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ENHANCING POWER SYSTEM STABILITY USING ANFIS-BASED POWER SYSTEM STABILIZER

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Abstract: This research introduces a novel method for improving power system stability using a Power System Stabiliser (PSS) based on ANFIS. Ensuring the reliability and security of the energy grid, particularly in demanding operational environments, relies heavily on power system stability. While conventional power system stabilisers have proven useful in reducing oscillations and enhancing stability, their capabilities may be limited in highly dynamic and intricate power systems. The promise of PSS based on ANFIS as a flexible and dependable way to improve power system stability. The ANFIS-based PSS helps create a more stable power grid by reducing oscillations and strengthening grid resilience. This makes the grid better suited to handle the demands of contemporary power networks, which are increasingly integrated with renewable energy sources and have complicated load dynamics. Power system operators and academics seeking to enhance power system stability in response to changing energy landscapes will benefit greatly from this study's results.

Subjects: ANFIS controller, power system stabiliser, stability, single machine system.

I. INTRODUCTION

A power system's stability is its capacity to maintain an operational equilibrium under typical operating circumstances. There are two types of stability: small signal and transient. When a system is tiny signal stable, it may recover quickly from even a little disruption and continue functioning normally. The capacity of a system to recover to its normal operating condition after a transient disruption, such as a generator loss or a single or multiple phase short circuit, is known as transient stability. A major issue in large power systems is low frequency oscillations. The electric producing unit's excitation system receives an additional control signal from a power system stabiliser, which dampens these low-frequency oscillations. Stabilisers for power systems have been widely utilised for a while now due to their adaptability, affordability, and ease of installation. To reduce low-frequency oscillation, the power system stabiliser generates an additional control signal. Existing power systems make extensive use of traditional power system stabilisers, which have helped improve power systems' dynamic stability [3]. Traditional power system stabiliser parameters revolve around the nominal operating point, which is based on a linearized model of the power system. Because power systems are inherently nonlinear, traditional power system stabiliser designs that rely on linearized power system models cannot provide reliable operation in real-world conditions [4]. One innovative and cutting-edge approach to power system stability issues is the use of an Adaptive Neuro-Fuzzy Inference System (ANFIS) based Power System Stabiliser (PSS). ANFIS is an AI hybrid that takes use of both neural networks' learning capabilities and fuzzy logic's language representation. When used together, these features let ANFIS simulate systems with complicated and nonlinear interactions. Maintaining synchronous operation under varying operating circumstances is what we mean when we talk about power system stability.A PSS is a control device that may be used to increase the power system's stability by dampening oscillations caused by changes in load, faults, or other reasons. Despite their usefulness in many situations, traditional PSSs may struggle to keep up with the ever-changing dynamics and complexity of today's power systems. Adaptive and intelligent elements are added to the control system by including ANFIS into the design of a PSS. This allows the system to adapt to changing situations.

Among the many benefits of implementing an ANFIS into a PSS are:

Robustness and effectiveness in dynamic scenarios are enhanced by ANFIS's capacity to react to changes in the operating conditions of the power system.Addressing Nonlinearity: ANFIS excels in modelling and controlling power systems that display nonlinear behaviour. In order to solve the problems caused by contemporary power grid complexity, this is essential.Ability to Learn: ANFIS can learn from its experiences and make incremental improvements to its performance by modifying its settings in response to the data it collects.By integrating expert knowledge via ANFIS's fuzzy logic component, a more transparent and interpretable control system is created.This work seeks to improve power system stability, particularly in cases when conventional stabilisers are inadequate, by including ANFIS into PSS design. Modern civilizations cannot run without reliable and secure power networks, and this novel technique adds to the continuing efforts in this direction.

II. SYSTEM DESIGN

A power system stabiliser, an excitation system, and a synchronous machine make up the system.

i) Synchronous Machine Model:

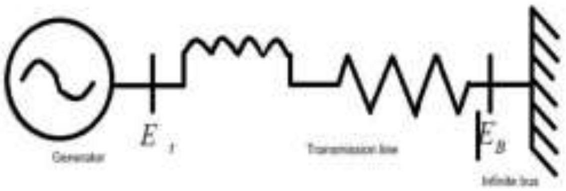

Fig.1 shows the synchronous machine connected to infinite bus through transmission line.

The Governing equations for machine model are:

$$p\dot{\Delta\omega}_r = 1/2H(\Delta T_M - \Delta T_e - K_d \Delta\omega_r)$$

$$p\Delta\delta = \omega_o \Delta\omega_r$$

$$\text{Where, } \Delta T_e = K_1\Delta\delta + K_2\Delta\psi_M$$

$$\Delta\psi_{fd} = K_3/(1+pT_3).\,[\Delta E_{fd} - K_4\Delta\delta]$$

Here we have the prime mover input denoted as TM, the electrical output torque as Te, the inertia constant as H, and the rotor angle and speed as R and A, respectively.

III. Excitation System:

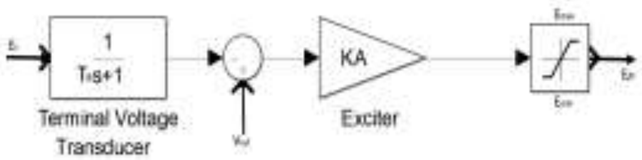

Fig.2: Block diagram of excitation system

To improve transient stability, the excitation system may react quickly to disturbances, and to improve small-scale stability, it can modulate the generating field. Exciters are responsible for supplying the rotor winding of alternators with the field current that is required for their operation. A voltage transducer at the generator's terminals detects the alternating current (ac) and converts it to direct current (dc) amount. A synchronous machine's field winding receives direct current power from the exciter, which is also known as the power angle of the excitation system.

IV. Power System Stabilizer (PSS):

In order to help reduce these oscillations, power system stabilisers (PSS) were created to modulate the excitation system of generators. By supplying additional damping to the oscillation of synchronous machine rotors via generator excitations, a PSS extends the angular stability limitations of a power system.

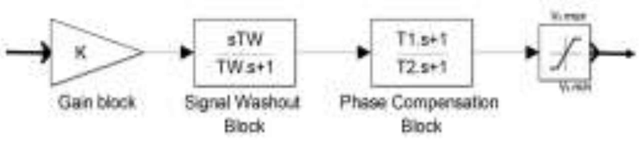

Fig. 4: Block Diagram of Conventional PSS

Figure 4 depicts the fundamental architecture of traditional PSS (4). The three parts that make it up are the gain block, the signal washout block, and the phase compensation block. The phase compensation block, which has the right phase lead characteristic, provides the necessary lag time between the exciter input and the generator's electrical output. A high-pass filter is provided by the signal washout block. As a function of stabiliser gain Kst, damping is defined. Traditional PSS transfer functions are:

$$\Delta v_2 = \frac{pT_W}{1+pT_W}(K_{STAB}\Delta\omega_r)$$

$$\Delta v_s = \frac{1+pT_1}{1+pT_2}(\Delta v_2)$$

As a result, the washout filter time constant is TWis.

V. Fuzzy Logic Controller (FLC):

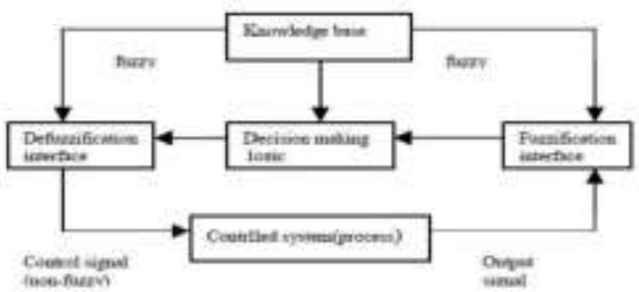

Fig. 3: Fuzzy Logic Controller Diagram

A fuzzy logic controller block diagram is shown in figure (3). A knowledge base, an interface for fuzzification and defuzzification, and decision-making logic make up its four main parts. A fuzzy controller is a part with two inputs and one output. By and large, it is a MISO setup [5].

In the knowledge base, you may find the rules that defined the control objectives using linguistic variables and the fuzzy membership function. All information on input-output fuzzy relationships is also saved in it.

It is a fuzzification interface that transforms the sharp numbers into fuzzy ones. Unlike random variables, which may have their membership values assigned using probability density functions, fuzzy variables can be assigned

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membership values in a variety of methods. Assigning membership values is done using algorithms, procedural approaches, logical reasoning, or intuition.

An interface for defuzzification can take a fuzzy set and transform it into a clear, single-valued number. "Rounding it off" is another possible name for it. The computational complexity and relevance to the problems at hand are the deciding factors in the technique selection process. Logic for Making Decisions: This component transforms the inferred choice based on language variables. As the central processing unit (CPU) of a feedback loop control (FLC) system, it may mimic human decision-making by using approximation reasoning to reach the target control strategy.

VI. FUZZY ARCHITECTURE:

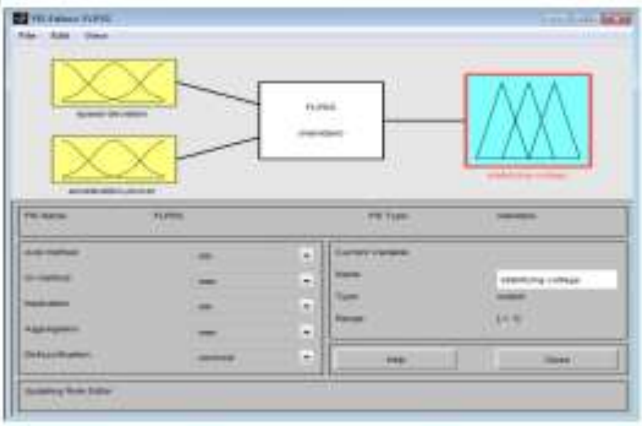

Fig4 fuzzy inference system editor

The rule base of the fuzzy logic controller is shown in the below table.The design procedures of FLPSS are shown below.

- Select input and output variables.
- Select MF's.
- Set up fuzzy rule.
- Finally choose defuzzification criteria.

Table 1 RULE TABLE OF FLC

		Power- acceleration						
		NB	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
Speed-deviation	**NB**	NB	NB	NB	NB	NM	NS	Z
	NM	NB	NB	NB	NM	NS	Z	PS
	NS	NB	NB	NM	NS	Z	PS	PM
	Z	NB	NM	NS	Z	PS	PM	PB
	PS	NM	NS	Z	PS	PM	PB	PB
	PM	NS	Z	PS	PM	PB	PB	PB
	PB	Z	PS	PM	PB	PB	PB	PB

VII. NEURO FUZZY LOGIC

A. fuzzy neural model

Below, you can see two examples of fuzzy neural system models. The input vector to the multi-layered neural network in the first model is provided via the fuzzy interface block, as illustrated below.

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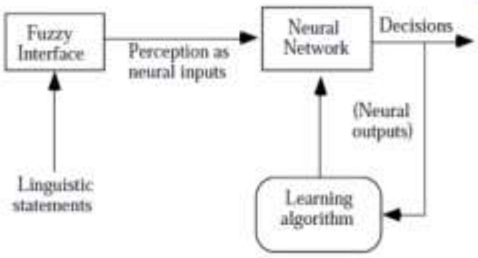

Fig (5): fuzzy neural system model 1

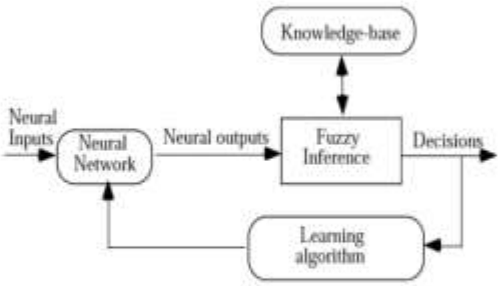

Fig (6): fuzzy neural system model 2

Figure 6 shows the second model's fuzzy inference process, which is driven by a multi-layered neural network.

VIII. ANFIS

When it comes to functionality, fuzzy inference systems are nothing compared to adaptive neural fuzzy inference systems (ANFIS). Two inputs, "speed (w)" and "change in speed (Δw)", and one "control output (Δu)" make up the ANFIS based SVC. Fuzzy logic takes these two parameters as input and fuzzifies them using a Gaussian membership function for seven language variables, including positive (P), negative (N), and zero (ZE). What follows is an illustration of the input/output membership function.

Nine rules are developed from the linguistic variables that are defined by the Gaussian membership function. The fuzzy IF-THEN rules of sugeno's first order type are included in the rule base.

IX. ANFIS ARCHITECTURE

The architecture of the ANFIS sensing the two inputs is shown in below fig.

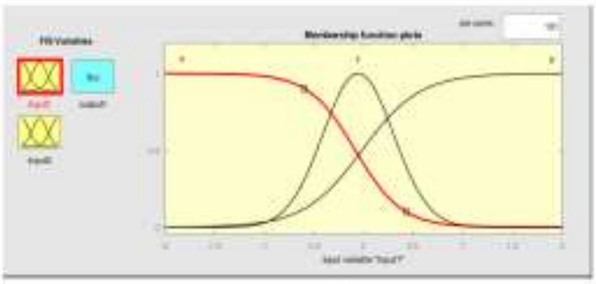

Fig 7 Input 1 (Error) Membership function.

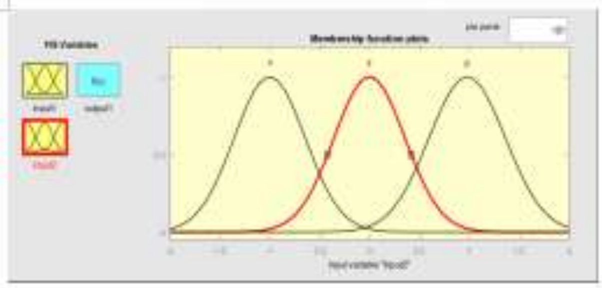

Fig 8 Input 2(Change in Error) Membership function.

1. If (input1 is n) and (input2 is n) then (output1 is p)
2. If (input1 is n) and (input2 is z) then (output1 is p)
3. If (input1 is n) and (input2 is p) then (output1 is z)
4. If (input1 is z) and (input2 is n) then (output1 is p)
5. If (input1 is z) and (input2 is z) then (output1 is z)
6. If (input1 is z) and (input2 is p) then (output1 is n)
7. If (input1 is p) and (input2 is n) then (output1 is z)
8. If (input1 is p) and (input2 is z) then (output1 is n)
9. If (input1 is p) and (input2 is p) then (output1 is n)

Fig 9. Membership function Rules of the ANFIS

What follows is a description of the node functions in each tier.

Level One: A square represents one of the parameters in this layer; they are utilised for fuzzification and are referred to as pre-condition or premise parameters. The equations for the corresponding nodes are:

$$O_i^1 = \mu A_i(ve_1)$$

$$\mu A_i(ve_1) = \left\{ \begin{array}{cc} 0 & ve_1 \leq a_i \\ \frac{ve_1 - a_i}{b_i - a_i} & a_i \leq ve_1 \leq b_i \\ \frac{c_i - ve_1}{c_i - b} & b_i \leq ve_1 \leq c \\ 0 & c_i \leq ve_1 \end{array} \right\}$$

where $i = 1,2,3$, O_i^1 is the output of the *i*th node in layer-1, and a_i, b_i, c_i are the parameters of the triangular membership function.

Layer-2: Parameters in this layer are labeled as π_i and represented by a circle. They are used for the firing system bymultiplying the incoming signals and forwarding them to the next layer. Corresponding node equations are:

$$w_j = \mu A_1(ve_1) \times \mu A_2(ve_1) \times \mu A_3(ve_1)$$

where j = 1,2,3.

Layer-3: Parameters in this layer are labeled N and represented by a circle. For each rule, the normalized firing strength is calculated in this layer as:

$$\overline{w_j} = \frac{w_j}{\sum_{k=1}^{3} w_k}$$

where j = 1,2,3.

Layer-4: Parameters in this layer are called consequent parameters represented by a square. They give the output of each node. Corresponding node equations are:

$$O_j^4 = \overline{w_j} f_j = \overline{w_j}(p_j ve_1 + t_j)$$

where $\overline{w_j}$ – is the layer-3 output, O_j^4 is the jth node layer-4 output, and p_j and t_j are determined during training. They are sets of consequent parameters.

Layer-5: Parameters in this layer are labeled ∑ represented by a circle. They are used for summation. This layer sums up all incoming signals to calculate the output *y*. Corresponding node equations are:

$$y = \sum_{j=1}^{3} \overline{w_j} f_i = \sum_{j=1}^{3} [(\overline{w_j} ve_1) r_j + (\overline{w_j}) t_j]$$

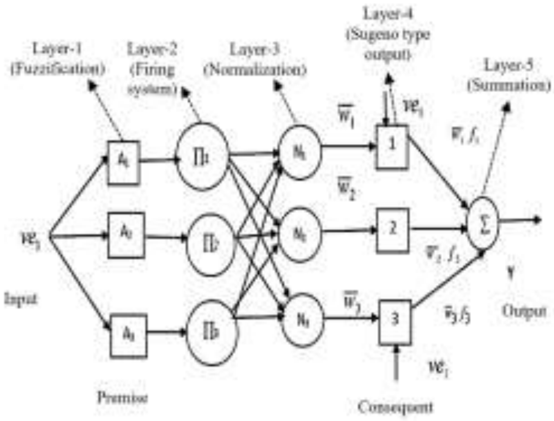

Fig 9 ANFIS architecture

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X. SIMULATION RESULTS

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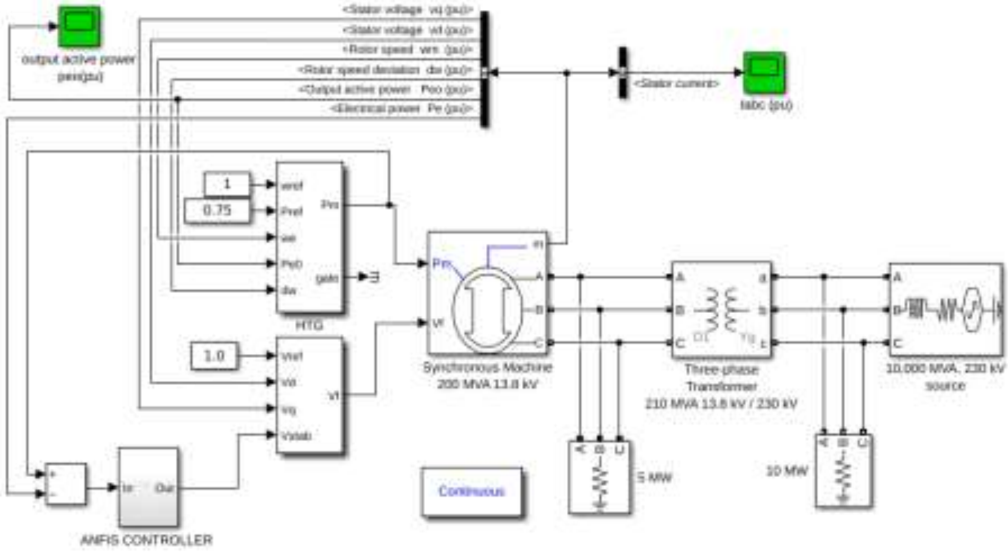

Fig 10. Simulation Block Diagram of the proposed system

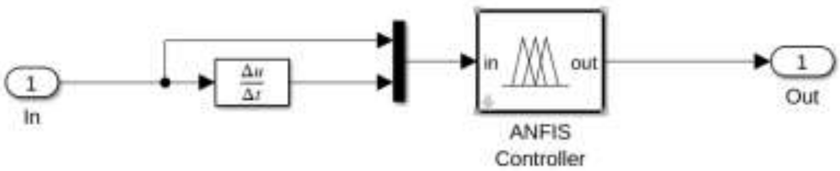

Fig11. Simulink Diagram of the Proposed ANFIS Controller

Simulation results

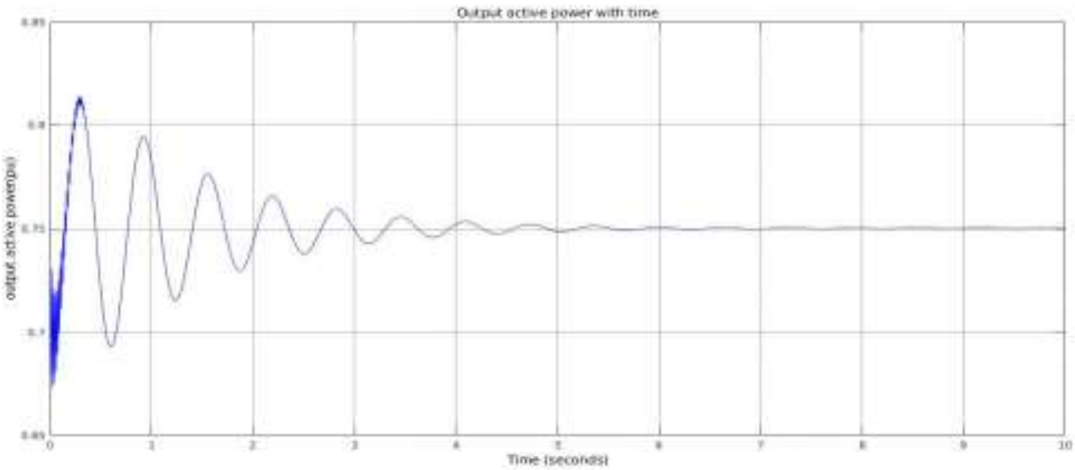

Fig 12. Conventional stabilizer without fault

In the Fig 12 with PSS is used to control the output active power, at t= 6sec it was stable to 0.75 and there are No fluctuations in the active power when the load is applied.

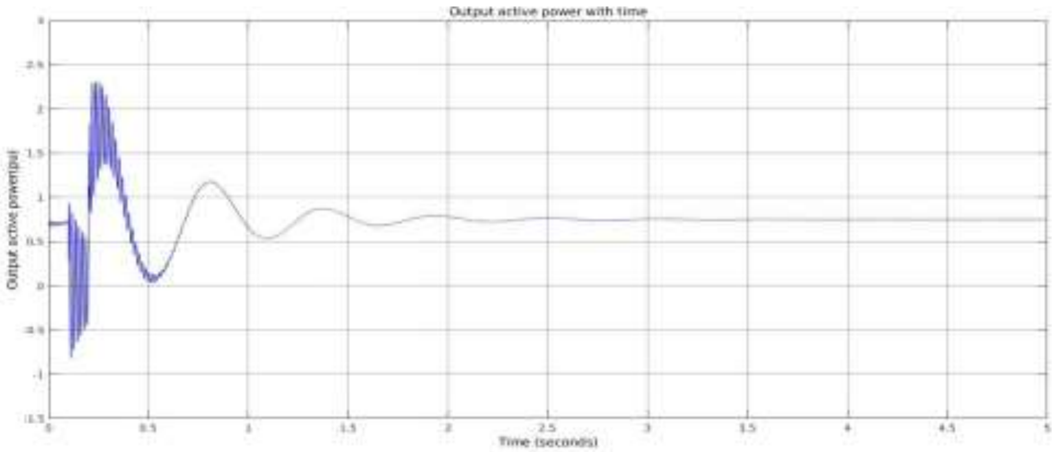

Fig 13. Conventional Stabilizer with fault

In the Fig 13 with PSS is used to control the output active power, at t= 3.5sec it was stable to 0.75 and there are No fluctuations in the active power when the fault is created.

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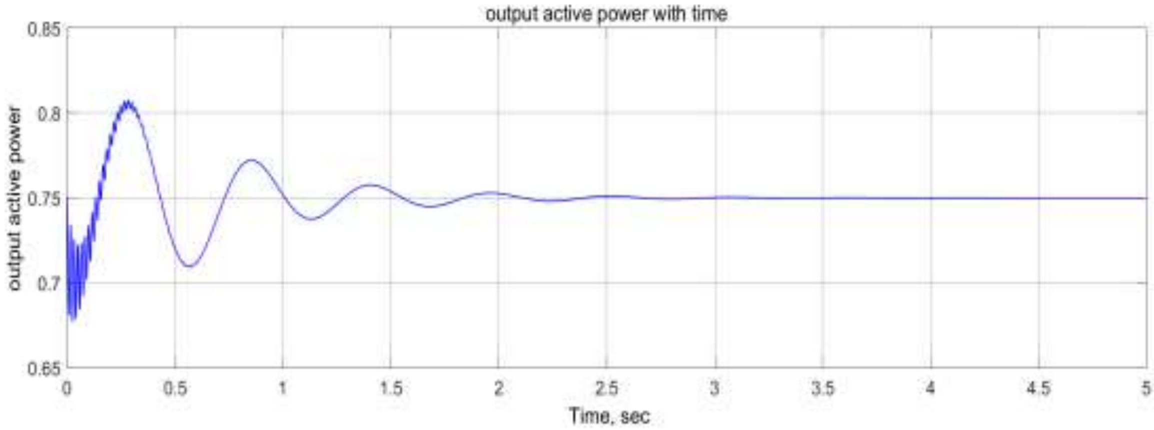

Fig14. Fuzzy logic Stabilizer without fault

In the Fig 14 Fuzzy is used to control the output active power, at t= 2.5sec it was stable to 0.75 and there are No fluctuations in the active power when the Stabilizer when load is applied.

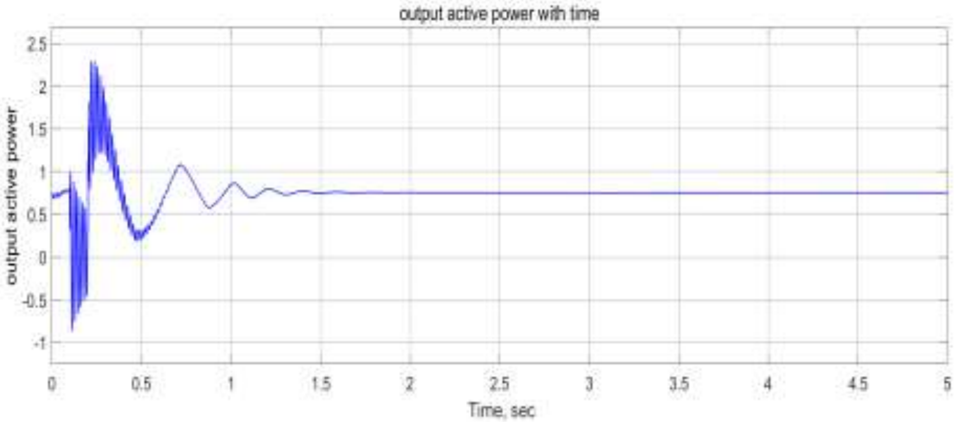

Fig15. Fuzzy logic Stabilizer with fault

In the Fig 15 Fuzzy is used to control the output active power, at t= 2.5sec it was stable to 0.75 and there are No fluctuations in the active power when the Stabilizer with fault is created.

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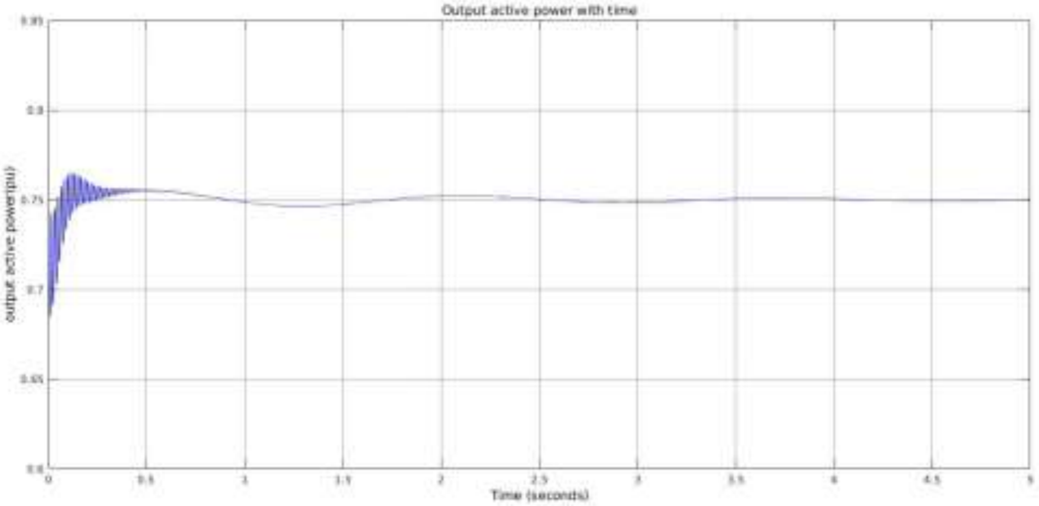

Fig16. ANFIS Stabilizer without fault

In the Fig 16 ANFIS is used to control the output active power, at t= 1.5sec it was stable to 0.75 and there are No fluctuations in the active power when the Stabilizer when load is applied.

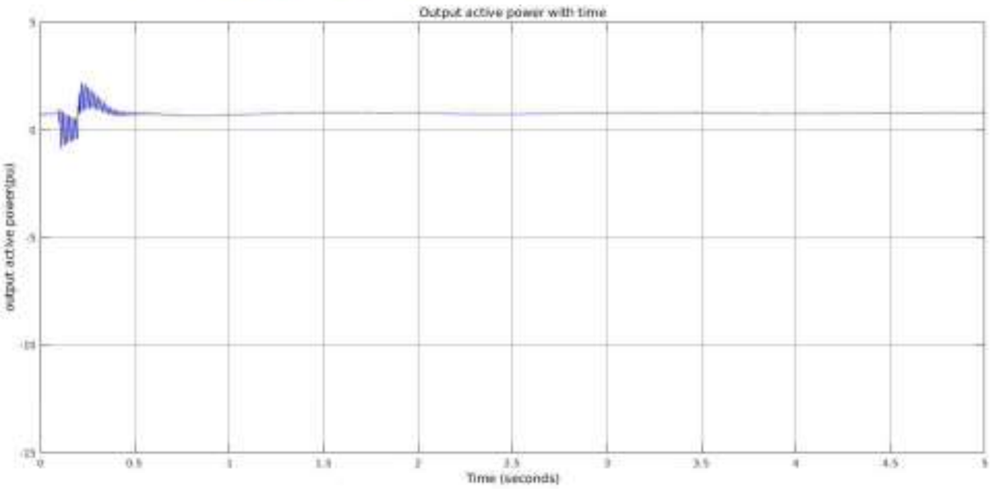

Fig17. ANFIS Stabilizer with fault

In the Fig 17 ANFIS is used to control the output active power, at t=0.5sec it was stable to 0.75 and there are No fluctuations in the active power when the Stabilizer with fault is created

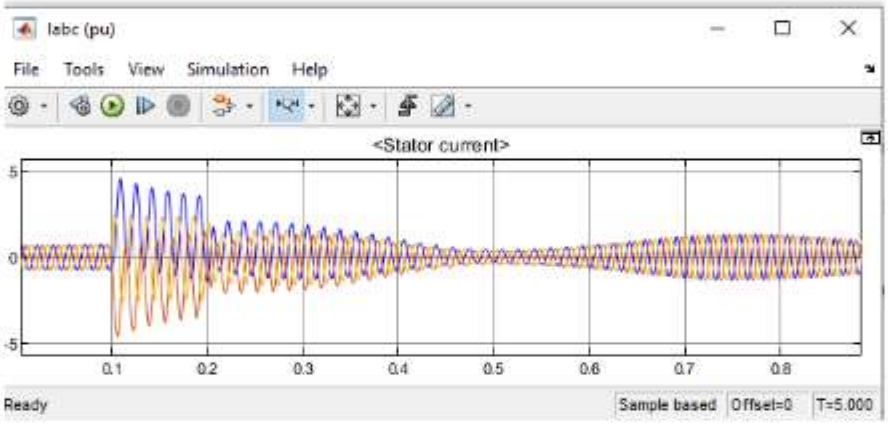

Fig 18. Stator current by ANFIS with fault

In the Fig 18 ANFIS is used to control the stator current, at t= 0.7 sec it was stable to 0.6A(PU) and there are fluctuations in the stator current when the fault.

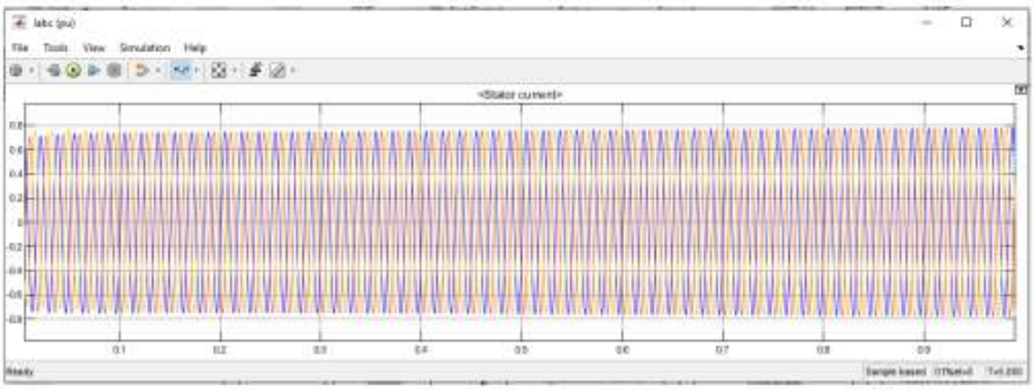

FIG19. Stator current by ANFIS without fault

In the Fig 19 ANFIS is used to control the stator current, at t= 0 sec it was stable to 0.7 A(PU) and there are fluctuations in the stator current when the load is applied.

Table I

Comparison of results between PSS and FLPSS (Without fault)

From Fig we can get the generator stabilization times as illustrated in the below table:

Results of response for a single generator connected to infinite bus	
With PSS	6sec
With FLPSS	2.5sec
With ANFIS	1.5 sec

Table II

Comparison of results between PSS, FLPSS and ANFIS
(With fault)

Results of response for a single generator connected to infinite bus	
With PSS	3.5 sec
With FLPSS	1.5 sec
With ANFIS	0.5 sec

CONCLUSION

Finally, a potential strategy for improving power system stability is the use of a Power System Stabiliser (PSS) based on an Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANFIS-based PSS has shown time and time again in this study that it can stabilise power networks by reducing oscillations. The ANFIS-based PSS demonstrates remarkable resilience and dependability in its performance because to its remarkable capacity to adjust and gain knowledge from system dynamics and operational circumstances.

Prospects for the Future

Although ANFIS outperforms PSS and FLPSS, there is currently no systematic approach to designing it so that its parameters may be fine-tuned. Furthermore, it is challenging to infer, from data analysis, which membership functions (MFs) should be used during modelling. In contrast, an ANN-based approach shows promise since it automatically adjusts the output to boost a system's efficiency.

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