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CONTROL OF POWER SYSTEM STABILITY – REVIEWED SOLUTIONS BASED ON INTELLIGENT SYSTEMS

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Abstract. *Electric power grid is a widely distributed system, consisting of dispersed generators interconnected through transmission lines, mounting real and reactive power compensators, etc. Moreover, with deregulation and growth of the power industry, power systems elements are forced to operate very near to their maximum capacity and hence, the system became vulnerable. Therefore, controlled operation of power systems is very critical and of utmost importance in order to achieve stable power system. Naturally, this paves ways for implementing fast, efficient and reliable control algorithms. Robustness and efficiency of power system controllers can be improved by using complimentary paradigms of intelligent systems; neural networks, fuzzy logic and bio-inspired optimization algorithms. Difficulties encountered in designing controls for nonlinear, dynamic and uncertain systems can be easily tackled by using intrinsic observability property of various intelligent systems. The other advantage of intelligent system is lesser modeling error, which leads to efficient control loop. Intelligent controllers have been successfully applied to enhance operation and control of power system. This paper reviews and summarizes implementation of intelligent controllers at the generator end of power systems, during the past decade. Few proposals are also given for further investigation in the realm discussed in this paper.*

Keywords: Generator control, Excitation system, Power system stabilizers, Transient stability, Intelligent control, Neural networks, Neurofuzzy, Adaptive critic design, Ensemble-ANN

1. **Introduction.** Stable operation of highly interconnected, geographically wide power system craves for matching of total generation with total load demand along with associated system losses [1]. On one hand, interconnection, restructuring of power system has brought very economical and quality energy for consumers. Poles apart, deregulation and with the increase of fast power consumption loads, such as testing plants, nuclear fusion plants, factories using arc furnace transformer have made the matching very critical. Additionally, power systems have become more unpredictable after the implementation of high speed electronic power controllers. This aggravates the stable operation of power systems even more. The review of reference [2] has revealed that, yet full advantages offered by restructuring electric power utility are not availed because of inappropriate control algorithms. The importance of enhanced operation and control of power system has increased particularly after recent interconnected blackouts in USA, UK and Europe, also [3].

Nowadays, power systems are observing shift from vertical integration to horizontal operation where competitive companies own GENCOs, TRANSCOs and DISCOs. This transition has resulted in power systems being operated at ever lesser security and stability margin and hence, threatening power systems reliability. Additionally, recent control actions are not designed for fast propagating disturbances [4] and are needed to be enhanced to meet the requirements of highly vulnerable to low-probability-events power systems of this era. Reference [5] provides excellent understanding about the impact of deregularization of utility on planning and management of the utility. As power systems continue to grow in size and complexity, it becomes increasingly important to comprehend system stability to preclude dynamic collapse and possible blackouts.

Research in power systems is currently being carried out in areas of power system transient stability [6], power quality [7], data quality [8], power system modeling [9], power system reliability [10], fast valving [11], reactive power management [12], power systems economics [13] and integration of renewable sources with national grid [14] are the areas, to name a few. As the title suggests this research work is concerned with power system stability.

2. Power System Stability: A Problem.

Power system stability is best defined as the ability of an electric power system to regain a state of operating equilibrium after being subjected to a physical disturbance, when variables are bounded so that practically the entire system remains intact [15]. Stability of power system is related to stability of synchronous generator. The mechanical angle between rotor magnetic field and armature magnetic flux of a generator is known as the load angle or power angle (δ). Basically power system stability is a synchronism between rotating field flux and circulating armature flux. Power system stability is classified into different classes based on the variables involved, magnitude of disturbance and time duration of disturbance, as illustrated in Figure 1.

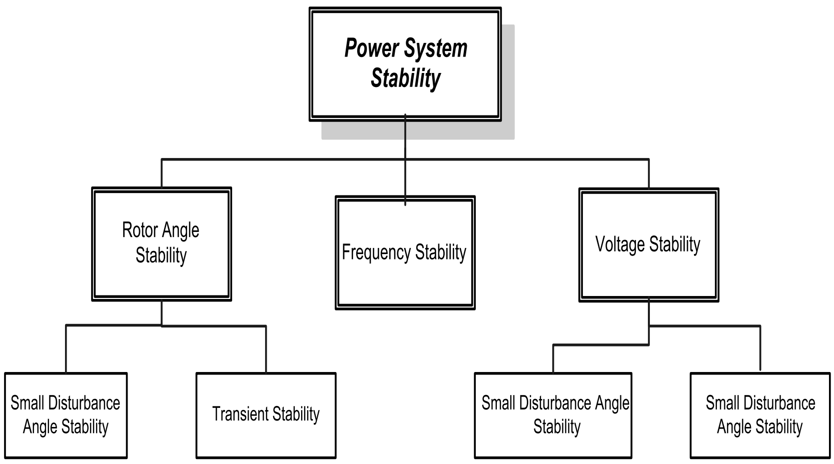


Figure 1. Classification of power system stability

Angle stability is the balance between electromagnetic torque and mechanical torque, whereas voltage stability is akin to match between reactive power generation and consumption. It is hard to draw a clear line of demarcation between these two types of instabilities, since one leads to another. However, it is well-established that voltage instability is caused by load characteristics, whereas angular instability is generator-rotor-dynamics phenomenon. Alternatively, for voltage stability, the vulnerable points of the power systems are generally among load buses, also referred as P-Q bus. Whereas, for angle stability vulnerable points of a system lie within generator buses, also known as P-V bus [16]. Ability of power system to maintain steady state frequency following a severe upset is known as frequency stability. The focus of this paper is transient stability, which is an important subset of angle stability of power system.

Transient stability is the ability of a system to remain intact following major disturbances. The time period of interest in transient stability studies generally varies within 3 to 5 seconds and may extend to 10-20 seconds for very large systems, following any disturbance [15]. In addition, transient stability behavior of power system is best characterized by generator angle and velocity. The problem of transient stability is divided into two main categories; evaluation and prediction [16]. Transient stability evaluation focuses on the time required to isolate faulty section before system becomes instable and it is called critical clearing time. On the contrary, in transient stability prediction the focus shifts to whether transient swings will finally converge or otherwise.

Power system transient stability can best be explained by equal area criterion [17], illustrated in Figure 2.

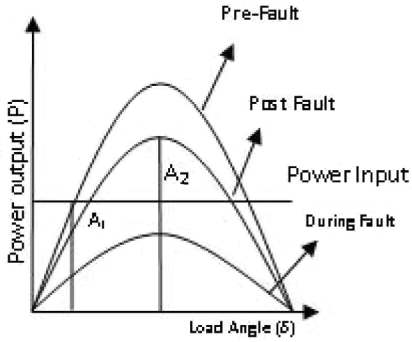


Figure 2. Variation of active power relative to load angle

The difference of input mechanical torque and electrical torque output acting on the rotor of synchronous generator is given by,

$$\tau_A = \tau_M - \tau_{EM} \tag{1}$$

where τ_A is the accelerating torque, τ_M is the mechanical input torque, τ_{EM} is the induced electromagnetic torque. Area A_1 in Figure 2 is the accelerating area because resultant of Equation (1) is positive in this case. Whereas A_2 is called the decelerating area as accelerating torque is negative in this case.

As stated by the definition of stability, rotor must remain in a state of dynamic equilibrium for a stable operation. To meet the condition, the magnitude of A_1 must be either equal to or lesser than A_2 during any contingency. This can be ensured by either increasing during-fault-curve or post-fault-curve or isolating faulty section in a very short time. Isolation of fault comes under the category of power engineering branch known as power system protection. The former is associated with effective controlling of generators and/or power flow controllers installed at transmission end. The primary control of a power system is carried out at generator end, whereas secondary control is through power flow control at transmission end [18]. Power system stability can be improved by using dynamic controllers as excitation systems, power system stabilizers and FACTS devices [19], controlled islanding [20] and HVDC.

3. **Power System Stability Enhancement.** Flexible AC Transmission System (FACT S) devices are example of enhancing power systems stability by controlling power flow at transmission end. They are divided into series, shunt and series-shunt categories according to the manner of device connection with the system. The concept behind enhancing power system stability by series FACTS devices such as Static Series Synchronous Compensator (SSSC) is to increase active power flow during faulty condition consequently

decreasing area A1 and increasing area A2 [21]. On the other hand, shunt devices as Static Synchronous Compensator (STATCOM) boost power system transient stability by injecting reactive power into system to support the system voltage during disturbance and ultimately leading to decrease of area A1 and increasing area A2 [22]. The most commonly used FACTS controller is Unified Power Flow Controller (UPFC). It consists of two branches; one is connected in series and the other is in shunt with the system. UPFC controller uses notion of both series and shunt FACTS controllers for increasing power system stability effectively than any other FACTS controllers [19,23].

Controlled Islanding is a technique in which whole power system is divided into sections, without having any interconnection, to avert major blackouts [15]. Controlled islanding is the last line of defense in strategy to keep power system stable. Additionally, it is not proposed as the answer to all instability problems in the system [20]. High Voltage DC (HVDC) transmission system is potentially a shield against synchronism loss. Nonetheless, it poses problem of voltage instability following disturbance, if the system depletes reactive power reserves [24].

The control actions at generator end to thwart the system instability are either in terms of excitation system or power system stabilizers or at mechanical end of power plants. The main cause of transient instability of generator is inability of mechanical torque to quickly balance out changes in electrical torque [25] and also generator rotor inertia plays major role. After disturbance the electrical torque can be resolved into two components, one is synchronizing torque and other is called damping torque given by,

$$\Delta T_E = K_S \Delta\delta + K_D \Delta\omega \tag{2}$$

where δ is load angle also known as torque angle, ω is angular speed and K is constant.

The first term of Equation (2) is synchronizing torque. This torque is dependent on air gap magnetic flux and magnetic coupling between rotor and armature of synchronous generator. This component of torque can be enhanced by high initial response Automatic Voltage Regulator (AVR) and negative field forcing capability of Exciter as well [3,26]. Excitation system comprises of AVR and Exciter. The second component of Equation (2) is damping torque. It has very profound impact on small signal stability and generator dynamics during transient state following short circuit fault. Damping torque results from the phase lag or lead of excitation current [25,26]. The first swing transient instability is due to lack of sufficient synchronizing torque. Power system can diverge after convergence of first swing mainly because of insufficient damping torque [16].

Currently, installed excitation systems are very fast responding systems and can immediately take corrective measures following very small oscillations. Nevertheless, from the time of recognition of desired excitation action to its real fulfillment, there is inevitable time delay owing to high time constant of field and armature windings. During this time period, position of oscillating system is bound to change and thus resulting in need of new excitation adjustment. The overall outcome of this time lag is induction of oscillations at the generator end. Power System Stabilizers (PSS) can effectively be used to damp out generator electromechanical oscillations by minimizing the phase lead and lag between synchronously rotating armature flux and rotor. AVR along with PSS are used to enhance power system stability [15,25].

The focus of this research is transient stability enhancement by using efficient controlling at generator end, as it is a primary control.

4. **Application of Intelligent Systems.** The loading of power system varies with time. Components attached with power system operate over very wide range and the range has become even wider since restructuring of utility [5]. Proportional-Integrator-Derivative

(PID), a very well-developed and linear controller has found better place in power system control. The deviation of device operating point from equilibrium point has very detrimental impact on performance of linear controllers. Reference [27] has compared the variation of PSS parameters with variation in operating point to assess impact on robustness of conventional PSS. It is found that slight change is required to be made when a synchronous machine operates with positive reactive power and active power. Whereas, PSS variables need drastic tuning with slight shift in operating domain has been observed when the synchronous machine operates with negative reactive power. This has paved the way for nonlinear controller implementation in recent times and has been proved better over wide range of operating conditions [28,29].

Nonlinear control is theoretically and computationally very complicated. Their performance is highly sensitive to modeling error. The degree of complexity grows geometrically with involvement of uncertainties, increase of unknown variables and inability to access every state vector intensify the complication [30]. The problem formulation becomes more complicated upon switching from Single Input Single Output (SISO) to Multi Input Multi Output (MIMO). Moreover, such methods can improve the performance of dynamic and nonlinear systems like power systems but they may not yield better results when applied in real time due to high computation time [31]. Generally, effective robust performance of closed loop system is proportional inversed with controller response time [32,33]. Therefore, it can be concluded that classical and nonflexible controllers do not represent good solutions due to nonlinear, multivariable and uncertain power system containing a wide array of devices each having different response rate. Additionally, contingencies and load variations smoothed the way for fast and highly flexible control schemes.

In recent years it has been recognized that it is necessary to incorporate other elements, such as logic, reasoning and heuristics into algorithmic techniques of conventional adaptive and optimal control theory to impart more flexible control systems. The intelligent control is defined as having the ability of learning, adaptation and operating over a wide envelope satisfactorily. Three paradigms of Intelligent Systems (IS) have been used in intelligent control: Fuzzy Logic, Optimization Algorithms-mostly Genetic Algorithm (GA) and Artificial Neural Networks (ANN). Fuzzy Logic (FL) is good at making decision and logic designing, once data is processed and GA performs well in optimization. ANNs have done well in data processing. Reference [34] has compared not only IS-based adaptive control but the conventional adaptive control, called analytical techniques too, and amalgamation of AI and conventional techniques. It was concluded that the approach to be used depends upon expertise and confidence of the designer. While, in comparison to conventional control margin of transient stability limit is increased by using adaptive control system. This eases the limit of critical clearing time a bit. Nonetheless, by reducing critical clearing time transient stability limit may increase even more. It is difficult to compare different techniques used in the realm since every researcher has carried out analysis at different operating conditions. More recently another research work [35] has used a combination of two techniques; one is ANN as model identifier and other is pole-shift adaptive controller, which is an analytic technique. In pole-shift algorithm a scalar has been adapted continuously and its value basically determines the stability of closed loop control. It is claimed that this control loop has lowest processing time.

Problem solution with FL becomes complex with increase of involved variables. Apart from that FL control is more empirical-based [36]. GA, stochastic in nature and insensitive to initial configuration, has the ability of derivative free global optimization and that lies in their so called notion of evolution behind their evolution. Overall performance of GA is fitness function dependant and hence, the function requires expert knowledge.

Furthermore, GA requires considerable time to converge and its efficiency is variable of many control parameters.

ANN on the other hand has intense parallel interconnections of simple processors. Although ANN has poor interpretation, it is one of the most promising control approach compared to all other approaches available [36]. The promise of fast computation, ability to map any nonlinear function satisfactorily, fault tolerance and robustness have made ANN to carryout sophisticated control tasks. The current trend is towards amalgamation of all three AI paradigms to implant features of each to cover up demerits of other such as to feed expert knowledge into ANN or optimize free parameters or structure of ANN [37-39].

5. **Artificial Neural Network: Common Architecture Models.** Following an initial period of enthusiasm and activity in realm of ANN, a tarnished period of reluctance is way behind now. Generally, ANN is seen as analogous to curve fitting polynomials, in which coefficients of variables and constant in polynomial are linked with weights and biases of ANN. In fact with classical approximating tools like polynomials, trigonometric series, splines and orthogonal functions the efficiency up to any extent can be achieved. Nonetheless, ANN enjoys advantages of lesser noise sensitivity, easy hardware implementation and use of fewer input features [40]. ANN is now a well-developed field with very few grey areas being researched and revisited rigorously with positive outcomes. The advancement in learning algorithms of ANN compelled researchers from different fields to heed towards ANN implementation. ANNs are really good at distinguishing system states on basis of input-output. On basis of this property ANN has found variety of applications in dynamical system control and the property is named observability.

The most commonly used ANN topologies are Multi Layer Perceptron (MLP), Radial Basis Function (RBF) and Recurrent Neural Network (RNN). This research survey revealed that only three references [41-43] have used dynamic neural network and rest have used either RBF or MLP. The strength of RNN lies in its massive feedback connections. Where, MLP and RBF are well proven universal approximators with one hidden layer. Although, it is believed that addition of hidden layer may give better accuracy. For the same degree of accuracy MLP requires lesser number of input features than RBF and thus will yield lesser information processing time. However, this can be compensated by higher information processing speed of RBF. RBF are local in nature means a given weight only effects over a part of the input space, therefore it affects output linked with the part only. Hence, RBF are better used for online training. It is well known, during adaptation the variance of Gaussians can become very broad and RBF may lose its local nature. MLP are global in nature meaning that every weight affects total output of the network. Hence, better for offline training, yet MLP has shown to exhibit local learning nature when trained with deviation signal ($\Delta\chi$) [44,45].

An excellent comparison between MLP and RBF network for model identification has been researched in [46]. In this work both networks have been compared when they have used deviations of the measured signals from set points as well as when they have been trained on actual measured signals. The deviation signals are used to provide better controller sensitivity and also their amplification is easier than actually measured signals. Poles apart, it is difficult to sense deviation signals since their magnitude is very close to zero. Moreover deviation signals in real time may severely be distorted with noise [47]. The results have depicted that MLP has slight upper hand over RBF when trained with deviation signals and tested on basis of global performance. Here, global means that network is trained on one operating condition and with those fixed free parameters tested on other operating region. Alternatively, MLP showed better generalization ability than

RBF. Whereas RBF performed better than MLP when trained on actual measured signals and tested on global performance basis. It is important to bear in mind that networks were trained online and training was stopped on basis of time duration. Reference [48] is extension of aforementioned reference [46]. The results manifested that performance of RBF neurocontroller is better than MLP neurocontroller when trained online with deviation signals. However, MLP contain fourteen hidden layer nodes and RBF has twelve centers. What's more the processing speed of RBF is higher [46] and good performance of closed loop system is inversely proportional to controller response time [32]. MLP may perform better if response time issue is tackled appropriately.

6. **Neuro-Control Systems.** Initially control, ANN and information science were gathered under the umbrella of Cybernetics. Afterword, unfortunately, these fields went apart and did not enjoy the hybridization for better results until [49] proposed application of ANN in dynamical systems control. The different types of control problems that are encountered in practice may be classified into the following groups [40].

1. Nonlinear control problems and nonlinear adaptive control problems.
2. Control systems based on state vectors and control systems based on only input-outputs.
3. Controller parameters chosen off-line and controller parameters chosen online.

In neurocontrol of excitation and power system stabilizers ANN is applied in terms of nonlinear model reference adaptive control, a branch of analytical nonlinear adaptive control based on input-output whereas parameters are tuned online as well as offline. The block diagram of model reference adaptive control is given in Figure 3. Model identifier is an ANN that mimics generator. The purpose of model identifier is to predict generator voltage and/or speed at $y(t+1)$ instant. This is compared with the desired response fed by a reference model and therefore, parameters of neurocontroller are updated on basis of the difference. The training of model identifier is carried out based on error between generator output variables and model identifier output. There are four different types of model identification based on linear and nonlinear Auto Regressive Moving Average (ARMA/NARMA). Few authors have also used ARMA model in nonlinear and dynamical power system control [34,35,50-52]. The overall linearized-nonlinear system can be represented by ARMA model, if the system is observable through output and Eigen values of unforced system are different from the zeroes of the transfer function. Out of the aforesaid four model identifiers, two contain linear combination of time delayed values of either plant output or controller output, hence are not used, whereas remaining two are stated by Equations (1) and (2). These equations are for SISO plants and they can easily be extended for MIMO systems by adding more variables.

$$\begin{aligned} y_p(t+1) = f[&y_p(t), y_p(t-1), y_p(t-2), \cdots, y_p(t-n+1); \cdots \\ &\cdots u(t), u(t-1), u(t-2), \cdots, u(t-m+1)] \end{aligned} \tag{3}$$

$$\begin{aligned} y_p(t+1) = f[&y_p(t), y_p(t-1), y_p(t-2), \cdots, y_p(t-n+1)] + \cdots \\ &\cdots g[u(t), u(t-1), u(t-2), \cdots, u(t-m+1)] \end{aligned} \tag{4}$$

where $y_p(\cdots)$ is the plant output, $u(\cdots)$ is the controller output.

For global plant identification it is affirmed that $(2n+1)$ past values of inputs and outputs are adequate [40]. Later on, authors of [44,48] have clearly mentioned that the use of time delayed values behind two delayed has not much impact on the performance of controller. Moreover, few authors have used time-delayed values up to five delayed-values [51,53]. Furthermore, identification models are classified according to the connection, alternatively according to inputs fed to identification model. One is called Parallel Identification Model (PIM) and other is known as Series-Parallel Identification Model (SPIM).

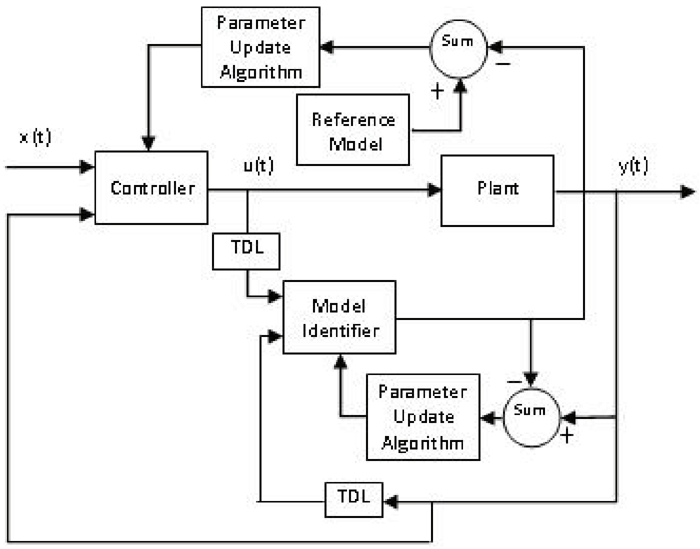


FIGURE 3. Block diagram of nonlinear model reference adaptive control

The Model Identifier portrayed in Figure 3 is SPIM. It takes $u(t)$ and $y(t)$ current and delayed values as input and parameters are updated on difference between model and plant outputs. Generally, SPIM is used in this area, since in spite of two decade of research, conditions under which the PIM parameters converge even in linear case are not known yet [49]. What's more, it is well known that SPIM has better convergence properties than PIM [54].

Table 1 gives a summary of ANN architecture used in [33,44,51,52,55,56]. The table shows the architecture of NeuroIdentifier (NI), NeuroController (NC) and ANN training algorithms. Dynamic backpropagation training algorithm gives fast convergence by using the previous inputs whereas static backpropagation uses only current values. It is very clear from the table that every work has used NARMA model for model identification, where NARMA-3 means that model identification is based on Equation (3). Another point worthwhile to note is that ANNs have been trained on deviation signals either to avoid usage of desired response predictor [55] or to avert MLP demerits [44,56]. The results have been compared with conventional PSS and even machines without PSS. Results have confirmed that neuro-PSS has performed better than conventional PSS. In the case of neuro-excitation system results have been compared with conventional controller, i.e., Proportional-Integrator-Derivative (PID) or its subset. The difference between research carried out in [44,56], lies in the number of neurocontrollers used. The results have portrayed slightly better performance at higher load conditions of scheme consisting of two neurocontroller. This better performance has been result of lesser computational burden and different sampling time for mechanical and electrical systems [56]. The sampling time taken for excitation system and turbine has been 20ms and 100ms respectively, since being mechanical system turbine has slower response. Reference [33] has researched the application of MRAC-based neurocontrol to PSS and the architecture detail is given in Table 1. Another work [30] has used a neurocontroller consisting of a single hidden layer with single neuron, trained online with modified error correction principle. The controller has been simulated in multi machine environment. Here free parameters of NC have been updated not only on basis of difference between previous and current output but it has taken account of previous difference.

A research work practically implemented on 18-machine environment has also been carried out in [51]. To authors' knowledge, this is the only research which has used

Functional Link Network (FLN). A FLN does not have a hidden layer. Instead it uses actual inputs and enhanced inputs. Enhanced inputs are nothing but the trigonometric or polynomial transformation of actual signals. Transformation is done by multiplying every input by cosine, sine and tangent trigonometric functions or by polynomial functions such as below.

$$f(x) = 1.0, \quad f(x) = x, \quad f(x) = 2x^2 - 1, \quad f(x) = 4x^3 - 3x$$

Table 1. ANN architectural model summary [33,44,51,52,55,56]

NC Architecture	*NI Architecture*	*NC Training*	*NI Training*	*Parameters*	*Excitation/ PSS*
MLP 6-8-1 [55]	MLP 6-8-1 SPIM NARMA-3	DBP Online-Training	DBP Online-Training	ΔP $\&\Delta\omega$	PSS
MLP 3-6-1 [33]	MLP 6-10-1 SPIM NARMA-3	SBP Online-Training	SBP Online-Training	$\Delta\omega$	PSS
One-NC MLP 6-10-2 [44]	MLP 12-14-2 SPIM NARMA-3	SBP Online-Training	SBP Online-Training	ΔP_M, ΔV_T & $\Delta\omega$	Excitation and Turbine
Two-NC MLP 6-8-1 [56]	MLP 12-14-2 SPIM NARMA-3	SBP Online-Training	SBP Online-Training	ΔP_M, ΔV_T & $\Delta\omega$	Excitation and Turbine
FLN [51]	FLN SPIM ARMA	DBP Online-Training	DBP Online-Training	$\Delta\omega$, V_T P_E, δ & P_A	PSS
RNN [52]	RNN SPIM ARMA	M-BPTT Offline-Training	M-BPTT Offline-Training	$\Delta\omega$, P & Q	PSS

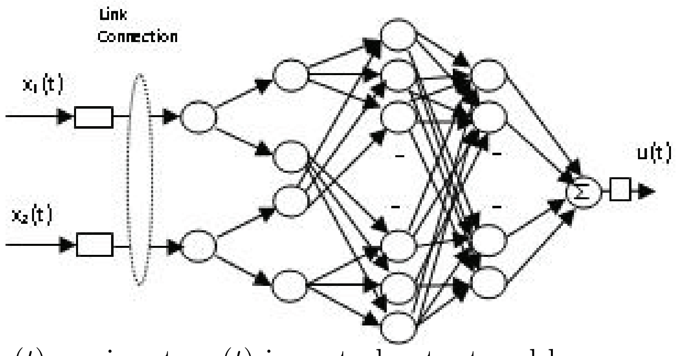
where $\Delta P_M = (P_{REF} - P_M)$, $\Delta V_T = (V_{REF} - V_T)$, $\Delta\omega = (\omega_{REF} - \omega_T)$, SBP stands for Static Backpropagation, DBP represents Dynamic Backpropagation and M-BPTT shows Modified – Backpropagation Through Time.

FLN has been preferred to MLP due to MLP's higher tendency to local optima trappings when trained using backpropagation algorithms. Nevertheless, the convergence of FLN is also not guaranteed as well as its results are very much comparable to conventional PSS. Another work by [52] has tried MRAC using ARMA-1 model and a modified form of Backpropagation Through Time (BPTT) to train recurrent ANN to mimic plant and controller. The modified form of BPTT has been named Recursive Gradient (RG) and has used optimization of an objective function based on the current and previous state vector and control inputs. The results have proved that neuro-PSS trained on proposed algorithm had far better tracking capability than conventional PSS.

7. **Neuro-Fuzzy Systems.** ANN and FL are two different paradigms of intelligent systems. Individually both these paradigms suffer disadvantages [53]. The main concern with ANN training is the requirement of efficient and sufficient data and unavailability of algorithms to optimally select ANN structure. On the other side, the performance of FL controller depends on the operating conditions of systems, although its sensitivity is lesser than a conventional controller. Additionally, FL requires expert knowledge explicitly. This is conceived as merit as well as demerit. To harvest full advantage of ANN capability to fine tune expert information by employing learning techniques and FL's ability to incorporate expert knowledge, these two classes of AI have been combined [57]. In controlling generator excitation and PSS, combination of FL and ANN is applied in different ways. One way to incorporate advantage of both paradigms is to use Adaptive Neurofuzzy Inference System [50,57,58,59]. The other way is the usage of ANN like Multi Layer Perceptron (MLP) in which weights are represented by membership functions, called fuzzy weights, and activation functions are defined with respect to the t-norm and t-conorm [60]. The synergized neural and fuzzy networks called Generalized Neuron (GN) [61,64]. The last method of applying both FL and ANN is to synthesize controller by FL and model identifier using ANN [53,63].

Adaptive Neurofuzzy Inference System (ANFIS) is a more systematic approach relying less on expert knowledge. It can serve as a basis to construct a set of fuzzy If-Then rules with suitable membership functions for generating sets of input-output pairs. It, basically, consists of fuzzy and defuzzy, knowledge base and decision making unit. It can incorporate various types of fuzzy membership functions inference. Unlimited approximation power of ANFIS is claimed yet it is linked with constructing ANFIS properly [64]. The architecture of ANFIS is shown in Figure 4. The ANN topology should be feedforward. Links between nodes do not carry any weights and represent the signal flow direction solely. The first layer represents membership function and fourth layer is for consequent parameters. Output of each node in second layer is firing strength of rule and third layer normalize firing strengths. Function of fifth layer is to sum all inputs and its output is control signal, $u(t)$. ANFIS can be trained on different learning algorithms, but a hybrid learning algorithm based on least square error and gradient descent has been proposed and claimed to be fast. For further detail interested readers are referred to [64].

Reference [50] has used indirect adaptive control system methodology to update the first layer parameters of ANFIS online. The strength of the proposed controller has been depicted on multi machine system. The results have shown that the proposed controller has performed better in terms of overshoot, undershoot as well as damping. The work presented in [57] is based on indirect adaptation of input link weights (Link Connections)



where $x_1(t)$ and $x_2(t)$ are inputs, $u(t)$ is control output and boxes are representing scaling factors.

Figure 4. ANFIS architecture

of ANFIS as shown in Figure 4. The optimal selection or adaptation of many parameters becomes computationally expensive. Since input link weights have major effect on overall performance, hence adaptation of these weights has been proposed. However, results have not shown much difference between conventional and proposed PSS. In addition, fine tuning of controller output may be problematic since connection link weights have affect on all other parameters of ANFIS.

The research work proposed in [58] has used evolutionary algorithm and ANFIS. The control algorithm is based on self-tuning and offline-trained. PSS has been tuned at five different operating points on two different objective functions using genetic algorithm. One objective function has minimized Integral Time Absolute Index (ITAE) having speed deviation as variable (GA-ITAE-PSS). The other objective function has included more system dynamics and is carried out using pole placement based on Eigen Values (GA-Eigen-value-PSS). Data have been generated by operating conventional PSS at five different loads on generator to train ANFIS. The objective of ANFIS has been generation of PSS parameters after sensing the generator operating load. From the results it can be concluded that by integrating system dynamics information into objective functions optimized by bio-inspired optimization algorithms, the system's performance is enhanced. However, it is essential to bear in mind that performance of GA deteriorates if the fitness function contains correlated parameters. The work proposed in [59] is based on model free estimation. Data have been generated by optimally tuning PSS at three different operating points. ANFIS has been trained on generated data to replace conventional PSS. The data have shown comparable results with conventional PSS. Yet ANFIS-PSS has lesser steady state error at higher loading condition following fault introduction.

A three layer Fuzzy Perceptron (FP) with two inputs, six hidden layer neurons and one output has been demonstrated in [60]. The inputs are magnitude and angle of speed deviation signal. In FP weights in between input and hidden layers are the If-part of Gaussian membership function, whereas hidden to output layer weights are represented by Then-part of the membership function. Thus weights have been initialized and further tuning of weights has been carried out using GA. The given results have illustrated the critically damped performance of proposed controller at lighter load when the system subjected to mechanical disturbance. Still post short circuit performance is comparable to conventional controller. Indirect adaptive control based scheme to adapt three variable of fuzzy based controller with ANN identifier has been used and called Neurofuzzy system [53]. The reason behind using FL as controller is to incorporate human knowledge whereas ANN identifier does not need. Fuzzy controller process information of the system dynamics based on angle and magnitude of angular speed (ω) whereas identifier is GN-based NARMA-3 Model. The testing of proposed system has been carried out on computer simulation and physical laboratory system. The results have portrayed that proposed controller has lesser overshoot.

GN is nothing but a summation of the fuzzified sigmoidal and gaussian aggregation functions. Research work simulated as well as implemented on single machine to infinite bus and multi machine environment has been proposed in [61,62]. GN-based controller generates control signal without any input from model-identifier and the results are compared with MLP. The results have shown that GN-based controller had better damping performance than MLP. It has been claimed that GN required lesser number of neurons, training data and training time compared with MLP consisted of 7-7-1 neurons while GN contained only one neuron with only one layer. On the other hand, training of MLP has terminated on epoch basis to achieve generalization of training data patterns when it is well known that epoch termination, most of the time, has resulted in poor generalization.

Table 2. Neuro-Fuzzy controller architecture summary [50,57,58,59]

NI	*NI_Training*	*ANFIS*	*Fuzzylogic Membership Functions*	*Parameters*	*Excitation PSS*
MLP ARMA-3 SPIM [50]	RLS Online Training	Sugeno-Type G-Descent 49 Rules	Gaussian	Deviation Signals $[P\&\omega]$	PSS
MLP NARMA-3 SPIM [57]	BP Online Training	Sugeno-Type G-Descent 49 Rules	Triangular	Deviation Signals $[\omega\&\alpha]$	PSS
[58]	– –	Sugeno-Type H-Learning	Gaussian	Deviation Signals $[\omega]$	PSS
MLP 6-13-1 [59]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	HDP	$\Delta\omega, \Delta V_T\&$ ΔP_M	Excitation & Turbine

where $\Delta P_M = (P_{REF} - P_M)$, $\Delta V_T = (V_{REF} - V_T)$, $\Delta\omega = (\omega_{REF} - \omega_T)$, RLS stands for Recursive Least Square, BP Backpropagation, H-Learning represents Hybrid Learning and G-Descent shows Gradient Descent.

Early stopping criterion should be carefully considered as it plays very important role to guarantee generalization of ANN.

The fuzzy inference system suffers problem in the case when adding or removing any variable where the whole rule-base need to be changed. Whereas in hierarchical-fuzzy systems the case is totally different and also the number of rules do not increase exponentially with addition of any new variable [63]. The aforementioned reference has designed a hierarchical-fuzzy-based controller and operating condition of the system has been decided by a three layer MLP trained with a backpropagation algorithm. The performance of proposed controller has been analyzed using computer simulation and the results have shown that the controller has good oscillations suppression capability.

8. **Adaptive Critic Design.** Optimal control deals with the problem of finding a control law for a system such that a certain optimality criterion is reached. The control problem includes an objective function J(.), which includes the system's state and control variables. An optimal control is a set of differential equations describing the path of the control variables those minimize the objective function J(.), cost-to-go function. The optimal control can be derived using dynamic programming. Dynamic programming is an exhaustive mathematical approach to handle optimistic and stochastic search to find optimal control trajectories. This backward search is based on rejecting all sub-optimal paths and retaining even slightly potential paths until reaching the finish point. The Hamilton-Jacobi-Bellman (HJB) equation, a partial differential equation, is a result of the dynamic programming theory. This has been pioneered by Richard Bellman and coworkers. ANN is not the only method to solve HJB equation for optimality [65,66].

In neural adaptive control, online adaptation of ANN free parameters is carried out. The continuous online training during operation is very risky in highly nonlinear and dynamical systems like power systems. The continuous online training with brute force like gradient descent algorithm can lead to instability under transient condition and make even linear systems unstable [65,66]. Additionally, the adaptive control law is implemented on basis of Model Reference Adaptive Control (MRAC). Due to the ignorance of connection between current system state and controller parameters by MRAC may lead to oscillatory response of system [52]. Generally, the time response of close loop control system has major impact on overall control performance [62], hence it is questionable that ANN consisting of many free parameters will converge fast enough to achieve better performance. Besides, requirement of high computational time for online adaptation can limit the maximum bandwidth in relatively short time close loop control systems [66]. These problems lead to find an optimal control trajectory based on Adaptive Critic Design.

Adaptive Critic Design (ACD) is suitable to learn in noisy, nonlinear and dynamic environment, and does not require continuous online training after commissioning of plant. HJB gives the solution to find optimal control in offline satisfying a partial differential equation. ACD techniques provide an effective method to construct an optimal and robust feedback controller by exploiting backpropagation for calculating all derivatives of target quantity in order to optimize the heuristic cost-to-go approximation [65]. ACD consists of three ANNs; one is Model or Identifier to estimate plant output one step ahead, second network is named Action or Actor network to minimize J(.) in immediate future thereby optimizing the overall cost-to-go and third is known as Critic to adapt free parameters of Model and Action networks. Alternatively, action network represents the mapping between the state and control variables whereas critic represents the mapping between state and costate variables. Critic learns the desired performance index for a function associated with an objective function. ACDs can work independent of Model Network, yet in field of this paper, no researcher has used Model free ACDs.

There are three types of ACDs; Heuristic Dynamic Programming (HDP) which optimizes J(.), Dynamic Heuristic Programming (DHP) that optimizes derivative of J(.) and Global Dual Heuristic Programming (GDHP) which optimizes J (.) in addition to derivative of J(.). GDHP is very complex to implement as it requires optimization of actual and derivative of J (.) and is supposed to give better results [67], but it is not exploited in this area of research. Whereas HDP and DHP both are employed and a comparison has been carried out in [67]. The results have demonstrated critically damped tracking capability of HDP whereas DHP had better rise time with slight overshoot. Nevertheless, both have same settling time. Working has also been compared by introducing fault in the system and from seeing outcomes it is clear that results with DHP are slightly better than HDP. Architectural details of ACDs are given in Table 3. Another interesting comparison between HDP implemented on RBF and HDP implemented on MLP has been researched in [65]. The results has exhibited that MLP-HDP has superior efficiency compared to conventional controller and has inferior to RBF-HDP in terms of tracking and damping both. The ANN architecture details are given in Table 3. DHP-based ACD has been implemented to replace conventional automatic voltage regulator and governor of turbine in multi-machine environment practically [66].

An interesting work has been researched in [68] by simulating the effect of indirect adaptive neurocontrol and HDP-based ACD neuro-control of PSS. The results have reported that performance of both control algorithms based on indirect adaptive neurocontrol and HDP are better than conventional PSS whereas behavior of HDP is minutely better in comparison to indirect adaptive neurocontrol. Another research work [69] has shown that performance of DHP-based excitation system optimal neurocontroller is even superior to synchronous generator equipped with conventional excitation mounting conventional PSS.

TABLE 3. ACD architectural models of reference [65-72]

Critic Architecture	*Action Architecture*	*Model Architecture*	*DHP/HDP*	*Parameters*	*PSS/WAC Excitation*
MLP 6-13-1 [65]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	HDP	$\Delta\omega, \Delta V_T$ $\&\Delta P_M$	Excitation & Turbine
RBF 6-9 -1 [65]	RBF 9-6-2	RBF 12-12-2 SPIM NARMAX-3	HDP	$\Delta\omega$, ΔV_T $\&\Delta P_M$	Excitation & Turbine
MLP 6-10-2 [66]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	DHP	$\Delta\omega, \Delta V_T$ $\&\Delta P_M$	Excitation & Turbine
MLP 6-13-1 [67]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	HDP	$\Delta\omega, \Delta V_T$ $\&\Delta P_M$	Excitation & Turbine
MLP 6-10-2 [67]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	DHP	$\Delta\omega, \Delta V_T$ $\&\Delta P_M$	Excitation & Turbine
MLP 3-6-1 [68]	MLP 9-10-2	MLP 6-10-1 SPIM NARMAX-3	HDP	$\Delta\omega$	PSS
RBF 6-6-1 [69]	RBF 6-6-2	RBF 12-12-2 SPIM NARMAX-3	DHP	$\Delta\omega, \Delta V_T$ $\&\Delta P_M$	Excitation & Turbine
MLP 4-6-6-1 [70]	– –	– –	DHP-SNAC	$\Delta\omega$	PSS
MLP 7-10-1 [71]	FLN 52-4	RBF	HDP	$\Delta\omega$	WAC
MLP 6-10-2 [72]	MLP 9-12-2	MLP 13-15-2 SPIM NARMAX-3	HDP	$\Delta\omega$	WAC

A research work proposed in reference [70] consists of simplified DHP-based critic neurocontrol and is named Single Network Adaptive Critic (SNAC). The difference between dual network adaptive critic (DNAC) and SNAC is elimination of action network. In latter type critic maps between state variable and, one step ahead, costate variable thus eliminating need of action network for generating control signal. It is claimed that SNAC retains all powerful properties of DHP with less complex training. The effectiveness of SNAC has been analyzed on slip-speed basis and results have illustrated that conventional lead-lag as well as linear-quadratic based PSS have been outperformed as operating point moved from linearized position.

9. **Wide Area Control.** Stability and security is very critical during this period of restructuring. Customarily, optimization of distributed control agents like PSS, excitation systems, FACTS and etc installed at specific points in power system is based on local constraints. However, a matter of contention is the interaction between these controlled devices installed close together that leads to adverse effects causing inappropriate control efforts by different controllers and may result instability [42,71]. This problem arises because each controller attempts to be good local controller and has no information of the system's control objective [71]. The insufficient coordination among local agents of different areas may develop oscillatory response such as inter-area oscillations [42]. There are three types of oscillations Inter-unit, Local-mode and Inter-area oscillations [25] and description is given below.

Inter-unit oscillations typically involve two or more synchronous machines swinging with frequency of 1.5-3.0 Hz against each other at a power plant or nearby pants.

Local-mode oscillations mostly engage one or more synchronous machines at a power station oscillating with frequency 0.7-2.0 Hz against a comparatively large power system or load center. This becomes troublesome particularly when areas are connected with high reactance transmission system.

Frequency of Inter-area oscillations is around 0.5 Hz and conventionally entail many machines of a power plant fluctuate against another part of the system.

These limits have raised the need for wide area control (WAC). The immensely important objective of WAC is reduction of undesirable interaction between local agents. Therefore, aim is to respond system disturbances with the least amount of control strives. Nevertheless, the striking contention with WAC is communication efficiency, communication lag or delay and strong probability of missing information of sensors being remotely located. The usual delay attached with communication links and sensor measurements is around 50ms to 1s [41]. [41,71] have proposed robust WAC to static and dynamic communication lag. Dynamic communication lag is the delayed data with few missing sensors information.

Four generator of similar rating within two-area eleven-bus power system model have been considered in the following researches. One generator in each area is equipped with PSS but all four generators are equipped with similar rating excitation system. WAC provided auxiliary signals to generators mounted with PSS. Research work [71] is a typical example of using multiple ANN topologies in one system and has considered infinite-bus instead of a generator in area-2. ACD-based controller is used to provide nonlinear optimal control at different operating points of the system. The MLP with hyperbolic tangent neurons has been chosen to model critic network and polynomial-based Functional Link Network (FLN) for the action network. In addition, RBF is used for model predictor and has taken inputs from missing sensor restoration block (MSR). MSR has extracted and compensated missing information out of available data and is nothing but an Auto-encoder network. Auto-encoder is not more than an MLP with hidden neurons lesser than inputs and have strong capability to reconstruct input set from reduced data set [73]. The results have suggested not much difference between local agent control and WAC outcome. Success of this research lies in mapping missing data and compensating maximum communication delay of even more than 1.0 sec.

Reference [41] employs continuous online training of single simultaneous recurrent network (SRN). The SRN has feedback without any delay and it is the difference between

TABLE 4. Transient energy (T.E.) differences

$Generator$	$Uncompensated$ $T.E.(MJ)$	PSS	$PSS\&WAC$ 0.5s delay	$PSS\&WAC$ 1s delay	$PSS\&WAC$ 1.5s delay
$G1$	51.47	26.86	19.77	19.44	22.00
$G2$	64.85	30.33	26.20	22.51	24.89

SRN and conventional recurrent network. From the results it is clear that WAC performance without addition of PSS signal has not much better response. Nonetheless, performance of WAC in combination with PSS is superior then local agents. The transient stability is greatly dependent upon the stored transient energy during fault. This research work has calculated the difference between transient energies obtained in each case and it has depicted pretty better picture of WAC success, shown in Table 4. Another reference [72] has implemented HDP-based ACD neurocontrol for WAC and again results have demonstrated that WAC along with local agent (PSS) has given better performance than only either local or uncompensated system. The ANN architectural detail is given in Table 3.

10. **Proposed Techniques.**

10.1. **Ensemble of ANN.** The above discussion shows that efforts have been made by a number of researchers to enhance transient stability of power system and have achieved tremendous improvement either by applying indirect adaptive control or by adaptive critic design based neurocontrol or neuro-fuzzy control. The works can be classified into two classes; either online adaptation of weights or offline optimization of a predefined objective function. It is very vivid from the scenario that no author in purely ANN-based control has utilized well-generalized neurocontroller. A well-generalized neurocontroller learns training patterns appropriately. The advantage of generalization is model free estimation of control signal, does not require continuous online training and keeps the control loop simpler. This is the well established fact that simpler control loop results more reliable and more robust control. Moreover, it is one of many requirements for successful running of power system.

There are two types of generalization, one is local generalization and other is known as non-local generalization. Local generalization can be achieved by any type of training. However, the non-local generalization cannot be achieved by using any training stopping criterion. Alternatively it is difficult to achieve. The extent of generalizing training patterns is highly sensitive to training stopping criteria of ANN. There are various criteria resulting in non-local generalization and have been successfully applied in field of digital signal processing, e.g., use of validation set besides use of training and testing sets to train ANN. Moreover, in ANN literature, it is reported that ensemble learning methodology has generated better generalized ANN and has always outperformed single best ANN [74]. An Ensemble of ANNs can be used to achieve non-local generalization capability.

The authors have carried out preliminary work on application of ensemble-neurocontroller for synchronous generator excitation system performance enhancement. Single machine infinite bus system has been considered to investigate application of well-generalized neurocontroller. The excitation model AC4A has been considered here and is as per IEEE 2005 recommendation [75]. The power system model considered in this work is as shown in Figure 5. The parameters of generator are given in Table 5. X_d' is the subtransient direct axis reactance, X_q' is the subtransient quadtratur axis reactance, T is time constant,

($''$) indicates transient and K is a constant. The conventional controller used to control excitation system was proportional and integrator (PI) controller.

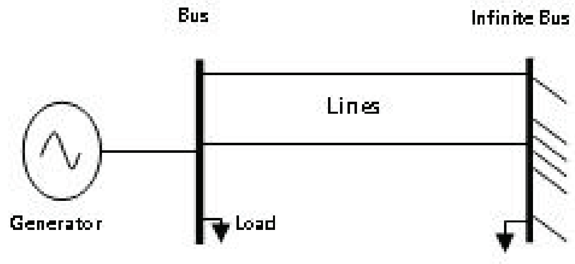


FIGURE 5. Single-generator infinite-bus model

TABLE 5. Synchronous generator parameters

X_d	1.83	X_q	1.7	R_{Stator}	0.003
X'_d	0.24	X'_q	0.43	$Inertia$	3.6
X''_d	0.20	X''_q	0.26	Hz	50
T'_d	0.3s	T''_d	0.04s	T''_q	0.03s

Simulation of the model has been carried out on Matlab/Simulink with 13.8 KV, 300 MW, 50 Hz generator. PI-controller (Conv) has been tuned at load $(0.051 + j0.024)\Omega$. A Multi Layer Perceptron (MLP) is the most commonly used feedforward network and has been used in this research work. The MLP has been trained on terminal voltage deviation from reference voltage, i.e., $ANN\_Input = V_{REF} - V_T$. Data generation for training of MLP has been tried at different sampling rates. The minimum error is obtained at 200 Hz. In this work, generated data have been divided into three sets; training, validation and testing in 4:2:4 ratios. To produce well-generalized MLP, validation criterion has been used to stop MLP training. Training of MLP has been carried out by using well-known learning algorithm, i.e., Levenberg-Marquardt error backpropagation (LM). Four MLPs, having lesser mean-square-error, have been selected to ensemble. Number of MLPs in ensemble has been chosen heuristically. These four MLPs have 7, 9, 10 and 12 hidden-layer neurons. However, least error is achieved at hidden layer size of nine neurons and it is named best MLP. MLPs with different hidden-layer size are selected not only because of lesser error but this also fulfills diversity requirement among neural networks for better performance of ensemble-MLP. The output of ensemble-MLP is average of all MLPs output and thus has increased predicting capability of MLP. The ensemble-neurocontroller replaces PI-AVR part of generator excitation system.

Figures 6 and 7 show the performance comparison of conventional controller (Conv), best-MLP named neurocontroller (NC) and ensemble-MLP called ensemble-neurocontroller (Ensemble-NC). The comparison has been carried out on basis of generator terminal-voltage and generator load-angle attending steady-state value after fault simulation. The performance of NC is superior to Conv but inferior to Ensemble-NC. This justifies theoretical explanation about better performance of ensemble neural network. This proves the fact that higher generalization capability results better performance.

Similar analysis has been carried out at higher load condition to analyze non-linear performance of the controllers. In Figures 8 and 9, non-linear capability of the controllers is depicted. At higher load of $(0.007+j0.004)\Omega$, 90ms fault has been simulated at generator terminals. Both figures vividly show dominance of Ensemble-NC over NC as well as

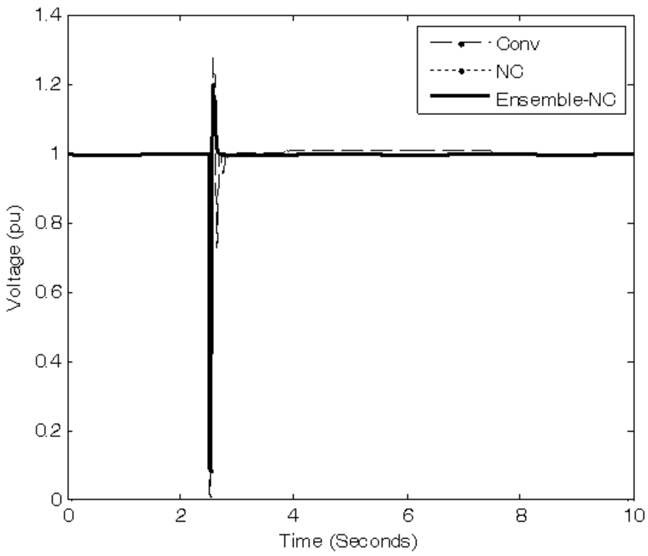


FIGURE 6. Terminal voltage; 60ms fault at $(0.051 + j0.024)\Omega$ load

Conv. The perfomance of Conv has detoriorated more as the system moved away from its controller-tuned position. The figures show that generator, when mounting Conv has become unstable at higher load conditions. Nonetheless, both types of neurocontrollers have kept the system stable still. Performance of Ensemble-NC is even better than NC, it has attended steady-state value earlier to NC.

As this work is preliminary, selecting the number of ANNs and also selection of every ANN has been done heuristically. There are systematic approaches available to select the number of ANN in constructing an ensemble and which ANN is to be included in ensemble-ANNs. Additionally, diversity among ANNs in an ensemble plays an important role in increasing efficiency. There are different approaches available to produce diverse neural networks. Random-weights-initialization is most inferior among all and has been used in this research. Training of ANNs using different algorithms, changing architecture of ANNs, training of individual networks on different data sets and use of bio-inspired optimization algorithms are other commonly used methods to produce diverse ANNs to ensemble. Hence, authors are optimistic about even better results of their future work.

10.2. **ANN initialization.** The convergence time taken by ANN greatly relies on the initial weights and biases of ANN. If weight initialization does not support the global optimum point on the error surface then the ANN will take longer time to converge and even it is hard to deny that ANN would diverge. The literature review suggested that every researcher has used small-random weight initialization. On the other hand, ANN literature suggested different systematic algorithms to initialize ANN with guaranteed convergence. Application of these algorithms not only increases the rate of convergence but also eliminates the risk of divergence. [76] has proposed a technique for initialization of weights and has claimed that the technique considerably reduces training burden of neural networks. A systematic weight initialization is particularly suitable for online training to reduce online training burden and to avert divergence during commissioning phase of plant.

10.3. **Bio-inspired optimization algorithms.** The study has revealed that optimization of either PSS parameters or ANN weights or FL membership functions is carried out

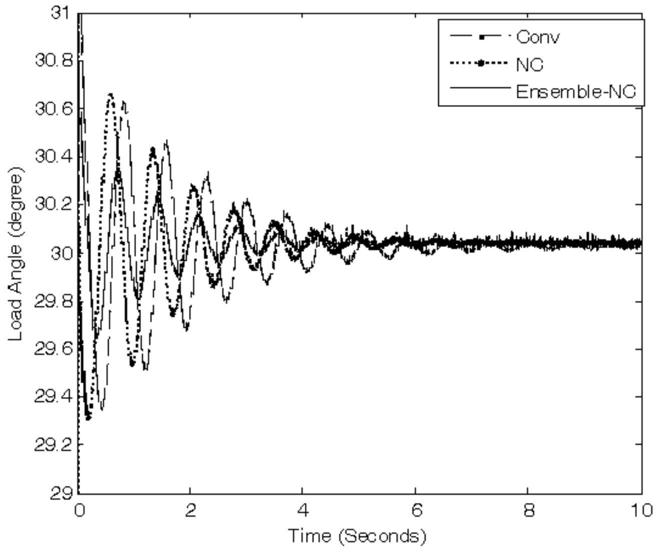


Figure 7. Load angle behavior; 60ms fault at $(0.051 + j0.024)\Omega$ load

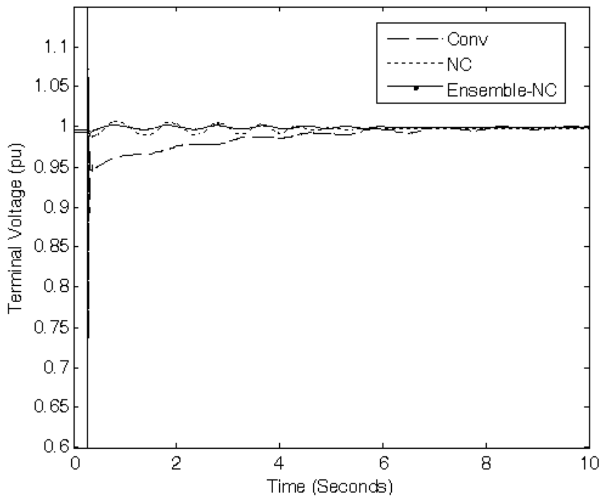


Figure 8. Terminal voltage; 90ms fault at $(0.007 + j0.004)\Omega$ load

using genetic algorithm, in this field of research. However, it is now well-developed that genetic algorithm is an inferior element of evolutionary optimization algorithms. Differential Evolution (DE), an element of evolutionary optimization algorithm class has performed better than GA in a number of optimization problems. Additionally swarm intelligence, a class of optimization algorithm using intelligence of different natural swarms to solve various problems, has outperformed evolution-based optimization algorithms. Therefore, authors are very positive of better performance if swarm optimization algorithms are used instead of genetic algorithm for optimization of the parameters. Authors propose application of Artificial Bee Colony (ABC) [77], a member of swarm intelligence-based optimization algorithm. ABC has proved it dominance over a number of bio-inspired optimization algorithms on various problems and would yield better results in the field. The ABC has lesser control variables to tune for better efficiency as compare to any other optimization algorithms.

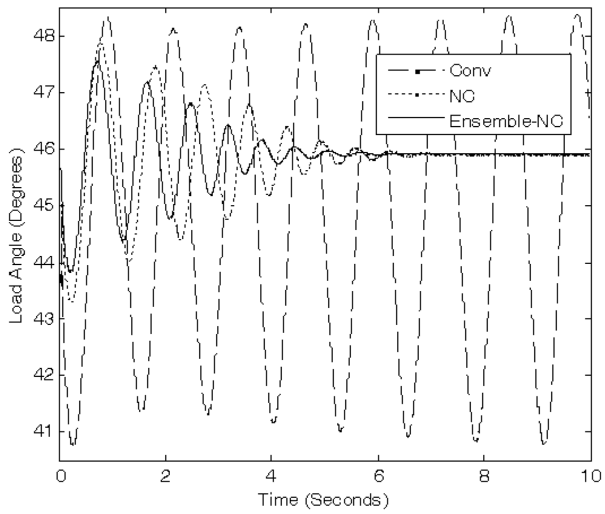


FIGURE 9. Load angle behavior; 90ms fault at $(0.007 + j0.004)\Omega$ load

10.4. **Dynamic ANN.** Another striking fact to be noted is that the discussed field has not yet fully utilized the benefits of dynamic ANN. The field of dynamic ANN is more developed nowadays in comparison to the last few decades. There are training algorithms and simpler topologies for these ANNs, retaining all power-full features of conventional dynamic ANN but require minimal effort to train. The typical example of successful story of dynamical ANN can be found in [42]. The reference has compared dynamic ANN with static ANN and proved that dynamic ANN has capability to perform better than static ANN.

11. **Conclusion.** MLP trained on deviation signal performs better than RBF. However, when training is carried out using actual signals, RBF's performance is better than MLP. The performance of bio-inspired optimization algorithms depends highly upon fitness function knowledge. Incorporation of the system dynamics into the fitness function of bio-inspired optimization algorithms enhances the quality of output. Dynamic heuristic programming ACD has a tendency to produce better results than heuristic dynamic programming ACD. ACD-based neurocontrol performs better than indirect adaptive neurocontrol. The performance of power system is enhanced by using local-agents and wide-area-control simultaneously. Wide-area-control alone does not enhance power system performance. The preliminary results have revealed ensemble-neurocontroller has performed better than conventional controller, reduces computational burden and have simpler control loop.

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