ADAPTIVE AND INTELLIGENT SYSTEMS FOR GENERATOR MONITORING AND PROTECTION PURPOSES

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Abstract: New adaptive scheme for signal parameter measurement for generator monitoring and protection is presented. The algorithm is based on the orthogonal components of currents and voltages obtained with adaptive orthogonal filters. The filter data window length and coefficients are adapted according to coarsely estimated signal frequency. As a result, the measurements can be performed with high accuracy in wide frequency band conditions, i.e. also for generator start-up, etc. The measured signals are further used for training of artificial neural networks with the aim to design a robust and effective classifier of generator operation mode. The main attention is paid to the phenomena accompanying pole slipping and out-of-step conditions.

Keywords: digital measurement, adaptive algorithms, artificial intelligence, neural networks, genetic algorithms, generator protection, simulation.

1. INTRODUCTION

Most of the digital measurement algorithms used for power system control and relaying purposes are designed to operate at fixed nominal frequency of input signals since frequency deviations in normal power system operating conditions are very small allowing to get proper accuracy of estimation. There are situations, however, when protections have to operate in serious off-nominal frequency conditions and, if their measuring algorithms are not designed properly, they have sometimes to be interlocked, thus impairing protection system reliability. Examples of such cases are start up (warm up) of a generator or operation mode changing form generating to motoring state (for reversible machines).

In digital protection systems the signals which the decision whether to trip the faulty element is based on are usually determined from orthogonal components of current and voltage phasors obtained by use of non-recursive digital filters. Selective frequency response of the filters and resulting selective features of estimators make them inadequate for application in off-nominal frequency conditions. Contradictory requirements to be selective (suppression of noise) and unselective (to have all-pass unity frequency response) call for adaptive features of the estimators. The idea of adaptive estimation has already been suggested in papers (Winkler and Wiszniewski, 1995; Rebizant, *et al.*, 1999; Moore, *et al.*, 1994).

In this paper a new approach to the problem of signal parameter measurement in off-nominal frequency conditions is presented. The adaptive estimators based on frequency deviation estimation are described. According to the frequency measurement results the orthogonal filters are tuned up to the new frequency band by modification of their data window length and coefficients. The proposed method of adaptive measurement is simple and effective in use.

In the second part of the paper the new intelligent system applying Artificial Neural Networks (ANNs) to protection of synchronous machines against out-of-step (OS) conditions is presented. The out-of-step conditions (loss of synchronism) of a synchronous machine may occur as a result of loss of excitation or during pole slipping. Both 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 (Elmore, 1994). Appropriate protection schemes against OS conditions are applied to avoid the threats mentioned, especially for generators of higher ratings (above 200 MW).

The newly developed and presented here ANN-based OS protection ensures faster and more secure detection of generator loss of synchronism when compared to traditional solutions. To determine the most suitable network topology for the recognition task a genetic algorithm (GA) is proposed (Rebizant *et al.*, 2001). The final ANN structure is found using the rules of evolutionary improvement of the characteristics of individuals by concurrence and heredity. The initial as well as further consecutive populations of ANNs were created, trained and graded in a closed loop until the selection criterion was fulfilled. The results of thorough testing of the designed protection scheme with the signals generated using the Alternative Transients Programme (ATP) are described. The scheme is able to detect but also to predict the coming OS cases with high selectivity. The decision is taken some 500ms-1s earlier than with standard impedance based protection schemes, which gives additional time for appropriate actions to prevent serious generator damage and longer outages for repairs and thus to improve reliability of energy supply to customers.

2. ADAPTIVE MEASUREMENT SCHEME

In this section basic algorithms of signal amplitude measurement as well as their extension for wide frequency band estimation are described. The adaptive approach proposed can be easily applied for measurement of other criterion values used for generator protection (impedance, power components, etc.), as reported in (Szafran, 1999).

2.1 Measurement Algorithms

For measurement of power system signal amplitudes (e.g. voltage |*U*|) the following digital algorithms are usually used:

$$|U|^2 = u_c^2(n) + u_s^2(n) \tag{1}$$

$$|U|^2 = \frac{1}{\sin(k\omega_1 T_s)}\left(u_c(n-k)u_s(n) - u_s(n-k)u_c(n)\right) \tag{2}$$

where u_c, u_s are voltage phasors at the orthogonal filter outputs (for instance full-wave Fourier ones), ω_1 is the angular fundamental frequency, T_s is the sampling period and *k* is a number of delay samples (chosen from the range 1 ... *N*/4, with *N* being number of signal samples in one period of the actual fundamental frequency component).

In order to minimize estimation errors in case of application of estimators (1) or (2) for wide fr frequency band measurements (e.g. for generator monitoring and protection), it is necessary to adapt the orthogonal filters to the actual frequency of the signals. It is realized by the following procedure:

- determine the number of samples in one period of input signals *N* (directly or by signal frequency estimation),
- set the filter data window length to *N* and modify filter coefficients (i.e. the filter impulse response).

Additionally, in case of estimator (2), the value of *k* resulting from the currently estimated signal frequency is forwarded to the measurement block, thus on-line updating the previously used delay value. The procedure of adaptive measurement can be represented by the block diagram shown in Fig. 1.

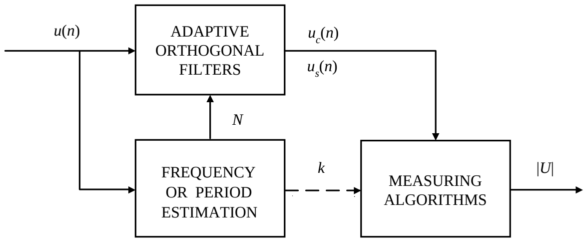

Fig. 1. Block scheme of the amplitude measurement with adaptive orthogonal filters.

2.2 Frequency Deviation - Based Adaptive Scheme

The adaptive estimator presented is based on calculation of the following function (written here for an arbitrary voltage signal):

$$g(\omega) = 0.5\frac{u(n-2k)u(n-d) - u(n)u(n-2k-d)}{u(n-k)u(n-d) - u(n)u(n-k-d)} \tag{3}$$

where d is certain time delay (d>0).

It can be shown that $g(\omega)$ is proportional to the frequency deviation, i.e.: $g(\omega) \cong -kT_S\Delta\omega$. The value of *k* is then updated according to the procedure:

$$\text{If}\begin{Bmatrix} g(\omega) < -\delta \\ |g(\omega)| \le \delta \\ g(\omega) > \delta \end{Bmatrix} \text{then} \begin{Bmatrix} \text{increment } k \text{ by } 1 \\ \text{no change of } k \\ \text{decrement } k \text{ by } 1 \end{Bmatrix} \tag{4}$$

where δ is a discrimination threshold assumed for the expected range of frequency changes. The value of delay *k* may be any fraction of *N*, however, once defined, determines clearly the actual value of *N*. For instance, if *k* was initially chosen to be equal to *N*/4, the current value of *N* is set to be 4 times *k*. Consequently, the data window length of the filters used is always extended (or compressed) to the actual value of *N* (for full cycle filters). More details on this approach may be found in (Rebizant, *et al.*, 1999).

2.3 Samples of Simulation Study Results

A number of various test signals have been prepared with MATLAB and ATP programs. Both accuracy and dynamics of the estimators have been tested. In this paper just one example of algorithm operation for ATP generated testing signals is presented.

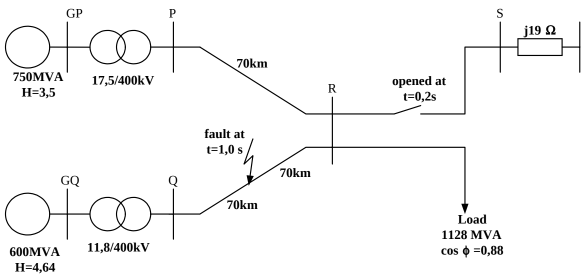

Fig. 2. Test power system modelled in ATP.

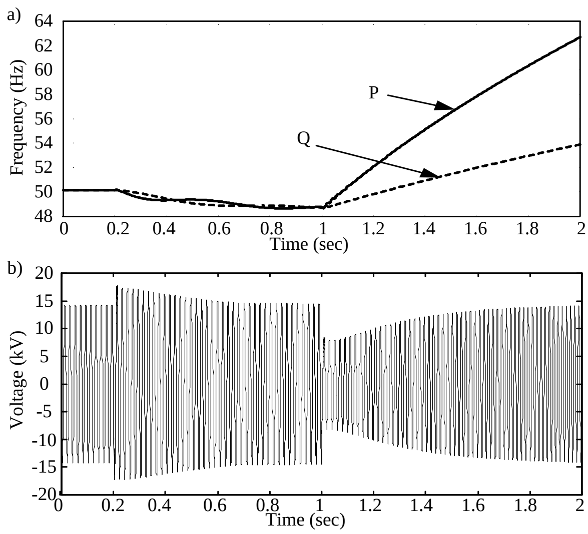

Fig. 3. Transient signals picked up at busbar GP: a) rotor's speed of generators P and Q, b) phase A voltage.

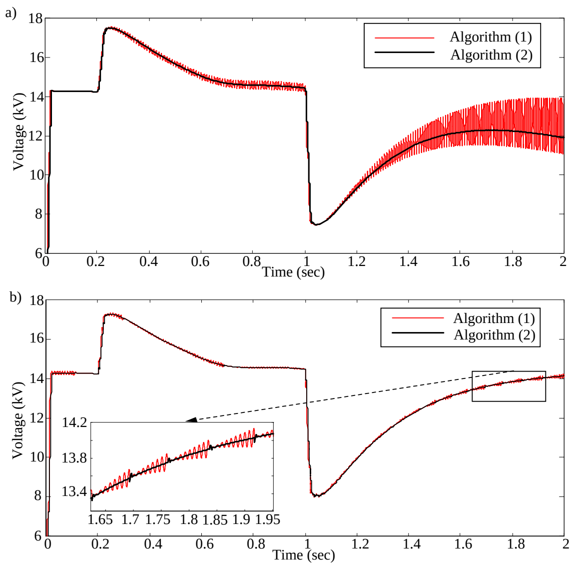

Fig. 4. Amplitude estimation with algorithms: a) non-adaptive, b) with adaptation.

The power system configuration used for tests is shown in Fig. 2. At time *t*=200ms the switch to the infinite bus is opened (the system becomes isolated). Additionally at *t*=1.0s a three-phase fault in the middle of the line Q-R was modeled. Transients in generators P and Q rotors' speed as well as the phase voltage at GP busbar are shown in Fig. 3. In consequence of new loading conditions the system frequency decreases (down to 48.5 Hz at the moment of fault inception). Since in this case the fault is not cleared within a reasonable period of time, both generators accelerate reaching speed values far beyond acceptable limits.

The amplitudes of voltage signal measured by non-adaptive and adaptive algorithms are shown in Fig. 4. The biggest differences are seen for larger frequency deviations when the filters used become untuned if the adaptation procedure is off. Then non-adaptive algorithms deliver inaccurate value of signal amplitude (with constant or oscillatory error). Small ripples seen on the measurement curves in Fig. 4b for the case of adaptive estimation are a result of slightly inadequate filter gains between consecutive on-line adjusting of the filter DW lengths.

3. ANN-BASED OUT-OF-STEP DETECTION

In the following sections the ANN design issues are discussed and the genetic method for ANN structure optimisation is proposed. Then the details of developed neural OS protection scheme are described, followed by the results of scheme training and testing with use of ATP signals.

3.1 ANN Design Issues

Artificial Neural Networks represent a modern and sophisticated approach to problem solving for power system protection and control applications. ANNs perform actions similar to human reasoning which rely on experience gathered during so called training. 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, neurone activation functions, ANN input signals),
- ANN training (training algorithm, initial values of synapse weights and biases), etc.

The ANN input signals have to be chosen in such a way that they provide maximum information suitable for solving of given protection task. Choosing the type of ANN structure and its further parameters is rather a matter of the designer experiences since, unfortunately, there are no general practical rules which could be applied for that purpose. The experimental way with sequential trial-and-error attempts can be followed, however, this may not guarantee the optimal ANN structure to be found.

3.2 Genetic Rules for ANN Design and Optimization

To determine the most suitable network topology a genetic algorithm is proposed. The optimisation procedure commences from a population of artificial organisms called individuals that are defined to describe the topology of the ANN to be optimised. Natural principles according to the theory of Darwin, such as heredity, crossover, mutation, and selection, are used over several generations to develop and improve the characteristics of individuals. The

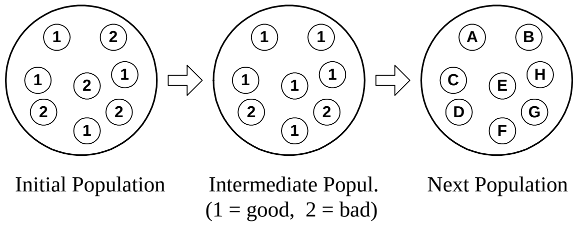

Fig. 5. Principles of the evolutionary process to optimise a network topology.

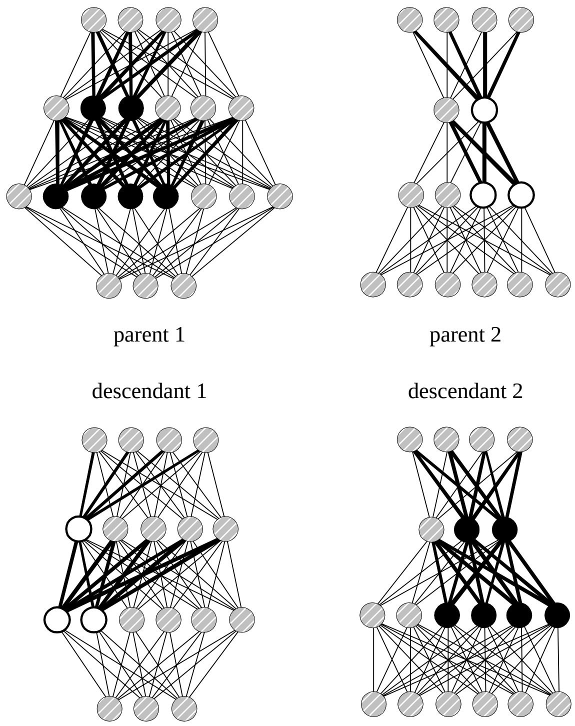

Fig. 6. Crossover of groups of neurones to create new descendent individuals.

selection is made according to the quality of each individual, which can be understood, as the capability to survive. The evolutionary process will end up into an optimum that represents the "stronger" individual, in this case - the most suitable ANN topology.

At the beginning a so-called initial population of neural networks is randomly created. While the number of neurones in the input and output layer are fixed according to the classification problem, the number of hidden layers and the number of neurones in these layers are randomly selected. All the individuals from the considered ANN population are trained with selected typical patterns and validated with all available patterns. This procedure keeps the training time short and emphasises on the generalisation of the network. After the quality of each individual was determined an intermediate population is created where successful individuals are reproduced more likely (Fig. 5).

On this intermediate population several genetic operations can be applied to create a new population. The most important genetic operation is the crossover of two "parent" individuals (Fig. 6) to produce "descendants". A crossover can be an exchange of single neurones, groups of neurones, or whole layers between two ANNs. Crossovers are very important and frequent at the beginning of a genetic algorithm so that a wide variety of different individuals can be produced. Furthermore, mutations can take place, which change randomly chosen genes of the individuals by adding or removing neurones. Another important genetic operation is the recombination, which stands for the creation of a descendant being an identical copy of a parent.

3.3 Implementation of the Genetic Algorithm

The genetic optimisation principles described in previous section have been implemented in MATLAB programme. The initial as well as further consecutive network populations were created, trained and graded in a closed loop until the selection criterion is fulfilled or the prescribed number of generation was reached. The coding of particular individuals was very compact - all the ANNs of given population were represented by the set of the following parameters (genes):

- ANN consecutive number k,
- number of layers l_k,
- vector of layer sizes (number of neurones in the layers) $\mathbf{N}_k$,
- matrix of the connection weights $\mathbf{W}_k$,
- matrix of the neurones' biases $\mathbf{B}_k$,
- quality index Q_k.

The trained population of nets was subjected to quality determination (grading). Various quality criteria may be used to assess the individual nets creating current population. The grading procedure has been organised in such a way that the "best" net (according to the criterion chosen) is always assigned the quality of 1 whilst the "worst" one would have the quality index equal to 0. To avoid accidental cancelling of the best ANN during operations of creating and genetic modifications of intermediate population, the net with quality 1 is always forwarded to the next generation without changes.

At each consecutive optimisation step (for successive population of nets) appropriate changes in the genome of each individual are carried out, depending on the genetic operation applied to the net (-s):

- new number of layers l_k and number of neurones in the layers $\boldsymbol{N}_k$ are assigned,
- elements of the matrices $\boldsymbol{W}_k$ and $\boldsymbol{B}_k$ are cut away, newly established or interchanged between the ANNs.

3.4 ANN Based OS Protection

The general scheme of the neural OS protection scheme developed is shown in Fig. 7. The decision part of the protection is realised with help of an ANN performing typical pattern recognition with appropriately chosen vector of criterion signal samples $\boldsymbol{X}(k)$. The decision (criterion) values have to be previously calculated from available power system signals with use of dedicated digital processing algorithms. The ANN is assumed to produce output equal to 0 for stable patterns and 1 for OS conditions. For the classification purpose a threshold value set to 0.5 is introduced. All the cases for which the ANN output is lower than 0.5 are classified as stable and those for which the threshold is exceeded are recognised as OS cases.

To obtain data for training of ANNs and further testing of the OS protection, the following simple single machine – infinite bus system has been modelled (Fig. 8) with use of the ATP software package. The synchronous machine G1 was connected to the infinite bus system S1 (220 kV) via the block transformer T1 and a 200-km long double-circuit line L1. Within the transmission line L1 a total of 108 symmetrical faults on one of the line circuits were applied, some of them responsible for further developing OS conditions.

Generator output voltages and currents as well as its angular speed were registered in ATP output files. Additional features like voltage/current amplitudes, components of generator power etc. were obtained after digital processing of voltage and current signals. In order to choose the best signals for application as ANN input features, the statistical properties of available signals were determined. The analysis of calculated PDFs allowed sorting the decision signals according to their relative recognition strength. Ultimately, the machine angular frequency deviation $\Delta\omega$ was taken as the most valuable recognition feature in the investigated case. The ANN input vector ***X(k)*** was being created on-line from a number of signal samples captured with use of a sliding data window (DW). The DW length was set to 360ms.

The choice of the ANN structure and size for the neural OS protection scheme developed has been done with use of the genetic optimisation procedure. The results given below were obtained for a population of 20 nets trained with a half of available short-circuit patterns and tested with all patterns. Fifty generations of nets were assumed. The investigations have been done for a set of networks trained with the Levenberg-Marquardt algorithm.

The nets constituting the population of individuals were graded according to two different quality indices, i.e. mean square error of the net output Q_{ms} (squared difference between desired and actual output values) and testing efficiency Q_{eff} (percentage of properly recognised OS cases). Consequently, different results of the genetic process have been reached. The "best" nets obtained after 50 generations had 6-1 and 3-1 neurones for the Q_{mse} and Q_{eff} grading indices, respectively. Fig. 9a shows the average remaining error over all ANN topologies of one population as a function of the number of generations. In Fig. 9b the average testing efficiency of the scheme is presented. Smaller values of the mean square error were achieved for Q_{mse} used as grading index, while the highest efficiency resulted

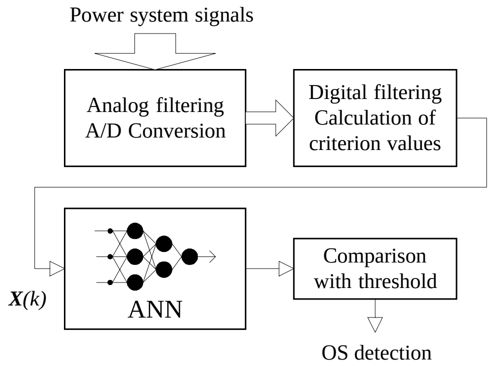

Fig. 7. Neural OS protection arrangement.

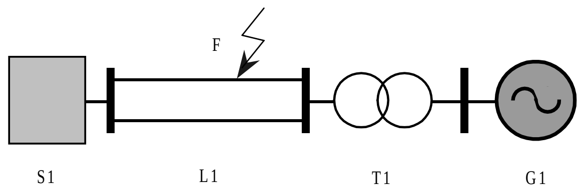

Fig. 8. Test power system modelled.

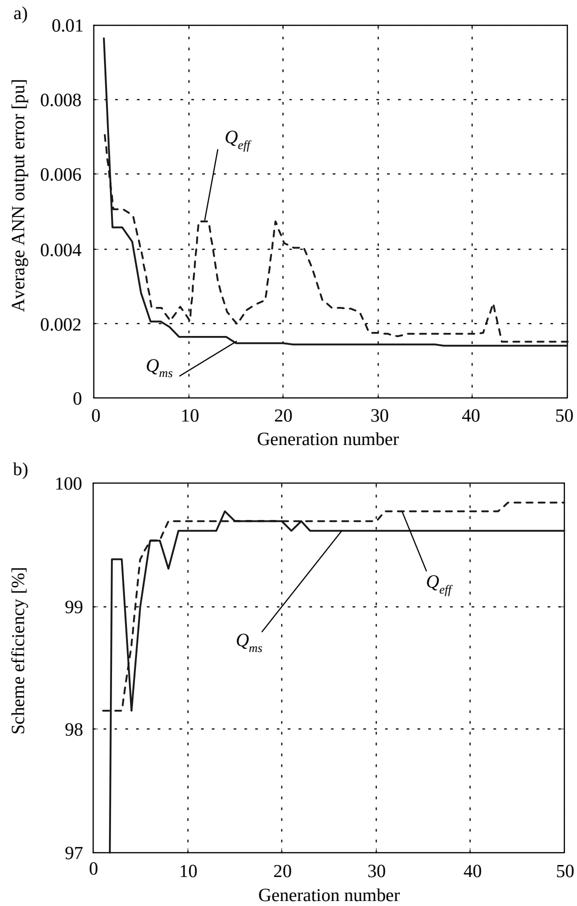

Fig. 9. Optimisation results: a) mean square error, b) recognition efficiency.

from grading the nets with Q_{eff} index. One can observe that monotonic change (decrease/increase) of the mean square error and scheme efficiency was associated with the genetic optimisation process performed with the respective grading indices. The curves for competitive indices, by similar general improvement tendencies, reveal significant oscillatory behaviour. It was found that minimising

Q_{ms} index required greater ANNs and was not always accompanied by good generalisation features. Contrary, smaller nets brought about better OS classification efficiency with non-optimal values of mean square error (well known memorisation vs. generalisation dilemma).

3.5 OS Protection Scheme Testing and Validation

The ANN-based OS protection scheme has been thoroughly tested with ATP-generated power system signals. The scheme displayed high efficiency and very short time of OS detection. It is worth to be mentioned that the values of ANN output error and scheme efficiency shown in Fig. 9 characterise an "average" individual over the whole population of ANNs. The OS protection equipped with the "best" ANNs (graded with quality indices equal to 1.0) displayed 100% selectivity which means that all considered ATP testing cases were correctly classified.

Comparing to other existing impedance-based OS protection devices, a kind of prediction of coming machine instability is performed instead of traditional detection of actually occurring phenomena. The decision was taken within approx. 500ms after fault inception (some 300-900 ms before actual OS appeared), thus leaving enough time for an appropriate action (machine tripping, fast valving) to protect the generator from stresses and preserve the stability of power system. Wide robustness features of the scheme with respect to both various fault types and other synchronous machine ratings have also been confirmed.

4. CONCLUSIONS

In the paper two modern advanced approaches to improvement of digital protection of synchronous generator against OS phenomena are presented. Both signal measurement and decision-making modules of the relay are optimised with introduction of the adaptivity concept and application of artificial intelligence techniques, respectively.

The following features of the adaptive amplitude estimation scheme are worth to be pointed out:

- The proposed scheme is capable of tracking signal amplitude with high accuracy and dynamics even if the system frequency (generator shaft speed) is varying in wide range.
- The adaptive amplitude estimators can be applied in generator digital monitoring, protection and control equipment. This is also valid for other electrical quantities, such as active and reactive power, impedance components or symmetrical components of generator terminal signals.
- Computational complexity of the proposed adaptive measurement scheme is relatively low. Thus practical implementation of the algorithm for simultaneous estimation of various generator signals in real time is utterly possible with currently available signal processors.

The investigations on ANN application to out-of-step protection presented in the paper allowed drawing the following conclusions:

- Promising results in shape of high classification efficiency (OS cases vs normal operation and other cases) have been achieved with application of the designed ANN-based recognition unit.
- Thanks to high sensitivity of the designed neural decision block, the scheme was able to detect or even predict the situations of generator instability basing on tiny symptoms of evolving OS conditions.
- The neural OS detection scheme developed was based on ANNs optimised with of use the genetic procedure. Application of such an approach allowed avoiding non-optimalities usually met with traditional ANN design heuristics and provided most favourable nets for given classification task.
- The obtained neural nets consisted of very few neurones, which allows implementing the scheme on traditional widely available signal processors (no specialised expensive neural chips are needed for implementation of ANNs of such small sizes).

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