Analysis of SSR using Artificial Neural Networks

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ABSTRACT

Artificial Neural Networks (ANNs) are being advantageously applied for power system problems. They possess the ability to establish complicated input-output mappings through a learning process, without any explicit programming. In this paper, an ANN based method for SSR analysis is presented. The designed NN outputs a measure of the possibility of the occurrence of SSR and is fully trained to accommodate the variations of the system parameters over the entire operating range. The effectiveness of this approach is tested by experimenting on the first bench mark model proposed by IEEE Task Force on SSR.

Keywords : Subsynchronous resonance, Eigen value analysis, Artificial Neural Networks, Natural frequencies.

1 INTRODUCTION

The use of series capacitor compensated transmission lines to increase the maximum transmittable power, use of Static VAR Compensators (SVC) for reactive power management and the HVDC converter links in the case of integrated AC/DC systems are some of the causes for SSR in power systems. The Subsynchronous Resonance, basically, involves the exchange of energy between

- Inductances and capacitances in the electrical system.
- Different masses in the mechanical counterpart of the synchronous generator
- The mechanical and the electrical systems mutually coupled through the rotor of the synchronous generator.

The different manifestations of SSR viz the Induction Generator effect, SubSynchronous Torsional Interaction (SSTI) and the transient torques are already well studied and documented [1,2,3,4]. Out of these, the exchange of energy between the capacitances and inductances of the system causes higher order power oscillations in a fast way. Hence, a detailed study of the phenomena of SSR in power systems involving series capacitor compensation and SVC is essential

Countermeasures for SSR problems are proposed by way of installing supplementary control for thyristor controlled shunt reactor [5], Supplementary self tuning of a PID controller for static VAR compensator [6], NGH damping scheme [7,8], series compensation driving unsymmetrical currents in the three phases of armature windings of the generator [9], co-ordinated SVC controllers with SubSynchronous Damping Controllers (SSDC) of HVDC rectifier in case of AC/DC systems [10], Power System Stabilizer (PSS) designed using Eigen structure assignment technique [11,12] etc The Eigen value analysis of the system under consideration is required as an indicative of the performance of any of these countermeasures Further, in some of the countermeasures involving Eigen structure assignment, the values of the pre-specified Eigen values are chosen arbitrarily governed only by the expectations of the damping of the SSR modes In such situations, a knowledge of the existing Eigen values is necessary for an optimal Eigen structure assignment. By an optimal Eigen structure assignment, it is possible to tune the parameters of the SSR countermeasure so as to demand minimal control effort However, Eigen value analysis is computationally intensive and the modeling complexity required for this method of analysis is quite high. Further, this method also suffers from the general level of difficulty in writing efficient Eigen value programs. Hence, it is necessary to design an efficient technique for Eigen value analysis for the study of SSR which could avoid the conventional computation of Eigen values and alleviate the modeling complexity, as well.

Artificial Neural Networks (ANN), Fuzzy Logic (FL) and their variations constitute a class of techniques which, in a generic sense, maps a set of inputs to a set of outputs based on some fundamental simplified knowledge which is derived with minimum dependency on the exact model of the system under consideration. ANNs are massively parallel system of interconnected neurons each of which may be viewed as a miniaturized processing element. The characteristic feature of a NN is the ability to achieve complicated input-output mappings through a learning process, without explicit programming Whereas ANN acquires this capability by way of training, the FL based system is provided with this knowledge in the form of a rule base where each of the rules is an if...then...else... statement involving the input-output parameters quantified by means of linguistic variables viz tiny, small, big, very big etc.

In the present paper, a multilayer ANN is used for the first time to implement Eigen value analysis for the study of SSR phenomena on the first benchmark model proposed by IEEE Task Force on SSR The components of the input vector are the series compensation levels and the mechanical damping introduced at the high pressure turbine and at the generator rotor mass. The components of the output vector are the real parts of the Eigen values of tlie system and the frequencies of oscillation corresponding to the electrical network. The NN is trained lo learn tlie underlying features of the relationship between the inputs and the outputs [13]. For the purpose of training, several input vectors and the corresponding output vectors are evaluated by off-line simulation. These input-output vector pairs fonn tlie training set. The training set is supplemented by a learning algorithm in implementing tlie training process. The Error Back Propagation (EBP) Learning Algorithm (LA) is used to train tlie NN. Once trained, the NN is validated by subjecting it to input vectors and evaluating the error between tlie desired **output** vector **and** the output generated by tlie NN.

2 THE TEST SYSTEM

Tlie test systein considered for our study is the IEEE first bench mark model whose one-line diagram is given in Fig.1 [2,4]. The synchronous machine has two stator circuits, one field winding, one d-axis damper winding and two q-axis damper windings. The transmission network is a single series compensated transmission line connected to the generator and is tenninated at an infinite bus. The mass-spring-dashpot representation of the turbine generator (TG) set which fonns the mechanical counterpart of the test system is depicted in Fig.2. The mechanical systein consists of six masses viz. one high pressure turbine (tIP), one medium pressure turbine (IP), two low pressure turbines (LPA and LPB), Generator rotor mass (GEN) and the exciter (EXC)[14]. T_{m1}, T_{m2}, T_{m3} and T_{m4} are the mechanical input torques at different masses of the TG shaft and are negative. T_e is tlie electrical torque output and is positive. d_1 thro' d_6 are the damping coefficients at different masses constituting tlie

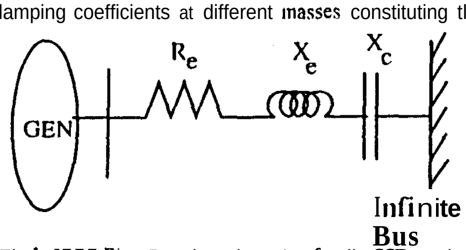

Fig 1. *IEEE* First Benchmark model **for** tlic **SSR** study

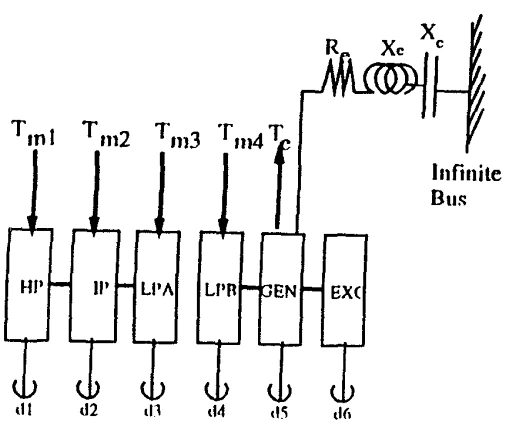

Fig.2
Schematic of the Electromechanical System

mechanical system The electrical **and** mechanical systein parameters are given in appendix - I

Tlic mathematical description of the system using state-space formulation consists of a set of twenty. first order differential equations linearized at the initial operating point The state variables are the six currents in different windings of the generator, six angular displacements, six angular velocities and tlie d- and q-axis components of the capacitor voltage The resulting linearized equation s of the form

$$\Delta\dot{X} = A\Delta X + B\,\Delta U \qquad (1)$$

where ΔX is a vector of dimension 20 representing the incremental changes in the state variables. A is a square matrix of order 20 x 20 whose terms depend on the system parameters and the initial conditions. ΔU is a vector representing the changes in the forcing functions and B is a matrix of constant coefficients.

3 ANN APPROACH TO SSR ANALYSIS

ANNs are the recent class of computing paradigms which can implement human-like reasoning while solving problems with complex functionalities. Fundamentally, ANNs map a set of input vectors onto a set of output vectors in a typical **Multi-Input** Multi-**Output (MIMO)** type of system using a non-linear transfer function, usually a sigmoid This capability of establishing correspondence between the input and output vectors is accrued by means of the training wherein the ANN is presented with a set of (input,output) pairs. Further, ANN, by virtue of being trained, possesses the capability to predict the output against an input situation which is not covered during training, with acceptable accuracy. This property of interpolation is termed the generalisation capability and is an important performance measure of any NN. The design of an ANN based system consists of the following steps[15]:

- Training set creation
- Training process
- Testing

These design steps are explained in tlie following paragraphs in reference to the problem **of SSR** analysis **of our** test systein.

3.1 Training Set Creation : The test system described in section 2 is, mathematically, represented using 20 linearized differential equations in state space **fonn.** To indicate the possibility **of SSR,** it is necessary to monitor tlie real part of those Eigen values of the system matrix whose imaginary part corresponds to frequencies of tlie oscillations of tlie TG shaft. Further, it is also required to monitor the frequencies of oscillation corresponding to the electrical network to assess the possibility of occurrence of resonance. The dimension of the input vector is 3 which include the series compensation level X_c, the mechanical damping at the high pressure turbine and at the generator mass d_1 and d_5. The dimension of the output vector is equal to nine which include the real parts of the Eigen values corresponding to tlie mechanical counterpart of the system and the Eigen values (both real and imaginary part) corresponding to the electrical network. Note that there are two modes of oscillations corresponding to tlie electrical network one in subsynchronous range and the other in supersynchronous range

For tlie training of the ANN, 15 levels of series compensation were considered between 0% to 70% which is the practical range of compensation provided in series compensated transmission system. Further, six levels of damping were provided at each of the high pressure turbine end at the generator rotor mass with which tlie total number of operating points became **540.** For each of these operating points, the systeni matrix A is modified by adjusting tlie initial values and Eipen value analysis was carried out, off-line using **MATLAB,** thus computing the output vector. The impedances of tlie generator rotor circuits are maintained constant for convenience. These **540** input-output vector pairs fonii the training set.

3.2 **Training : The** Error Back Propagation (EBP) learning algorithm (LA) developed by Rumelhart et al which is one of the most popular LA is used for tlte Purpose of training of tlie multilayer NN. Tlie EBP LA is a generalization of delta nile wherein the synaptic weights are changed to minimize the error which is the difference between tlte actual output patterns and tlie target output patterns. The error is given by

$$E_p = 1/2\Sigma(t_{pj} - O_{pj})^2$$

where

t_{pj} = The target output at unit j for p-th pattern.

O_{pj} = The actual output of unit j for p-th pattern

$$O_{pj} = f_j(\Sigma\omega_{ji}O_{pi})$$

where

f_j = The activation function which is typically a continuous sigmoid.

ω_{ji} = Strength of the synapse connecting neuron i to neuron j.

The weight is adjusted as

$$\omega_{ji}(n+1) = \omega_{ji}(n) + \Sigma\Delta_p\omega_{ji}(n)$$

where

n= The number of tlie epocli.

$\Delta_p\omega_{ji}$ =Change in weight for the p-th pattern.

$$\Delta_p\omega_{ji}(n+1) = \eta\delta_{pj}O_{pi} + \alpha\ \Delta_p\omega_{ji}(n)$$

where

η = The learning rate

α = The momentum rate.

δ = Error tenn which depends on the derivative of the activation function.

A tliree layer ANN consisting of an input layer, a hidden layer and an output layer is considered. The schematic of the NN used for the present work is given in Fig.3. The input and the output layers consist of three and nine neurons, respectively, corresponding to the number of inputs and tlie number of outputs. The neural network toolbox of the MATLAB was used to train this neural network with **350 (out** of **540)** input-output pairs as the training set. These 350 input-output pairs were selected approximately to encoinpass tlie entire range of operating points. The number of neurons for the hidden layer and the momentum were detennined by trial and error and it was possible to achieve convergence to a Sum Squared Error (SSE) of 0.002 with 15 neurons in the hidden layer. Fig.4 depicts, graphically, the variation of the SSE with the number of epochs encountered during tlie training procedure.

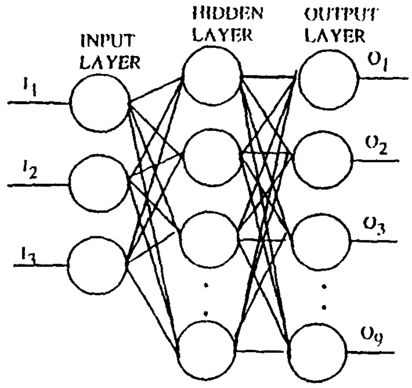

Fig.3. Multilayered feedforward Neural Network

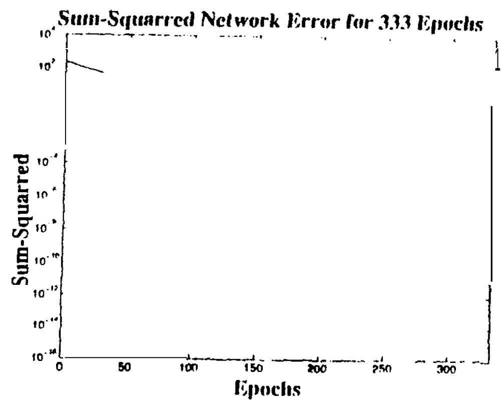

Fig.4. Variation of SSE with the number of Epochs

3.3 Testing : After Ilie training process, the ANN is tested by subjecting it to input patterns, from among the training set as well as from outside the training set and computing the error which is tlte difference between tlte desired output and the output produced by the Neural Network, The maximum percentage error, for input pattenis from among the training set and for input pattenis outside the training set is found to be, approximately, 10.0 arid **15.0,** respectively. However, for most of the situations presented to the neural network, the error is found to be less than **5%.** Hence, by a judicious selection of the input patterns for die purpose of training frorii the entire operating range, it is possible to reduce tlie maximum error to acceptable levels. Table 1 depicts tlie comparison of the desired (Computed) output with the output of the NN for a few test pattenis applied at the input of tlie NN.

4 CONCLUSION

In this paper, the suitability of using an ANN for SSR analysis is investigated with the IEEE first benchmark model as the test systeni. The training set for llie NN is designed to encompass all possible situations and as a result, during the testing phase, a good generalisation has been observed. But for the computationally intensive task of training tlie NN, tlte rest of the design process is simple and so is tlie operational requirements of tlie systeni With the availability of tlie Electrically 'Traiiiable Artificial Neural Network **(ETANN)** chips, it is possible to build a Iiardwnre driven

SSR monitor using the technique explained in this paper so that it can be installed at the generating points where the network involves series compensating capacitors, SVC or HVDC converters. Further, it is envisaged that the NN based SSR monitor shall be followed by a NN based SSR countermeasure, using Static VAR Compensators in AC systems or supplemental Damping Controller for HVDC rectifier in the case of an AC/DC systems. This further research is the future work of the authors.

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Sl. No	Computed outputs							
	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8
1	-0.9551	0.6523	0.9779	-0.7835	0.0000	0.0009	0.0002	0.0002
2	-0.9575	0.7047	0.8493	-0.7578	0.0000	0.0024	0.0003	0.0003
3	-0.9646	0.7788	0.6703	-0.7462	0.0000	0.0484	0.0018	0.0006
4	-0.9699	0.8289	0.5473	-0.7758	0.0000	0.0018	0.1353	0.0025
5	-0.9706	0.8357	0.5309	-0.6476	0.0000	0.0015	0.0393	0.0035
6	-0.9741	0.8704	0.4437	-0.5717	0.0000	0.0007	0.0020	0.2479
7	-0.9754	0.8836	0.4116	-0.4948	0.0000	0.0006	0.0012	0.0394
8	-0.9762	0.8924	0.3891	-0.4678	0.0000	0.0005	0.0009	0.0125
9	-0.9764	0.8939	0.3851	-0.4653	0.0000	0.0005	0.0009	0.0108
10	-0.9774	0.9053	0.3544	-0.6171	0.0000	0.0004	0.0006	0.0047
11	-0.9794	0.9258	0.3136	-0.3668	0.0000	0.0003	0.0004	0.0019
12	-0.9811	0.9453	0.2634	-0.1842	0.0000	0.0003	0.0003	0.0011
13	-0.9828	0.9640	0.2176	-0.0215	0.0000	0.0003	0.0003	0.0008
14	-0.9843	0.9819	0.1746	0.1856	0.0000	0.0003	0.0002	0.0007
15	-0.9858	0.9991	0.1342	0.4546	0.0000	0.0002	0.0002	0.0006
16	-0.9551	0.6523	0.9779	-0.7835	0.1727	0.0093	-0.1091	0.0388

Table 1a. Computed Output for few sample cases

Sl. No.	Output of ANN							
	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8
1	-0.9551	0.6524	0.9780	-0.7835	0.0000	0.0009	0.0002	0.0002
2	-0.9576	0.7048	0.11193	-0.7578	0.0000	0.0025	0.0004	0.0003
3	-0.9647	0.7709	0.6703	-0.7445	0.0000	0.0484	0.0021	0.0006
4	-0.9699	0.8289	0.5476	-0.7611	0.0000	0.0019	0.1369	0.0029
5	-0.9706	0.8357	0.5313	-0.6290	0.0000	0.0015	0.0413	0.0033
6	-0.9741	0.8704	0.4445	-0.5272	0.0000	0.0007	0.0064	0.2318
7	-0.9754	0.8836	0.4126	-0.4426	0.0000	0.0006	0.0064	0.0210
8	-0.9763	0.8924	0.3901	-0.4089	0.0000	0.0005	0.0061	0.0081
9	-0.9764	0.8940	0.3860	-0.4159	0.0000	0.0005	0.0063	0.0072
10	-0.9775	0.9053	0.1553	-0.5652	0.0000	0.0004	0.0057	0.0036
11	-0.9794	0.9258	0.3143	-0.3304	0.0000	0.0004	0.0040	0.0010
12	-0.9812	0.9454	0.2638	-0.1658	0.0000	0.0003	0.0021	0.0050
13	-0.9828	0.9640	0.2178	-0.0147	0.0000	0.0003	0.0009	0.0003
14	-0.9844	0.9819	0.1746	0.1876	0.0000	0.0003	0.0004	0.0006
15	-0.9858	0.9991	0.1343	0.4551	0.0000	0.0003	0.0003	0.0006
16	-0.9696	0.8188	0.5751	0.1567	0.1723	-0.0027	-0.0531	0.0200

Table 1b. ANN Output for few sample cases

Table 1. Comparison of computed output with ANN output

APPENDIX - 1

Transmission line:

$R_e = 0.02pu \quad X_e = 0.7pu \quad X_c = 0.371pu$

Generator:

d-axis $r_F = 0.001406pu \quad r_D = 0.004085pu$
$l_F = 0.062pu \quad l_D = 0.0055pu$
$l_d = 0.31pu$

q-axis $r_{Q1} = 0.014058pu \quad r_{Q2} = 0.008223pu$
$l_{Q1} = 0.326pu \quad l_{Q2} = 0.095pu$
$l_q = 0.13pu$

$L_{AD} = kM_F = kM_D = M_R = 1.66pu$
$L_{AQ} = kM_{Q1} = kM_{Q2} = M_Q = 1.58pu$

Mechanical System:

Mass	Inertia H (sec.)	Shaft section	Spring Constant
HP	0.092897	HP-IP	7277.0
IP	0.155589	IP-LPA	13168.0
LPA	0.858670	LPA-LPD	19618.0
LPB	0.004215	LPB-Gen	26713.0
Gen	0.868495	Gen-EXC	1064.0
EXC	0.034216		