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Wide Area Power System Protection Using a Learning Vector Quantization Network

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***Abstract*—This paper presents a wide area monitoring and protection technique based on a Learning Vector Quantization (LVQ) neural network. Phasor measurements of the power network buses are monitored continuously by a LVQ network in order to alert the control room operators of possible faults. The proposed scheme could be used in a wide area monitored network to provide remedial action when primary local protection schemes for transmission lines fail to function. This technique could also be extended to the actuation of the secondary protection schemes, hence, preserving the integrity of the power network especially when the faults are spreading over a wide area network to the other areas of the system. The scheme has been applied to a two-area power system in this paper and the LVQ results show that it is a promising scheme for system protection against partial or total blackouts or brown outs.**

***Index Terms*— Wide Area Power System, Monitoring, Protection, System Protection, Learning Vector Quantization, Protection Relays**

I. Introduction

Wide area monitoring and protection of power networks is a matter of concern for power system engineers due to the importance of clearing faults occurring especially in the transmission lines, since these elements are widely spread over long distances and are vulnerable to natural disasters. This would be so critical when these lines are responsible for transmission of power over different areas of the power system, as delays in clearing the faults could result in cascaded blackouts of the entire power system. Technical developments in communication technology and measurement synchronization, like applying PMUs (Phasor Measurement Units) [1] have made global monitoring and protection schemes possible. Recently, there have been major steps towards the prevention of the cascading outages, as a result of faults and voltage sags, by monitoring and controlling the system from a more global view than the previously local ones. Some developments have been made in the southern Swedish transmission system in order to provide the necessary actions under emergency conditions [2]. This system mainly uses the bus voltages from the transmission system, reactive power outputs from the generators connected to the transmission system, and current limiter information from main generators as the input signals. An expert system to prevent cascading outages in power systems has been proposed in [3], where two ways in which wide-area backup protection can prevent cascading trips have been recommended: 1) precise location of a fault so that only the necessary circuit breakers act and 2) avoidance of unnecessary trips, due to hidden failure or overloading. Other applications of wide area monitoring include voltage stability protection and control [4, 5].

In this paper, a wide area monitoring and protection scheme has been proposed using a continuous wide area measurement of three phase RMS bus voltages. The scheme could be used as a backup system protection when primary local protections do not act accordingly. A small two area power system has been used to demonstrate the potential of the scheme to distinguish the different faults on the transmission lines. Fault detection is carried out using a LVQ neural network which uses a Self Organizing Map (SOM) scheme for categorizing the faults of the system.

The rest of the paper is organized as follows: Section II describes the two area power system considered in the initial studies of this work. Section III describes the wide protection scheme proposed in this paper. Section IV provides a brief description on the learning vector quantization (LVQs) networks. Section V describes the implementation of the wide protection scheme and its results. Finally, the conclusions and future work is given in Section VI.

II. The Two Area Power System

A two area power system, illustrated in Fig. 1, has been used in this paper for implementation of the proposed protection scheme. The power system consists of two fully symmetrical areas linked together by two transmission lines between buses 3, 4 and 5 Each area is equipped with two identical synchronous generators rated 20 kV/900 MVA. All the generators are equipped with identical speed governors and turbines, and exciters and AVRs. The loads in the two areas are such that area 1 is exporting 413MW to area 2. The power system parameters and models are given in [6, 7]. The transmission part of the network consists of 7 buses and 8 lines, and there are 16 circuit breakers (CB1 to CB16) in the network which are responsible for clearing the faults that occur in the lines.

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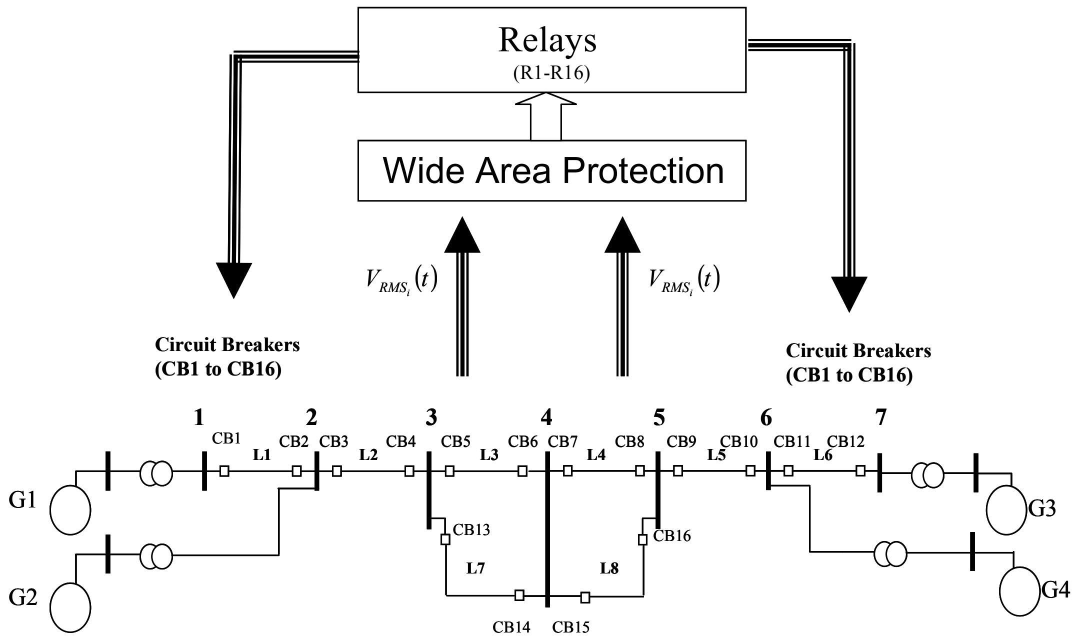

Fig. 1. Two area multimachine power system with transmission lines (L1 to L7) equipped with circuit breakers (CB1 to CB16) and relays (R1 to R16).

III. Wide Area Protection Scheme

The proposed scheme is used as a secondary or a backup protection for a wide area to provide alerts to control room operators and, if desired and allowed, override the local protection mechanism when they fail to isolate a faulted transmission line. The importance of this scheme could specially be beneficial when the system protection can isolate one faulty area from the other and hence preventing cascading of faults over a number of areas.

The protection scheme uses a rather straightforward rule that any faulted transmission line will cause some voltage drops at the system buses. The magnitudes of the voltage drops are expected to be different for every bus according to where and how the system has been faulted. In other words, there could be different types of symmetrical or unsymmetrical faults in different locations on the transmission lines. It is important to distinguish which line is faulted according to the voltage behavior of the buses. As a rule of thumb, it could be said that the voltages at the buses close to the fault will have fastest change in the bus voltages (dV/dt).

In this paper, a Learning Vector Quantization (LVQ) neural network is used to identify the different types of faults and the circuit breakers in the power network to be tripped. The LVQ inputs are the RMS bus voltages of the power network. The power system bus voltages can be sampled at rate feasible with the communication technology and the LVQ output be refreshed also at this frequency. The output of the LVQ as mentioned above can be used to provide alerts to control room operators in the respective areas/substations on the status of the protection required if any every sample period or if allowed can automatically override local protection schemes if they have failed to isolate the fault in a given period of time, thus, saving the integrity of the power network. This is illustrated in Fig. 2.

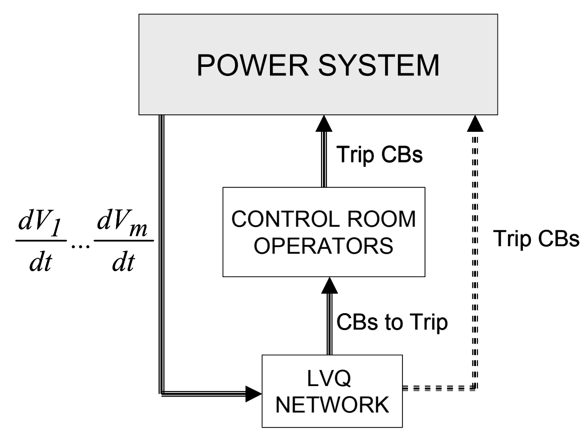

Fig. 2. Wide protection architecture

IV. LVQ Neural Network

The Learning Vector Quantization (LVQ) neural network is a hybrid network. It uses both unsupervised and supervised learning to form classifications [8]. In the LVQ network, as it is seen in Fig. 3, each neuron in the first layer is assigned to a class. There are usually several neurons assigned to the same class. Each neuron is then assigned to one neuron in the second layer. The number of neurons in the first layer, S1, will therefore always be at least as large as the number of neurons in the second layer, S2, and will usually be larger.

The net input and output of the first layer of the LVQ is given by (1) and (2) respectively.

$$n_i^1 = -\|W1_i - p\| \tag{1}$$

$$a^1 = compet(n^1) \quad (2)$$

The neuron whose input weight vector is closest to the input vector will output a one, and the other neurons will output zero. The winning neuron indicates a subclass. There may be several different neurons (subclasses) that make up each class. The second layer of the LVQ network is used to combine subclasses into a single class and this is done with the *W2* matrix, the output weights. The columns of *W2* represent subclasses, and the rows represent classes.

The learning in the LVQ network combines competitive learning with supervision. As with all supervised learning algorithms, it requires a set of examples of proper network behavior for training. Before learning can occur, each neuron in the first layer is assigned to an output neuron. This generates *W2* matrix. The input weights *W1* are trained as follows: In every iteration, an input vector *p* is presented to the network, and the distance from *p* to each prototype vector is computed. The neurons in the Kohonen (SOM) layer compete, a neuron *i* wins the competition, and the ith element of *a1* is set to 1. Then, *a1* is multiplied by weight matrix *W2* to get the final output class *a2*.

The Kohonen rule is used to improve the SOM layer of the LVQ network for the winning and non-winning neurons according to the following rules, respectively:

$$W1_i(q) = W1_i(q-1) + \alpha(p(q) - W1_i(q-1)) \quad (3)$$

$$W1_i(q) = W1_i(q-1) - \alpha(p(q) - W1_i(q-1)) \quad (4)$$

Where q is the number of iteration and α is the learning weight.

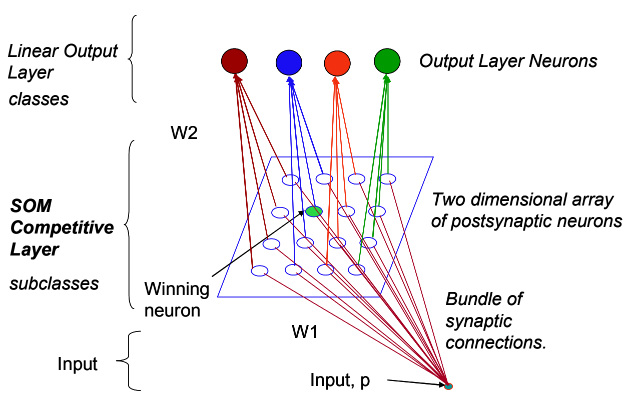

Fig. 3 Learning vector quantization neural network.

V. Implementation And Results

As was mentioned in the previous sections, an LVQ neural network is trained for estimating the correct states of circuit breaker(s) of the power system which should clear the faults avoiding partial or total network blackout or brown-outs. The inputs of the LVQ are three phase RMS bus voltages of the power system and the outputs of the LVQ network are the appropriate states of the circuit breakers of the transmission lines. The LVQ is trained using the simulated data of the different types of short-circuits implemented at different locations on every transmission line of the power network. The power network is simulated in the PSCAD/EMTDC environment [9]. Table 1 show some sample input data which have been used for training of the LVQ. The first column of the table shows the faulted line and the second column shows the type of short-circuit implemented on the line. Third column shows the location on the line (in percent) at which the fault is applied. The remaining 7 columns show the rate of change of RMS voltages of the system buses ($\Delta V/\Delta t$), which are differences between the bus voltages measured at two time instances divided by the monitoring time period. The time period in this study is taken to be 10 ms, i.e. the bus voltages are monitored every at 100 Hz.

Twelve training points on every line has been simulated. These points are categorized according to the four common types of faults: Three-Phase to Ground, Single-Phase to Ground, Double-Phase and Double-Phase to Ground at 10%, 50% and 90% of the line length respectively. A total of 96 points are included in the LVQ training data set for the two-area power network of Fig. 1.

Nine subclasses (neurons in the Kohonen layer) have been defined for the LVQ network. These subclasses, illustarted in Table 2, show the faulted lines and their associated classes. It should be noted that, as Table 2 shows, for faults applied on parallel lines, like L3 or L7, the LVQ is not trained to distinguish the exact line at which the fault has applied, and. both 3 and 7 subclasses are mapped onto class 3. The scope of this paper is limited to demonstrating the potential of LVQ networks. Further refinement will address distinguishing faults on parallel lines. Table 3 shows the classes or the states of the circuit-breakers for every subclass winning neuron. State ‘1’ shows that the circuit breaker (CB) is closed, while ‘0’ shows that it is open.

For verification of the validity of the proposed protection scheme, the trained LVQ neural network is tested using simulated faults on the lines in locations other than those used in the training set (10%, 50% and 90% length). The results show that for 95% of the faults, the LVQ is able to predict the states of the circuit breakers accurately. The 5% false state predictions are with single phase to ground faults. This is as a result that for single phase to ground faults, voltage of the faulted phase decreases, while the voltages of the two other phases could increase. Thus the proposed scheme based on the RMS voltages is not the most efficient.

For large power networks, the above method for the simple two area network can be applied. The key to the application of the method is to find as many training points as possible through some automatic procedures through several simulations. It is also desirable to place different types of faults at various locations on the lines for improving the accuracy of the LVQ network.

TABLE I

SAMPLE INPUT DATA TO THE LVQ NETWORK

Faulted Transmission Line	Short-Circuit Fault Type	Location of the Fault	$\Delta V_1 / \Delta t$ (pu/S)	$\Delta V_2 / \Delta t$ (pu/S)	$\Delta V_3 / \Delta t$ (pu/S)	$\Delta V_4 / \Delta t$ (pu/S)	$\Delta V_5 / \Delta t$ (pu/S)	$\Delta V_6 / \Delta t$ (pu/S)	$\Delta V_7 / \Delta t$ (pu/S)
L1	ABC->G	50%	2.712	1.889	1.262	0.348	0.141	0.062	0.025
L3	C->G	10%	0.008	0.022	0.013	0.018	0.003	0.005	0.000
L4	AB	90%	0.008	0.009	0.022	0.053	0.028	0.013	0.007
L6	AB->G	50%	0.002	0.013	0.007	0.016	0.065	0.100	1.006

TABLE II

SUBCLASSES DEFINITION

Subclass No.	Class No.	Faulted Line(s)
1	1	L1
2	2	L2
3	3	L3 & L7
4	4	L4 & L8
5	5	L5
6	6	L6
7	3	L3 & L7
8	4	L4 & L8
9	7	None

TABLE III

CLASSES DEFINITION (CIRCUIT BREAKER STATES)

Class No.	Subclass No.	CB 1	CB 2	CB 3	CB 4	CB 5	CB 6	CB 7	CB 8	CB 9	CB 10	CB 11	CB 12	CB 13	CB 14	CB 15	CB 16
1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1
3	3	1	1	1	1	0	0	1	1	1	1	1	1	0	0	1	1
4	4	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	0
5	5	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1
6	6	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1
3	7	1	1	1	1	0	0	1	1	1	1	1	1	0	0	1	1
4	8	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	0
7	9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

VI. CONCLUSION

An LVQ neural network has been developed for identifying and isolating different types of faults occurring on transmission lines. The results show that the wide area protection scheme is successful in finding the faulty lines in the transmission system. The proposed scheme using intelligent methods such as the LVQ neural networks could assist the control room operators have a better view of the power system and in making decisions under emergency conditions, Thus, saving the integrity of the power network and avoiding cascaded partial or total blackouts and brown-outs.

Future work involves the improving the accuracy of the proposed scheme and validating the scheme on large multiple area power systems. The authors are also working on the methods for distinguishing the faulted lines in the case of parallel lines. In addition, the real-time laboratory implementation of the scheme is also considered.

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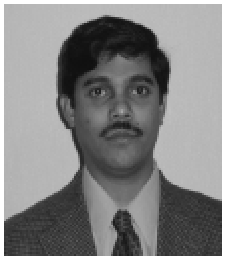
VIII. BIOGRAPHIES



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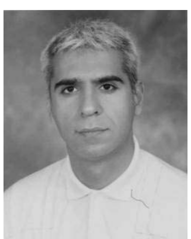

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