AN ADVANCED HYBRID SOLUTION FOR AUTOMATED SUBSTATION MONITORING USING NEURAL NETS AND EXPERT SYSTEM TECHNIQUES

M. Kezunovic, I. Rikalo
Texas A&M University

C. W. Fromen, D. R. Sevcik
Houston Lighting & Power Company

USA

***Abstract* — This paper describes a new solution for an automated analysis of the substation equipment operation during fault disturbances. An expert system, developed earlier for automated analysis of digital fault recorder (DFR) files, is the basis for the new solution. The expert system makes an analysis based on outputs of the signal processing algorithms used to calculate waveform parameters for the faulted transmission line. The new solution utilizes neural nets to perform both fault detection and classification for a given transmission line. Therefore, the signal processing and a part of the fault analysis expert system logic are substituted in the new solution with the neural nets. The paper discusses constraints of the earlier solution, gives details of the new implementation, and provides summary of the benefits as well as the test results obtained using EMTP simulations.**

Keywords: Expert systems, Neural nets, Real-time processing, Fault disturbance analysis, EMTP.

I. INTRODUCTION

Substation monitoring using digital fault recorders (DFRs) is a common utility practice in most countries. The DFRs capture both analog and contact data using synchronous sampling across all the input channels. In the case of a disturbance, the recorder is triggered and an event is stored. This data can be transmitted to the operators at a remote location via a telephone link. Based on this data, operators are able to determine if the relaying, as well as related communication and switching equipment have operated correctly.

The analysis approach described has several advantages and disadvantages. The main advantage is that the DFR data captured represents the best choice of the data for the analysis due to the synchronous mode of sampling and high sampling rates. This data provides more information than what may otherwise be available from digital relays, sequence of event recorders or remote terminal units of a SCADA system. The main disadvantages are related to the large amounts of data recorded. It takes a long time to transmit this data to a remote site. The manual analysis is also quite tedious due to the fact that there may be a large number of events recorded. In summary, automating the analysis process at the substation level is a desirable solution.

The automated substation monitoring has become feasible using advanced signal processing and expert system techniques [1, 2]. The authors have developed an expert system aimed at automating the analysis of DFR data [3]. The system is installed at a switchyard of a power plant. The system consists of a DFR interfaced to a dedicated PC. The PC performs data format conversions for the DFR files, executes the signal processing and expert system logic, and communicates the analysis results to the operators at a remote site.

This paper discusses enhancements to the substation monitoring system where fault detection and classification are performed using a neural net. A new type of a neural net suitable for real-time processing and interfacing to an expert system is introduced [5, 6, 7]. This neural net is used to substitute the signal processing aimed at calculating waveform parameters and the logic aimed at detecting and classifying faults in the previous solution. This enhancement provides for more selective fault analysis and gives further time response improvements.

The paper provides results obtained by simulating faults using an Electromagnetic Transient Program (EMTP) [8]. Various strategies for determination of the neural net input data and training sets are tested and discussed. The application example used for EMTP modeling and simulation is taken out of a real power system.

The final part of the paper gives some design details for incorporating the neural net enhancement into the existing expert system solution.

II. EXPERT SYSTEM DESCRIPTION

Figure 1 shows the existing configuration of the expert system for automatic processing of the events recorded by digital fault recorder. This system is installed at the South Texas Project (STP) substation and monitored by the Houston Lighting & Power (HL&P) company. The expert eystem communicates with DFR over a fast GPIB interface. It interrogates the recorder in prespecified time intervals and uploads new events. These events are stored locally and then processed. The expert system generates an analysis report that contains plain English description of the event. This report is then faxed to several different locations. An example of the report is given in Figure 2.

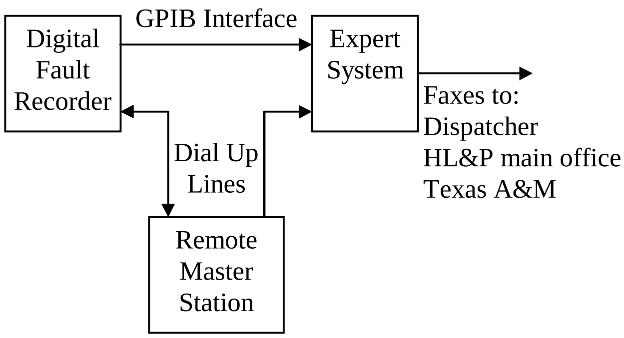

Figure 1. Expert system configuration

The expert system software consists of several modules (see Figure 3). The signal processing part does the following:

- detects the most disturbed line by analyzing the magnitudes of the current transients for each transmission line,
- calculates RMS and peak voltages and currents for prefault, fault and postfault intervals,
- calculates the fault location if disturbance is a fault,
- extracts the operating times for protective relays, communication contacts and breakers for the selected transmission line, if they operated for a given event.

The calculated parameters are processed through the rule base that contains approximately 60 rules. The rule base was built by interviewing experts, using an empirical approach based on Electromagnetic Transient Program (EMTP) simulation during initial system design, and finally using actual field data from the South Texas Project (STP) substation.

This expert systems is designed to use contact data coming from relays, communication channels and circuit breakers, as well as samples of analog signals (i.e., voltages and currents). Figure 4 shows the organization of the rule base that contains logic for:

- performing fault detection and classification,
- determining expected protection system operation,
- extracting actual operation of the protection system.
- comparing expected and actual protection system operation,
- assessing protection system performance based on the results of the comparison.

Date\Time Stamp of Event: 04/04/95, 12:44:44.938
Event number: 017 **Sample rate:** 5.99 [kHz]
Number of pretrigger samples: 1198 (12.0 cycles)
Total number of samples: 2926 (29.3 cycles)
Size of the event in tracks: 10 (320Kb)
Machine name: S.T.P. **Serial number:** 20299
Converted: 1755 **Starting sample:** 898.

***** EVENT DESCRIPTION USING ANALOG DATA *****
D427 is the circuit with largest current disturbance.
The disturbance is a **phase B to ground** fault.
The fault is cleared by the protection at this substation.
Prefault Values: Fault Values: Postfault Values:
I0pf = 0.0087 [kA]; I0f = **24.190** [kA]; I0f = 0.001 [kA]
Iapf = 0.2076 [kA]; Iaf = 0.801 [kA]; Iaf = 0.000 [kA]
Ibpf = 0.1868 [kA]; Ibf = **22.830** [kA]; Ibf = 0.000 [kA]
Icpf = 0.1672 [kA]; Icf = 0.272 [kA]; Icf = 0.004 [kA]
V0pf = 0.0008 [kV]; V0f = **0.0860** [kV]; V0f = 0.0008 [kV]
Vapf = 283.70 [kV]; Vaf = 272.60 [kV]; Vaf = 282.20 [kV]
Vbpf = 283.90 [kV]; Vbf = **106.40** [kV]; Vbf = 282.80 [kV]
Vcpf = 284.70 [kV]; Vcf = 272.70 [kV]; Vcf = 283.60 [kV]
Vabpf = 491.2 [kV]; Vabf = **327.6** [kV]; Vabf = 488.8 [kV]
Vbcpf = 493.1 [kV]; Vbcf = **342.6** [kV]; Vbcf = 491.5 [kV]
Vcapf = 492.0 [kV]; Vcaf = 483.5 [kV]; Vcaf = 489.4 [kV]
All above values are peak values.

***** PROTECTION SYSTEM OPERATION ANALYSIS *****
Backup relay operation starts at **0.0337 sec [2.0202 cycles]**
and ends at **0.0487 sec [2.9202 cycles]**.
The middle 52B contacts operate at **0.0605 sec. [3.63 cycles]**.
The bus 52B contacts operate at **0.0537 sec. [3.2202 cycles]**.
The bus breaker status change after trip is applied is **1.2 [cyc]**.
The middle breaker status change after trip is applied is **1.6 [cyc]**.

***** FAULT LOCATION *****
Fault Location is x = **10.63** %.

Figure 2. An example of the expert system report

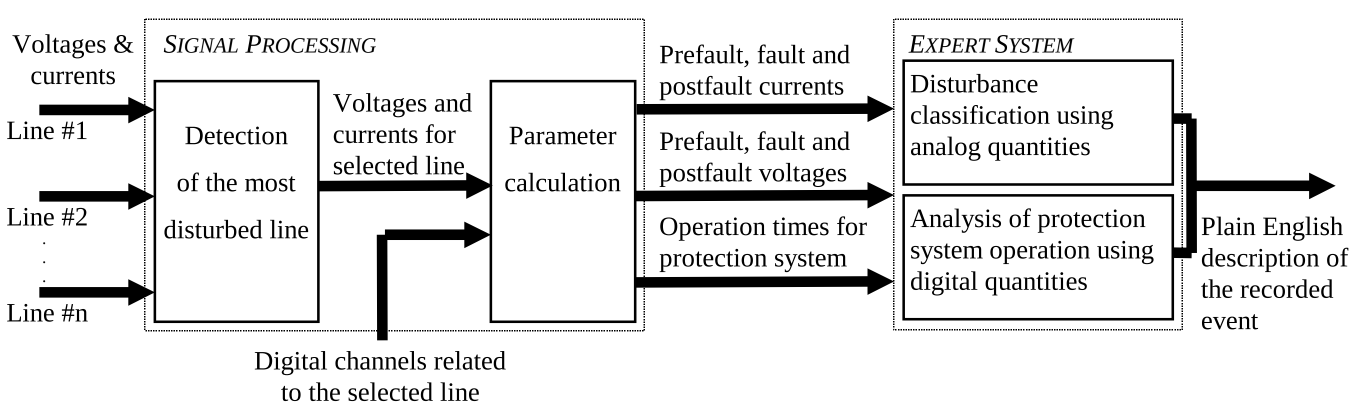

Figure 3. Data flow diagram of the expert system

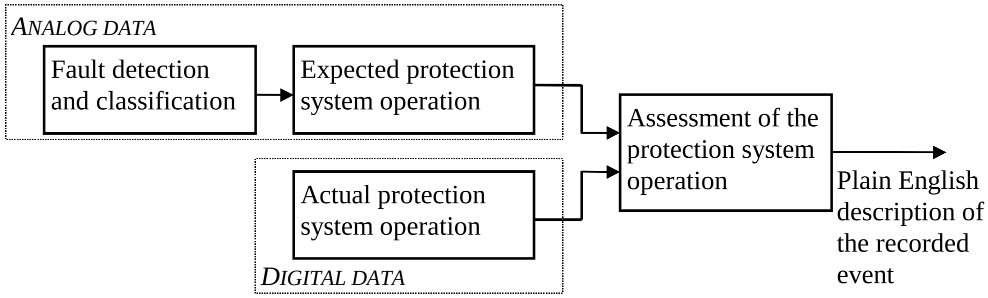

Figure 4. Expert system rule base organization

It has been noticed that, potentially there are some problems with generalization capabilities of such a system. Namely, as in every rule-based system, certain thresholds (i.e., the knowledge) have to be specified in the rules. These thresholds are used to determine the relationship between the analog values (e.g., the phase currents and voltages) for different events or faults that can happen in the transmission system. The problem arises because of the dynamics present in a power system. The load and generation are constantly changing, as well as the transmission grid configuration, so it is hard to fine tune the thresholds in the rules.

Also, the conventional rule-based expert systems are too slow to be applied in real-time environments since they require time-consuming process of rule- and knowledge-base search. The size of the rule- and knowledge-base is a limiting factor for these systems. The speed of diagnosis is inversely proportional to the rule-base size, because the inference process is sequential in nature (i.e., expert system sequentially searches for the solution by pattern matching to the hypothesis).

Due to all of the mentioned constraints of the expert system solution, a study of the neural net application to the fault detection and classification was initiated.

III. NEURAL NET DESCRIPTION

The NN algorithm used for this study embodies the ISODATA clustering algorithm which is well known in classical pattern recognition [5, 6, 7, 9]. This type of neural net assumes no teaching and performs unsupervised learning. The process performs comparison of a given input with previously encountered patterns. If the input is similar to any of the patterns, it will be placed in the same category. If the input is not similar to any of the previously presented patterns, a new category will be assigned. Category proliferation is controlled by the threshold parameter. A NN system with low threshold will permit grouping of patterns with high similarity and vice-versa.

Figure 5 shows the block diagram of the algorithm that combines both unsupervised learning (USL) and supervised learning (SL). The initial data set, containing all the patterns, is processed using unsupervised clustering algorithm.

The output is a stable family of clusters, defined as hyperspheres in N dimensional space, where N denotes the number of features in each pattern. The task of supervised learning is to separate non-homogeneous clusters from the homogeneous ones.

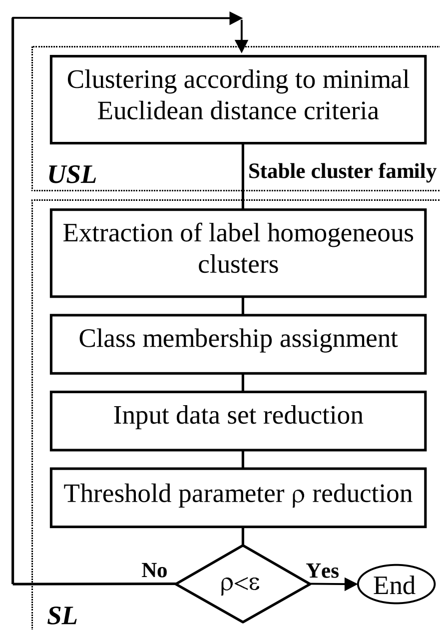

Figure 5. Artificial neural network learning process

Next, class membership is assigned to homogeneous clusters. The training data set is reduced to contain only patterns from non-homogeneous clusters. The threshold parameter ρ is decreased, and the whole procedure is reiterated. Figure 6 shows a schematic illustration of the outcome of the training process in the feature space. This illustration is based on the fault detection and classification as an example of the discrete classes generated based on analog inputs. Details of the NN algorithm are given in the Appendix.

After completion of the training procedure, all generated clusters contain uniform data patterns, and are characterized by their centroids, corresponding radii (i.e., threshold parameter ρ), and inherited class membership. It can be observed that the cluster topology is not uniform, and that two or more clusters may have the same class membership.

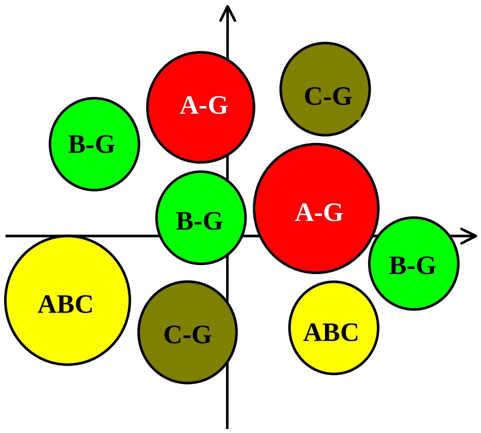

Figure 6. Schematic illustration of the outcome of the training process

More elaborate explanation of the training procedure with several application examples is given in [5, 6, 7]. The neural net fault detector and classifier were extensively tested using EMTP simulation in both real-time and off-line environments.

The following section presents a novel approach to automatic analysis of DFR recordings. It consists of the neural net and expert system. Described neural net utilizes the concept of supervised clustering which demonstrates following important properties:

- the number of iterations in the learning process is greatly reduced using unsupervised learning with supervised class membership inheritance process.
- the training is far less complex than in standard supervised learning.
- the outcome of the processing is presented in a symbolic form (class names), thus allowing that the detection and classification results of the neural net are further utilized in a rule-based expert system.
- the neural net training is efficient and straight forward, thus facilitating a fast and simple re-training for adapting to the changing power network conditions.

IV. COMBINED NEURAL NET AND EXPERT SYSTEM IMPLEMENTATION

As mentioned earlier, the expert system solution described in the previous sections suffers from two inherent problems, namely:

- generalization capabilities of rule based expert system are weak (i.e., thresholds have to be fine tuned), and problems arise when the operating conditions change (e.g., change of load, generation or configuration in the power system),
- expert systems are too slow to be applied in the real-time environments.

These shortcomings of the expert systems are, on the other hand, compensated by the advantages of the neural networks. Neural nets have strong generalization capabilities, and an easy way to automatically improve their performance by additional learning (often, without a need for a human intervention). Also, since the neural nets are parallel in nature, they can be used for real-time processing.

Figure 7 shows a hybrid system that contains neural nets for disturbance detection and classification, and expert system for evaluation of the protection system performance. A separate neural net is trained for every transmission line in the substation. Trained net is, then, used for fast disturbance detection and classification. The results of this classification are used together with the digital contacts data (e.g., relays, communication channels, breakers, etc.) in the expert system part to assess the performance of the substation protection system.

This system can be used in two different modes of operation:

- event processing based on a "snapshot",
- event processing based on a "continuous" data flow.

The first mode of operation is a conventional approach, where digital fault recorder, based on its internal triggers, records the event. The event is then transferred to the neural net/expert system for automatic processing.

The second mode of operation requires continuous data flow from digital fault recorder (or, any other data

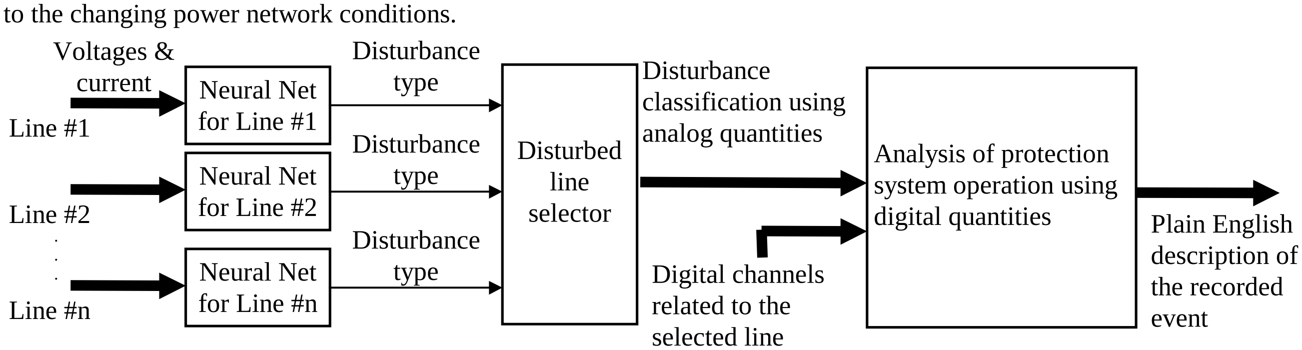

Figure 7. Combined neural net and expert system solution

acquisition device). In this case, the neural network "triggers" the analysis based on its detection capabilities.

Figure 8 shows the basic principle of operation for a single neural net. The input data vector contains a "snapshot" of voltage and current samples. These "snapshots" can also be organized in the form of a "sliding" window, thus enabling a "continuos" data input into the net.

Neural net calculates the Euclidean distances between the input pattern and all of the clusters. These clusters are generated during the training phase and each one has a unique class label and associated radius in the feature space (cluster geometry, as described here, is a hypersphere, but it can also be hypercube or hypercone). If the input pattern falls within a certain cluster, it is assigned corresponding class label. If the input pattern does not fall into any of the existing clusters, then the class membership is assigned based on the nearest neighbor rule. Figure 8 shows K different types of disturbances (e.g., phase to ground fault, phase to phase fault, etc.). The cluster that is selected based on the given input pattern is shown in black (disturbance type 1). The Appendix contains further details of the neural net algorithm.

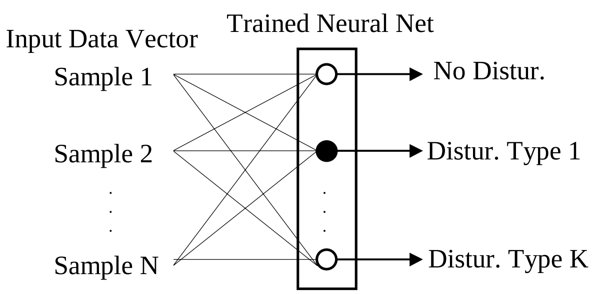

Figure 8. Neural net disturbance detector and classifier

Preliminary tests of the neural net fault classifier were conducted using two different power system segment models. The modeling and simulations were done using EMTP and several thousands of different fault cases were generated.

Three different types of inputs were used for the study. In one case, the neural net input contained both phase voltage and current samples. In the other case, inputs consisted of only phase current samples. In the last case, the input vector into the neural net contained only three phase voltage samples. Table 1 shows the classification rates for the neural net.

TABLE 1
CLASSIFICATION RESULTS OF THE NEURAL NET CLASSIFIER

Neural Net Inputs	*Classification Rates [%]*
all currents and voltages	91.22
only 3- phase currents	92.28
only 3- phase voltages	81.82

Further results of these studies can be found in [5, 6, 7].

V. CONCLUSIONS

Based on the discussions given in this paper, the following can be concluded:

- An automated analysis of the substation equipment operation under fault conditions on the transmission lines can be implemented by processing of digital fault recorder data using an expert system and digital signal processing algorithms.
- The mentioned solution, implemented at a substation, is quite efficient since it reduces the overall analysis time by eliminating elaborate data communications as well as manual search and analysis of data.
- Further improvements in the mentioned solution can be achieved by introducing the neural nets as a substitute for the signal processing as well as for the fault detection and classification logic.
- The use of neural nets provides easy adaptability to the prevailing system conditions, improved speed of processing, and natural interfacing between the waveform processing and expert system rules.

VI. ACKNOWLEDGMENT

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Mladen Kezunovic (S'77, M'80, SM'85) received his Dipl. Ing. degree in electrical engineering in 1974, and the M.S. and Ph.D. degree from the University of Kansas, in electrical engineering in 1977 and 1980 respectively. His industrial experience is with Westinghouse Electric Corporation in the USA, and the Energoinvest Company in Sarajevo. His academic experience is with the University of Sarajevo and Washington

State University. He has been with Texas A&M University since 1987 where he is an Associate Professor. He is member of the IEEE PSRC, member of CIGRE and a registered Professional Engineer in the State of Texas. Dr. Kezunovic is the chairman of the PSRC working group F-8 on " Digital Simulator Performance Requirements".

Igor Rikalo received his Dipl. Ing. degree from the University of Sarajevo, and M.Sc. degree from Texas A&M University, all in electrical engineering in 1992, and 1994, respectively. Currently, he is working for TLI, Inc. as a systems engineer and for Texas A&M University as a research engineer. His main interests are in the area of intelligent system applications to power systems.

Charles W. Fromen (M'68, SM'85) received his B.Sc. degree in Electrical Engineering from Texas A&M University in 1968. He joined Houston Lighting & Power Company upon graduation. Since 1984, he has held the title of Senior Consulting Engineer. Mr. Fromen has been the HL&P Company representative to the IEEE Power Systems Relaying Committee since 1973 and is a member of that committee. He is a registered Professional Engineer in the State of Texas.

Donald R. Sevcik (M'81) received his B.Sc. in Electrical Engineering from Texas A&M University in 1975. He was employed by Houston Lighting & Power Company in 1975 and is currently a Lead Engineer. He has worked in the following areas: Power Plant Electrical System (1975 to 1977), System Studies (1977 to 1979), and Transmission and Generation Protection (1979 to present). He is a registered Professional Engineer in the State of Texas.

APPENDIX

The mathematical foundation of the NN used is described as follows.

Given is a set of P (p=1, 2, ..., P) patterns $\underline{x}^{(p)}$ where

$$\underline{x}^{(p)} = \left[x_1^{(p)}, x_2^{(p)}, \ldots, x_N^{(p)}\right]^T \tag{1}$$

Initialization run

Step 1:

Form cluster no. 1 , $\underline{b}_1(1) = \underline{x}^{(1)}$, (Meaning cluster C_1 with centroid $\underline{b}_1$ contains 1 pattern).

Step 2:

If $\left(\underline{x}^{(2)} - \underline{b}_1\right)^T \left(\underline{x}^{(2)} - \underline{b}_1\right) \le \rho^2$ then adapt $\underline{b}_1$ as

$$\underline{b}_1(2) = \underline{b}_1(1) + \frac{1}{2}\left(\underline{x}^{(2)} - \underline{b}_1(1)\right) . \tag{2}$$

If $\left(\underline{x}^{(2)} - \underline{b}_1\right)^T \left(\underline{x}^{(2)} - \underline{b}_1\right) > \rho^2$ then form cluster 2 as $\underline{b}_2(1) = \underline{x}^{(2)}$.

In doing so, after presenting $q < P$ patterns the situation is as follows:

m - clusters exists, their centroids $\underline{b}_m$ are known and we know how many patterns belong to each cluster n_m.

When we present next pattern $q+1$ we first allocate the closest cluster τ, by

$$\min_j \left\{ \left(\underline{x}^{(q+1)} - \underline{b}_j\right)^T \left(\underline{x}^{(q+1)} - \underline{b}_j\right) \right\} = r_\tau^{\,2} \ , \tag{3}$$

and then compare $r_\tau^{\,2}$ and ρ^2:

If $r_\tau^{\,2} \le \rho^2$ then adapt cluster as

$$\underline{b}_\tau\left(n_\tau + 1\right) = \underline{b}_\tau\left(n_\tau\right) + \frac{1}{n_\tau + 1}\left(\underline{x}^{(q+1)} - \underline{b}_\tau\left(n_\tau\right)\right). \tag{4}$$

If $r_\tau^{\,2} > \rho^2$ then form new cluster as $\underline{b}_{m+1}(1) = \underline{x}^{(q+1)}$.

This procedure is repeated until the entire set of patterns is processed once.

Stabilization run

Step 3:

We present every pattern, $\underline{x}^{(p)}$, again. Let say presently pattern p belongs to cluster C_k.The shortest distance between $\underline{x}^{(p)}$ and all existing centroids $\underline{b}_j$ is found using eq. (3).

- If $\tau = k$ and $r_\tau^2 \le \rho^2$ then no learning occurs; check next pattern $p+1$.
- If $\tau \ne k$ and $r_\tau^2 \le \rho^2$ then adapt $\underline{b}_\tau$ using eq. (4) and $\underline{b}_k$ as

$$\underline{b}_k\left(n_k - 1\right) = \underline{b}_k\left(n_k\right) - \frac{1}{n_k - 1}\left(\underline{x}^{(p)} - \underline{b}_k\left(n_k\right)\right),\ n_k > 1. \tag{5}$$

- If $r_\tau^2 > \rho^2$ form new cluster C_m, $\underline{b}_m(1) = \underline{x}^{(p)}$ and adapt previous" centroid $\underline{b}_k$ using eq. (5)

Stabilization is repeated until no patterns change their cluster membership.