

Improvement of Transient Stability in a Three-Machine Power System by using Neuro-Fuzzy Controller

Ansar Shaik Satuluru¹, G.Gurumurthy²

Assistant Professor, EEE, SPEC, Hyderabad, India¹

Assistant Professor, EEE, ICFAI University, Agartala, India²

Abstract: In this article, computationally simple and accurate expert system, i.e., neuro-fuzzy system based on the artificial neural network (ANN) is applied to design a static synchronous series compensator (SSSC)-based controller for improvement of transient stability in a three-machine power system. The proposed neuro-fuzzy controller combines the advantages of fuzzy controller as well as quick response and adaptability nature of ANN. The neuro-fuzzy structures were trained using the generated database of fuzzy controller for SSSC. The results prove that the proposed SSSC-based neuro-fuzzy controller is found to be robust to fault location and change in operating conditions. A thorough comparison with the conventional lead-lag controller is carried out, taking into account the results of previous publications. The SSSC-based neuro-fuzzy controller output provides promising results in terms of accuracy and computation time. Finally, conclusions are duly drawn.

Keywords: Artificial neural network (ANN); ,multi-machine power system; neuro-fuzzy controller; static synchronous series compensator (SSSC); transient stability.

I. INTRODUCTION

Series capacitive compensation was introduced decades ago to cancel a portion of the reactive line impedance and thereby increase the transmittable power [1]. Recent development of power electronics introduces the use of flexible ac transmission system (FACTS) controllers in power systems [2]. Subsequently, within the FACTS initiative, it has been demonstrated that variable series compensation is highly effective in both controlling power flow in the lines and in improving stability [3, 4]. The voltage sourced converter based series compensator, called static synchronous series compensator (SSSC) provides the virtual compensation of transmission line impedance by injecting the controllable voltage in series with the transmission line. The ability of SSSC to operate in capacitive as well as inductive mode makes it very effective in controlling the power flow of the system [5, 6]. Static Synchronous Series Compensator (SSSC) is one of the important members of FACTS family which can be installed in series in the transmission lines. With the capability to change its reactance characteristic from capacitive to inductive, the SSSC is very effective in controlling power flow in power systems [5]. An auxiliary stabilizing signal can also be superimposed on the power flow control function of the SSSC so as to improve power system oscillation stability [7]. The applications of SSSC for power oscillation damping, stability enhancement and frequency stabilization can be found in several references [8-11].

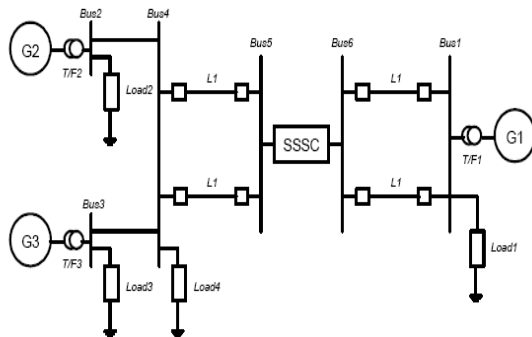
In recent years, new artificial intelligence-based approaches have been proposed to design a FACTS-based supplementary damping controller. These approaches include particle swarm optimization [12, 13], genetic algorithm [14], differential evolution [15], multi-objective evolutionary algorithm [16]. Since 1989, artificial neural networks (ANN) methodology has captured the interest in

a large number of applications in electrical power engineering. The applications include economical load dispatching, power system stabilizers (PSS), etc. The results have shown that ANNs have great potential in improving power system online and off-line applications [17-20]. The proposed controller has been applied and tested under different disturbances for a multi-machine power system. The system consists of three generators divided into two subsystems and are connected via an intertie. The artificial neural network controller based on fuzzy control, i.e., (neuro-fuzzy controller) is applied for series FACTS device, i.e., static synchronous series compensator (SSSC). For the design purpose, MATLAB/Simulink model of the power system with SSSC controller is developed. Simulation results are presented at different operating conditions and under various disturbances to show the effectiveness of the proposed controller. The results prove that the proposed SSSC-based neuro-fuzzy controller can improve the voltage profile and transient stability of the test system more efficient than the conventional lead-lag controller of above devices [13].

II. POWER SYSTEM UNDER STUDY

The multi-machine power system with SSSC shown in Fig. 1 is considered in this study. It is similar to the power system used in references [21, 22]. The system consists of three generators divided into two subsystems and are connected through an inter-tie. The generators are equipped with hydraulic turbine and governor (HTG) and excitation system. The HTG represents a nonlinear hydraulic turbine model, a PID governor system, and a servomotor. The excitation system consists of a voltage regulator and DC exciter, without the exciter's saturation function. Following a disturbance, the two subsystems swing against each other resulting in instability.

To improve the stability the line is sectionalized and a SSSC is assumed on the mid-point of the tie-line. In Fig. 1, G_1 , G_2 and G_3 represent the generators; T/F_1 , T/F_2 and T/F_3 represent the transformers and L_1 , L_2 and L_3 represent the line sections respectively. The relevant data for the system is given in Appendix.



III. NEURO-FUZZY APPROACH

Neuro-fuzzy or Adaptive Neuro-Fuzzy Inference System (ANFIS) approach is considered to be an adaptive network, which is very similar to neural networks. Adaptive network has no synaptic weights, but so called adaptive and non-adaptive nodes. It must be said that adaptive network can be easily transformed to neural networks' architecture with classical feed forward topology. ANFIS is an adaptive network which works like adaptive network simulator of Takagi-Sugeno's fuzzy controllers. This adaptive network is functionally equivalent to a fuzzy inference system (FIS). Using a given input/output data set, ANFIS adjusts all the parameters using back propagation gradient descent and least squares type of method for non-linear and linear parameters, respectively. It is assumed for simplicity that the fuzzy inference system under consideration has two inputs x and y and one output z . Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type [23-26]. The given concept of ANFIS structure can be explained using a simple example whose rule base is given below.

Rule 1: If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$,

Rule 2: If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$.

The three layers Multi Layer Perceptron (MLP) structure model of ANN is applied for designing the SSSC-based neuro-fuzzy controller. This structure of ANN has an input layer, an output layer, and one hidden layer. Research has proved that ANNs have a wide number of applications in the power engineering due to many advantages [17, 18]

- Capability of synthesizing complex and transparent mappings.
- Rapidity due to parallel mechanism.
- Robustness and fault tolerance.
- Adaptability due to its inherent property to adopt new conditions.
- Easy software simulation and hardware implementation.
- Less memory required.

In this paper, application of neuro-fuzzy approach is done in MATLAB/Simulink because the

neuro-fuzzy controller provides faster control and enhanced stability than the compared result of lead-lag controller [13]. The proposed ANN controller uses back propagation-through-time algorithm [27]. The back-propagation is an iterative method employing the gradient decent algorithm for minimizing the min. square error between the actual output and the target for each pattern in the training is applied, the generalized delta rule in the back-propagation algorithm. In this paper, we present a data pattern from training set with fuzzy inputs and fuzzy desired output vectors. Then update the network weights in a recursive algorithm starting from the output layer and working backward to the first hidden layer. The learning procedure of ANFIS system takes the semantically properties of the underlying fuzzy system into account. This results in constraints on the possible modifications applicable to the system parameters. The ANFIS system consists of the components of a conventional fuzzy system except that computations at each stage is performed by a layer of hidden neurons and the neural network's learning capacity is provided to enhance the system knowledge.

3.1 Modeling of SSSC-based Neuro-Fuzzy Controller

The proposed neuro-fuzzy controller utilizes Sugeno-type Fuzzy Inference System (FIS) controller, with the parameters inside the FIS decided by the neural-network back propagation method. The neuro-fuzzy controller is designed by taking speed deviation & acceleration as the inputs, and the injected voltage by SSSC as the output. The output stabilizing signal, i.e., injected voltage is computed using the fuzzy membership functions depending on the input variables. The effectiveness of the proposed approach to modeling and simulation of SSSC controller is implemented in Simulink environment of MATLAB. ANFIS-Editor in MATLAB is used for realizing the system and implementation of the proposed neuro-fuzzy or ANFIS approach.

In a conventional fuzzy approach the membership functions and the consequent models are fixed by the model designer according to a prior knowledge. If this set is not available but a set of input-output data is observed from the process, the components of a fuzzy system (membership and consequent models) can be represented in a parametric form and the parameters are tuned by neural networks. In that case the fuzzy system turns into an ANFIS system.

The fuzzy controller uses 49 rules and 7 membership functions in each variable to compute output and exhibits good performance. Now main aim is to extract a smaller set of rules using ANFIS learning and to do the same the following steps are followed:

Data generation: To design the SSSC-based neuro-fuzzy controller, some data is needed, i.e., a set of two-dimensional input vectors and the associated set of one-dimensional output vectors are required. Here, the training data has been generated by sampling input variables, i.e., speed deviation & acceleration uniformly, and computing the value of stabilized signal for each sampled point

Rule extraction and membership functions: After generating the data, the next step is to estimate the initial

rules. Thenafter applying Subtractive Clustering algorithm [28], rules are extracted. These rules are not so close to the identified system. Hence, there is a need of optimization of these rules. Hybrid learning algorithm is used for training to modify the above parameters after obtaining the Fuzzy inference system from subtracting clustering. This algorithm iteratively learns the parameter of the premise membership functions via back propagation and optimizes the parameters of the consequent equations via linear least-squares estimation. The training is continued until the error measure becomes constant.

Results: The ANFIS learning has been tested on a variety of linear and nonlinear processes. The objective here is to justify whether the neuro-fuzzy controller with less number of rules and membership functions can provide the same level of performance as that of the original one (system with 49 rules). To demonstrate the effectiveness of the proposed combination, the results are reported for system with 25 rules and system with optimized rule base. After reducing the rules the computation become fast and it also consumes less memory. The ANFIS structure for SSSC-based neuro-fuzzy controller is shown in Fig.2.

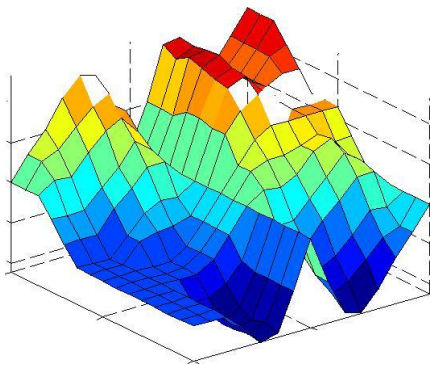


Fig 2. Control surface of SSSC-based neuro-fuzzy controller

IV. SIMULATION RESULTS

The SimPowerSystems (SPS) toolbox is used for all simulations and SSSC-based neuro-fuzzy controller design [29]. In order to optimally tune the parameters of the SSSC-based neuro-fuzzy controller, as well as to assess its performance, the model of example power system shown in Fig. 1 is developed using SPS block-set. The ratings of the generators are taken as 2100MVA each (G2 and G3) in one subsystem and 4200MVA (G1) in the other subsystem. The generators with output voltages of 13.8KV are connected to an inter-tie through 3-phase step up transformers. All of the relevant parameters are given in the Appendix.

Local control signals, although easy to get, may not contain the inter-area oscillation modes. So, compared to wide-area signals, they are not as highly controllable and observable for the inter-area oscillation modes. Owing to the recent advances in optical fiber communication and global positioning systems, the wide-area measurement system can realize phasor measurement synchronously and deliver it to the control center even in real time, which makes the wide-area signal a good alternative for control input. In view of the above, the speed deviation and

acceleration of generators G1 and G2 are chosen as the control input of the SSSC-based neuro-fuzzy controller in this article. To assess the effectiveness and robustness of the proposed neuro-fuzzy controller, load flow is performed with Machine 1 as a swing bus and Machines 2 and 3 as PV generation buses. The initial operating conditions used are:

Machine 1 generation: $P_{e1} = 3480.6$ MW (0.8287 p.u.),

$Q_{e1} = 2577.2$ MVAR (0.6136 p.u.)

Machine 2 generation: $P_{e2} = 1280$ MW (0.6095 p.u.),

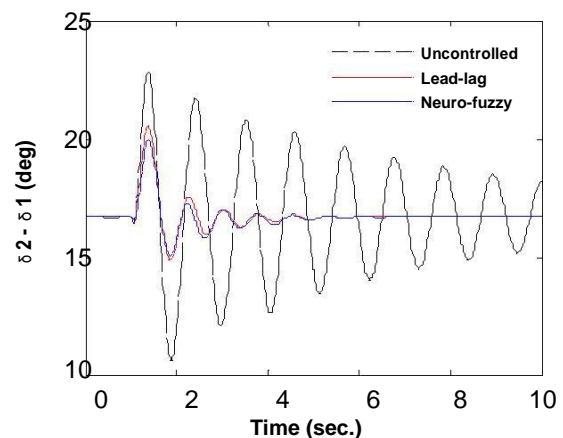
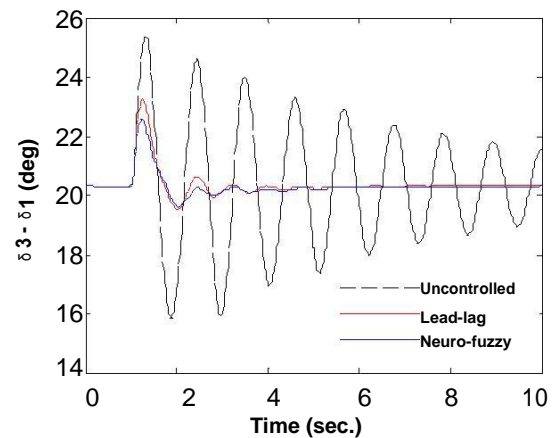
$Q_{e2} = 444.27$ MVAR (0.2116 p.u.)

Machine 3 generation: $P_{e3} = 880$ MW (0.419 p.u.),

$Q_{e3} = 256.33$ MVAR (0.1221 p.u.)

Simulation studies are carried out for the example power system subjected to various severe disturbances as well as small disturbances. The simulation results are also compared with the result of lead-lag controller as given by ref. [13]. The original system is restored upon the clearance of the fault. A three-cycle, three-phase fault is applied at one of the line sections between Bus 1 and Bus 6, near Bus 6, at $t = 1$ sec. The fault is cleared by opening the faulty line, and the line is reclosed after three cycles.

The original system is restored after the fault clearance. Figs. 4(a)–4(d) show the variations of the inter-area and local mode of oscillation and the SSSC-injected voltage against time.



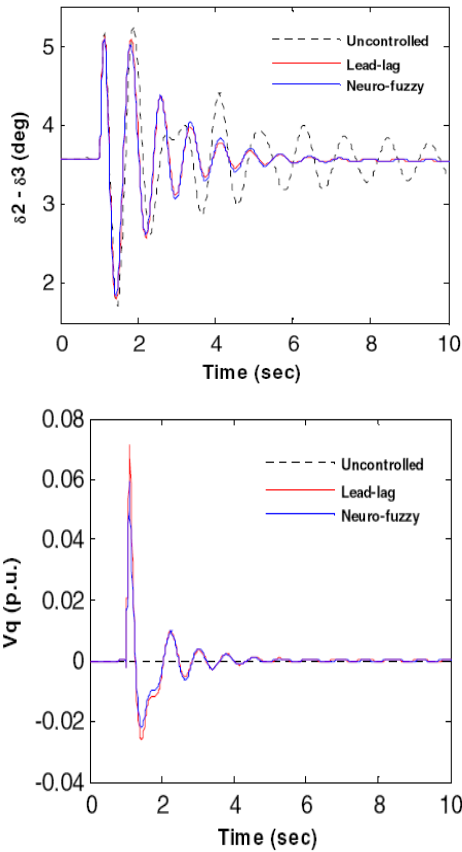


Figure 3. Variation of inter-area and local modes of oscillations against time for a three-cycle, three-phase fault near Bus 6: (a) and (b) inter-area mode; (c) local mode; (d) SSSC-injected voltage, V_q

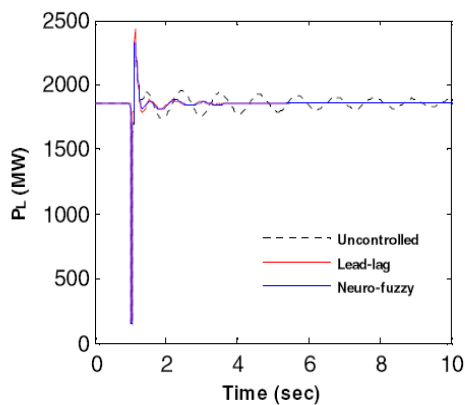


Figure 4. Variation of tie-line power flow for a three-cycle, three-phase fault near Bus 6 cleared by a three-cycle line tripping.

From these figures, it can be seen that the inter-area modes of oscillations are highly oscillatory in the absence of both. SSSC-based damping controller as well as neuro-fuzzy controller, and the proposed neuro-fuzzy controller significantly improves the power-system stability by damping these oscillations. Furthermore, the proposed controller is also effective in suppressing the local mode of oscillations. The power flow through the tie-line (at Bus 1) for the above contingency is shown in Fig. 5, which

clearly shows the effectiveness of the proposed controller to suppress power-system oscillations.

The effectiveness of the proposed controller on unbalanced faults is also examined by applying self-clearing type unsymmetrical faults, namely L-G, L-L-G, and L-L, each of three -cycle duration at Bus 1 at $t = 1$ sec. The inter-area and local modes of oscillations against time are shown in Figs. 6-7. It is clear from the figures that the power-system oscillations are poorly damped in the uncontrolled case, even for the least-severe L-G fault, and the proposed SSSC-based neuro-fuzzy controller effectively stabilizes the power angle under various unbalanced fault conditions.

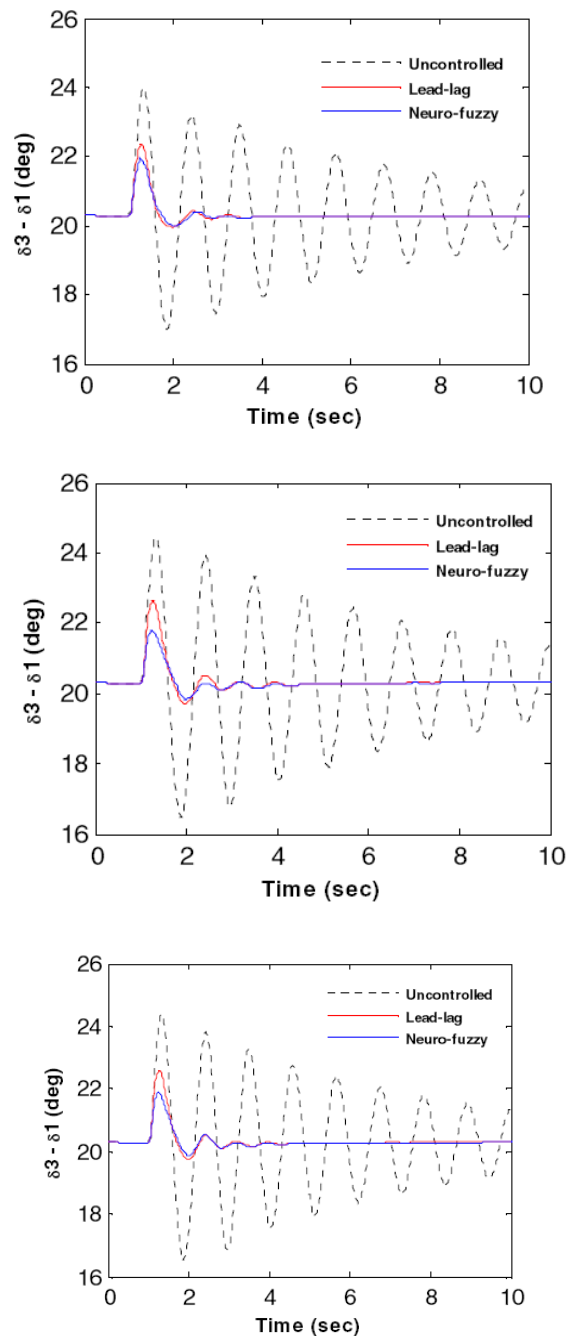


Figure 5. Variation of inter-area mode of oscillations against time for three-cycle unbalanced faults at Bus 1: (a) L-G fault; (b) L-L-G fault; (c) L-L fault.

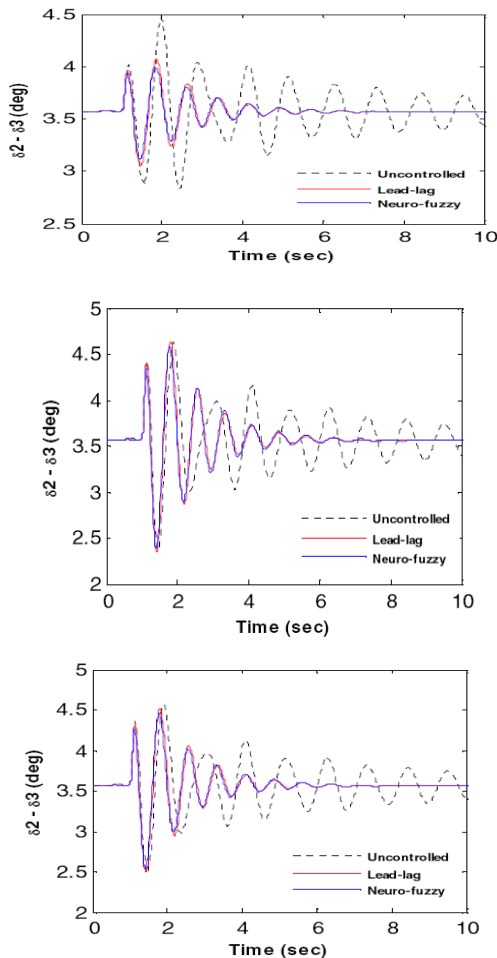


Figure 6. Variation of local mode of oscillations against time for three-cycle unbalanced faults at Bus 1: (a) L-G fault; (b) L-L-G fault; (c) L-L fault.

Simulation results show that the performance of the neuro-fuzzy controller is better than that of conventional lead-lag controller. In all cases, the damping following the disturbance has improved significantly. It is clear from these figures that the neuro-fuzzy controller improves the stability performance of the example SSSC-based power system and, also, power system oscillations are well damped out.

V.CONCLUSION

This article presents an SSSC-based neuro-fuzzy controller for transient stability improvement in a three-machine power system. The effectiveness of the proposed SSSC-based neuro-fuzzy controller in improving power-system stability is also demonstrated. The dynamic performance of proposed SSSC-based controller under various loading and disturbance conditions are analyzed and compared. It is observed that the proposed SSSC-based neuro-fuzzy controller provides efficient damping to power system oscillations and greatly improves the system voltage profile. The inter-area and local modes of power system oscillations are effectively damped by using the proposed SSSC controller. The research work is intended to find the most suitable configurations of the neuro-fuzzy controller for the FACTS device. The superiority of neuro-fuzzy controller is evident from the simulation results for all types of disturbances.

System data: All data are in p.u. unless specified otherwise

Generators:

Nominal powers: $S_{B1}=4200\text{MVA}, S_{B2}=S_{B3}=2100\text{MVA}$
Nominal voltages: $V_B=13.8\text{KV}$, Nominal frequency $f=60\text{Hz}$, Reactances $X_d=1.305, X_d'0.296, X_d''=0.252, X_q=0.474, X_q'=0.243, X_q''=0.18$, Time constants $T_d=1.01\text{s}, T_d'=0.053\text{s}, T_{q0}=0.1\text{s}$ stator resistance: $=2.8544e^{-3}$ coefficient of inertia and pair of poles= $3.7\text{s}, P=32$

Excitation systems: Low-pass filter time constant: $T_{LP}=0.002\text{s}$ regular gain and time constants $K_A=200, T_A=0.0001\text{s}$, Exciter gains and time constants: $K_e=1, T_e=0$, Transient gain reduction: $T_b=0, T_c=0$
Damping filter gain and Time constants: $K_f=0.001, T_f=0.1\text{s}$
Regulator output limits and gains: $E_{fmin}=0, E_{fmax}=7, K_p=0$

Hydraulic Turbine and Governor:

Servo motor gains and time constants: $K_e=3.33, T_a=0.007$, gate opening limits: $G_{min}=0.001, G_{max}=0.97518$, $V_{gmin}=-0.1\text{p.u./s}, V_{gmax}=0.1\text{p.u./s}$ permanent droops: $R_p=0.005$, PID regulators: $K_p=1.163, K_i=0.105, K_d=0$, $T_d=0.001\text{s}$, hydraulic turbines: $\beta=0, T_w=2.67\text{s}$

Transformers:

Nominal powers: $S_{B1} = 4200 \text{ MVA}, S_{B2}=S_{B3} = 2100 \text{ MVA}$, Winding connections: D_1/Y_g Winding parameters: $V_1=13.8 \text{ kV}, V_2= 500 \text{ kV}, R_1 = R_2 = 0.002, L_1 = 0, L_2 = 0.12$, Magnetization resistance: $R_m= 500$, Magnetization Reactance: $L_m=500$

Transmission lines:

Number of phases: 3-Ph, Resistance per unit length: $R_1 = 0.02546 \Omega/\text{km}, R_0 = 0.3864 \Omega/\text{km}$ Inductance per unit length: $L_1 = 0.9337 \times 10^{-3} \text{ H/km}, L_0 = 4.1264 \times 10^{-3} \text{ H/km}$, Capacitance per unit length: $C_1= 12.74 \times 10^{-9} \text{ F/km}, C_0 = 7.751 \times 10^{-9} \text{ F/km}$, Line lengths: $L_1 = 175 \text{ km}, L_2 = 50\text{km}, L_3 = 100\text{km}$.

SSSC: Converter rating: $S_{nom} = 100 \text{ MVA}$, System nominal voltage: $v_{nom} = 500 \text{ KV}$, Frequency: $f = 60 \text{ Hz}$, Maximum rate of change of reference voltage (v_{qref}) = 3 p.u./s , Converter impedances: $R = 0.00533, L = 0.16$, DC link nominal voltage: $V_{DC} = 40 \text{ kV}$, DC link equivalent capacitance $C_{DC} = 375 \times 10^{-6} \text{ F}$, Injected Voltage regulator gains: $K_p = 0.00375, 0.1875$, DC Voltage regulator gains: $K_p = 0.1 \times 10^{-3}, k_i = 20 \times 10^{-3}$, Injected voltage magnitude limit: $v_q = \pm 0.2$

Loads:

$\text{Load}_1 = 7500\text{MW} + 1500\text{MVAR}, \text{Load}_2 = \text{Load}_3 = 25\text{MW}, \text{Load}_4 = 250\text{MW}$

REFERENCES

- [1] P. Kundur, "Power System Stability and Control", McGraw-Hill, 1994.
- [2] N. G. Hingorani, and L. Gyugyi, "Understanding FACTS: Concepts and Technology of Flexible AC Transmission Systems", IEEE Press, New York, 2000.
- [3] L. Gyugyi, "Solid-state control of electric power in ac transmission systems", *Int. Symp. Elect. Energy Conv. in Power Syst.*, Invited Paper, no. T-IP 4, 1989.
- [4] L. Gyugyi, "Dynamic compensation of ac transmission lines by

- solid-state synchronous voltage sources”, *IEEE Trans. Power Delv.*, vol. 9, no. , pp. 904-911, 1994.
- [5] L. Gyugyi, C. D. Schauder, and K. K. Sen, “Static synchronous series compensator: a solid state approach to the series compensation of transmission lines”, *IEEE Trans. Power Delv.*, vol. 12, no. , pp. 406-417, 1997.
- [6] K. K. Sen, “SSSC-static synchronous series compensator: theory, modeling, and applications”, *IEEE Trans. Power Delv.*, vol. 13, no. 1, pp. 241-246, Jan 1998.
- [7] H. F. Wang, “Static synchronous series compensator to damp power system oscillations”, *Elect. Power Syst. Res.*, vol. 54, no. 2, pp. 113-119, May 2000.
- [8] K. R. Padiyar, and K. Uma Rao, “Discrete control of series compensation for stability improvement in power systems”, *Elect. Power & Energy Sys.*, vol. 19, no. 5, pp. 311-319, June 1997.
- [9] R. Mihalic, and I. Papic, “Static synchronous series compensator—a mean for dynamic power flow control in electric power systems”, *Elect. Power Syst. Res.*, vol. 45, no. 1, pp. 65-72, April 1998.
- [10] D. Menniti, A. Pinnarelli, N. Scordino, and N. Sorrentino, “Using a FACTS device controlled by a decentralised control law to damp the transient frequency deviation in a deregulated electric power system”, *Elect. Power Syst. Res.*, vol. 72, no. 3, pp. 289-298, Dec. 2004.
- [11] I. Ngamroo, J. Tippayachai, and S. Dechanupaprittha, “Robust decentralised frequency stabilisers design of static synchronous series compensators by taking system uncertainties into consideration”, *Elect. Power & Energy Sys.*, vol. 28, no. 8, pp. 513-524, Oct. 2006.
- [12] S. Panda, and N. P. Padhy, “Comparison of particle swarm optimization and genetic algorithm for FACTS-based controller design”, *Appl. Soft Comput.*, vol.8, no.4, pp. 1418-1427, 2008.
- [13] S. Panda, N. P. Padhy and R. N. Patel, “Power system stability improvement by PSO optimized SSSC-based damping controller”, *Electr. Power Comp. Syst.*, vol. 36, no.5, pp. 468-490, 2008.
- [14] M. A. Abido, “Analysis and assessment of STATCOM-based damping stabilizers for power system stability enhancement”, *Electr. Power Syst. Research*, vol. 73, no. 2, pp. 177-185, Feb. 2005.
- [15] S. Panda, “Differential evolutionary algorithm for TCSC-based controller design”, *Simulat. Model. Pract. Theory*, vol. 17, no. 10, pp. 1618-1634, 2009.

BIOGRAPHIES

ANSAR SHAIK SATULURU was born in Guntur India. He received the B.Tech degree in electrical and electronics engineering from JNTU Hyderabad and m.tech degree in control systems from JNTU Hyderabad, India in 2008 and 2011 respectively. He is presently working as an assistant professor in St. Peter's engineering college from 2011 to till date. His area of interest is speed controllers.

G.GURUMURTHY was born in Kadapa, India 1989. He received the B.Tech degree in electrical and electronics engineering from JNTU Anantapur and m.tech degree in control systems from JNTU Hyderabad, India in 2010 and 2013 respectively. He worked as assistant professor in St. Peter's engineering college from 2012-2014. He is presently working as Asst. Professor in ICFAI University, Agartala. His areas of interest is micro grid.