A Neuro-Fuzzy Method of Power Disturbances Recognition and Reduction

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Abstract - The paper combines two major neuro-fuzzy applications in power engineering: stabilizing power systems at a generation stage and reducing disturbances at a delivery stage. It presents a neural-fuzzy classifier for recognition of power disturbances and a fuzzy excitation controller comprising both the exciter and the power system stabilizer.

I. INTRODUCTION

Modern power generation and delivery systems are required to provide significant improvement in stabilizing the parameters of the electricity supply and disturbance reduction. Up to date, considerable efforts have been focused on this area, for instance, assessing impacts brought about by deterioration of power quality, monitoring variant disturbances occurred in generation, transmission and distribution networks, and seeking measures for power service improvement [1]. This paper combines two major neuro-fuzzy applications in power engineering: stabilizing power systems at a generation stage and reducing disturbances at a delivery stage.

As the prerequisite of solutions to power quality problems, an initial investigation is necessary for identifying the exact circumstances utilities experienced and verifying the countermeasures to adopt. In practice, electric power delivered at certain customer sites is monitored continuously, which can produce yearly gigabyte size data files. In this paper, the authors present a novel classifier based on neural-fuzzy technologies. The neural networks with the architecture of Frequency Sensitive Competitive Learning and Learning Vector Quantization (FSCL-LVQ) are trained using a set of samples including thirteen types of power quality disturbances. After the FSCL and the LVQ two training phases, each type of disturbances in the training set is represented by a certain number of code-words. These code-words are to be used in later recognition for determining how well an input waveform matches the thirteen patterns respectively in terms of similarity measures. To handle the uncertainty existing in the training set and the pattern recognition, the similarity measures are each quantified into the selected membership functions derived from the statistical distributions of the training samples. Finally, the fuzzy associative memory (FAM) recalling is activated to identify the disturbance type that the input waveform most possibly falls into. The identification is accompanied by a belief degree that is introduced as an estimate to the recognition accuracy. The classifier is designed to recognize up to thirteen types of waveforms. Diversities of variant disturbances increase the difficulty to achieve high recognition accuracy. The huge size of the time-domain data files further complicates the problem. Consequently, a pre-processing procedure is necessary.

The second part proposes a hybrid structure for a fuzzy logic based excitation control (FLC) system comprising both the exciter and the power system stabiliser (PSS) for a synchronous generator connected to an infinite bus through a transmission line. The combined structure is based on some new techniques of educing the most appropriate parameters that can represent the status of the machine. The system considers the speed deviation and applies a nonlinear scaling for this parameter based on operational sectors. The terminal voltage error is another factor considered by the system.

II. DISTURBANCE RECOGNITION

In the design of the proposed recognition scheme, the thirteen types of waveforms to be classified are divided into Group-A, Group-B and Group-C. As shown in Table 1, disturbances in each group are denoted by A1~A4, B1~B8, or C1 and C2 accordingly. For the definition of the listed disturbances, please refer to [2].

TABLE 1 POWER QUALITY DISTURBANCES

Disturbance Categories	Descriptions
Group-A	A1&A2: High&low frequency capacitor switching, A3: Impulsive transients, A4: Notching. The group disturbances have short elapsed-time, causing no fundamental frequency f_1 change in the steady-state condition.
Group-B	B1&B2: Fundamental frequency deviation (higher&lower), B3: Sag, B4: Swell, B5: Momentary interruption, B6: DC offset, B7: Voltage fluctuation, B8: Harmonics containing low-frequency components (<4 f_1)*. Long duration or steady state disturbances.
Group-C	C1: Harmonics without containing low-frequency components*, C2: Normal waveform.

* The two distorted waveforms B8 and C1 are regarded as one disturbance type in the final classification. In Group-B, waveforms containing only high frequency harmonics are clustered as normal ones with the recognition being deferred to the Group-C classification.

It is seen from Table 1 that Group-A includes transient or “fast changing” disturbances (much higher frequency compared with the fundamental frequency f_1). On the contrary, Group-B contains long-duration or steady state disturbances. This group of distortions is caused either directly by the variation of the fundamental frequency (higher or lower deviation) or by certain "slow changing" disturbances (at the order comparable to the f_1). Group-C comprises only two members, the normal waveform or the one with high frequency harmonics (above 4^{th}). As shown by the spectrum analysis in the following section, disturbances of Group-A and Group-B can be recognized respectively from the upper- and the lower-end frequency component of the transformed data. Since a wide range of harmonics ($0\sim50^{th}$) is concerned by the classifier, however, quite a number of spectral components are needed for identifying harmonic distortions. In the designed classifier, harmonics below 4^{th} are categorized into Group-B because the same lower-end spectral component can be utilized for the identification. In Group-B pattern recognition, nevertheless, it is difficult to differentiate harmonics without containing low-frequency components from normal waveforms. Consequently, the classification is deferred to Group-C where the middle sub-band spectral contents are exploited to sort out the two

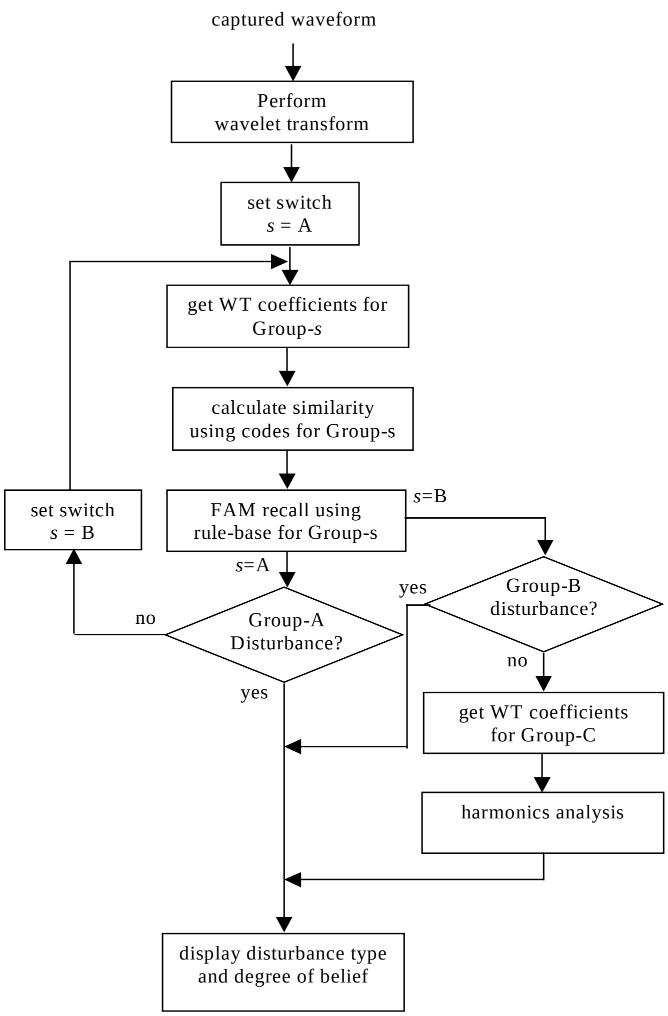


Figure 1. Classification of power quality disturbances.

members. It is seen that the division of the three group disturbances is based on their behaviors in frequency domain. By processing different type of disturbances separately, the recognition accuracy can be increased significantly. The training and testing data used in the developed recognition scheme are from the measurements carried out at a number of customer sites in Tasmania, Australia.

III. DISTURBANCE CLASSIFICATION

Among different types of neural networks, the LVQ architecture is particularly appealing to pattern recognition applications. Unlike its counterparts MLP restricted to a single distortion measure, the LVQ can choose an appropriate criterion from a number of selections according to the specific problem. Aside from this, the LVQ architecture allows common training for general classification tasks and subsequent special training for a particular application [3]. It is known that each specific task needs an independent training in MLP design.

The neural approach also suffers a problem, i.e. the difficulty in estimating how well a given training set reflects an unknown underlying distribution of points and whether the neural networks encode the original structure [4]. In practice, statistical neural estimators require a "statistically representative" training set, which is not always satisfied unfortunately. For the available training samples, furthermore, inaccuracies or even errors are unavoidable. All these factors add uncertainties to the input-output relationship described by the training set. The fuzziness of the notion "statistically representative" compounds the problem.

Based on the considerations addressed above, a neural-fuzzy classifier is developed by exploiting the powerful capability of the LVQ architecture in pattern recognition and the flexibility of the FAM mapping in handling uncertainties. Fig. 1 illustrates the procedures throughout the classification of the power quality disturbances. A 5-level discrete WT is first applied to the captured waveform for isolating the disturbance features represented by the feature vectors, i.e., the approximation coefficients and the five-scale detail coefficients. Then the CD_1 is utilized for classifying the four disturbances of Group-A. After that, if desired (the input is not a Group-A member), the CA_5 is to be checked for the pattern recognition of Group-B. The classification of these two group disturbances is performed by evaluating the similarity measures with the code-words of the LVQ networks, and by inferring with the FAM rule-bases. Hence a database containing the code-words and a rule-base performing the FAM mapping should be built up in advance for Group-A and Group-B respectively. If fail to identify any disturbances belonging to these two groups, the input waveform must then be either of the two members of Group-C: a normal waveform or a one with high frequency harmonics (above 4^{th}). To sort out the two patterns, the middle scale transform-coefficients CD_2~CD_5 are employed. Due to the orthogonality of the wavelet adopted, the rms of the transform coefficients directly indicates the energy of the harmonics in the corresponding frequency range. Hence the rms is used as the criterion for Group-C classification. It should be noted that the CA_5 used in Group-B could only be employed to ascertain the existence of low frequency harmonics (below 4^{th}) other than excluding this type of distortion completely since the harmonics usually spread a wide spectrum.

IV. FUZZY ASSOCIATIVE MEMORIES

It can be seen that the similarity measure, although more reliable in dealing with the uncertainty of the training samples, is actually a modified Euclidean distance. Should the criterion of maximum similarity measure (shortest distance) be adopted, the classification results would be similar to that when only the neural network technologies were employed. During training and testing of the LVQ networks, it has been found that the minimum distance may not always indicate the right type of the input waveform. This is due to the fact that the training samples can hardly be sufficiently representative and the code-words thereby extracted may be unable to define perfect boundaries separating different patterns. To improve the classification, as a result, the developed recognition scheme uses the FAM rule-matrix to recall the disturbance type from the similarity measures, rather than directly reaching the conclusion with the winner of the competitive quantizer.

V. DISTURBANCE RECOGNITION EXPERIMENTS

A testing set containing the thirteen types of waveforms is used to verify the performance of the developed classifier. The input waveforms are processed by a 5-level WT to decompose into the approximation coefficients CA_5 and the 5-scale detail coefficients CD_1~CD_5. With the code-words evaluated from the training samples, the similarity measures are computed for each testing sample. By employing the FAM rules, the type of the disturbances is recognized.

The recognition scheme has achieved a satisfactory performance. Table 2 summarizes the experiment results. For the whole testing set, the average correct recognition rate is higher than 93%, with each individual rate exceeding 90%. The average belief degree for the total classification is 0.929, which is very close to the average recognition rate.

Should only the classification with the belief degrees above certain level be accepted, the accuracy will be increased accordingly. Table 3 provides the classification results using three different belief criteria. It is found that the recognition rate is approximately proportional to the belief degree criterion. This observation shows that the defined belief degree is a proper measure for the validity of the classification.

TABLE 2. PERFORMANCE OF CLASSIFICATION

Disturbance types	Number of testing samples	Recognizing rates (%)	Average belief degree
A1	100	92	0.933
A2	100	91	0.916
A3	100	100	0.950
A4	150	91	0.921
B1	100	92	0.927
B2	100	91	0.934
B3	100	93	0.920
B4	100	94	0.938
B5	100	100	0.949
B6	100	96	0.952
B7	150	90	0.909
C1*	100	91	0.913
C2	100	92	0.912
Recognizing rate for whole testing set	93.3%	Average belief degree for whole testing set	0.929

*Including B8 and C1 defined in Table 1.

TABLE 3. RECOGNITION RATES WITH DIFFERENT BELIEF DEGREE CRITERIA

Degree of belief / Disturbance types	0.95	0.92	0.88
A1	98.1%	95.8%	94.0%
A2	96.6%	93.1%	92.0%
A3	100%	100%	99.7%
A4	94.4%	94.1%	91.1%
B1	95.9%	94.5	93.3%
B2	96.0%	94.2%	92.3%
B3	100%	100%	100%
B4	97.2%	94.2%	93.6%
B5	99.3%	98.9%	98.5%
B6	97.1%	96.3%	95.5%
B7	93.4%	93.1%	91.5%
C1	93.0%	92.7%	91.5%
C2	92.9%	91.7%	90.5%
Average	96.5%	95.3	94.1%

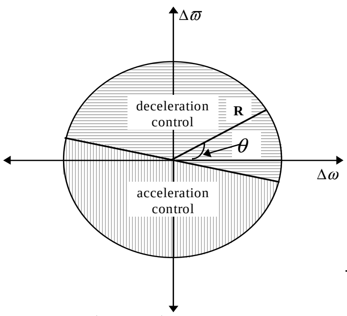
VI. DISTURBANCE REDUCTION AT GENERATION

The most advanced area of neuro-fuzzy applications in power system generation control is the area of PSS design, where many successful applications were reported, Hsu et. al.[5]. The most popular FLC structure and algorithm used in PSS design is the one proposed by Hiyama [6]. In that design the stabilising signal U_{PSS} is derived from the speed deviation $\Delta\omega$ and the acceleration $\Delta\varpi$. These two parameters are used to divide the phase plane $\Delta\omega - \Delta\varpi$ into two control sectors, acceleration and deceleration as shown in Fig 2.

The angle θ derived from the phase plane is used to generate the PSS control signal U_{PSS} in the form

$$U_{pss}(k) = G_c(k)\frac{[N(\theta) - P(\theta)]U_{max}}{[N(\theta) + P(\theta)]}$$

where $G_c(k)$ is a gain determined by a discontinuous function



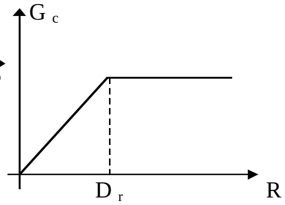


Figure 2: $\Delta\omega - \Delta\varpi$ plan proposed by Hiyama

Figure 3: Gain function

as shown in Fig. 3. Both $N(\theta)$ and $P(\theta)$ are fuzzy membership functions. However, this algorithm seems to be more system dependent than a FLC structure is ought to be. The above scheme has many parameters (e.g. F_a, U_{max}, G_c and D_r) that are adjusted and optimised according to some performance indices. This point would limit the superiority of such schemes within certain operational regions of the system.

Rule base type FLCs are also used in many applications, however they seem to be of less popularity than the Hiyama algorithm. Due to the need of a large rule base that causes lots of computational difficulties, some authors tend to optimise the number of rules used in the rule base, see Chakraborty [7].

Two control concepts are used in the above mentioned FLC schemes: one based on the fuzzy set theory is applied in the PSS part and the other is based on the classical control in the exciter and regulator part. This mixed type control leads to facing some problems associated with both FLCs as well as conventional controllers design. This section introduces a novel excitation system that is totally based on fuzzy set theory in a combined single controller called Shay-Exciter to produce the overall excitation control signal. The basic idea behind this scheme relies on the pre-controller manipulation and refining of the input parameters that are chosen to represent the status of the generation unit. Dynamics problems are covered by considering the speed deviation $\Delta\omega$, and steady state conditions are covered through consideration of the error in the generator terminal voltage.

The parameter that needs to be processed previously to the final control action is $\Delta\omega$. The manipulation of $\Delta\omega$ associates it a phase and an amplitude that is to be added directly to the error signal in the terminal voltage. The output of the summation point is the input to the final control stage, Shay-Exciter. Processing $\Delta\omega$ is performed more or less close logic as that followed by Hiyama in his FLBPSS. However, it differs in having fuzzy logic techniques to optimise and update the controller parameters on line.

Manipulation of $\Delta\omega$ is performed on the basic idea of dividing the generator operation into six different operational sectors based on three factors, $\Delta\omega(k)$, $\Delta\omega(k-1)$ and $\varpi(k)$ where $\varpi(k) = \omega(k) - \omega(k-1)$. These six different sectors can be realised in a boolean logic based on the sign of the three parameters as in Figure 4.

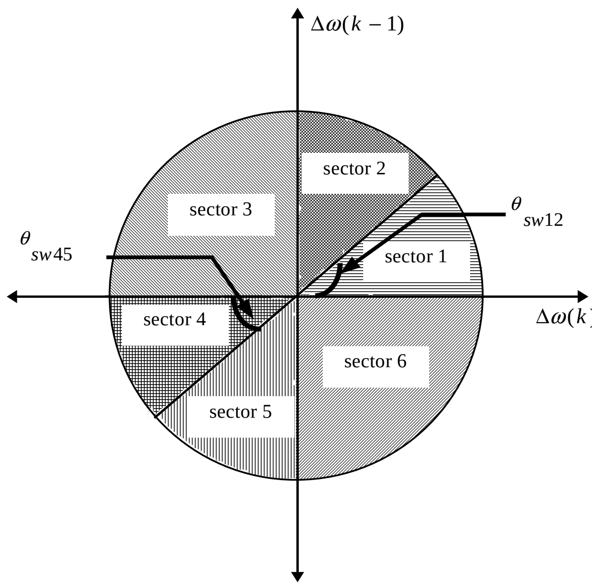
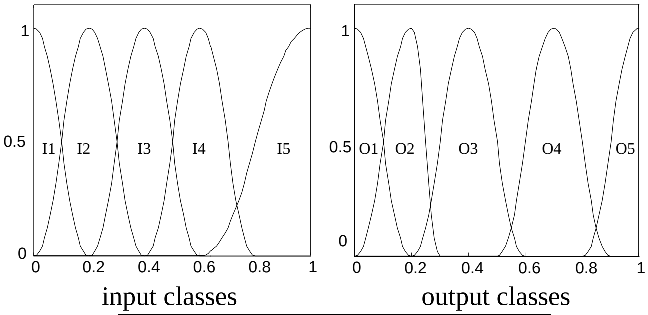


Figure 4: Operation sectors representation

The first step of the Shay-Exciter pre-control manipulation involves the determination of the operation sector at the current moment. The magnitude of the processed signal as well as the sign are determined through different types of input processing for different sectors. In sectors 3 and 6 the amplitude associated to the $\Delta\omega$ factor is calculated at the initial design stage by the single input single output (SISO) FLC that uses $|\Delta\varpi|$ as an input and produces a nonlinear step up or down amplification of $\Delta\omega$. The SISO classes and rule base are shown in Figure 5, the L/R COG defuzzification method is applied in this controller.

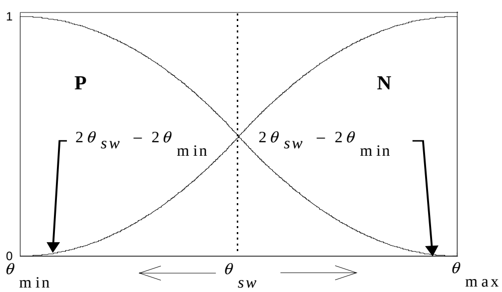
The sign of the weighted output is determined at these two sectors to be positive (sector 6) and negative (sector 3). This sign definition is based on the equal area criterion analysis of the stability of a single machine connected to an infinite bus through a transmission line. For the remaining sectors, where the dynamics of the generator unit is of the most important concern, using the suggestions by Ishigame et. al [8] for the sign of the weighted $\Delta\omega$ would result in a less robust controller under variations of operating conditions. In order to provide the fine switching between each two neighbouring sectors 1 and 2, 4 and 5, a fuzzy representation of these sectors is introduced based on the angle θ_{SW}. The sectors are represented as in Figure 6. Here the signed value of SHY (see the table in Figure 6) represents the desired sign and magnitude to be associated to the output signal resulting from the SISO system in Figure 5.



input	I1	I2	I3	I4	I5
output	O1	O2	O3	O4	O5

rules table of pre-control SISO

Figure 5. $\Delta\omega$ pre-control SISO FLC representation



sectors	θ_{min}	θ_{max}	SHY
1-2	0	90	P-N
4-5	180	270	N-P

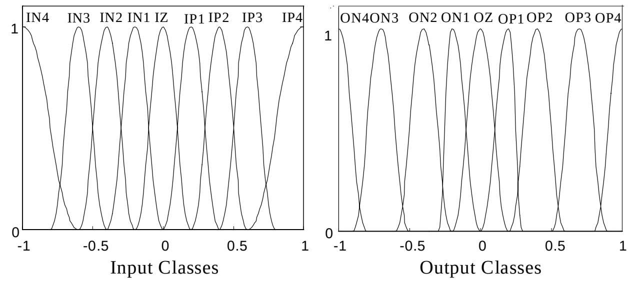
Figure 6. Fuzzy sectors representation

The rules used to update the angle θ_{sw} are implemented in a SISO FLC in the following form:

If the operation is at sector 1 and the acceleration is large,...
Then increase θ_{sw} large (move it to the right).
....
If the operation is at sector 2 and the acceleration is large,...
Then decrease θ_{sw} large (move it to the left).

This system has proved easier to implement than a classical FLC. The auxiliary FLCs used to update and tune the controller parameters apply relative measures that do not require careful adjustment of their internal characteristics when used for different systems.

The last stage consists of a single SISO FLC having the representation shown on Figure 7 and using the L/R COG defuzzification method. The input to this controller is the F.B. signal resulting from a linear summation of the error in the terminal voltage and the refined $\Delta\omega$ input signal.



input	IN4	IN3	IN2	IN1	IZ	IP1	IP2	IP3	IP4
output	ON4	ON3	ON2	ON1	OZ	OP1	OP2	OP3	OP4

rules table of Shay-Exciter

Figure 7. Shay-Exciter representation

VII. COMPUTER SIMULATION

The Shay-Exciter system was tested and compared with a conventional exciter system Kothari et. al. [9], see appendix for system data. For a synchronous generator connected to an infinite bus through a transmission line, Figure 8.

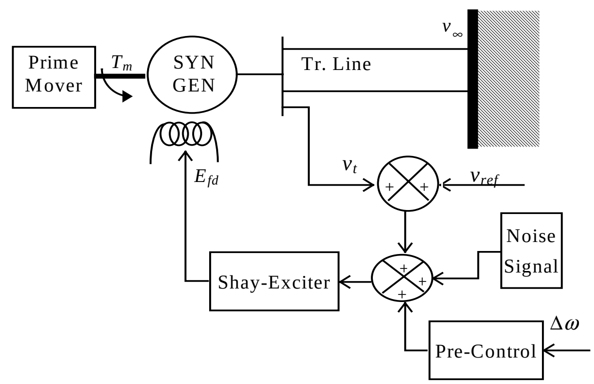


Figure 8. General block diagram of the generator system

The generator was subject to the disturbance of 20% reduction in its input mechanical torque T_m with the existence of noise added at the summation point. Figures 9-10 show the results of these tests.

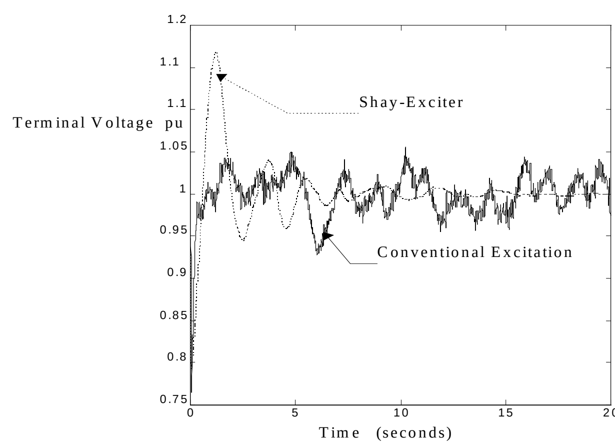


Figure 9. Terminal voltage after 20% reduction in T_m

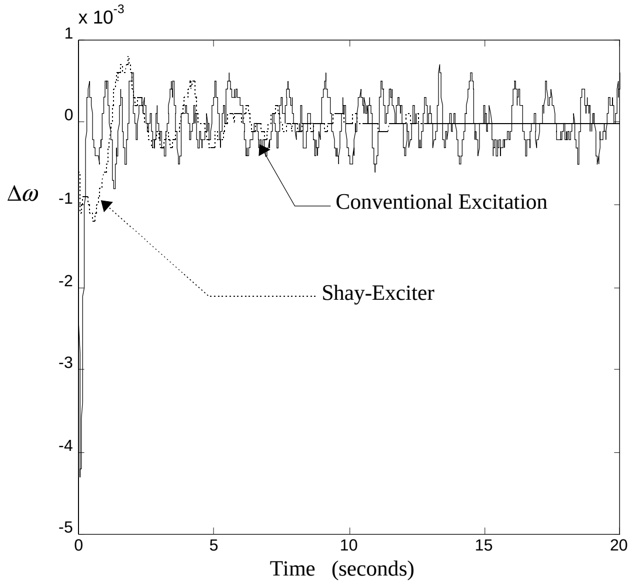


Figure 10. Speed deviation ($\Delta\omega$) after 20% reduction in T_m

VIII. CONCLUSIONS

The proposed recognition system provides a promising approach applicable in power quality monitoring as being verified by the experiment. The reasons of achieving high accuracy in the recognition lie in the effective removal of redundancy existing in the input waveforms. The unique signature of each disturbance can then be identified easily from the transform coefficients of the related sub-bands.

Aside from the feature extractions, the recognition scheme has been designed to take advantage of the tremendous capability of LVQ networks to classify patterns and the flexibility of FAM rule-matrix to deal with the uncertainty of the underlying input-output relationship. After the training phase, the computation cost involved with the classification has been reduced significantly owing to the efforts in removing the redundancies and simplifying the scheme. Consequently, the proposed approach has the potential for on-line applications.

The simulation results demonstrate that the proposed fuzzy control system is superior to the conventional system under the effect of noise, that is the case in most practical implementations. The pre-control input refining stages and sector division of the operation have been proved as necessary for power generation control because they allow to cope with the highly nonlinear nature of the system and provide a suitable input representation of the dynamics of the system.

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APPENDIX

System parameters simulated:

Generator:

$H = 5.0\ s \quad x_d = 1.6\ \ s \quad x_d^{'} = 0.32 \quad x_q = 1.55 \quad T_{do}^{'} = 6.0\ \ s$

IEEE Type I excitation system:

$K_A = 50.0$ $T_A = 0.05$ s

$K_E = -0.05$ $T_E = 0.05$ s

$K_F = 0.05$ $T_F = 0.5$ s

Transmission line:

$x_e = 0.4$ $r_e = 0.0$

Operating condition:

$P = 0.8$ $Q = 0.6$ $v_\infty = 1.0$ $f = 50$ Hz.