

Received February 8, 2022, accepted March 5, 2022, date of publication April 4, 2022, date of current version April 8, 2022.

## *Digital Object Identifier 10.1109/ACCESS.2022.3164455*

# Fully Adaptive Recurrent Neuro-Fuzzy Control for Power System Stability Enhancement in Multi Machine System

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This work was supported by the Project IntellECoss by the Joint European Union (EU)-Dk Industry 4.0 Program.

**ABSTRACT** Voltage instability in a power system produces low-frequency oscillations (LFOs), causing adverse effects in power distribution. Intelligent control schemes can overcome the limitations of fixed-parameter structures in power system stabilizers (PSS). Flexible alternating current transmission system (FACTS) control along with some supplementary control have remarkable potential in damping the oscillations. This paper proposes an adaptive neurofuzzy based recurrent wavelet control (ANRWC) scheme to enhance the power system stability. The proposed scheme utilizes recurrent Gaussian as antecedent part's membership function and recurrent wavelet function in consequent parts. Our scheme uses gradient descent, adadelta, adaptive moment estimation (ADAM) and proximal gradient descent algorithms for optimization in which parameters of the scheme are updated using a back-propagation algorithm. A multi-machine power system is used for testing the controller. We evaluate the proposed control scheme in comparison to conventional lead-lag control and an adaptive neurofuzzy takagi sugeno kang (ANFTSK) control scheme. For comparison, we calculate the performance indices (PIs) for different controllers. Both quantitative and qualitative evaluations assert the effectiveness of the proposed control as compared to other schemes.

**INDEX TERMS** Power system stability, low-frequency oscillations, neurofuzzy controller, FACTS controllers, adaptive controllers, optimization.

#### **I. INTRODUCTION**

The smart grid (SG) is an advanced technology that comprises a variety of components and offers many operations, utilizing digital communication for detecting and reacting to rapid changes. It also combines advanced metering infrastructure and smart meters for intelligent control. Load management [1]–[3], power system stability and control [4], secure data transmission [5]–[7] and voltage sag control [8] are some of the prime issues in a SG. Power stability is one of the most notorious problems in an SG. When power flows from generation to end-user, it is subject to fluctuations [9]. During the mid 20*th* century, most of the power generation systems were

The associate editor coordinating the review of this manuscript and approving it for publication was Chandan Kumar<sup>1</sup>[.](https://orcid.org/0000-0002-4856-6578)

equipped with automatic voltage regulators (AVRs) with continuous operation. It is well-known that AVRs regulated the voltage efficiently, but had limitations in damping LFOs [10]. In the few decades after its inception, the performance of AVRs degraded which led to the instability of the system causing the sustainment of disturbances or oscillations for a long time.

Figure [1](#page-3-0) illustrates different classes and subcategories of stability. The stability analysis of a multi-machine system is more complex as compared to a single machine system because a stable operation of the power system requires a larger number of interconnected equipment including generators, transformers, and other components. All generating units are required to operate synchronously. A study of small disturbances in the domain of small-signal stability indicates

that these perturbations are below 10% in a system. Large area stability or transient stability involves large disturbances such as short circuits, breakage of tie lines, load disconnection, etc [11], [12]. PSS was one of the earlier solutions to the problem. PSS damps oscillations by modulating the supply to the synchronous machine [13], [14]. Power systems have several interconnections with communication and protection. This complex nature of the power system demands proper monitoring and control to avoid any type of instability or unbalance. The disturbance or fault occurring in a system affects the operation of generators in the power system causing low-frequency oscillations. If these oscillations (LFOs) are not quickly and properly damped, they may cause system failure or even cascading outages. The frequency range for LFOs is determined to be 0.2Hz to 2Hz [15]. Oscillations are subdivided as forced and electromechanical. Forced oscillations may result due to some external periodic force. Local mode, inter-area, and intra-area are all types of electromechanical oscillations [16].

Transient instability is the most important and challenging stability type and has always been a major focus of research [17]. It can be classified as: [18]

- Rotor angle stability
- Frequency stability
- Voltage stability

Rotor angle stability deals with the ability of interconnected machines to remain in synchronism. In a multimachine system, effective control for each generating unit is required for rotor synchronism [19]. Rotor angle stability demands the system to maintain equilibrium between electrical and mechanical torques of synchronous machines. Any sort of mismatch or disturbance in the equilibrium state will lead to angular swings in some generators and may cause loss of synchronism in the system. The equilibrium point between the torques is disturbed when a fault appears in the system. Rotor angle stability is further classified as:

- Small signal stability
- Large signal stability

Power electronics-based FACTS exhibit important attributes to avoid the crises of the power system and improves ac transmission over long distances. Besides these can also act as reliable control devices for power flow. FACTS are used along with power systems in series, shunt, or hybrid connection. The transmission capacity of the power system can be increased up to several GW using FACTS [20]. FACTS controller improves the stability of the system impressively by changing system parameters effectively. First-generation of FACTS included static var compensator (SVC), thyristorcontrolled series capacitor (TCSC), and thyristor-controlled phase shifters (TCPS) [21]. Literature shows the successful implementation of SVC to enhance transient stability of synchronous machines. Pole placement and time-optimal control are developed for TCSC. TCPS uses phase shift angle as a function non-linear to rotor angle and speed in the control architecture. The emergence of the second

generation came with a static-compensator (STATCOM), static-synchronous series compensator (SSSC), and unified power flow controller (UPFC) [22]. STATCOM provides better characteristics in the case of dynamic stability. Integration of SSSC in a power system, with different control methods and designs, is proposed and evaluated. UPFC is a remarkable FACTS device that can simultaneously control bus voltage, phase angle between two buses, and reactance of transmission line [23]. First-generation devices perform as passive elements using tap changer transformers that are controlled by thyristors while second-generation devices perform as angle-controlled voltage sources [24]. SSSC belongs to the second generation FACTS and has better performance as compared to conventional devices due to its storage element. The prime aim of SSSC is to control the current and reactive power directly between SSSC and the system. SSSC employed systems cannot show resonance problems as they do not affect the impedance of the system [25]. Besides being effective, SSSC is also an economical choice to suppress power system oscillations.

FACTS control can better be understood by viewing it from an optimization point of view. As compared to traditional optimization methods, genetic algorithms (GA) are efficient and flexible [26]. In the area of controller parameter optimization, GA grabbed prime attention. Artificial intelligence (AI) has emerged as a powerful tool for identification and estimation of power system parameters. Artificial neural networks (ANNs) showed great success in analyzing and estimating dynamic parameters in case of transient instability [27]. Fuzzy logic is used as a soft computing technique that uses a set of rules to specify the control algorithm. The control mechanism depends upon the comparison of fuzzy logic to a logical neural system. As compared to traditional control techniques, fuzzy logic control (FLC) performs well in a complex system. Implementation of FLC alone is a difficult process, so it is better to process with the help of conventional algorithms [28]. Fuzzy controllers showed great success in non-linear operations. Implementation of fuzzy logic controllers in non-linear power systems is a good solution to deal with complexity. To make full advantage of ANN and FLC, the best option is to use them simultaneously leading to the evolution of the adaptive neurofuzzy inference system (ANFIS) [29]. The architecture of FLC consists of a knowledge base, fuzzification, defuzzification, and decision making. Fuzzy logic deals with uncertainties in a system. Fuzzification is the process of converting crisp input to fuzzy values. Crisp values are 0 and 1 only, fuzzification allows more values between these two extremes. These values show a degree of membership, showing how much a specific fuzzy value relates to the given set. The membership function is used to define a fuzzy set [30].

Different intelligent methods such as evolutionary programming, GA, particle swarm optimization, sine cosine algorithm, exist for optimization of task in power systems [31]–[33], and applied for single machine infinite bus and multi-machine design parameters. Problems arising in PSS design are well met using these techniques; however, in the case of optimization of a complex and high dimensional objective function, there is a need for some more efficient approach. Besides, the complexity of the system makes it difficult to reach optimal control parameters using these techniques [34]. As an extension to our previous work on stability issues of the single-machine power system [35], we proposed a recurrent-based wavelet adaptive neurofuzzy control for SSSC to damp oscillations. This research particularly highlights the stability issues of the multi-machine power system and proposes an optimal solution for stability enhancement. In this paper, an AI controller along with a neurofuzzy controller is tested on a multi-machine test system and the FACTS controller is used as a supplementary control. A multi-machine test system is considered to verify the effective control and enhance the transient stability of the system.

The major contributions of this paper are:

- The scheme uses an adaptive neurofuzzy controller with wavelet function for enhancing the stability of a multi-machine power system.
- The architecture of the suggested controller applies recurrency in the antecedent as well as consequent parts.
- The experiments check the efficiency of the proposed controller comparison with traditional LLC and ANFTSK.

The rest of the paper is organized as follows: next section provides a comprehensive overview of related work. Sections III and IV elaborate the proposed model and problem formulation respectively. Section V specifies the experimental setup and system specification. Finally, section VI concludes the paper.

## **II. RELATED WORKS**

In the case of any disturbance in the power system due to some faults, LFOs occur when there is insufficient damping torque. These oscillations resist the power transfer and adversely affect the stability. A simple, economic and cost-effective scheme was the use of PSS. PSS dealt well with oscillation damping [36], [37], but due to fixed-parameter structure, it found limitations in the case of dynamic systems. PSS has low flexibility as it cannot perform well under changing states of system [38]. PSS with GA is also studied in [39]. Advancements in the field of power electronics lead to FACTS controllers which not only damp oscillations but also provide voltage regulation, reactive power compensation, and power flow control [40]. Supplementary control for devices is designed so their primary objected is not disturbed.

In [41], authors investigate the performance of FACTS controllers such as SVC and TCSC in a multi-machine electrical power system to enhance power system stability. The main objective was to develop the mathematical model of a multi-machine electrical system incorporating series and shunt controllers in an individual and coordinated fashion. Methodology and techniques of the proposed model were tested on a 3-machine and 9-bus system. In [42] a switching electrical power system stabilizer is proposed to improve the power system stability by having multi machines. The switching stabilizer switches between a conventional stabilizer and a bang-bang stabilizer using a switching methodology. Bang bang stabilizer effectively damps the oscillation of rotor speed, while conventional stabilizer manages the stability of the closed-loop system. Experimental studies were performed on 4-machines 11-bus systems and the IEEE 16-machines 68-bus systems. Novel frameworks enable the coordination between synchronous generators and doubly-fed induction generators [43]. The proposed coordinated methodology was implemented on a multi-machine 39-bus system and based on a zero dynamics approach with the aim to improve transient stability. The simulation results of the proposed methodology were compared to various conventional approaches and showed significant improvements in improving the transient stability of the system.

Ahmed *et al.* performed the transient stability analysis of multi-machine systems by taking into account real weather data [44]. The author incorporated the weather impacts on stability analysis of distribution and transmission networks by adding time-domain faults simulation. Results showed that different weather conditions influence the rotor angles and faults removing time. A fuzzy and particle swarm optimization-based power system stabilizers are proposed in [45]. The major objective was to boost the stability of power system operations. Experiments were performed by employing various fault tests at power lines on a multi-machine grid system. Another study on power system stabilizers and static var compensators is proposed to improve the transient and dynamic stability of power systems [46]. The authors have designed the controller for SVC devices on power lines and modeled it with 4 machines infinite bus system. In [47] authors have proposed a sliding mode controller for a STATCOM, and examine its indications on the improvement of power stability. To overcome the limitations of the sliding mode controller, the authors also proposed a super twisting sliding mode controller. The effectiveness of the designed controller is examined in comparison with the nonlinear and traditional controllers. A 14-bus and multi-machine system were taken into account for experimental purposes.

In [48], the authors used the generator's excitation and proposed the controller based on an observer to enhance the power systems stability. The main objective was to achieve the highest damping and improve transient stability while maintaining the excellent performance of voltage regulation. The proposed controller needed sensing currents techniques and the speed of the rotor. The authors also performed comparisons of multi-machine power systems with conventional PSS and proved the viability of the proposed approach. Ramesh *et al.* proposed four variants of grey wolf optimization for tuning the parameters of PSS under the multi-machine power system scenario [49]. The authors performed three statistical tests such as Quade, Feidman, and Anova tests. Further, the authors presented a comprehensive



<span id="page-3-0"></span>**FIGURE 1.** Classifications of stability.

comparative study under the self-removing errors to demonstrate the appropriateness of the proposed methods. A unique approach called distributed power flow controller is proposed to the 2 regions of an electric system for improving the stability of a system [50]. The authors also suggested a fault current limiter along with a distributed power flow controller for mitigating the faulty currents and power quality issues. Dubey and Singh *et al.* presented the mathematical models of a UPFC along with a power system by employing linear quadratic regulator methods for improving system stability [51]. The author discussed the implication of the control procedure of the multi-machine system with and without the proposed controller at various operating conditions. In order to improve the power system stability, a hybrid combination of a TCSC and PSS is proposed in [52].

Numerous modern techniques for better optimization have emerged in the last few decades [53]–[55]. GA and particle swarm optimization are used to optimize the parameters of proposed controllers. The experimental results revealed that the mixture of the proposed algorithm guides to a more reliable design and system stabilities. The authors proposed an innovative control strategy that employs a STATCOM to damp the oscillations having low-frequencies and voltage fluctuations of a multi-machine electrical system [56]. The proposed strategy included two controllers to regulate the gate signal of the static compensator. Also, gain parameters were tuned by using an ant colony optimization. A three-phase, six-cycle symmetrical faults such as LLL-G faults are used for the experimental setup. Authors in [57] developed and tested various mathematical models that illustrate the dynamics of an electrical system having multi-machines. The investigation involved fault scenarios on the IEEE 39-bus system connected with 10-generators. The experimental results revealed that during the contingency study, the generators underwent fluctuations in the power input and notable power deviations that are closer to the fault area.

In [58] authors have used a synchronous motor-generator combination for the improvement of system stabilities with a combination of renewable energy sources. A study focusing on the power distributed controllers has been addressed to improve transient stabilities of multi-machine systems in [59]. Sub-synchronous resonance has been used to improve the stability of the systems with larger PV units [60]. In [61], larger PV units are controlled for the mitigation of LFOs in the power system.

Our proposed scheme uses an adaptive neurofuzzy wavelet control for SSSC. Wavelets are employed in the combination of neurofuzzy. The system uses traditional TSK with recurrent morlet wavelets in the consequent part and the recurrent membership function used in the antecedent part is Gaussian. The effectiveness of the proposed controller is checked with the neurofuzzy TSK controller and conventional LLC. Damping is tested under different faults for the multi-machine system. In a multi-machine system, the proposed controller exhibits superior performance by achieving a stable state earlier as compared to other controllers.

#### **III. PROPOSED MODEL**

The closed-loop structure of the suggested scheme is shown in Figure [2.](#page-4-0) It shows all the three controllers to be used in this research work. The test system to be used for experimentation is a multi-machine plant. The input signal to the plant is represented by *u* which may be *u*1, *u*2, or *u*3 depending upon the type of controller to be used. *u*1 is the output for LLC, *u*2 shows the output signal in the case of ANFTSK and *u*3 represents the output of ANFRWC. Update parameters of neurofuzzy controllers are adjusted by using an adaptation mechanism and used gradient descent, adadelta, adaptive moment estimation (Adam) and proximal gradient descent (PGD) as an optimization method to minimize the error [62], [63]. The premise part contains recurrent membership functions while in the latter half of the system, recurrency is introduced in the wavelet functions.

Using wavelet function in a neurofuzzy controller improves the flexibility of the overall system. Also, a small number of tunning parameters explains the nature of dynamic systems in more detail. This is a seven-layer network with input nodes in the first layer. Input layers have to pass the values of the input signal to the next layer directly. Layer 2 has membership functions, the second layer stores the information in the nodes. Gaussian is used as a membership function in this layer. The membership function is expressed as:

$$
G = Exp\left[-\frac{(x_i - \alpha_{ij})^2}{2\sigma_{ij}^2}\right]
$$
 (1)

Here,  $\sigma_{ij}$  expresses variance, and  $\alpha_{ij}$  represents the mean of the membership function. Subscript *ij* denotes the association



<span id="page-4-0"></span>**FIGURE 2.** Closed loop architecture.

of  $j<sup>th</sup>$  term with  $i<sup>th</sup>$  input variable. Due to the application of recurrency in the membership function, nodes in this specific layer behave as memory units.  $G(K - 1)$   $\zeta_{ij}$  is the memory term that stores the previous state of the system. ζ*ij* is link weight for feedback component and related with Gaussian as:

<span id="page-4-1"></span>
$$
G = Exp\left(-\frac{(x_i + G(k-1)\zeta_{ij} - \alpha_{ij})^2}{2\sigma_{ij}^2}\right) \tag{2}
$$

 $\alpha_{ij}$ ,  $\sigma_{ij}$ , and  $\zeta_{ij}$  are three update parameters for layer 2. The firing strength of the rule base system is determined in the third layer, which shows output correspondence to the input. The consequent part of the architecture starts after layer 3. Layer 4 consists of *n* number of wavelet functions. There are four flexible parameters in layer 4 including translation and dilation parameters of Morlet wavelet denoted by *l<sup>j</sup>* and  $m_{ij}$ .  $w_j$  is the third parameter that is the flexible weight of the consequent part and feedback weight being the fourth update parameter is denoted by *fij*. Morlet is used as a wavelet function. A Gaussian function when multiplied with a sine wave, forms a morlet wavelet. The application of artificial convergence in the computation can be avoided by using morlet wavelets.

Morlet wavelet can be expressed as:

<span id="page-4-2"></span>
$$
\psi_z(x_i) = \cos(5Z_j)e^{\frac{-1}{2}}Z_j^2
$$
\n(3)

After the application of feedback weight:

$$
Z_j = \left[ \frac{x_i + w_i o_i - tr_j}{d_j} \right]
$$
 (4)

 $x_i$  shows the input of the wavelet function and it has two parameters to be updated. A wavelet function has dilation and translation parameters represented here as *d<sup>j</sup>* and *tr<sup>j</sup>* respectively. Dilation is the contraction and translation is the localization parameter. The output of layer 4 is expressed as  $o_j$ . Recurrency in this layer is employed in wavelet functions with feedback weight expressed as *w<sup>j</sup>* .

<span id="page-4-3"></span>
$$
O_j = W_j \sum_{j=1}^n \psi_z(x) \tag{5}
$$

Defuzzification is done in the fifth and sixth layers of the architecture consequently. The final output of the system is

calculated in layer seven. The overall output of architecture is expressed as:

<span id="page-4-4"></span>
$$
U = \frac{\sum_{j=1}^{n} \eta_j(x) o_j}{\sum_{j=1}^{n} \eta_j(x)}
$$
(6)

#### **IV. PROBLEM FORMULATION**

The cost function that is required to be reduced is expressed as;

$$
E = 0.5e^2 + 0.5hu^2 \tag{7}
$$

$$
e = y_{ref} - y \tag{8}
$$

The desired output is denoted as *yref* and y is the actual output of the system.

$$
E = 0.5(y_{ref} - y)^2 + 0.5hu^2
$$
 (9)

*u* expresses the output of ANFRWC and *h* is the weight factor for adjustment of controller's output. Backpropagation is used for updating the parameters of the proposed ANFRWC and used various optimization, such as gradient descent, adadelta, adaptive moment estimation (Adam) and proximal gradient descent optimization. Adadelta is an extension version of gradient descent optimization, to speed up the optimization process by minimizing the number of function evaluations needed to get to the optima and to enhance the optimization capability. Adadelta update rule is provided below,

$$
F[g^{2}]_{t} = \gamma F[g^{2}]_{t-1} + (1 - \gamma)g^{2}]_{t}
$$
 (10)

where  $\gamma$  is a decaying constant and set as 0.9.  $g_t$  is the gradients at time step *t* and can be computed as, i.e.,

$$
g_t = \frac{1}{q} \sum_{i=1}^{q} \nabla_{\theta} \xi(a^{(i)}, b^{(i)}, \theta_t)
$$
 (11)

Adam computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients. Instead of adapting the parameter learning rates based on the average first moment, Adam also makes use of the average of the second moments of the gradients.

$$
V_t = \beta_1 * V_{t-1} - (1 - \beta_1) * g_t \tag{12}
$$

$$
S_t = \beta_2 * S_{t-1} - (1 - \beta_2) * g_t^2 \tag{13}
$$

$$
\Delta D_t = -\tau \frac{V_t}{\sqrt{S_t + \epsilon}} * g_t \tag{14}
$$

$$
D_{t+1} = D_t + \Delta D_t \tag{15}
$$

Here  $\tau$  is the initial learning rate,  $g_t$  represents as gradient at time *t*, exponential average of gradients and exponential average of square of gradients are denoted as *V<sup>t</sup>* and *S<sup>t</sup>* respectively. Hyper-parameters are  $\beta_1$  and  $\beta_2$ . The hyperparameters,  $\beta_1$  and  $\beta_2$ , are kept around 0.9 and 0.99 respectively. Epsilon is set as  $e^{-10}$ .

PGD is category of such algorithms that fit statistical models into data form. This fitting demands some kind of optimization. PGD makes use of two mathematical tool like sub-gradients and proximal operators. Sub-gradients are a generalization of the concept of the gradient and can apply on non-differentiable functions. The proximal operator takes a value  $h$  in a space and returns another value  $h'$ .

$$
prox_{\varphi}(b) = arg \min_{h \in H} \varphi(h) + \frac{1}{2} ||b - h||_2^2
$$
 (16)

A common rule for updating the parameters for gradient decent is given as,

$$
\delta(t+1) = \delta(t) - \alpha \frac{\partial E}{\partial \delta} \tag{17}
$$

$$
\frac{\partial E}{\partial \delta} = \frac{\partial E}{\partial y} \frac{\partial y}{\partial u_3} \frac{\partial u_3}{\partial \delta} + \frac{\partial E}{\partial u_3} \frac{\partial u_3}{\partial \delta} \tag{18}
$$

All the updated parameters are combined in a row vector  $\delta = [\alpha_{ij} \,\sigma_{ij} \,\zeta_{ij} \,W_j \,d_{ij} \,t_{ij} \,w_{ij}].\,\alpha_{ij}, \sigma_{ij}, \zeta_{ij}$  and  $W_j$  are the update parameters for antecedent part while parameters to be updates for consequent part are expressed as *dij*, *tij* and *wij*.

$$
\frac{\partial E}{\partial \delta} = -(y_{ref} - y) \frac{\partial y}{\partial u_3} \frac{\partial u_3}{\partial \delta} + hu_3 \frac{\partial u_3}{\partial \delta} \tag{19}
$$

where,  $e = y_{ref} - y$ 

$$
\frac{\partial E}{\partial \delta} = (-e \frac{\partial y}{\partial u_3} + hu_3) \frac{\partial u_3}{\partial \delta}
$$
 (20)

Considering plant sensitivity factor,  $\frac{\partial y}{\partial u_3} = 1$  [64].

$$
\frac{\partial E}{\partial \delta} = (-e + hu_3) \frac{\partial u_3}{\partial \delta} \tag{21}
$$

Controller's output is exhibited as:

$$
U = \frac{\sum_{j=1}^{n} \eta_j(x) o_j}{\sum_{j=1}^{n} \eta_j(x)}
$$
(22)

$$
\frac{\partial u_3}{\partial \delta} = \frac{\eta_j}{\sum_{j=1}^n \eta_j} (y_j - u_3)
$$
 (23)

## **V. SYSTEM SPECIFICATIONS AND EXPERIMENTAL SETUP**

This section explains different fault scenarios for the test power system. Various parameters of multi-machine are used for simulation in order to check the efficiency of the proposed controller. The multi-machine system is a 3 area, 3 machine system with 9 buses. Each area consists of *G*1, *G*2, and *G*3 generating units, respectively. *G*1 has a power rating of 247.5*MVA*, *G*2 and *G*3 have 192*MVA*, and 128*MVA*



**FIGURE 3.** Three machine nine bus test power system installed with SSSC.

<span id="page-5-0"></span>

**FIGURE 4.** Adaptive neurofuzzy recurrent wavelet.

respectively. Each area is distinguished from others through a transmission line distance of 100*km*. An SSSC of 100*MVA*, 50000*V*, and 60*Hzfrequency* are connected in series with the transmission lines. Three types of loads of 90*MW*, 100*MW*,



<span id="page-6-1"></span>**FIGURE 5.** Multi-machine (Case II).

and 125*MW* are tied at buses 6, 8, and 5 respectively. A single line diagram of the power system is depicted in Figure [3.](#page-5-0) The input signal to the controller is the difference of rotor speed deviation while controller output provides a reference voltage signal for SSSC internal control. Proposed controller works in following steps. First, it initializes the parameters of controllers in the antecedent and consequent part such as  $\alpha_{ij}$ ,  $\sigma_{ij}$ ,  $\zeta_{ij}$ ,  $W_j$   $d_{ij}$ ,  $t_{ij}$ , and  $w_{ij}$ . Then, Update parameters of controllers by using adaptation mechanism. Then uses Gaussian membership to store the information using equation [2.](#page-4-1) Next, it determine the firing strength and compute the wavelet function by using Morlet wavelet using equation [3,](#page-4-2) and uses recurrency in wavelet functions to calculate the output using equation [5.](#page-4-3) Lastly, uses equation. [6](#page-4-4) for defuzzification.

Turbine and governor data for three machines are expressed in Tables [1](#page-6-0) and [2.](#page-7-0)

**TABLE 1.** Turbine and governor data for machine 1.

<span id="page-6-0"></span>

Parameters	Hydro		
$K_a$	10/3		
$T_a(s)$	0.07		
$G_{min}(p.u.)$	0.01		
$G_{max}(p.u.)$	0.97518		
$V_{gmin}(p.u./s)$	$-0.1$		
$V_{gmax}(p.u./s)$	0.1		
$R_p, K_p, K_i$	0.05, 1.163, 0.105		
$K_d, T_d(s)$	0.0.01		
$\beta.T_w(s)$	0, 2.67		

#### A. PERFORMANCE PARAMETERS

Different controllers that are used in this research for oscillation damping are also compared quantitatively using PIs. An index with minimum values depicts the best control performance. PI is integral to the product of time and error. Rotor speed deviation is used as an error signal. The number of



<span id="page-7-1"></span>**FIGURE 6.** Multi-machine (Case I).

**TABLE 2.** Turbine and governor data for machine 2,3.

<span id="page-7-0"></span>

Parameters	Steam 2	Steam 3
$R_p$	0.05	0.05
$K_p$		
$G_{min}(p.u.)$		
$G_{max}(p.u.)$	4.496	4.496
$V_{amin}(p.u./s)$	$-0.1$	$-0.1$
$V_{qmax}(p.u./s)$	0.1	0.1
$T_2, T_3(s)$	0.10	0.10
$T_4, T_5(s)$	3.3,0.5	3.3,0.5
$T_{sr}, T_{sm}$	0.001, 0.15	0.001, 0.15
$F_2, F_3$	0.5, 0.5	0.5, 0.5
$F_4, F_5$	0,0	0, 0

PIs used for quantitative comparison includes the evaluation of integral square error (ISE), integral absolute error (IAE), integral time absolute error (ITAE), and integral time square error (ITSE).

$$
PI = \int_0^{t_m} t^a \Delta(\omega^b) dt
$$
 (24)

where,  $t_m$  indicates total time of simulation and  $a$ ,  $b$  are constants,  $(a, b) \in (0, 1), (0, 2), (1, 1), (1, 2)$  [35]. For a multimachine system, containing more than two generating units, the general equation of PI will be:

$$
PI = \int_0^{t_m} t^a \left( \left| \Delta \omega_2 - \Delta \omega_3 \right|^b + \left| \Delta \omega_2 - \Delta \omega_1 \right|^b + \left| \Delta \omega_3 - \Delta \omega_1 \right|^b \right) \tag{25}
$$

where,  $\Delta \omega_2 - \Delta \omega_3$ ,  $\Delta \omega_2 - \Delta \omega_1$  and  $\Delta \omega_3 - \Delta \omega_1$  are inter-area means of oscillations. Performance improvement in percentage for ANFTSK and ANFRWC as compared to LLC is calculated quantitatively as [65]:

$$
\frac{PI_{LLC} - PI_{ANFTSK}}{PI_{LLC}} \times 100
$$
 (26)

$$
\frac{PI_{LLC} - PI_{ANFRWC}}{PI_{LLC}} \times 100
$$
 (27)





<span id="page-8-0"></span>**FIGURE 7.** PI for multi-machine system (Case I).

#### B. RESULTS AND DISCUSSION

redThis section explains in detail the simulation results of two fault scenarios with different optimization techniques. Comparison of controller with different optimization techniques is also provided by Table [3.](#page-10-0) The results of only the best optimization techniques are provided by figures, which in our case is gradient decent. Case 1 presents a small disturbance that is coped with by using different control schemes. While in case 2 the behavior of the proposed control scheme is tested for large disturbance.

#### 1) CASE 1: SMALL DISTURBANCE

A small disturbance is any fault for a small duration that can be overcome and the system can get back to its original state. To verify the effectiveness of the proposed control scheme, a small fault of 0.1 p.u. step increase is applied in the mechanical power Pm of the generator at  $t = 1$  sec. This fault is cleared at  $t = 3$ sec and the steady-state of the system is regained by the controller. Fault clearing performance of comparative controllers is observed in the simulation results as shown in Figure [6.](#page-7-1)

Among the comparison of different controllers, optimum control is one in which stability is achieved quickly. These simulation results emphasize the robustness of the proposed

controller as the proposed ANFRWC gained the steady-state earlier than other controllers and shows good damping performance. Figure [6a](#page-7-1) explains the deviation in rotor speed of machine 1 concerning machine 2. Similarly, changes in rotor speeds of machine 1 concerning machine 3 and machine 2 concerning machine 3 are shown in Figure [6b](#page-7-1) and Figure [6c](#page-7-1). Simulation results of line power flow of the considered system in Figure [6d](#page-7-1) show that the power increased drastically to 115MW after the occurrence of a fault and when the fault is cleared, the steady-state value of power 95MW is re-achieved. Figure [7](#page-8-0) represents graphical PIs for this scenario showing the performance of proposed ANFRWC most effective. The best control is one with the least index value. The index curve of ANFRWC has the minimum value, making it superior control over others. ANFRWC has a minimum value for all the four performance parameters calculated.

#### 2) CASE 2: LARGE DISTURBANCE

Large disturbances are the faults in which the power system takes a long time to regain its stable state. To check the behavior of the system under large disturbance a three-phase, the self-clearing fault is applied at transmission line 4 between bus 6 and bus 9 at time  $t = 1$  sec. After five cycles, when the fault is settled, the system regained its original state.



<span id="page-9-0"></span>**FIGURE 8.** PI for multi-machine system (Case II).

Simulation results are shown in Figure [5.](#page-6-1) This large disturbance caused the loss of Synchronism between all three machines which in turn affected the steady speed of rotors. Figures [5a](#page-6-1), [5b](#page-6-1) and [5c](#page-6-1) explains clearly the deviations of rotor speed with respect to each other. An abrupt increase of 205 MW in Power is observed as a result of this disturbance which is maintained back to 95MW once the fault is cleared. All the observed parameters after fault clearance got back to normal values because of the system control. It is obvious from the results that LLC is the least and ANFRWC is the most effective in damping inter-area means of oscillations and bringing back the system to a stable position. Performance indices for this case are shown in Figure [8.](#page-9-0) PIs for this large disturbance scenario proves the validity of the proposed controller with the best damping results. A comparison of these performance parameters shows the efficacy of the proposed controller over LLC and ANFTSK.

Performance percentage for different optimization methods are calculated in Table [3.](#page-10-0) Both ANFTSKC and ANFRWC are compared with conventional LLC. In both cases, ANFRWC showed a better response as compared to ANFTSKC. The performance margin of controllers is better in case of step increase fault. While in the case of a

three-phase fault for the multi-machine system, relatively lower performances are observed. This quantitative analysis shows percentage improvement in performances for both cases. Performance margin in case 1 is more as compared to case 2. It is observed that for the case of step increase, the percentage performance of ANFTSK is low compared to ANFRWC. The same condition is noticed in a three-phase fault scenario, where the percentage evaluation of ANFRWC is observed better than the performance of ANFTSK.

Four different parameters are calculated for the comparison of the class of controllers with different optimization methods used in this research. These parameters include the evaluation of ISE, IAE, ITAE, and ITSE. ISE computes the performance of the system by integrating the square of the error of the system over a fixed time interval. IAE calculates the set of errors from a fixed point. ITAE takes the product of time absolute error and divides it with time. This tuning method weighs more the errors that exist after a long time as compared to the errors at the start of response. ITSE calculates the system performance by integrating the square of the error over a fixed interval of time. All these four indices are measured to determine the comparative analysis of controllers.

<span id="page-10-0"></span>**TABLE 3.** Performance improvement w.r.t. LLC using different optimization methods (%) (\*\* GD = Gradient Decent, PGD = proximal gradient descent optimization).

<b>Test Case</b>	Controller	<b>IAE</b>	<b>ISE</b>	<b>ITAE</b>	<b>ITSE</b>
	<b>ANFTSKC</b> with GD	39.24	43.53	45.99	48.14
	<b>ANFRWC</b> with GD	55.92	62.45	62.96	67.02
	<b>ANFTSKC</b> with Adadelta	39.53	45.53	48.19	48.41
	<b>ANFRWC</b> with Adadelta	54.14	59.86	62.76	66.14
Case-I	<b>ANFTSKC</b> with Adam	40.74	41.72	45.45	45.74
	<b>ANFRWC</b> with Adam	54.22	60.76	61.13	68.14
	<b>ANFTSKC</b> with PGD	37.25	41.85	46.76	45.14
	<b>ANFRWC</b> with PGD	56.45	60.87	61.55	66.21
	<b>ANFTSKC</b> with GD	30.62	19.68	42.34	27.40
$Case-II$	<b>ANFRWC</b> with GD	33.40	34.82	43.27	39.97
	<b>ANFTSKC</b> with Adadelta	28.54	22.18	40.13	30.14
	<b>ANFRWC</b> with Adadelta	31.14	35.21	45.13	37.27
	<b>ANFTSKC</b> with Adam	28.76	21.76	41.92	37.71
	<b>ANFRWC</b> with Adam	31.89	33.98	44.25	38.13
	<b>ANFTSKC</b> with PGD	31.22	21.76	40.14	30.14
	<b>ANFRWC</b> with PGD	31.45	33.42	43.87	39.64

## **VI. CONCLUSION AND FUTURE WORKS**

This article proposed an adaptive neurofuzzy control to operate static-synchronous series compensators. The combination of neural networks with fuzzy logic allows the control system to be more flexible. The proposed scheme utilizes Gaussian as the membership function and wavelets in the consequent part. In this research, we introduced recurrency both in antecedent and consequent parts. The approximation and learning abilities of the proposed scheme make the proposed control a better option. Furthermore, we use ANFTSK and LLC as a comparison to check the effectiveness of the proposed controller. Proposed controller is also evaluated with different optimization techniques, showing gradient decent perform best amongst all. Our scheme checks oscillation damping characteristics of different controllers for a multi-machine test system. It also uses two fault scenarios of small and large disturbances and checks oscillations damping with all three controllers. In large disturbance multi-machine case, ANFTSK is combative, but the suggested controller scheme showed higher performance by gaining stability earlier. The proposed control reduces the oscillations efficiently and improves the transient stability of the system.

As a future work, Mexican hat or haar wavelets can be employed to verify the effectiveness of the proposed controller. In this research, we used multiple inputs single output algorithm which can be expanded to multiple inputs multiple outputs. Control parameters can also be changed to create a different test scenario.

## **CONFLICT OF INTEREST**

The authors declare that there is no conflict of interest. Nonfinancial competing interests.

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