

OUT-OF-STEP PROTECTION WITH AI METHODS

W Rebizant, K Feser

Wroclaw University of Technology, Poland
University of Stuttgart, Germany

ABSTRACT

In the paper the results of investigations on the application of Artificial Intelligence (AI) methods to the out-of-step (OS) protection of synchronous machines are presented. The main efforts have been focused on development of new Artificial Neural Network (ANN) based and mixed protection techniques which should ensure better (faster and more secure) detection of generator loss of synchronism. The designed AI-based OS protection schemes have been thoroughly optimised and tested with EMTP-generated case signals. Wide robustness analysis as well as comparison with chosen standard OS detection method have also been performed.

INTRODUCTION

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. Thus appropriate protection schemes are to be applied to avoid the threats mentioned.

The loss of excitation protection guards against the consequences for a generator of a partial or complete failure of the excitation. 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 recommended, Elmore (1).

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. The parameter supervised to detect pole slipping is the impedance vector measured at the machine terminals. Crossing of the impedance vector trajectory with properly set characteristic on the impedance plane is checked to detect the pole slipping, (1). The other methods used for OS protection are based on the equal area criterion, Centeno et al (2), direct method of Liapunov, Roemish and Wall (3) or rate of change of apparent resistance augmentation, Taylor (4). With a communication channel available, an OS protection system may use observations of phase differences between substations, Ohura et al (5). It must be said that all the above methods allow to detect the OS conditions not before the first slip actually occurred.

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

ANN-BASED OS PROTECTION SCHEME

Among various AI techniques the ANNs have become most frequently used modern data processing / decision algorithms to solve numerous complex engineering problems. Thanks to their well-known advantages (e.g. possibility of learning from examples, generalisation ability, parallel computation etc.) the number of ANN applications grows continuously covering also the field of power system protection, Neibur (6).

Below an approach towards new neural OS protection is described and discussed. The general scheme of the developed ANN-based scheme is shown in Fig. 1. 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. The decision (criterion) values have to be previously calculated from available power system signals with use of dedicated digital processing algorithms.

While designing the ANN classification unit for the OS protection scheme the following important issues have been taken into account:

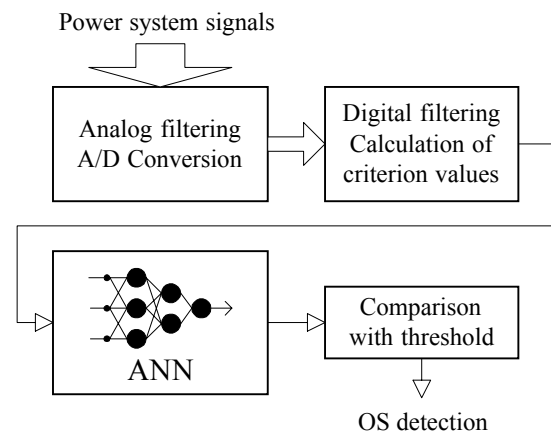


Figure 1: Neural OS protection arrangement

- ANN structure choice (structure type, number of layers and neurones, neurone activation functions),
- ANN training (training algorithm, initial values of weights and biases),
- ANN inputs (signals and their measurement).

The choice of adequate (carrying highest amount of information) decision signals for the ANN feeding has been made on basis of the EMTP/ATP simulations described in the next section.

Simulation data

To investigate the proposed ANN-based OS protection the following simple single machine power system has been modelled (Fig. 2, parameters may be found in Rebizant (7)). 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 the elements of analogue pre-processing (VTs, CTs, anti-aliasing filters etc.). Within the transmission line L1 various three-phase faults on one of the line circuits were applied. A total of 108 short-circuit cases were simulated with the following parameters being varied:

- 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 measurement algorithms utilised orthogonal components of voltage and current signals obtained after their filtration with use of pairs of full-cycle orthogonal Fourier filters.

Optimal selection of the decision signals for ANN feeding has been done with help of statistical measures of distance between calculated dynamic conditional probability density functions (PDFs) of considered signals, (7). The mean and maximum values of chosen indices (Δ_1 – difference of PDF expected values, Δ_2 – difference of PDF standard deviations) taken over 1.44 sec interval after fault clearance are gathered in Table 1.

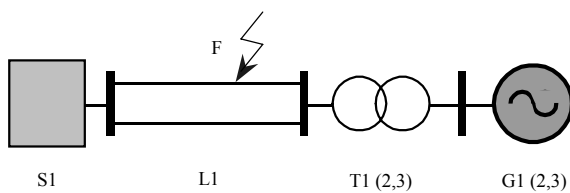


Figure 2: Fragment of power system modelled

TABLE 1 - PDF distance indices

PDF distance	Decision signal					
	$\Delta\omega$	Arg(Z)	P	Q	R	X
mean (Δ_1)	0.31	0.20	0.14	0.24	0.07	0.04
max (Δ_1)	0.66	0.60	0.22	0.39	0.10	0.11
mean (Δ_2)	0.07	0.07	0.02	0.04	0.02	0.03
max (Δ_2)	0.10	0.10	0.03	0.06	0.07	0.08
Ranking	1	2	5a	3	5b	4

The analysis of obtained statistics allowed to order the decision signals according to their relative recognition strength (the greater distance coefficients, the higher ranking position was assigned). In the investigated 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 design and scheme assessment

In the design phase of the OS protection scheme numerous three-layer non-linear feed-forward neural networks (Multilayer Perceptron type) have been examined. The ANNs were trained to produce output equal to 0 for stable patterns and 1 for OS conditions. 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.

ANNs of various sizes (3-3-1 ... 30-30-1 neurones) and 12 different numbers of input signal samples (data window length, DWL, from 0.12 to 1.44 sec) have been trained and tested with use of MATLAB programme. 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 in order to avoid convergence problems while training and simultaneously to make the scheme independent of the machine size. From a total of 720 network configurations examined the optimal ANN structure having 9-9-1 neurones was found.

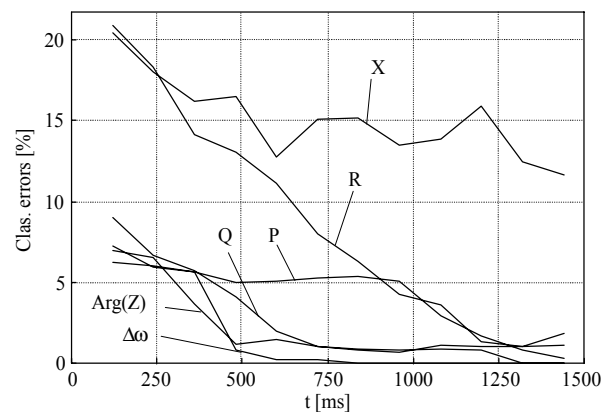


Figure 3: OS detection/prediction errors

Fig.3 shows the classification results (average over various ANN sizes) for all considered ANN input signals. The results obtained confirmed our previous expectations as to the recognition abilities assessed with use of statistical indices. The best classification efficiency was achieved for ANNs fed with $\Delta\omega$ signal - less than 1% of errors for 0.48 sec long data window and no false recognition at 0.8 sec after fault clearance.

The developed ANN based OS scheme has been subjected to extensive tests and robustness checking 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. It turned out that the neural OS detector designed could properly recognise all new unsymmetrical fault testing cases. The other group of 72 testing cases was prepared by simulating various symmetrical faults for two other synchronous machines (G2, G3 - $J_{G2,3}=0.4, 0.8 J_{G1}$). 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 worse results (ca. 5% errors) were obtained for some ANN input features, yet still perfect recognition abilities (comparable to those for machine G1) were maintained for ANNs fed with $\Delta\omega$ signal.

The developed neural detection scheme (ANN with 9-9-1 neurones, DWL=320 ms) has been compared with chosen standard impedance-based OS protection scheme. The scheme modelled consisted of two blinder couples - outer and inner, with assistance of the supervisory MHO circle, Imhof (8). The out-of-step conditions were detected by the scheme and tripping commands issued when the left outer blinder was passed and the supervisory MHO element was reset. The detection parameters of both the ANN-based and standard OS schemes as given in Table 2. The detection statistics show that the standard OS scheme modelled was able to recognise pole slipping conditions just before (or close after) it actually took place. The ANN-based scheme, on the contrary, was able to recognise all OS cases within 360 ms time. It means that for most of the cases a prediction instead of detection action was really performed.

TABLE 2 - Operation parameters of the blinder-MHO and ANN-based OS detection schemes.

Pole slip	Time [ms]		
	min	mean	max
a) observed	420	660	1300
b) detected (standard sch.)	345	610	1350
c) detected (ANN scheme)	320	322	360

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,
- optimisation of the threshold value,
- introduction of fuzzy concepts (hybrid solutions).

In the next section the results of research on the mixed OS protection solutions are reported.

HYBRID ANN-FUZZY SOLUTIONS

Further optimisation of the protection scheme has been done introducing some concepts of Fuzzy Logic (FL), thus making the scheme an AI hybrid. Two cascade-type neuro-fuzzy configurations have been examined. The Fuzzy Inference System (FIS) module was used as a pre-processor of natural power system signals (the FIS output was further processed by an ANN) or as an interpreter of the ANN outputs (Fig. 4). Apart from the output signal of the pre-processing unit (FIS or ANN, respectively) some additional inputs may also be added. Their character, number as well as time position are to be examined in order to become the most optimal operation of the scheme under investigation.

Both mixed ANN – FIS structures shown in Fig. 4 have been thoroughly studied. The investigations described here have been done for a Sugeno-type FIS structure where the output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output. Initial FIS structures were generated with data clustering and then were represented as adaptive multi-layer feed-forward networks (ANFIS), Jang (9). The ANFIS parameters were tuned for the OS classification task with use of a hybrid supervised learning procedure being a combination of the least-squares algorithm and the back-propagation gradient descent method. The advantages of the hybrid FIS-ANN signal processing can be analysed in Fig. 5, where the scheme input signals ($\Delta\omega$ vector) together with relevant intermediate and final outputs are presented. The structure a) from Fig.4 was examined, with current samples of $\Delta\omega$ used as additional input for the ANN.

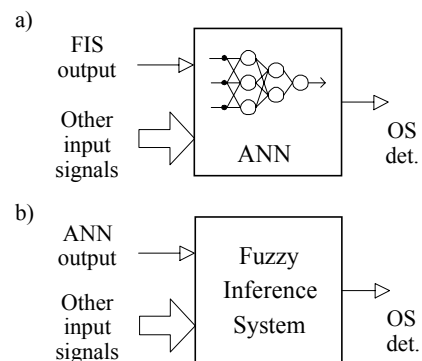


Figure 4: Hybrid configurations studied
 a) FIS – ANN, b) ANN – FIS.

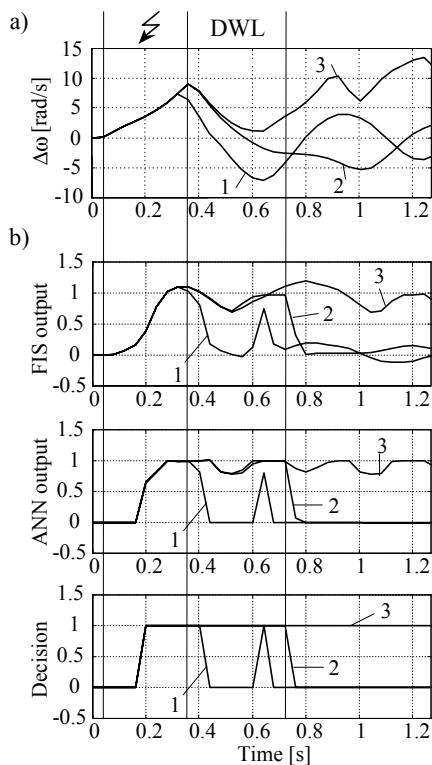


Figure 5: Examples of FIS-ANN operation for test signals (1, 2 – stable cases, 3 – OS case)
a) input signals, b) intermediate and final outputs

The testing cases from Fig. 5 were delivered by our industrial partner (ABB Power Automation) as a part of the COMTRADE file libraries developed within the Accurate Generator Model for Power System Applications project and intended for testing of ABB relaying equipment. One OS and two stable cases owing to a long lasting (300ms) symmetrical faults are presented. For the sake of space shortage the primary signals shown are limited to $\Delta\omega$ calculated from relevant phase voltages. It can be observed that during the short-circuit interval the OS algorithm picks up for all three cases but after the fault clearance and 320ms transient period (data window length) its output stabilises around 0 or 1 giving correct state classification. Such a performance was expected since the FIS-ANN scheme had been trained with post-fault samples only. It is seen that additional processing of FIS output by an ANN brought about significant narrowing of the uncertainty area around tripping threshold. The ANN outputs are closer to 0 and 1 and thus more reliable decision can be issued. As a result the hybrid system becomes more robust than the other single-technique schemes developed.

CONCLUSIONS

The investigations on application of AI techniques 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. Relatively compact structures (ANN with 9-9-1 neurones, FIS with 3 rules) were achieved which implies that they

may be easily implemented on-line on traditional signal processors without need for any expensive specialised neural/fuzzy chips. The developed OS detectors proved to be robust against changing power system conditions (different fault types) and may be used for synchronous machines of various ratings. The developed hybrid OS detectors were able to recognise coming OS conditions 100-1000 ms before they actually took place (a prediction action) thus providing a chance to undertake proper preventive operations to maintain system stability and to avoid presumable stresses to the protected machine.

ACKNOWLEDGEMENTS

The first author would like to extend his gratitude to the Alexander-von-Humboldt-Foundation (Germany) for financial supporting of this work. The authors thank also Dr. J. Bertsch from ABB Power Automation, Baden, Switzerland for delivering of testing signals.

REFERENCES

1. Elmore W.A. (edited by), 1994, "Protective relaying theory and applications", Marcel Dekker, New York, US
2. Centeno V, Phadke A.G. and Edris A., 1997, "Adaptive out-of-step relay with phasor measurements", IEEE Conf. Publ. No. 434, „Developments in Power System Protection”, London, 210-213
3. Roemish W.R. and Wall E.T., , A "new synchronous generator out-of-step relay scheme. Part I. Abbreviated version", IEEE Trans. PAS-104, No. 3, 563-571
4. Taylor C.W., Haner J.M., Hill L.A., Mittelstadt W.A. and Cresap R.L., 1983, "A new OS relay with rate of change of apparent resistance augmentation", IEEE Trans., PAS-102, No.3, 631-639
5. Ohura Y., Suzuki M., Yanagihashi K., Yamaura M., Omata K., Nakamura T., Mitamura S. and Watanabe H., 1990, "A predictive out-of-step protection system based on observation of the phase difference between substations", IEEE Trans. on PD, Vol. 5, No. 4, 1695-1704
6. Neibur D. (convenor), 1995, "Artificial neural networks for power systems", Report by TF 38.06.06, Electra, 159
7. Rebizant W., 2000, "ANN based detection of OS conditions in power systems", 12th Int. Conf. on Power System Protection, Bled, Slovenia, 51-56
8. Imhof, J.A. (Chairman), 1977, "Out of step relaying for generators. Working Group Report", IEEE Trans., PAS-96, No. 5, 1556-1564
9. Jang J-S.R., 1993, "ANFIS: Adaptive-Network-Based Fuzzy Inference System", IEEE Trans. on Systems, Man, and Cybernetics, 23, No. 3, 665-685