Fuzzy Logic Application To Out-Of-Step Protection Of Generators

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Abstract: Efficient protection scheme against out-of-step (OS) conditions based on fuzzy logic (FL) technique is presented. The protection proposed makes use of an adaptive-network-based fuzzy inference system (ANFIS). The FL-based OS protection scheme developed has been thoroughly optimized and tested with ATP-generated case signals. The scheme designed displays almost perfect efficiency and high speed of OS detection. With the scheme designed the OS cases are identified much earlier comparing to standard impedance-based protection schemes. Wide robustness features of the ANFIS-based scheme have also been achieved.

Keywords: synchronous machines, synchronous generator stability, protective relaying, artificial intelligence, fuzzy logic, inference mechanisms, transient analysis, simulation

I. INTRODUCTION

Protecting of a generator against faults and other abnormal conditions requires different types of protective functions. With such possible abnormal circumstances in mind as faults in windings, overload, overheating of windings or bearings, motoring, single phase or unbalanced current operation, overspeed, out-of-step, etc., traditional protection schemes consist usually of a number of discrete protective relays, which are combined together with external auxiliary relays and wiring to produce the necessary trip logic. The amount of protection that should be applied for given machine varies according to the size and importance of the generating unit.

In this research the main attention was focused on the problems related with the detection of out-of-step conditions. The latter may occur in the aftermath of loss of excitation or pole slipping. Various methods for the OS detection have been developed so far and are still in use in protection practice. Among others, the following are worth to be mentioned [1-5]: tracking trajectory of the impedance vector measured at the generator terminals, methods based on the equal area criterion, Liapunov theory, apparent resistance augmentation or observations of the voltage phase differences between substations.

In this paper the results of investigation on application of artificial intelligence (AI) techniques to out-of-step protection is presented, with special attention paid to fuzzy logic (FL) inference algorithms. New FL-based protection schemes, which ensure faster and more secure detection of generator loss of synchronism, have been developed and tested. The paper starts with an introduction to fuzzy inference systems (section II), then the new FIS-based protection is described (section III) and its design and testing results are presented (section IV). Finally, robustness analysis of the scheme and comparison with standard OS protection are shown (section V), followed by concluding remarks (section VI), which close the paper.

II. FUZZY LOGIC INFERENCE METHODS

The family of algorithms based on fuzzy approach was introduced to power system protection at the beginning of last decade. The new techniques met considerable approval for the sake of ability to describe quantitatively the uncertainties appearing during the operation of protective relay. Implementation of fuzzy criteria signals together with fuzzy settings brings antidotes to uncertainties caused by dynamic measurement errors and may constitute a remedy against problems related with sharp boundaries in the universe of criteria signals between areas of faulty and failure-free operation of a protected plant. The use of fuzzy algebra rules in the process of aggregation of different in nature and reliability protection criteria enables easy realization of multi-criteria decision-making. Sample applications of this approach to power system protection include fault type identification [6], multi-criteria protection of power transformers [7], etc.

Fuzzy Inference Systems (FIS) employ the theory of fuzzy sets and fuzzy if-then rules to derive an output. Various types of FIS are often used either for fuzzy modeling or fuzzy classification purposes. Typically an FIS scheme performs its action in several steps including (Fig. 1):

- fuzzification (comparing the input values with membership functions to obtain membership values of each linguistic term),
- fuzzy reasoning (firing the rules and generating their fuzzy or crisp consequents),
- defuzzification (aggregating rule consequents to produce a crisp output).

The investigations described here have been done for a Sugeno-type FIS structure [8] (Fig. 2a), where the output of each rule (y_1 ... y_n) is a linear combination of input variables (x_1, x_2, x_3) plus a constant term, and the final output z is the weighted average of each rule's output:

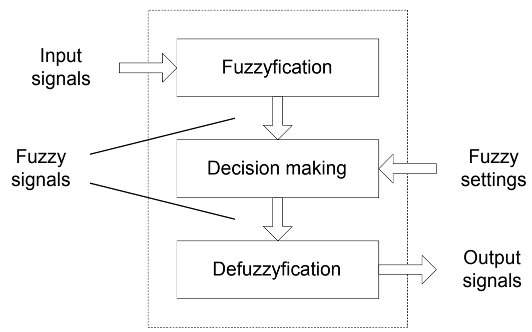

Fig. 1. Fuzzy reasoning system.

$$z = \frac{w_1 y_1 + w_2 y_2 + ... + w_n y_n}{w_1 + w_2 + ... + w_n} \quad (1)$$

$$y_k = a_k x_1 + b_k x_2 + c_k x_3 + d_k \quad (2)$$

$$w_k = \mu_{1k}(x_1)\mu_{2k}(x_2)\mu_{3k}(x_3) \quad (3)$$

where:

$\mu_{ik}(x_i) \in \{\mu_{iLOW}, \mu_{iMEDIUM}, \mu_{iHIGH}\}$ - membership functions (MF) for the linguistic terms *LOW*, *MEDIUM*, *HIGH* associated with the *i*-th input signal,

w_i - weighting factor for the *i*-th rule consequent.

In the design phase the FIS examined were represented as adaptive multi-layer feed-forward networks (ANFIS) [9]. The structure of an ANFIS with three inputs and one output is shown in Fig. 2b. The ANFIS consists of three layers of nodes performing different operations on incoming signals. The nodes in particular layers are responsible for determination of membership grades for each linguistic term, executing the rules and generating the weighted output. Additional factor is introduced to normalize the firing strengths of the rules with respect to the sum of all firing strengths. The possibility of parameters adjusting via training (similar as for neural network schemes) is an important feature of the ANFIS structure. A hybrid training algorithm being a combination of the least squares method and back-propagation gradient descent method was used here to prepare the FIS for the OS classification task.

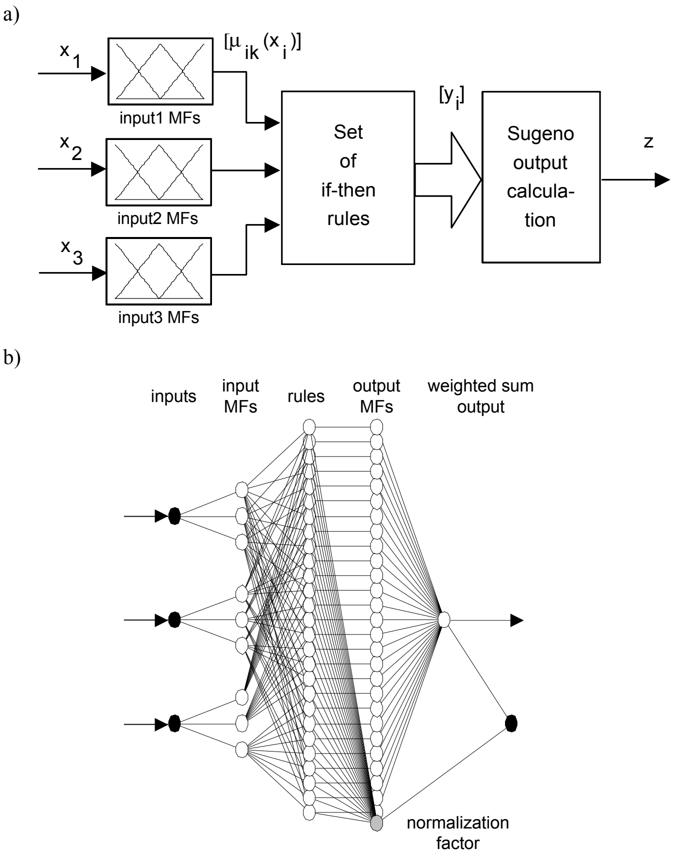

Fig. 2. FIS studied: a) general structure, b) adaptive network representation.

III. FIS-BASED OS PROTECTION SCHEME

The general scheme of the FL-based scheme developed is shown in Fig. 3. The reasoning part of the protection is realized with help of the FIS performing a kind of 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. Orthogonal components of phase voltages and currents are calculated first with use of full-cycle Fourier filters, basing on which further criterion signals are determined.

The FIS input vector consists of a number of signal samples captured with use of a sliding data window (DW), as shown in Fig. 4. Chosen criterion signal is observed with the measurement rate MR within the DW having the length being a multiple of MR and number of samples *m* (DWL=MR**m*). Constant value of *m*=3 was kept in this case, while MR was being varied in the range (80–480) ms, which resulted in DWL from the interval (160–960) ms. The data window beginning (DWB - measured from the fault inception time), is moving and thus consecutive sets of signal samples (input vectors **X**(k)) are delivered to the FIS-based reasoning unit.

The FIS applied is assumed to produce output equal to 0 for stable patterns and 1 for OS conditions. For classification purposes a threshold value set to 0.5 is introduced. All the cases for which the FIS output is lower than 0.5 are classified as stable and those for which the threshold is exceeded are recognized as OS cases.

The FIS-based reasoning unit itself has the following design parameters:

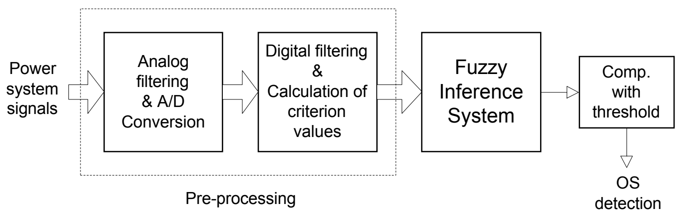

Fig. 3. General structure of the FIS-based OS protection.

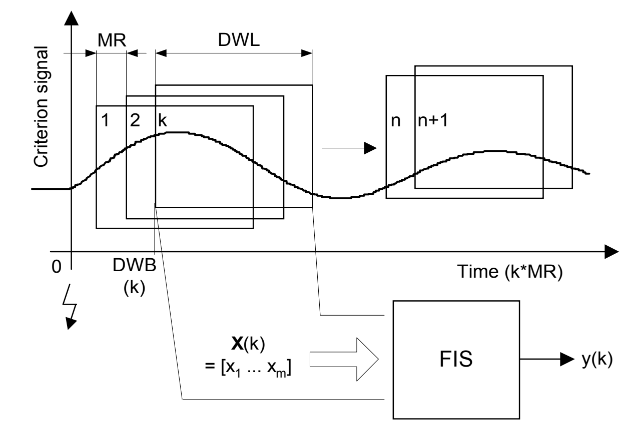

Fig. 4. Data capturing with sliding data window.

- type - Sugeno,
- 3-sample data window,
- triangle membership functions,
- 3 linguistic terms (low, medium, high) for each input MF,
- 27 linear terms for output MFs,
- 27 rules (resulting from number of inputs and MF terms),
- rule weights and connections set to 1,
- fuzzy operators: product (and), maximum (or), product (implication), maximum (aggregation), center of gravity (defuzzification),
- initial FIS structure generated with grid partitioning of the data, then trained.

The detailed shape and parameters of the membership functions as well as values of coefficients in (2) are tuned during training with a set of signals obtained from simulation of a test power system with use of ATP software package.

IV. OS PROTECTION SCHEME TRAINING AND EVALUATION

A. *Data for scheme training and testing*

Similar as in case of neural networks, chosen ANFIS networks have been trained with a set of input-output patterns generated with ATP simulation program. To obtain data for training of ANFIS and further testing of the OS protection, a simple single machine – infinite bus system was modeled (Fig. 5). The synchronous machine G1 was connected to the infinite bus system S1 via a block transformer T1 and a 200-km long double-circuit overhead line L1. Within the transmission line a total of 108 symmetrical faults on one of the line circuits were applied, some of them responsible for further developing OS conditions [10].

Additional testing cases for robustness analysis were also prepared including unsymmetrical short-circuit cases as well as 3-phase fault cases for other machine ratings (generators G2,3 with corresponding transformers T2,3 – Fig. 5).

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 FIS input features, the statistical properties of available signals were determined [11]. In the investigated case the most valuable recognition feature turned out to be the machine angular frequency deviation $\Delta\omega$, followed by the impedance angle Arg(Z) measured at the machine terminals. All the results described below have been obtained for the scheme fed with $\Delta\omega$ signal only.

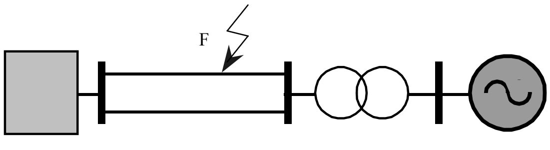

Fig. 5. Test power system modeled in ATP.

B. *OS protection efficiency assessment*

The proposed FL-based OS detection scheme was put to extensive tests, which brought about promising results with regard to the detection speed and classification efficiency.

Fig. 6 presents the values of average FIS output errors (as a function of time after fault switching-off) understood as the difference between ideal values (0, 1) and actual value observed at the FIS output. As one can notice, higher FIS output errors occur for the initial time period, where no significant OS symptoms can really be observed. The values of FIS output errors decrease with time passing and the classification process becomes more and more reliable. Better results are always obtained for longer DWLs, for which more information about phenomena to be classified is available.

The relationship of the FIS classification efficiency (percentage of correctly classified cases) vs. time (DWB location) for various values of DWL is shown in Fig. 7. As could be expected, extending the DWL implicates better operation results of the scheme. Naturally, the FIS output becomes more accurate and the classification more reliable when the DW is moved with time towards "better developed" (more clearly recognizable) OS symptoms.

Valuable information on the FIS operation results deliver the indices of average efficiency and average output errors gathered in Table 1. The average values were calculated over all 108 fault cases and time instants for which the FIS rules were fired (0–500ms after fault switching-off).

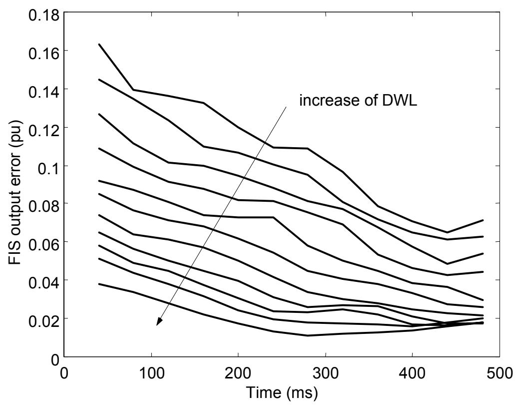

Fig. 6. Average FIS output error vs. time (DWB location).

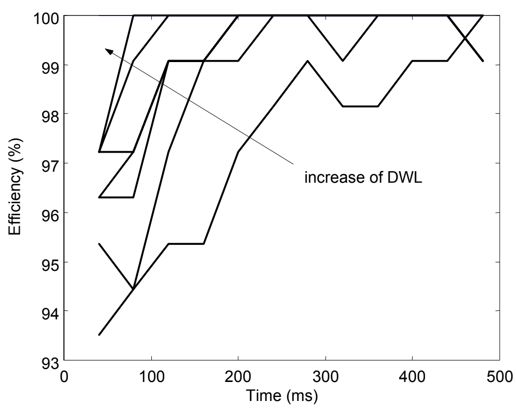

Fig. 7. Average FIS operation efficiency vs. time (DWB location).

Table 1. Average parameters of FIS operation.

DWL (ms)	FIS efficiency (%)			FIS output errors (pu)		
	a)	b)	c)	a)	b)	c)
160	97.3	97.4	96.4	0.108	0.105	0.167
320	99.1	98.6	99.1	0.084	0.079	0.107
480	99.2	100.0	97.8	0.061	0.063	0.085
640	99.7	99.5	99.8	0.042	0.047	0.055
800	100.0	100.0	100.0	0.030	0.033	0.042
960	100.0	100.0	100.0	0.020	0.016	0.026

a) FIS trained and tested with all the patterns, b) FIS trained and tested with half of the patterns, c) FIS tested with second half of the patterns.

Table 2. Error-free operation of the FIS-based scheme.

DWL (ms)	DWB (ms)	Dec. time (ms)	FIS error (pu)
160	480	740	0.071
320	200	520	0.095
480	200	680	0.073
640	120	760	0.061
800	80	880	0.049
960	80	1040	0.034

It may be noticed that the average efficiency of 99% and better is achieved for DWL equal or greater than 320 ms. The longer DW is applied, the lower FIS output errors appear and the better classification results are obtained. A reasonable compromise between DWL and FIS efficiency has, however, to be worked out when possibly earliest decision is to be issued. The FIS generalization properties can be studied analyzing columns b) and c) in Table 1. As usual, the scheme operation is worse for cases unseen during training (output errors higher, efficiency lower). However, the results obtained do not differ drastically from those achieved for training patterns, thus confirming quite good general qualification of the scheme for the OS classification task.

In Table 2 the FIS operation parameters assuring error-free recognition are gathered. It can be seen that the effectiveness of 100% (all cases properly classified) is achieved at t=200ms for DWL=320ms but also at t=120ms for DWL=640ms and at t=80 ms for DWL≥800ms. It means that the error-free classification of OS conditions with designed FIS may be expected at the earliest 520 ms after fault switching-off, which is similar as by the neural OS detection scheme described in [10]. Moreover, the greater value of DWL, the smaller average FIS output and the recognition more reliable, however, not optimal as far as the classification speed is concerned.

C. *Optimization analysis*

In order to check the optimality of the FIS recognition unit designed, further analysis for various parameters, possibly having an impact on the scheme operation, have been performed. Table 3 presents the efficiency and average output error obtained for one specific FIS structure (Δω input signal, DWL=320ms) with different shape of the membership functions and number of the MF terms (3 – as previously, 2 and 4).

Looking at the results one can surely notice that the worst FIS operation parameters are obtained when the membership functions adopted have two linguistic terms only. For such an arrangement the average FIS output error has increased by 25–50%. Simultaneously the classification efficiency has dropped by maximum 3.5%, depending on the MF shape. The best results are achieved for MFT=4, however, the difference obtained is not very significant. The relationship of FIS efficiency vs. MF shape is distinctive for MFT=2 only and becomes flat for higher number of MF terms. The gauss-shaped MFs seem to be most promising in the investigated case. Choosing the shape and number of terms of MFs for given application should, however, be done with great care, having in mind the possibility of on-line implementation of the scheme. Applying non-linear MFs and high MFT values entails considerable increase of computational burden by executing the FIS algorithm. One ought to bear in mind that the number of rules to be fired at each time step is a power function of MFT and number of FIS inputs m (MFT^3 in this case). Thus taking MFT=4 instead of 3 increases the set of FIS rules 2.4 times – from 27 up to 64.

Table 3. FIS efficiency and average output error vs. MF shape and number of terms (MFT).

MF shape	Efficiency (%)			Average output error (pu)		
	MFT=2	MFT=3	MFT=4	MFT=2	MFT=3	MFT=4
triangle	98.9	99.1	99.1	0.100	0.084	0.069
trapezoid	96.0	99.1	99.5	0.116	0.080	0.039
bell	98.8	99.3	99.4	0.094	0.071	0.052
gauss	99.1	99.1	99.3	0.090	0.077	0.058
pi-shaped	95.4	99.1	99.1	0.132	0.084	0.043
sigmoid	97.0	99.1	99.4	0.116	0.073	0.052

Table 4. FIS operation parameters for other decision vectors.

Input vector **X**	Efficiency (%)	Aver. error (pu)	100% dec. time (ms)
Δω input vector	99.1	0.095	520
[Δω, Δω, ArgZ][a)]	96.3	0.104	720
[Δω, Δω, ArgZ][b)]	99.3	0.040	520
[Δω, ArgZ, ArgZ][c)]	99.0	0.054	480
[Δω, ArgZ, $P_{post-fault}$][d)]	99.3	0.062	560
[Δω, ArgZ, $P_{pre-fault}$][e)]	99.2	0.059	520

Further tests have been done for chosen FIS structure (MF='triangle', DWL=320 ms, MFT=3) fed with other combined decision vectors including, apart from Δω input, also impedance angle and active power components:

a) **X**(k)=[Δω(k+DWL/2)–Δω(k), Δω(k+DWL) –Δω(k+DWL/2), ArgZ(k+DWL)–ArgZ(k+DWL/2)],
b) **X**(k)=[Δω(k+DWL)–Δω(k), Δω(k+DWL), ArgZ(k+DWL)],
c) **X**(k)=[Δω(k+DWL), ArgZ(k+DWL)–ArgZ(k+DWL/2), ArgZ(k+DWL)],
d) **X**(k)=[Δω(k+DWL), ArgZ(k+DWL), P(post-fault)],
e) **X**(k)=[Δω(k+DWL), ArgZ(k+DWL), P(pre-fault)].

One can observe (Table 4) that, apart form the vector a), all variable combinations used as FIS inputs brought comparable results. Taking only the time differences of Δω and Arg(Z) (no data on actual value of input signals) makes the recognition both less efficient and much slower than for other input vectors. Error-free operation (all cases correctly classified) was obtained at the earliest for vector c) – 480 ms after fault switching-off.

V. ROBUSTNESS AND COMPARATIVE ANALYSIS

A. *Robustness analysis*

Similarly as by the neural OS detection scheme [10], the designed FIS were put to additional tests with the signals coming from other power system fault cases, as mentioned in section IV.A. 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. The other group of 72 testing cases was prepared by simulating various three-phase faults within line L1 but for the other two synchronous machines (G2, G3 as in [10]).

Three different FIS structures having DWL=320, 560 and 800ms have been chosen for robustness analysis. The average results of testing (over time and all fault cases), along with data for initial parameters (results for training data set) are gathered in Table 5. It can be observed that the scheme occurred to be quite robust against both different fault types and other synchronous machine ratings. The average classification efficiency has dropped by 1–3% in comparison with the results for training patterns. Smaller drops were achieved for structures with greater DWL (efficiency still above 99%).

Table 5. Robustness studies - average classification efficiency.

Input vector **X**(k)	DWL (ms)	Efficiency (%)		
		a)	b)	c)
$\Delta\omega$ samples	320	99.1	95.7	96.0
	560	99.3	96.5	97.3
	800	100.0	99.1	98.7

a) results for training patterns,
b) testing with unsymmetrical fault cases,
c) testing with signals for other synchronous machines.

Analysis for other decision vectors has shown that increased robustness of the OS detection scheme may be obtained when the information on pre-fault active power is also included (vector e), section IV.C).

B. *Comparison with standard OS protection scheme*

In the capacity of standard OS protection, various impedance-based solutions may be considered [12]. A stand-alone MHO characteristic, single or double blinders with or without MHO element, double or triple lens schemes or concentric circle scheme may be used, to name only the most popular versions. For the purpose of comparison with the AI-based scheme developed, a double-blinder + MHO OS detection scheme was modeled, as shown in Fig. 8. All the impedances in Fig. 8 are given in (Ω) as viewed from the generator terminals (17.5kV bus).

The scheme consists of two blinder couples - outer (lines A, D) and inner (lines B, C), with assistance of the supervisory MHO circle (E). In the sample OS case shown in Fig. 8, the inner blinder area (B-D) is entered twice by the trajectory of impedance Z measured at the machine terminals (curve marked with points (1) – (11)). After fault inception the impedance vector moves rapidly from the load area (1) to the fault region (4), within a very short traverse time t_3–t_2 between

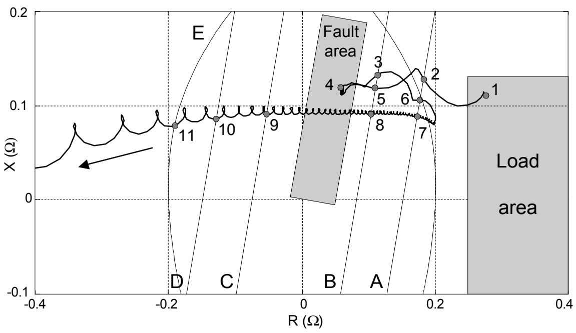

Fig. 8. Standard impedance-based OS detection scheme.

Table 6. Operation parameters of the standard (STD) and FIS schemes.

	min	mean	max
Pole slip observed at t (ms)	620	860	1500
Detection with STD scheme at t (ms)	545	810	1580
Detection with FIS-based scheme at t (ms)	440	505	520

lines A and B. After fault switching-off the impedance trajectory leaves the blinder area moving towards the load region, however, shortly after that it begins to move counterclockwise and crosses the entire blinder-MHO characteristic. The A-B traverse time t_8–t_7 is much longer than previously which confirms that severe power swing takes place. The out-of-step is detected and tripping command issued when the left outer blinder D is passed (10) or the supervisory MHO element is reset (11), depending on the particular logic being used. It can be seen that the impedance trajectory around point (11) is no longer smooth but rather spring-shaped. This is an effect of increasing errors of measurement with the algorithms set for 50Hz voltage and current signals, while the generator speed deviation in that region reaches quite high values.

The above OS protection scheme was “executed” for all simulated fault cases. All the OS cases were recognized, with the average detection parameters as given in Table 6. The detection statistics show that the standard OS scheme modeled was able to recognize pole slipping conditions just before (or close after) it actually took place. The time needed to issue the tripping command was dependent on the phenomena dynamics for each specific case. On the contrary, the FIS-based protection developed was able to recognize all OS cases within 520ms. It means that for most of the cases a prediction instead of detection action was really performed.

Fig. 9 presents chosen four cases of OS conditions represented by a $\Delta\omega$ waveform, along with the corresponding outputs of the developed FIS detection scheme (FIS) and the impedance-based double-blinder scheme (STD) adopted. One can notice that the FIS scheme recognized all of the four simulation runs as OS cases at t=520 ms after fault inception. The standard OS detector needed 545 up to 1580ms, and thus was 25–1060ms slower as the scheme developed, depending on the dynamics of the $\Delta\omega$ changes for given cases. The STD algorithm was not able to issue its decision on OS conditions until considerable angular frequency deviation of about 15–20 rad/s (2.4–3.2 Hz) was observed. Contrary, in case of FL-based scheme the detection was made basing on the early gentle symptoms of coming generator instability.

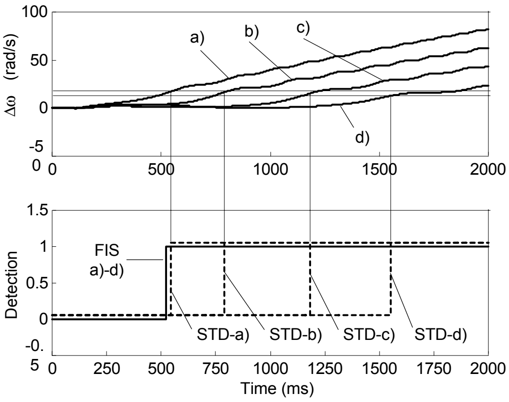

Fig. 9. Response of FIS-based (FIS) and standard (STD) OS protection for chosen simulation cases: a) severe fault by high pre-fault load, b) middle pre-fault load, c) low pre-fault load, d) case with autoreclosure.

VI. CONCLUSIONS

A new approach to out-of-step protection applying fuzzy inference methods has been proposed in the paper. The FIS-based scheme developed displays high efficiency and very short time of OS detection. Comparing to other existing impedance OS protection devices, a kind of prediction of coming machine instability is performed instead of traditional detection of actually occurring phenomena. The decision is taken within approx. 500ms after fault inception, thus leaving enough time for an appropriate action (tripping, fast valving) to protect the generator from stresses and preserve the stability of power system.

The OS protection scheme proposed makes use of the adaptive network version of FIS. With such an arrangement all the advantages of fuzzy processing are combined with the virtues of training on examples, as in case of neural networks. Thus all the problems connected with burdensome heuristic setting process of the fuzzy system are avoided and a kind of optimization is realized.

The OS protection developed has been thoroughly tested with ATP-generated power system signals. Wide robustness features of the scheme with respect to both different fault types and other synchronous machine ratings have also been confirmed.

VII. ACKNOWLEDGEMENTS

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IX. BIOGRAPHIES

Dr. Waldemar Rebizant was born in 1966 in Wroclaw, Poland. He received his M.Sc. and Ph.D. degrees (both with honors) from Wroclaw University of Technology, Poland in 1991 and 1995, respectively. Since 1991 he has been a faculty member of Electrical Engineering Faculty at the WUT. In June 1996 he was awarded Siemens Promotion Prize for the best dissertation in electrical engineering in Poland in 1995. In 1999 he was granted a prestigious Humboldt research scholarship for the academic year 1999/2000. In the scope of his research interests are: digital signal processing and artificial intelligence for power system protection purposes.

Prof. Kurt Feser was born in 1938 in Garmisch Partenkirchen, Germany. He studied electrical engineering at the Technical University of Munich and graduated in 1963. After a year with the Brown Boveri & Cie AG in Mannheim, Germany, he joined the High Voltage Institute of the University of Munich. In 1970 he received his Dr.-Ing. from the University of Munich. And in 1971 he joined Haefely & Cie AG Basel, Switzerland, as chief development engineer for high voltage test equipment. From 1980 onwards he was responsible at Haefely & Cie for capacitors, high voltage test equipment and accelerators and was, as director, member of the executive board of Haefely. During 1977 to 1980 Dr. Feser was member of the board of directors of American High Voltage Test Systems, Accident, Maryland. In April 1982 he joined the University of Stuttgart as head of the Power Transmission and High Voltage Institute. Prof. Feser is a Fellow of the IEEE, member of VDE and CIGRE, chairman of TC 42 "High voltage test technique” and author of more than 180 papers.