unattainable. The signals from digital recorders installed in power system may be treated only as supplementary training patterns or may be used for further testing of designed units. It is common practice to divide the entire set of patterns into two subsets (e.g. 50%-50%) and use the first one for training and the other one for testing of trained ANN. The latter is very important since the designed solution has to possess the ability of knowledge generalisation (stability), i.e. the ANN should produce reasonable outputs also for unseen previously input signals.

The other problems refer to the ANN input signals themselves. Here at least the following issues should be carefully examined:

- number and type of input signals (carrying possibly the largest amount of information),
- pre-processing of power system signals (algorithms of measurement of certain features),
- data window length (number of signal samples).

Choosing the type of ANN input signals is a matter of the designer experience with ANN usage as well as good acquaintance with given technical problem to be solved. Unfortunately, there are no general practical rules on how to choose proper features for ANN training and how long the data window should be. This must be checked experimentally, often by subsequent trial-and-error attempts.

### Statistical approach to effective choice of ANN input signals

The author's previous experience in the field of ANN usage [11] have shown that in order to obtain good effectiveness of pattern recognition the features used as ANN input signals for both (or more) event classes to be distinguished should differ from each other to the highest possible extent. Having gathered a number of simulation cases covering the variety of situations that can happen in real life, the statistical properties of various features can be analysed [12]. First the conditional probability density functions (PDFs) of considered decision signals are to be prepared. Next chosen probabilistic measures of their difference (or distance) are to be calculated.

For proper choice of a decision value among a set of possible ones, the following time-dependent distance factors $\Delta$ between PDFs ($X_0$, $X_1$) may be suggested:

- difference of PDF expected values

$$\Delta_1(k) = E\lfloor X_0(k)\rfloor - E\lfloor X_1(k)\rfloor \qquad (1)$$

- difference of PDF standard deviations

$$\Delta_2(k) = st\_dev\lfloor X_0(k)\rfloor - st\_dev\lfloor X_1(k)\rfloor \qquad (2)$$

- cumulative mean of the product of latter two indices

$$\Delta_3(k) = \frac{1}{k}\sum_{i=1}^{k}\left[\Delta_1(i) * \Delta_2(i)\right] \qquad (3)$$

It is obvious that the best recognition efficiency will be achieved for a decision signal with highest value of distance $\Delta$. An ideal criterion value would be such which conditional PDFs are completely separated one from another. In such case a decision would be issued with 100% of probabilistic confidence.

## DATA FOR ANN TRAINING AND TESTING

To investigate the possibility of ANN application to OS protection, the following simple single machine – infinite bus system has been modelled (Fig.1, parameters given in Appendix A) with use of EMTP/ATP programme [13]. The synchronous machine G1 is connected to the infinite bus system S1 via the block transformer T1 and a 200 km long double-circuit line L1 on which different fault events are assumed to occur. The simulation model included also generator voltage and speed controllers as well as all elements of the analogue pre-processing path (VTs, CTs, anti-aliasing filters etc.), not shown in Fig.1.

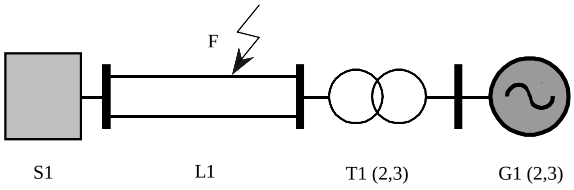


Fig.1. Fragment of power system modelled in EMTP/ATP.

Within the transmission line L1 different three-phase faults on one of the line circuits were applied. A total of 108 short-circuit cases were simulated with the fault parameters being changed:

- fault duration time (80, 100, 120 ms),
- fault termination (self-extinction, switching-off the faulty circuit, switching-off + autoreclosing),
- machine loading (0.1 ... 1.1 times rated power).

Generator output voltages and currents as well as its angular speed were registered in EMTP output files. Additional feature signals like voltage/current amplitudes, components of generator power, impedance vector (seen from machine terminals) were obtained after digital processing of phase voltages and currents. The calculation algorithms utilised orthogonal components of the voltage and current signals obtained after their filtration with use of pairs of full-cycle orthogonal Fourier filters [14].

In Fig.2 some exemplary signals are shown for both stable cases and OS conditions for the time during (100-200 ms) and after (200-2100 ms) a short circuit. It may be observed that for stable cases each of presented signals tends to a new equilibrium point after shorter or longer swinging transient period. When OS conditions take place the synchronous machine accelerates and both the machine angle (Fig. 2a) and the impedance angle (Fig. 2b) begin to increase with a speed depending on machine loading, its kinetic energy, average acceleration during fault etc. In such cases also the machine voltage controller is no longer able to maintain generator terminal voltage at stable level (Fig. 2c).

Theoretically each of presented signals may be used as a discriminative quantity for OS detection scheme since, at least after fault clearance time, significant (even optical) difference can be seen for both classes of phenomena to be classified.

In order to choose the best signals for application as ANN input features the statistical properties of available signals have been determined. The calculations have been performed for such decision quantities as: machine angular frequency deviation $\Delta\omega$, impedance angle *Arg(Z)*, active power *P*, reactive power *Q*, resistance *R* and reactance *X* (measured at the generator terminals from machine phase currents and voltages). In Fig. 3 the shape of calculated distance characteristics $\Delta_1$ is shown, as functions of data window length (observation time after fault clearance). Since the phenomena observed are non-stationary, likewise the obtained PDFs and their distance measures change strongly with time.

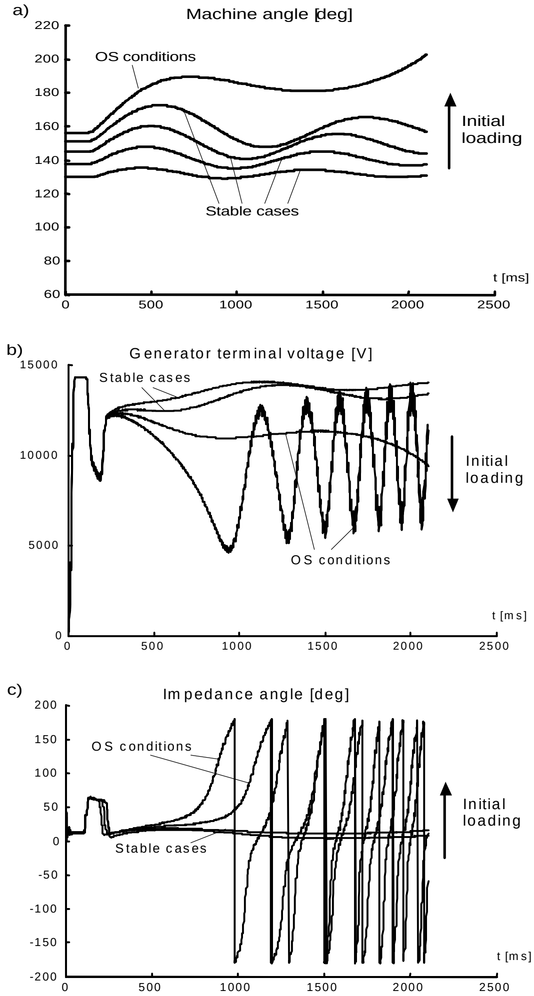


Fig. 2. Exemplary machine signals for stable cases and OS conditions: a) machine angle, b) generator terminal voltage, c) impedance vector angle.

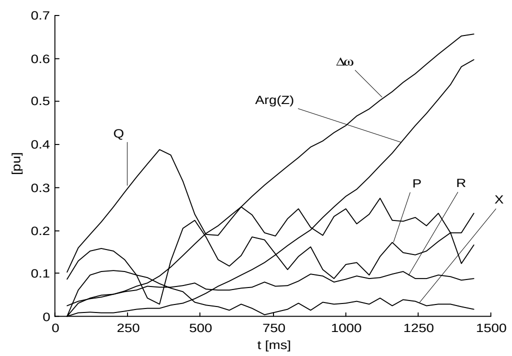


Fig. 3. PDF distance $\Delta_1$ for various decision signals.

Considerable increase of the distance factor with time for almost all signals implies a suggestion that possibly long data window should be applied for better recognition effects since the amount of information carried by the decision signals becomes higher and higher as time passes.

Table 1. PDF distance indices for various decision signals.

| PDF distance | Decision signal | | | | | |
|---|---|---|---|---|---|---|
| | $\Delta\omega$ | Arg(Z) | P | Q | R | X |
| mean ($\Delta_1$) | 0.31 | 0.20 | 0.14 | 0.24 | 0.07 | 0.04 |
| max ($\Delta_1$) | 0.66 | 0.60 | 0.22 | 0.39 | 0.10 | 0.11 |
| mean ($\Delta_2$) | 0.07 | 0.07 | 0.02 | 0.04 | 0.02 | 0.03 |
| max ($\Delta_2$) | 0.10 | 0.10 | 0.03 | 0.06 | 0.07 | 0.08 |
| mean ($\Delta_3$) | 1.04 | 0.49 | 0.17 | 0.75 | 0.18 | 0.33 |
| max ($\Delta_3$) | 2.64 | 1.78 | 0.22 | 0.98 | 0.26 | 0.57 |
| Ranking | 1 | 2 | 5a | 3 | 5b | 4 |

The mean and maximum values of calculated statistical distance measures over considered time range are gathered in Table 1. The analysis of obtained statistics allow to order the decision signals according to their relative recognition strength (the greater distance coefficients, the higher ranking position may be assigned). In our case the most valuable recognition feature turned out to be the angular frequency deviation, followed by the impedance angle and reactive power measured at the machine terminals. The statistics for the remaining signals do not promise good classification abilities.

## ANN BASED OS PROTECTION

The research on ANN application to OS recognition included attempts to design of simple OS detectors in traditional sense as well as to develop new OS prediction units. The ANN training and testing was performed with use of MATLAB programme.

### OS detection with neural networks

For realisation of the OS detection task numerous three-layer non-linear feed-forward neural networks (Multilayer Perceptron type) have been tested. The ANNs of various size (3-3-1 ... 30-30-1 neurones – 10 cases) have been trained with back-propagation learning rule. To avoid focusing on the first patterns, the ANNs were trained several times applying random sequence of pattern presentation. Only the half of prepared patterns was used during training, the second half of cases was used for further network testing. The ANNs were fed with either $\Delta\omega$ or *Arg(Z)* signals, observed within 1.6 sec long data window (40 signal samples taken at each 40 ms). The ANNs were trained to produce output equal to 0 for stable patterns and 1 for OS conditions. The training process was being stopped after 1500 epochs or earlier, if the sum-squared error goal set to 0.01 was reached.
The performance of trained ANNs was tested with both training and testing data sets. It was observed that the network outputs were almost never equal precisely to 0 or 1 (desired output values). This is yet not critical since not the output accuracy but the classification efficiency is important in our case. For classification purpose a threshold value set to 0.5 was introduced. All the cases for which the ANN output was lower than 0.5 were classified as stable and those for which the threshold was exceeded were recognised as OS cases. With such an arrangement it has occurred that all the cases from both the training and testing data sets were classified correctly for each of ANN input signals.
Although the designed neural OS detectors exhibited 100%-efficiency and stability to unseen cases, it must be said that obtained solution does not introduce new quality in the field of OS protection since the other non-AI schemes deliver similar detection results. The substantial improvement would be achieved if the ANN-based detectors could recognise the OS conditions before they actually occur, i.e. instead of detection – a prediction action would be realised, which is not possible with known conventional OS detection methods.

### OS prediction

In order to check whether it is possible to detect the OS conditions earlier or even predict it when no significant OS symptoms are yet visible, the analysis for different ANN data window lengths have been performed. The ANNs of various size (10 cases as previously) and 12 different number of input signal samples (data window length from 0.12 to 1.44 sec) have been trained and tested. Six different input features were considered: $\Delta\omega$, *Arg(Z)*, *P*, *Q*, *R* and *X*. The signals *P* and *Q* were standardised through their division by the machine rated power to avoid convergence problems while training and simultaneously to make the scheme independent of the machine size. In total 10x12x6=720 different network configurations have been examined.
The average results of OS detection (over various ANN sizes) for considered ANN input features are given in Table 2 and in Fig. 4. The results obtained for various ANN input signals confirmed our previous expectations as to their recognition abilities

Table 2. Average values of classification errors
a) training data set

| Input signal | ANN window length [s] | | | | | |
|---|---|---|---|---|---|---|
| | 0.24 | 0.48 | 0.72 | 0.96 | 1.20 | 1.44 |
| $\Delta\omega$ | 5.6 | 0.6 | 0 | 0 | 0 | 0 |
| Arg(Z) | 6.7 | 0.6 | 0 | 0 | 0 | 0 |
| P | 6.7 | 2.6 | 3.5 | 3.7 | 0 | 0 |
| Q | 6.5 | 2.0 | 0.2 | 0.2 | 0.2 | 0.2 |
| R | 18.7 | 14.0 | 10.2 | 4.3 | 0.6 | 0.6 |
| X | 19.4 | 17.8 | 16.1 | 11.8 | 11.7 | 5.7 |

b) testing data set

| Input signal | ANN window length [s] | | | | | |
|---|---|---|---|---|---|---|
| | 0.24 | 0.48 | 0.72 | 0.96 | 1.20 | 1.44 |
| $\Delta\omega$ | 5.9 | 0.8 | 0.2 | 0 | 0 | 0 |
| Arg(Z) | 6.5 | 1.2 | 1.0 | 0.8 | 0.8 | 0 |
| P | 6.0 | 5.0 | 5.3 | 5.1 | 1.7 | 0.3 |
| Q | 6.7 | 4.1 | 1.8 | 0.6 | 1.0 | 1.8 |
| R | 18.3 | 13.0 | 8.0 | 4.2 | 1.3 | 1.1 |
| X | 18.0 | 16.5 | 15.1 | 13.5 | 15.9 | 11.7 |

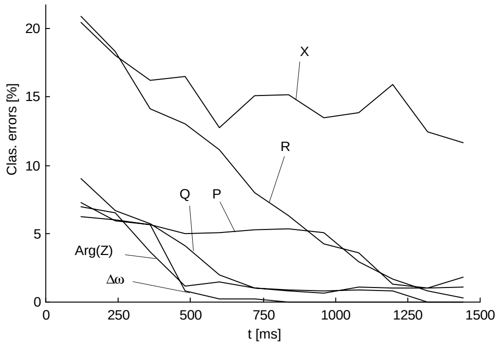


Fig. 4. OS detection/prediction errors (testing data set).

assessed with use of proposed statistical indices. The best classification efficiency was achieved for ANNs fed with $\Delta\omega$ and *Arg(Z)* signals. For these features no false recognitions for training set cases were observed after 0.6 sec long time period and less than 1% of errors for 0.48 sec long data window. Testing the designed ANNs with signals not presented during training (testing data set) brought very good results - with 1% or less misclassified cases at 0.48 sec after fault clearance.

One can observe that the ANN efficiency is time dependent and increases when longer data window is applied. This is an effect of processing larger amount of information also from the period when the OS symptoms are more clearly visible in the input signals. This property was already foreseen on the basis of performed statistical analysis.

Looking more closely at the results for ANNs of various size (Table 3), it may be found that no significant dependency of classification effects against network size is observed. Apart from the smallest networks for which greater errors in case of some decision signals (*P*, *Q*, *R*, *X*) were obtained, relatively compact structures (9-9-1, 12-12-1) deliver similar effects as much greater networks. Having in mind practical application problems, possibly compact networks are to be recommended. Due to lesser computational burden such ANNs may be implemented on traditional processors without need for any expensive specialised neural chips.

**OS recognition effects vs. measurement rate**

Further analysis have been made in order to investigate the impact of providing more frequent measurements ("measurement rate" – MR in Table 4) on the results of OS classification. The studies have been done for $\Delta\omega$ and *Arg(Z)* signals taken (measured) at each 10 and 20 ms (previously at each 40 ms). The data window length was considered in the range between 0.24 and 0.48 s only.

The results gathered in Table 4 show that filling the data window with higher density (more signal samples within the same time period) did not bring significant improvement. The same classification efficiency for more dense data window was achieved 40 – 80 ms earlier than for initial MR=40 ms, yet it must be said that it was done at the cost of higher

Table 3. Average recognition errors for various ANN sizes

| ANN size | ANN input signal | | | | | |
|---|---|---|---|---|---|---|
| | Δω | Arg(Z) | P | Q | R | X |
| 3-3-1 | 1.8 | 1.8 | 6.6 | 5.2 | 11.7 | 19.1 |
| 6-6-1 | 1.8 | 1.5 | 4.2 | 2.9 | 9.3 | 15.3 |
| 9-9-1 | 1.5 | 1.7 | 3.1 | 2.3 | 10.4 | 15.9 |
| 12-12-1 | 2.0 | 1.5 | 3.1 | 2.2 | 8.2 | 12.8 |
| 15-15-1 | 1.5 | 1.5 | 2.6 | 2.2 | 8.3 | 14.0 |
| 18-18-1 | 1.4 | 1.5 | 2.6 | 1.4 | 9.3 | 11.6 |
| 21-21-1 | 1.5 | 1.5 | 2.9 | 2.2 | 8.6 | 13.4 |
| 24-24-1 | 1.4 | 1.4 | 2.6 | 1.8 | 8.6 | 13.4 |
| 27-27-1 | 1.4 | 1.7 | 2.3 | 2.0 | 7.9 | 11.4 |
| 30-30-1 | 1.4 | 1.8 | 2.6 | 1.8 | 7.8 | 10.9 |

Table 4. Classification errors for various MRs.

| Inp. sig. | MR [ms] | ANN window length [s] | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 0.24 | 0.28 | 0.32 | 0.36 | 0.40 | 0.44 | 0.48 |
| Δω | 40 | 5.9 | x | x | 5.6 | x | x | 0.8 |
| | 20 | 5.2 | 5.2 | 5.2 | 1.4 | 0.7 | 0.6 | 1.2 |
| | 10 | 5.1 | 5.5 | 4.4 | 0.6 | 0.9 | 0.7 | 1.2 |
| Arg (Z) | 40 | 6.5 | x | x | 3.7 | x | x | 1.2 |
| | 20 | 5.9 | 6.3 | 5.0 | 2.3 | 1.9 | 1.8 | 1.8 |
| | 10 | 5.8 | 5.8 | 4.4 | 1.7 | 1.4 | 1.6 | 1.8 |

x – points not investigated

computational burden due to greater amount of data being processed. The investigation proved that no more information can be drawn out from the signals by more frequent measurements only simply because they do not contain enough symptoms of further phenomena at this early stage. Thus, additional amelioration of classification efficiency may be acquired by either extending the viewing period or using another (or additional) signals presumably better suited for our prediction task.

**Robustness checking**

In order to check whether the developed neural OS detection/prediction scheme possesses some wider understood features of robustness, chosen ANNs were tested with patterns obtained from further EMTP simulations. First, 72 cases of single and double phase faults within line L1 (Fig. 1) were prepared, some of them being responsible for OS conditions after short-circuit switching-off. Two types of ANNs (6-6-1 and 18-18-1 with various data window length) trained with previous symmetrical fault cases were then tested with new unsymmetrical short-circuit patterns. It turned out that designed neural OS detectors could properly recognise all or almost all testing cases depending on the type of input feature and data window length. The highest robustness was observed for ANNs fed with $\Delta\omega$ signal. For this input feature only two fault cases were misclassified with 0.48 sec data window and just one after 0.6 sec. No decision errors were generated for longer data windows. It was also found that better classification efficiency and robustness was achieved for smaller ANN structures (6-6-1) than for bigger ones. The latter seem to be memorised (strongly focused on patterns presented during training) and have more problems with knowledge generalisation.

The other group of 72 testing cases was prepared by simulating various three-phase faults within line L1 (Fig. 1) but for two other synchronous machines (G2, G3 – App. A). It was found that the robustness degree of trained ANNs is inversely proportional to the discrepancy between considered generators - the higher difference of machine inertia moments, the more misclassified OS cases observed. However, also in this concern quite good robustness was achieved. In case of machine G2 (inertia moment not far from that for machine G1) the classification efficiency remained practically unchanged. In case of machine G3 ($J_{G3}$=0.4 $J_{G1}$) worse results (ca. 5% errors) were obtained for some ANN input features, yet still very good recognition abilities (comparable to those for machine G1) were maintained for ANNs fed with $\Delta\omega$ signal. As previously, better results were achieved for smaller neural networks.

## CONCLUSIONS AND FURTHER RESEARCH

The investigations on ANN application to out-of-step detection/prediction in power systems have been presented in the paper. After thorough design/optimisation analysis promising results in shape of high classification efficiency have been achieved. The developed ANN based OS detectors proved to be robust against changes in fault conditions and synchronous machine ratings.

The results described in the paper do not aspire to be final and the research has to be continued. It is the author's belief that further improvement of proposed neural OS detection scheme may be obtained with additional careful analysis, considering:

- another (traditional or new) input patterns,
- other ANN structure and parameters,
- optimisation of the threshold value,
- introduction of fuzzy concepts (hybrid solutions).

The results of further work on the problem will be reported in next papers.

## APPENDIX A - Parameters of the power system

Infinite bus system S1: 220 kV, Z=0.05
Block transformers:
T1: 17.5 / 220 kV, dY, Z=0.1
T2,3: 15.75 / 220 kV, dY, Z=0.1
Transmission line L1: double-circuit line, l=200 km,
$R_1$'=0.056, $X_1$'=0.39, $R_0$'=0.206, $X_0$'=0.96 Ω/km,
$B_1$'=2.827, $B_0$'=1.571 μS/km,
Synchronous machines:
G1: $U_n$=17.5 kV, $S_n$=750 MVA, $X_d$=$X_q$=1.75, $X_d$'=
=$X_q$'=0.265, $X_d$''=$X_q$''=0.20, J=0.0532 Mkg $m^2$
G2: $U_n$=15.75 kV, $S_n$=200 MVA, $X_d$=1.88, $X_q$=1.75,
$X_d$'=0.283, $X_q$'=0.328, $X_d$''=0.19, $X_q$''=0.273,
J=0.0405 Mkg $m^2$
G3: as G2, J=0.0202 Mkg $m^2$
where not specified - [pu] (related to generator $S_n$)

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