

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:

$$p\Delta\omega_r = 1/2H(\Delta T_M - \Delta T_e - K_d\Delta\omega_r)$$

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

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

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

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:

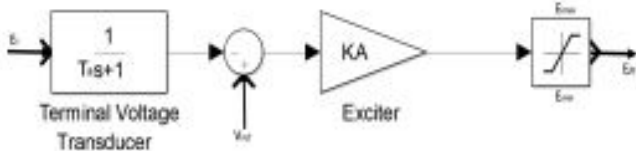


Fig.2: Block diagram of excitation system

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.

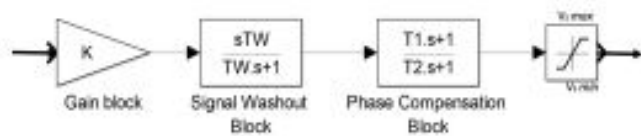


Fig. 4: Block Diagram of Conventional PSS

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):

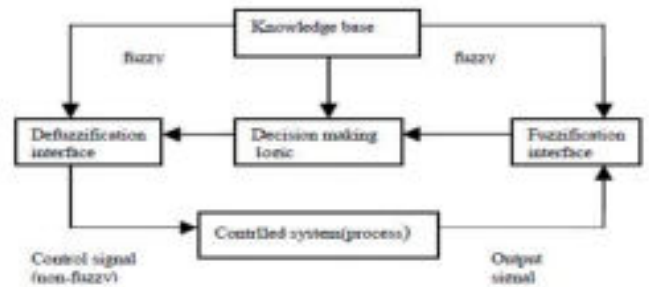


Fig. 3: Fuzzy Logic Controller Diagram

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 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:

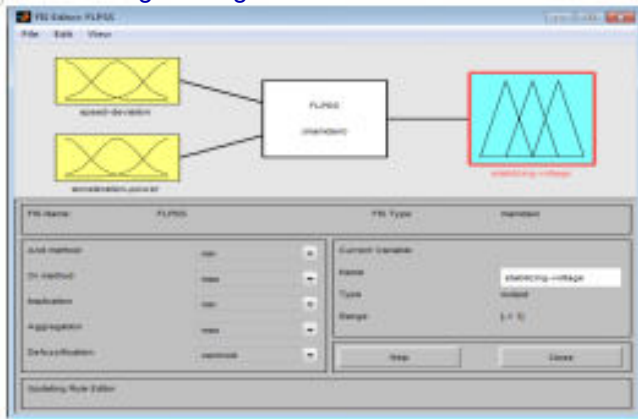


Fig4 fuzzy inference system editor

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	NB	NM	NS	Z
	NM	NB	NB	NB	NB	NM	NS	Z	PS
	NS	NB	NB	NB	NM	NS	Z	PS	PM
	Z	NB	NM	NS	Z	PS	PM	PB	PB
	PS	NM	NS	Z	PS	PM	PB	PB	PB
	PM	NS	Z	PS	PM	PB	PB	PB	PB
	PB	Z	PS	PM	PB	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.

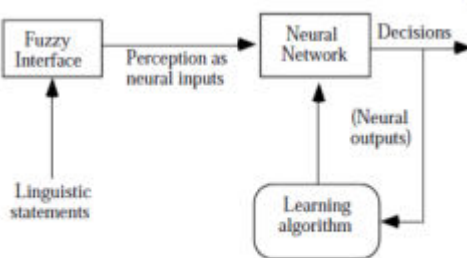


Fig (5): fuzzy neural system model 1

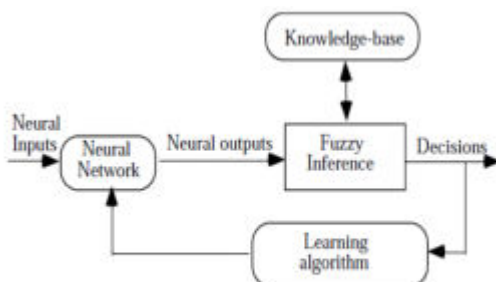


Fig (6): fuzzy neural system model 2

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.

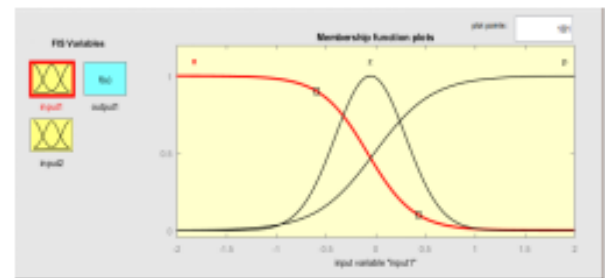


Fig 7 Input 1(Error) Membership function.

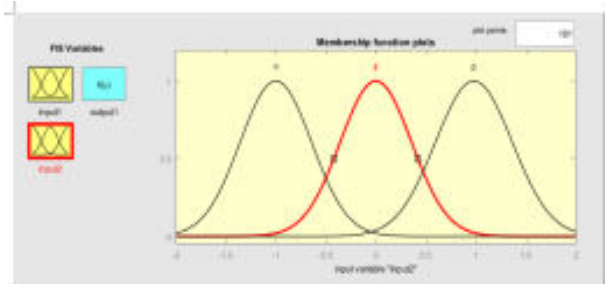


Fig 8 Input 2(Change in Error) Membership function.

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:

$$O_i^1 = \mu A_i(v_{e1})$$

$$\mu A_i(v_{e1}) = \begin{cases} 0 & v_{e1} \leq a_i \\ \frac{v_{e1}-a_i}{b_i-a_i} & a_i \leq v_{e1} \leq b_i \\ \frac{c_i-v_{e1}}{c_i-b} & b_i \leq v_{e1} \leq c \\ 0 & c_i \leq v_{e1} \end{cases}$$

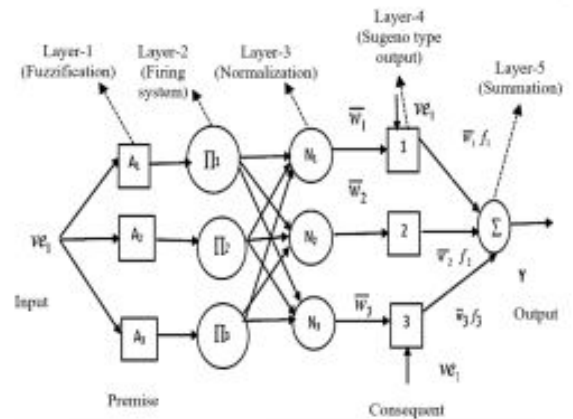


Fig 9 ANFIS architecture

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 by multiplying the incoming signals and forwarding them to the next layer. Corresponding node equations are:

$$w_j = \mu A_1(v_{e1}) \times \mu A_2(v_{e1}) \times \mu A_3(v_{e1})$$

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:

$$\bar{w}_j = \frac{w_j}{\sum_{k=1}^3 w_k}$$

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:

$$O_j^4 = \bar{w}_j f_j = \bar{w}_j (p_j v_{e1} + t_j)$$

where \bar{w}_j is the layer-3 output, O_j^4 is the j th 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 Σ 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:

$$y = \sum_{j=1}^3 \bar{w}_j f_j = \sum_{j=1}^3 [(\bar{w}_j v_{e1}) r_j + (\bar{w}_j) t_j]$$

X. SIMULATION RESULTS

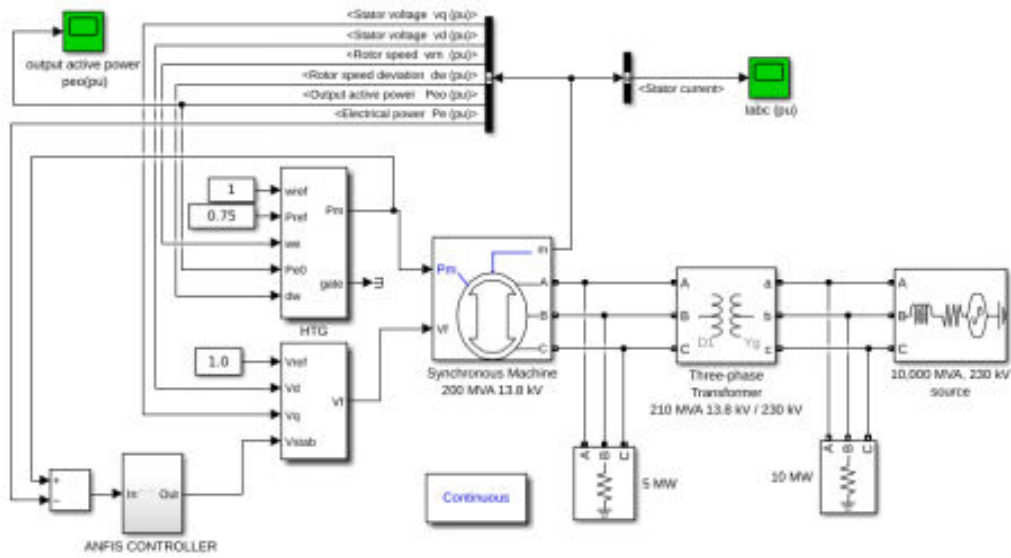


Fig 10. Simulation Block Diagram of the proposed system

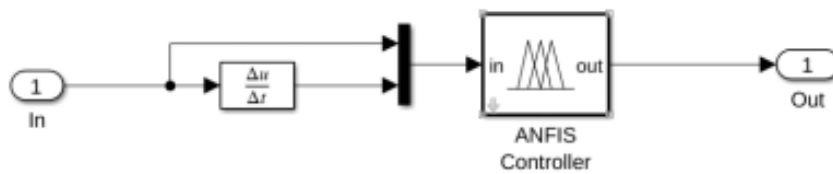


Fig11. Simulink Diagram of the Proposed ANFIS Controller

Simulation results

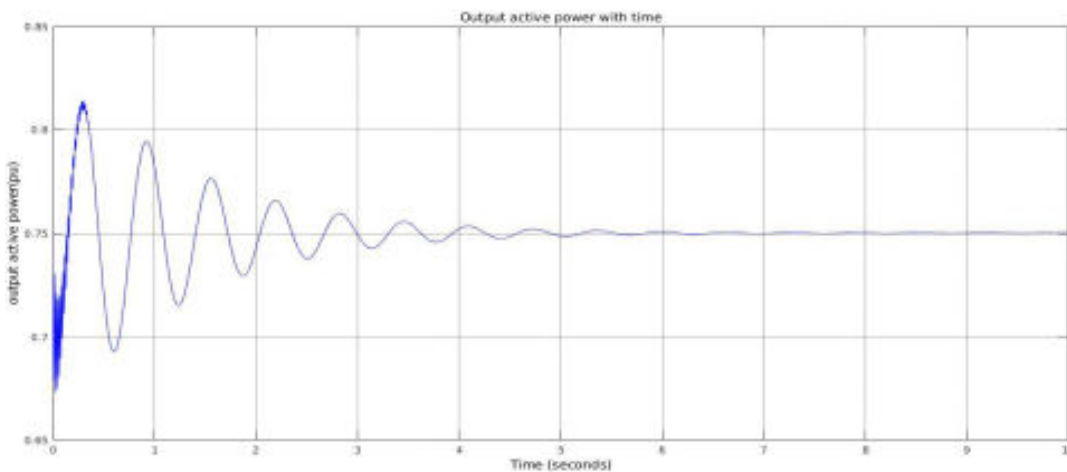


Fig 12. Conventional stabilizer without fault

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

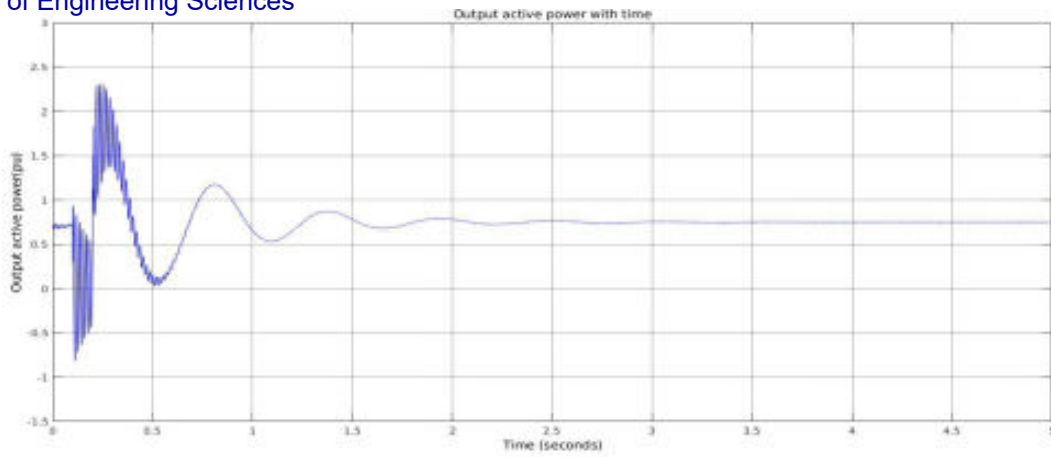


Fig 13. Conventional Stabilizer with fault

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

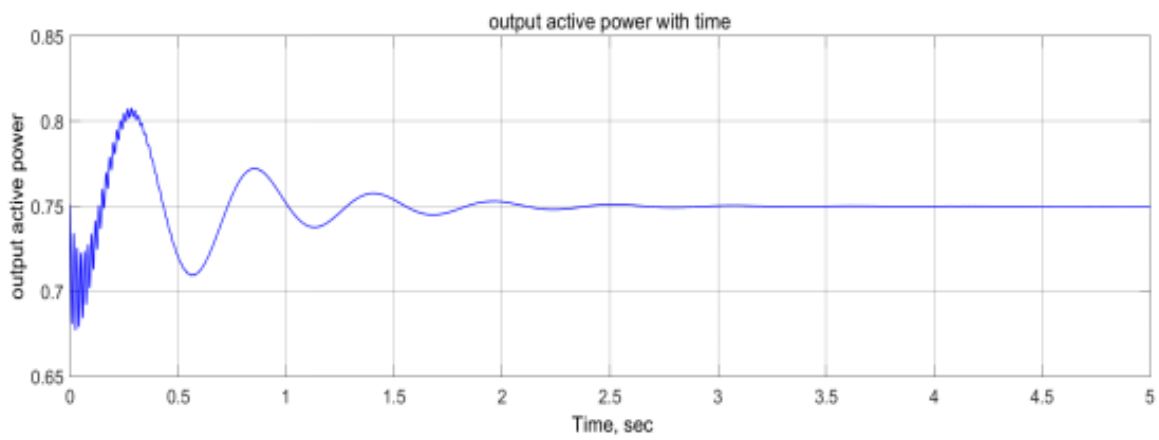


Fig14. Fuzzy logic Stabilizer without fault

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

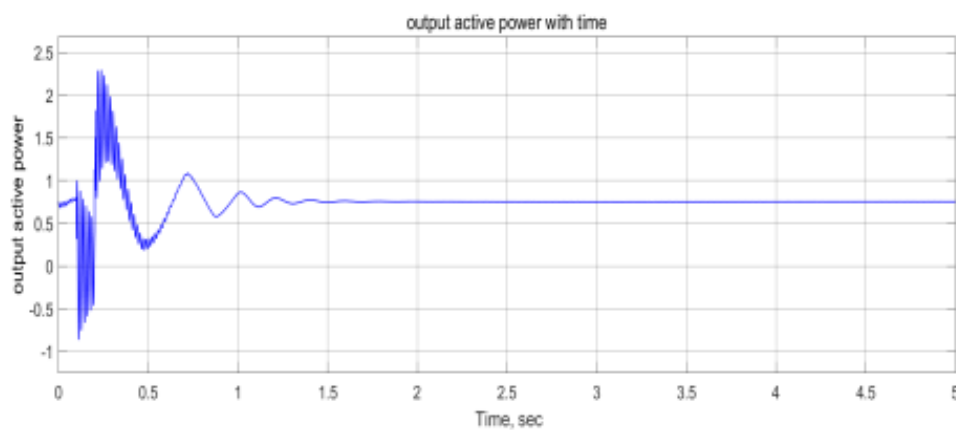


Fig15. Fuzzy logic Stabilizer with fault

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

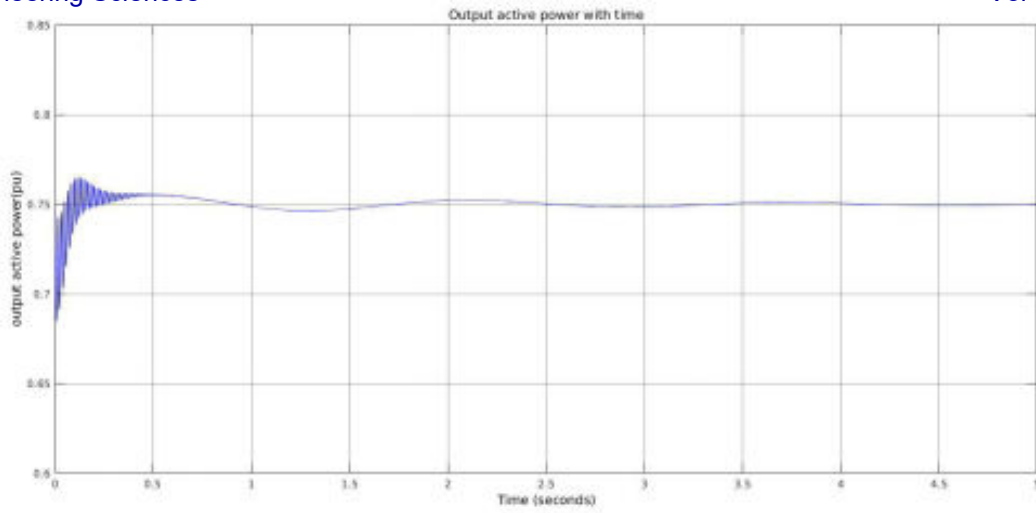


Fig16. ANFIS Stabilizer without fault

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

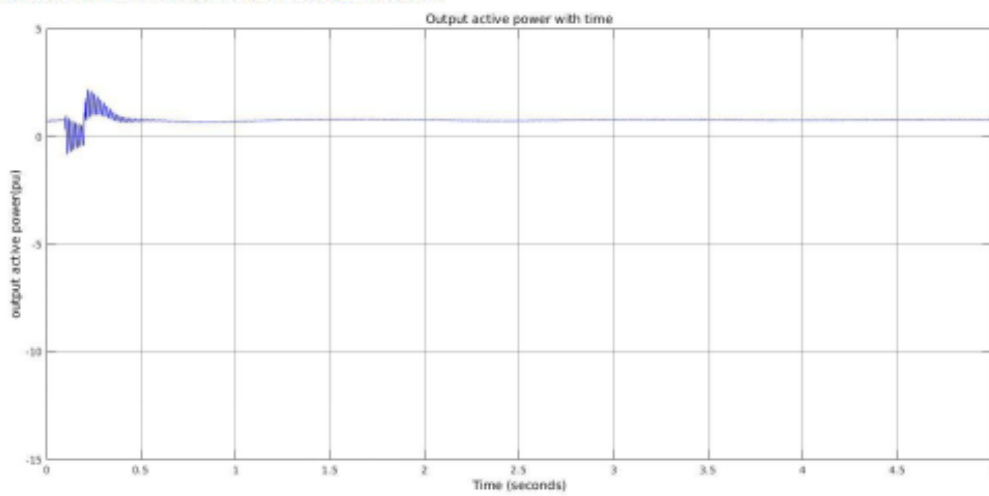


Fig17. ANFIS Stabilizer with fault

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

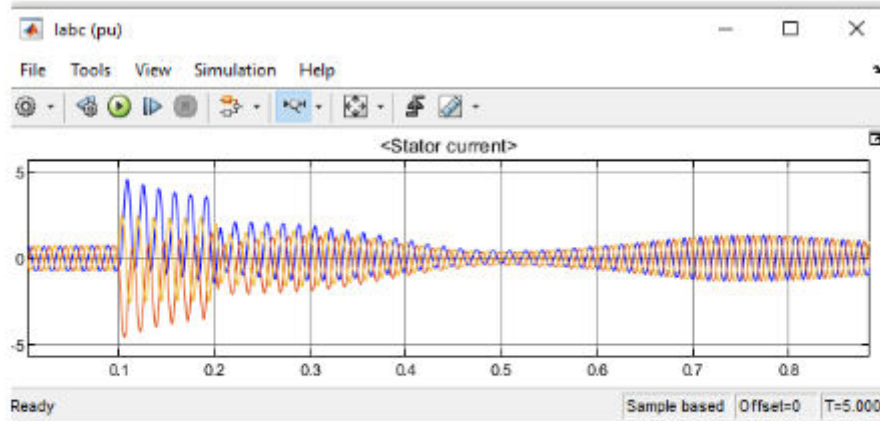


Fig 18. Stator current by ANFIS with fault

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.

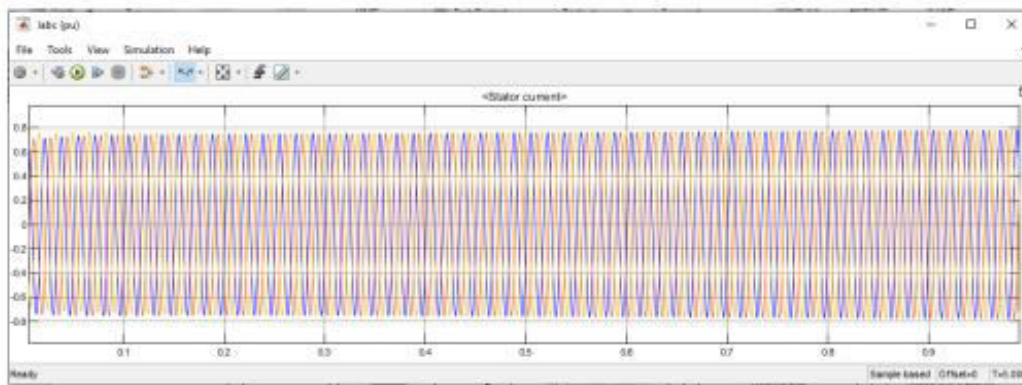


FIG19. Stator current by ANFIS without fault

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.

REFERENCES

[1] Wenxin Liu, Ganesh K. Venayagamoorthy, Donald C. Wunsch. Adaptive neural network based power system stabilizer design. IEEE 2003, page 2970-2975

[2] Y. Zhang G. P. Chen, O. P. Malik G. S. Hope, "An Artificial Neural Network Based Adaptive Power System Stabilizer", IEEE Transactions on Energy Conversion, Vol. 8, No. 1, March 1993

- [3] Neeraj gupta, Sanjay k. Jain, "Comparative analysis of fuzzy power system stabilizer using different membership functions", International journal of computer and electrical engineering, Vol.2, No. 2, April,2010,1793-8163.
- [4] Jenica Ileana corcau, Eleonor stoenecu, "Fuzzy logic controller as a power system stabilizer",International journal of circuits, systems and signal processing, Issue 3, Volume 1, 2007.
- [5] C J Wu and Y Y Hsu, "Design of Self-tuning PID Power System Stabilizer for Multimachine Power System", IEEE Transactions on Power Systems, vol. 3, pp. 1059-1064, Aug. 1998.
- [6] K A El-Metwally and O P Malik, "Fuzzy Logic Based Power System Stabilizer", IEEE Proc- Gener.Transm. Distri., vol. 142, pp.277-281, May 1995.
- [7] H Taliyat, J Sadeh and R Ghazi "Design of Augmented Fuzzy Logic Power System Stabilizer to Enhance Power System Stability" IEEE Transactions on Energy Conversion, vol 11, pp, 97-103, March 1996.
- [8] T Hiyama, "Development of Fuzzy Logic Power System Stabilizer and Further Studies", IEEE International Conference on Systems, Man and Cybernetics '99, vol. 6, pp.545-550.
- [9] S Majid, H A Rahman and O B Jais, "Study of Fuzzy Logic Power System Stabilizer", IEEE Student Conference on Research and Development 2002, pp. 335- 339.
- [10] Jaun, L H Herron and A Kalam, "Comparison of Fuzzy Logic Based and Rule Based Power System Stabilizer", IEEE Conference on Control Application, pp.692- 697, sept.1992.
11. Xu, Wenyuan, and Qiang Lu. "A new stabilizer design technique for multimachine power systems." Electric power systems research 15, no. 2 (1988): 89-97.
12. Toliyat, Hamid A., Javed Sadeh, and Reza Ghazi. "Design of augmented fuzzy logic power system stabilizers to enhance power systems stability." IEEE Transactions on Energy Conversion 11, no. 1 (1996): 97-103.
13. Liu, Wenxin, Ganesh K. Venayagamoorthy, and Donald C. Wunsch. "Adaptive neural network based power system stabilizer design." In Proceedings of the International Joint Conference on Neural Networks, 2003., vol. 4, pp. 2970-2975. IEEE, 2003.
14. Zhang, Y., G. P. Chen, O. Pr Malik, and G. S. Hope. "An artificial neural network based adaptive power system stabilizer." IEEE transactions on energy conversion 8, no. 1 (1993): 71-77.
15. Hussein, T., A. L. Elshafei, and A. Bahgat. "Design of a hierarchical fuzzy logic PSS for a multi-machine power system." In 2007 Mediterranean Conference on Control & Automation, pp. 1-6. IEEE, 2007.
16. Khobaragade, Tejaswita, and Amol Barve. "Enhancement of power system stability using fuzzy logic controller." International Journal of Power Electronics and Drive Systems 2, no. 4 (2012): 389.
17. Othman, H., J. J. Sanchez-Gasca, M. A. Kale, and J. H. Chow. "On the design of robust power system stabilizers." In Proceedings of the 28th IEEE Conference on Decision and Control., pp. 1853-1857. IEEE, 1989.
18. Yu, Y-N., and Q-H. Li. "Pole-placement power system stabilizers design of an unstable ninemachine system." IEEE transactions on power systems 5, no. 2 (1990): 353-358.
19. We, C. J., and Y. Y. Hsu. "Design of self-tuning PID power system stabilizer for multimachine power system." IEEE Trans. on PWRs 3, no. 3 (1988).
20. El-Sherbiny, M. K., M. M. Hasan, G. El-Saady, and Ali M. Yousef. "Optimal pole shifting for power system stabilization." Electric Power Systems Research 66, no. 3 (2003): 253-258.
21. Nambu, Masahiko, and Yasuharu Ohsawa. "Development of an advanced power system stabilizer using a strict linearization approach." IEEE Transactions on power systems 11, no. 2 (1996): 813-818.
22. Radman, Ghadir. "Design of power system stabilizer based on LQG/LTR formulations." In Conference Record of the 1992 IEEE Industry Applications Society Annual Meeting, pp. 1787-1792. IEEE, 1992.
23. Scavoni, F. Escudero, A. S. e Silva, A. Trofino Neto, and J. M. Campagnolo. "Design of robust power system controllers using linear matrix inequalities." In 2001 IEEE Porto Power Tech Proceedings (Cat. No. 01EX502), vol. 2, pp. 6-pp. IEEE, 2001.
24. Boukarim, George E., Shaopeng Wang, Joe H. Chow, Glauco N. Taranto, and Nelson Martins. "A comparison of classical, robust, and decentralized control designs for multiple power system stabilizers." IEEE Transactions on Power Systems 15, no. 4 (2000): 1287-1292.
25. Gibbard, M. J., and D. J. Vowles. "Design of power system stabilizers for a multi-generator power station." In PowerCon 2000. 2000 International Conference on Power System Technology. Proceedings (Cat. No. 00EX409), vol. 3, pp. 1167-1171. IEEE, 2000.
26. Majid, Md Shah, H. A. Rahman, and Othman B. Jais. "Study of fuzzy logic power system stabilizer." In Student conference on research and development, pp. 335-339. IEEE, 2002.
27. Shi, Juan, Len H. Herron, and Akhtar Kalam. "Comparison of fuzzy logic based and rule based power system stabilizer." In [Proceedings 1992] The First IEEE Conference on Control Applications, pp. 692-697. IEEE, 1992.
28. Kundur, Prabha, Neal J. Balu, and Mark G. Lauby. Power system stability and control. Vol. 7. New York: McGraw-hill, 1994.
29. Shah, Bhavans. "Comparative study of conventional and fuzzy based power system stabilizer." In 2013 International Conference on Communication Systems and Network Technologies, pp. 547-551. IEEE, 2013.
30. Kumar, PK Arun, S. Vivekanandan, C. Krishna Kumar, and V. Kumar Chinnaiyan. "Neural network tuned fuzzy

logic power system stabilizer design for SMIB." In 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I), pp. 446-451. IEEE, 2016.

31. Kharadi, G. S., G. D. Gohil, and N. B. Parmar. "DEVELOPMENT OF MATLAB SIMULINK MODEL OF FUZZY BASED POWER SYSTEM STABILIZER FOR POWER QUALITY."

32. Oraibi, Waleed Abdulrazzaq, Mustafa Jameel Hameed, and Ahmed K. Abbas. "An Adaptive Neuro-Fuzzy based on Reference Model Power System Stabilizer."