Intelligence in enhancing power system stability under unbalanced load conditions

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Abestract:
With the liberalization and growth of the energy sector, if we make -by force- components of energy systems operate at near-maximum capacity, this will put the systems at risk. the grid of electrical power is widespread system, which consist of real and reactive power converters , interconnected generators ……, etc. Therefore, to achieving stability for power system we must use controlled operation of power systems. This requires fast and effective solutions based on control algorithms which are efficient and reliable. when we use intelligent systems with integrated models, The reliability and efficiency of power system controllers will improve using. More advantages of intelligent system is its efficient control loop, which reduces modeling errors.
Intelligent controllers applied to improve the operation and control of power systems successfully.
Keywords: Neuro fuzzy, Generator control, Power system stabilizers, Transient stability, Intelligent control.

دور الذكاء الاصطناعي في تعزيز استقرار أنظمة القدرة الكهربائية تحت ظروف الأحمال غير المتوازنة

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الملخص:
مع تحرير قطاع الطاقة ونموّه، فإن إجبار مكوّنات أنظمة الطاقة على العمل بالقرب من حدودها القصوى قد يعرّض هذه الأنظمة لمخاطر جسيمة. وتُعد شبكة القدرة الكهربائية نظامًا واسع الانتشار يتكوّن من محوّلات القدرة الفعّالة وغير الفعّالة، ومولّدات مترابطة، وغيرها من المكوّنات. وعليه، فإن تحقيق الاستقرار في أنظمة القدرة الكهربائية يتطلّب اعتماد تشغيل مُتحكَّم فيه لتلك الأنظمة، وهو ما يستدعي حلولًا سريعة وفعّالة قائمة على خوارزميات تحكّم كفوءة وموثوقة. وعند توظيف الأنظمة الذكية ذات النماذج المتكاملة، تتحسّن موثوقية وكفاءة متحكّمات أنظمة القدرة الكهربائية بشكل ملحوظ. كما تتميّز الأنظمة الذكية بامتلاكها حلقات تحكّم فعّالة تقلّل من أخطاء النمذجة. وقد أُثبت نجاح تطبيق المتحكّمات الذكية في تحسين تشغيل أنظمة القدرة الكهربائية والتحكّم فيها بكفاءة عالية.
الكلمات المفتاحية: المنطق العصبي الضبابي، تحكّم المولّدات، مثبّتات أنظمة القدرة، الاستقرار العابر، التحكّم الذكي.

1. Introduction:

A fundamental requirement for the stable operation of a geographically dispersed, matching of total load demand with total generation is interconnected power system, as well as the associated system losses [1]. after the implementation of high-speed electronic power controllers the Power systems have become more unpredictable. Exacerbates the deterioration of operational stability of power systems. A review of the reference [2] revealed .
The full benefits of restructuring electric power facilities are not being exploited due to unsuitable control algorithms.
As power systems continue to grow in both size and complexity, it has become increasingly important to understand system stability to prevent dynamic breakdowns and potential power outages.

Research is conducted on multiple axes, including (stability of transient power systems [6], quality of power [7], quality of data [8], modeling of power system [9], reliability of power system [10], rapid valve adjustment [11], management of power which is reactive [12], economics of power system [13], and to integrant sources of renewable energy with the local grid [14]). This research work study the stability of power systems.

Artificial intelligence can be defined as a branch of software science that emerged during the last century. It is based on the assumption that the actions, behavior, and objective behavior of computers can be designed to mimic higher cognitive processes [19]. On the other hand, we can define artificial intelligence (AI) as a dominant intellectual ability that includes special additional abilities, such as (the ability to find cause and purpose - achieve intention - use terminology - solve problems - acquire knowledge). It can be emphasized that the study of artificial intelligence depends on specific skills, and this study seeks to develop action plans capable of performing a limited function that requires that skill [12]. The main goal of artificial intelligence is to create a system with the intelligence and logic of an adult.

Methodology:

this research do methodology at first defined the stability of power systems and study conditions and its problems, then study how to Enhanc power system stability system one of fields is using smart systems or intelligent systems, we study of intelligent methods as : Artificial Neural Networks, (Neural control) systems, Systems by Fuzzy Neural, Adaptive Critical Design. In addition, show advantages and disadvantages for all of them. We apply methods group on power system by equipping it with a neural network controller based on artificial intelligence at case study and by matlab simulink of the system we get results and discus it, and suggest to use Bio-inspired optimization algorithms to get the best of results.

2. power system stability:

Power system stability is ability to return to state operational balance after disturbance, entire system remains good practically [15].

power system stability relay with the stability of synchronous electrical generator.

In other words: power system stability is the synchronization between rotary field motion and circular motor motion. Stability Power system can be divided to different categories based on variables involved, magnitude duration disturbance as :

1- Stability of output Voltage
2- Stability of frequency
3- stability of Rotor angle

The angle between the rotary magnetic field and generator's armature magnetic flux the is called power angle (δ).

we can defined as:

1- Angular stability: balance between electromagnetic and mechanical torque torque.

2- Voltage stability: matching of reactive power generation and consumption.Thus: load characteristics is caused Voltage instability.

instability of angle Angular instability is a dynamic case associated with the generator's rotor relationship.

We can divide problem of transient stability two parts: evaluation then prediction [16].

stability transient stage assessment search on required time to isolate bad term before the system losses his stability, called the critical cleanup time. Conversely, stability transient prediction shifts its focus if transient fluctuations will converge. stability of Transient system power is explained by criterion equal-areas [17], illustrated at Figure 1.

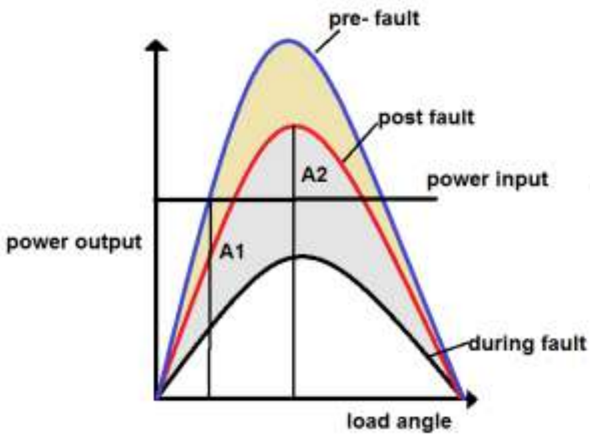

Figure 1. output power Vs load angle

difference between the incoming torques mechanical and electrical effects on rotor generator given by

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

- A acceleration torque,
- M mechanical input torque,
- EM induced electromagnetic torque.
- A1 acceleration region
- A2 deceleration region.

rotor must stay in a dynamic equilibrium To achieve stability and ensure stable operation. To achieve this condition, during any emergency value of A2 must be equal to or more than A1

That can be achieved by :

- increasing the fault curve during - after the fault.
- isolating the faulted part in a very short time.

We can improve stability power system when use dynamic controllers excitation systems, FACTS devices [19], system power stabilizers, high-voltage direct current.

3- How to Enhanc power system stability.

There are several types of devices that work to enhance power system stability, by devices for Transmission System :

1- Flexible alternating current systems (FACTS) enhance the stability power systems by controlling flow power at the consumer. The concept of enhancing stability of power system through series FACTS devices to increase the active flow of power during a fault, thus area A1 decreases the and area A2 increases [21].

2- Static synchronous compensator (STATCOM), enhances stability of transient power system when inject reactive power to the system during a disturbance, decreasing the A1 and increasing A2 [22].

3- controller UPFC The concept of series and bypass controllers FACTS increases the stability of system more effectively than FACTS controllers [19,23].

4- the technique Controlled islanding in it the entire power system is divided into several sections, with no interconnections, avoid large power outages [15]. Controlled islanding the last defense in the plane of maintaining system stability. Furthermore, it is not sugested as solution to all problems of system instability [20].

5- (HVDC) High-voltage direct current system: potential buffer against loss of synchronism. it has the problem of instability voltage after a disturbance, if system exhausts its reserves of reactive power [24].

we can divid electric torque into synchronizing torque and damping torque, as following equation:

$$\Delta T_E = K_S \Delta\delta + K_D \Delta\omega \qquad (2)$$

load angle known is as the torque angle

(δ) the angular velocity,

K is a constant.

first term synchronous torque. torque depends on magnetic flux of the air gap and magnetic coupling between (rotor - synchronous generator armature).

second term is damping torque. torque damping come of phase lag of current excitation [25, 26].

4. Intelligent controll a systems

Intelligent controll is defined as a system that has the ability to learn, adapt, and operate efficiently over a wide range of applications.

intelligent control used models of intelligent systems:

1- Fuzzy logic(FL).

2- Optimization algorithms.

3- Genetic algorithms (GAs).

4- Artificial neural networks (ANNs).

(FL) is highly efficient to make decision and get a logic design after data processing, while genetic algorithms perform well in optimization. Artificial neural networks (ANNs) have also performed well in data processing.

Not only IS systems basedon adaptive control, also traditional adaptive, and called analytical technology, integrates artificial intelligence and traditional technology. Compared with traditional control, the limit of margin transient stability has increased by using system with adaptive control [34].

By using two techniques [35]:

- artificial neural networks as a model identifier .
- adaptive electrode displacement controller that is an analytical method.

In algorithm pole shift, a numerical parameter is continuously adapted, and its value determines the control stability of closed-loop. This control loop to have the shortest time for processing. Solving problems using differential (FL) algorithms becomes more complex as the variables involved increase. Furthermore, the control of FL algorithms relies more heavily on practical experiments [36].

Differential algorithms (GAs) are characterized by their random nature and their insensitivity to initial configuration. However, they possess the ability to freely optimize global derivatives, a feature underlying their so-called evolutionary concept. The overall performance of GAs depends on the stability function, and therefore, the function requires specialized knowledge.

Genetic algorithms require converging a long time, and its efficiency varies across many parameters of control. And artificial neural networks (ANNs) feature extensive parallel interconnections between simple processors. Despite their poor interpretability, they are most promising methods comparing for other methods [36].

4.1. Artificial Neural Networks:

artificial neural networks have lower sensitivity to noise, are easier to implement with hardware, and use fewer input features [40].

Artificial neural networks are a highly developed field. Advances in artificial neural network (ANN) learning algorithms have led researchers from various fields to become interested in their application. ANNs are highly efficient at distinguishing system states based on inputs and outputs. Based on this property, Artificial neural networks have found diverse applications in the dynamic control of systems, a property called "observability".

artificial neural network which is most common tools are:

- multilayer perceptron (MLP)
- radial basis function (RBF)
- recurrent neural network (RNN)

several studies [41-43] used the network of dynamic neural. large number of feedback connections make The strength of the RNN lies.

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very important to note the networks were trained online, then topped training based on the time duration. The results showed that RBF neural controller performed better than MLP controller neural when it trained on-line using drift signals [48]. MLP has fourteen hidden nodes layer, while RBF has 12 cores. Furthermore, RBF has a higher processing speed [46], good performance of system (closed-loop) is inversely proportional to controller time response [32]. if response time issue is addressed appropriately MLP's performance will be even better.

4 .2. (Neural control) systems.

In neural control of excitation and power system stabilizers, artificial neural networks (ANNs) are applied in conditions of non-linear (reference -model) control adaptive, branch of input-output-based adaptive analytical control and nonlinear, where parameters are adjusted either directly or indirectly Figure 2.

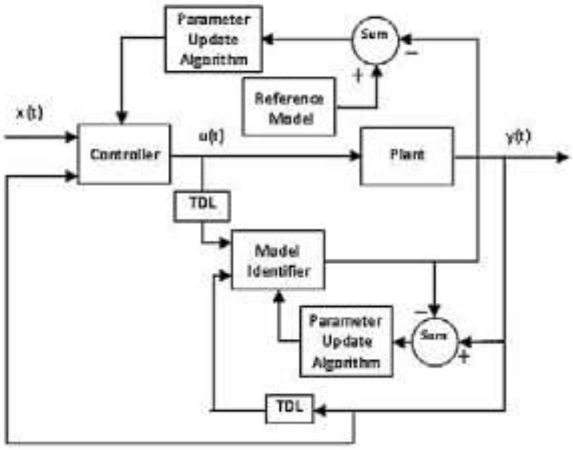

Figure 2. diagram of the non-linear model reference control adaptive

identifier model is an artificial neural network that simulates generator. purpose of the model identifier to know the generator's voltage - speed at instant y(t + 1). model identifier trained based on differences between actual output generator and output identifier model, as linear and non-linear autoregressive moving average (ARMA/NARMA).

There are four types of identification model. A few ARMA-based models have been used in the control of nonlinear - dynamic power systems [34, 35, 50–52].

$$y_p(t+1) = f[y_p(t), y_p(t-1), y_p(t-2), \cdots, y_p(t-n+1); \cdots \cdots u(t), u(t-1), u(t-2), \cdots, u(t-m+1)] \quad (3)$$

$$y_p(t+1) = f[y_p(t), y_p(t-1), y_p(t-2), \cdots, y_p(t-n+1)] + \cdots \cdots g[u(t), u(t-1), u(t-2), \cdots, u(t-m+1)] \quad (4)$$

Where yp()output factory, u()output controller.

global definition of factory, it is certain that the prior values (2n + 1) for inputs and outputs are sufficient [40].

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according to connectivity or by the inputs into the model identification we can are classify Identification models, One calls parallel identification model (PIM) and the other (SPIM)serial parallel identification model.

Figure 3 is SPIM. It get the current - lagged values of u(t) and y(t'0) as inputs, and based on the difference between the model and the plant output the parameters are updated..In Table 1 we see architecture of artificial neural networks use in [33, 44, 51, 52, 55, 56].
In other side worth noting is artificial neural networks were trained by deviation signals either to avoid using predictor of desired response [55] and drawbacks of MLP [44, 56]. We compared The results by conventional PSS systems even with devices without PSS.
In neural excitation system, were compared with results of conventional controller.
In terms number of neural controllers used, slightly results showed better performance under load conditions higher for the two-neuronal controller scheme [44,56].

Table 1. Summary of ANN architectural model [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 VT = (VREF- VT): , ΔPM = (PREF -PM), $\Delta w = (w_{REF} - w_T)$

SBP Static Back propagation
DBP Dynamic Back propagation
M-BPTT Modi_ed Back propagation by Time**.**
results demonstrate : neural PSS trained on the proposed algorithm better than the traditional PSS in tracking ability.

4.3. Systems by Fuzzy Neural.

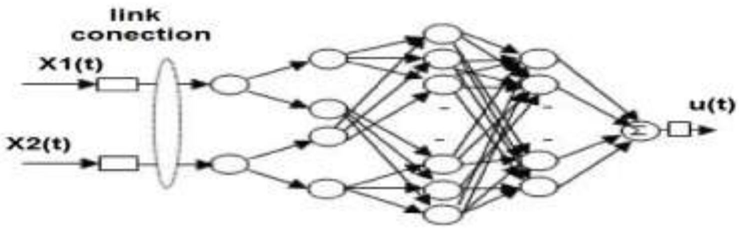
(ANNs) Artificial neural networks - (FL) fuzzy programming are two different models in intelligent systems. Both models, each with its own set of drawbacks [53]

by combining the advantages of two models to use an adaptive neuro-fuzzy inference system [50,57,58,59].

The system essentially consists of :knowledge base- a decision-making moduleand fuzzy/non-fuzzy rules. ANFIS is claimed to have unlimited approximation power, but this is dependent on the correct construction of the ANFIS [64].

Figure 4 illustrates the architecture of an ANFIS. The links between nodes represent only direction of signal flow and do not carry no weights and. first layer is the membership of function, while the fourth dedicated to parameters of subsequent.

The output of nodes in the second layer represents the energy of the base loop, while the third equals strength of the loop. The fifth layer sums all the inputs, and the control signal is its output, u(t).



x1(t) - x2(t) inputs, u(t) control output, squares represent the scaling factors.

Figure 3. ANFIS structure[50]

algorithm control based on self-tuning and then offline training.

To use genetic algorithm PSS tuned is by two functions different objective and five different operating points.

we were generat The data by tuning the PSS system at three different operating points optimally.module cosist of [60] :

- fuzzy perceptron(FP) of three-layers
- six hidden neurons
- two inputs and one output.

inputs are volume and velocity drift signals. In the fuzzy perceptron, the weights between hidden layers and input represent IF part of function Gaussian, while hidden weights to output layer represent part of the function

Table 2. Summary of the Neuro-Fuzzy control unit architecture [50,57,58,59]

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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	$\Delta\omega$, ΔV_T& ΔP_M	Excitation & Turbine

ΔPM = (PREF -PM).
VT = (VREF- VT).
$\Delta w = (w_{REF} - w_T)$ **.**
RLS: Recursive Least Squares.
G-Descent: Gradient Descent.
H-Learning: Hybrid Learning.
BP: Back propagation.

Fuzzy inference systems have problem when removing or adding any variable, as entire rule set must chang. In fuzzy hierarchical systems, the situation completely different [63].

4.4. Adaptive Critical Design.

In neural adaptive control, the parameters of free-floating artificial neural networks are directly adapted. Continuous direct
adaptive critical design by three artificial neural networks:
- model or identifier for estimating factory production step by step.
- the action network for minimizing J(.) in the near future.
- critical network for adapting the free parameters of action networks and model.

action network represents the matching between control variables and state, while critical network represents matching between cost variables and state.
work was compared with introducing a fault into the system, and by examining the results. Table 3 details the architecture of AC controllers (ACDs).
results showed both INC-based and HDP-based control algorithms performed better than conventional PSS, while HDP performed slightly better than INC.
Another study showed that the performance of an optimized neurocontroller for a DHP-based excitation system even outperforms that of a conventionally excitation synchronous generator mounted on a conventional PSS.

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Table 3. Reference architectural models for ACD [65]

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	$\Delta\omega$, ΔV_T &ΔP_M	Excitation & Turbine
RBF 6-9 -1 [65]	RBF 9-6-2	RBF 12-12-2 SPIM NARMAX-3	HDP	$\Delta\omega$, ΔV_T &ΔP_M	Excitation & Turbine
MLP 6-10-2 [65]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	DHP	$\Delta\omega$, ΔV_T &ΔP_M	Excitation & Turbine
MLP 6-13-1 [65]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	HDP	$\Delta\omega$, ΔV_T &ΔP_M	Excitation & Turbine
MLP 6-10-2 [65]	MLP 9-10-2	MLP 12-14-2 SPIM NARMAX-3	DHP	$\Delta\omega$, ΔV_T &ΔP_M	Excitation & Turbine
MLP 3-6-1 [65]	MLP 9-10-2	MLP 6-10-1 SPIM NARMAX-3	HDP	$\Delta\omega$	PSS
RBF 6-6-1 [65]	RBF 6-6-2	RBF 12-12-2 SPIM NARMAX-3	DHP	$\Delta\omega$, ΔV_T &ΔP_M	Excitation & Turbine
MLP 4-6-6-1 [65]	– –	– –	DHP-SNAC	$\Delta\omega$	PSS
MLP 7-10-1 [65]	FLN 52-4	RBF	HDP	$\Delta\omega$	WAC
MLP 6-10-2 [65]	MLP 9-12-2	MLP 13-15-2 SPIM	HDP	$\Delta\omega$	WAC

A simplified critical neural control system based on DHP is called Single Network Adaptive Critical Neurocontrol (SNAC).

5. Simulating a power system and equipping it with a neural network controller based on artificial intelligence methods.

Based on the previously reviewed methods and mechanisms of artificial intelligence, the previous study was implemented using a neural network controller to improve the system excitation performance of a synchronous generator. A set of artificial neural networks was used to achieve non-local generalization. The AC4A excitation model was studied.

The application was performed on a power system model, as shown in Figure 4.

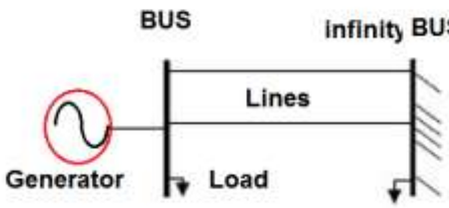

Figure 4. generator in_nite-bus

The generator has the following specifications: 13.8 kV, 300 MW, 50 Hz.

Table 5 shows the generator's parameters.

X_d	1.83	*Xq*	1.7	*RStato*	0.003

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				r	
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

The parameters of generator are given in Table 5.
X'_d subtransient direct axis reactance, X'_q subtransient quadtratur axis reactance, *T* time constant,($''$) indicates transient and *K* is a constant.
controller conventional used to control system excitation it was controller proportional and integrator (PI).
The model was simulated under the above conditions using **Matlab/Simulink** Figure 5, using the following conditions:
- To control the excitation system We used a conventional controller, it is proportional-integral (PI) controller.
- A PI (Conv) controller operated with a load of (0:051+j0:024).
- A multi-layer receiver (MLP)
- Using a feed-forward approach.
- MLP was trained to deviation between terminal voltage and voltage reference.

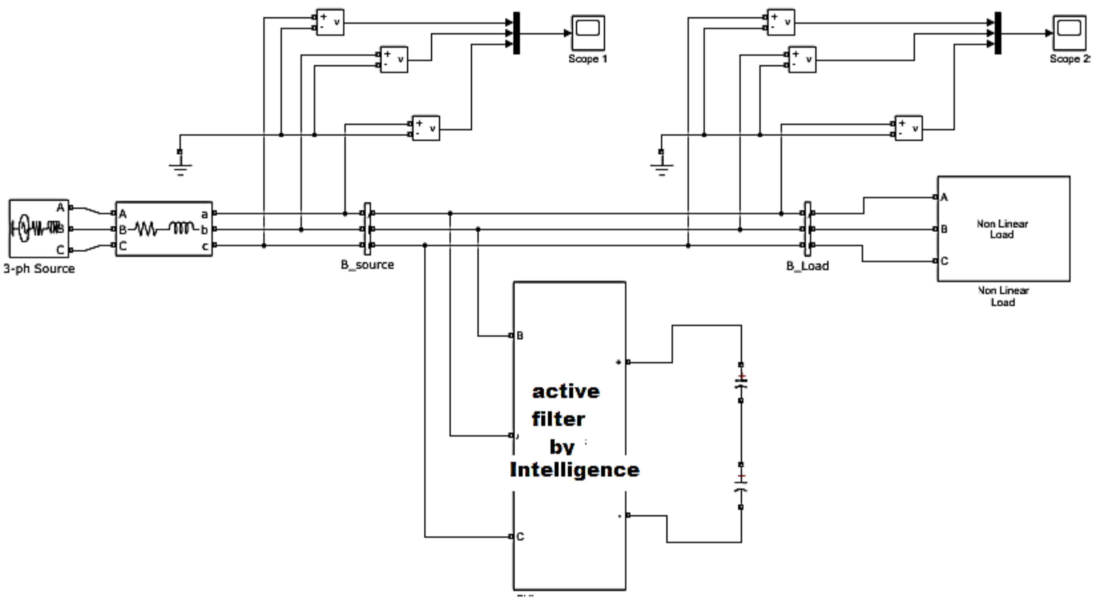

Figure 5. Simulation model of a power system with an active filter using an AI-based controller.

A generator terminal fault was simulated for fault 90 ms Figure 6.

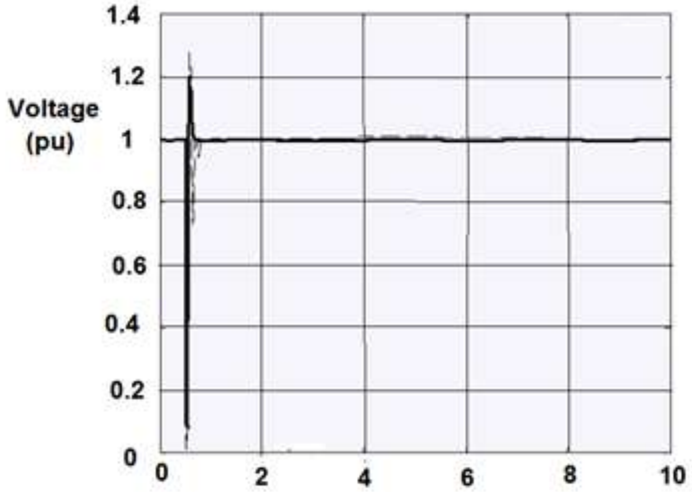

Figure 6. Terminal voltage
90 ms fault - load (0.051 + 0.024)

Figure 7 shows that the generator, when fitted with Conv, became unstable under higher load conditions. This demonstrates the dominance of Ensemble-NC over NC. Both types of neurocontrollers maintained system stability. Ensemble-NC performed better because it optimized the pre-NC (steady-state) value.

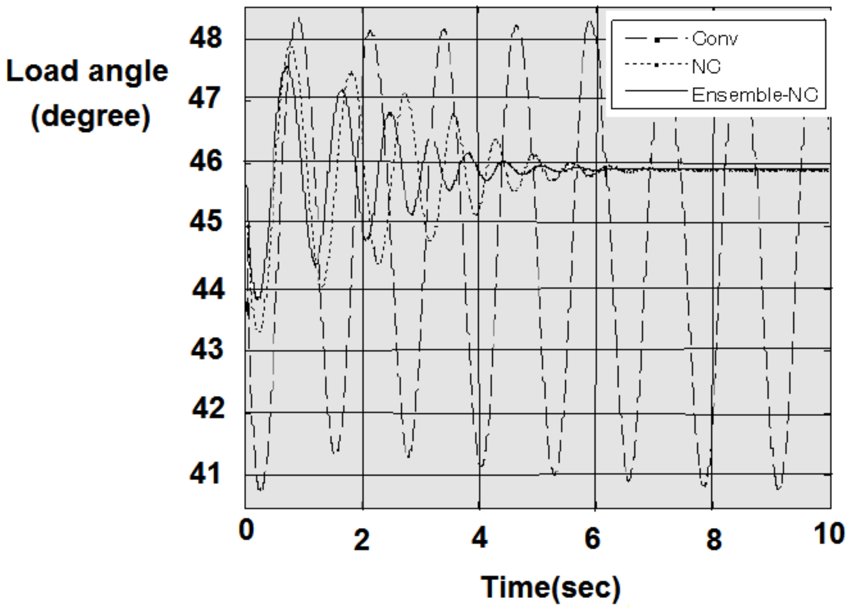

Figure 7. behavior of Load angle
fault 90ms- load (0:007 + *j*0:004)

A similar analysis was conducted under high load conditions to analyze the nonlinear performance of the controllers. Figures 8 and 10 show nonlinear power controllers. Under high load (0.007 + j0.004)

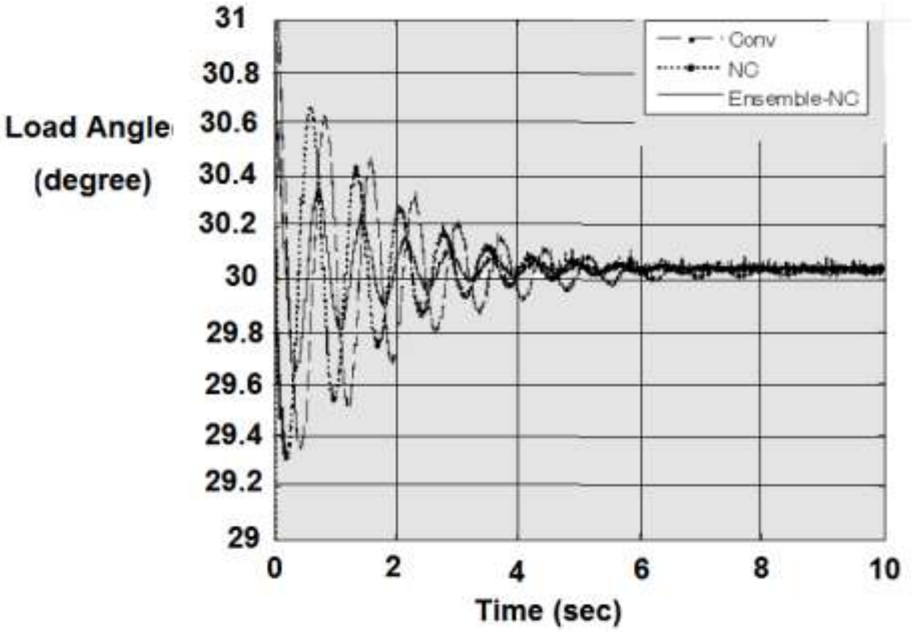

Figure 8. Load angle behavior:
(fault 90ms - load (0.004 + *j*0.007)

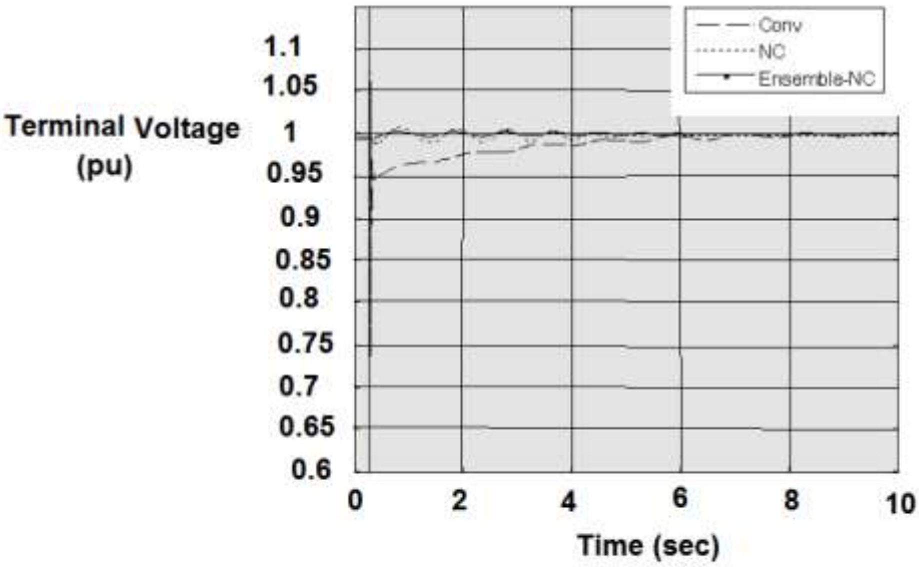

Figure 9. Terminal voltage
fault 90ms- load (0:007 + *j*0:004)

6. Conclusion and Suggestion.

When using artificial intelligence methods and algorithms by incorporating a neuromorphic controller that relies on multiple algorithms in its operation, the power system's response to interference signals or sudden loads or unbalanced loads is remarkable. In the case we studied, stabilization occurred in less than 5 seconds, which is an ideal time for such systems.

The combined neural controller is superior to a traditional controller, reduces computational burden, features a simple loop control .
MLP algorithm also performs better when signal drift occurs.
We can improve the quality of results by incorporating dynamics systems into biologically inspired tness function optimization algorithms.
Currently, the field of dynamic artificial neural networks is more developed, and by comparing dynamic artificial neural networks with static artificial neural networks, we expect that dynamic artificial neural networks perform better than static artificial neural networks.

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