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Original article

Comparative Performance Evaluation of Feedback Error Learning and Adaptive Neuron-PI Controllers for Small-Signal Stability Enhancement in a Single-Machine Infinite-Bus Power System

Issa Ali*[1], Alyaseh Askir[2]

[1]*Department of Electric and Electronic Engineering, College of Science and Technology, 16328 Jadu, Libya*
[2]*Department of Chemistry, University of Zawia, 16418 Zawia, Libya*
Corresponding Email. *essali@cstj.edu.ly*

Abstract
Small-signal stability remains a fundamental challenge in the operation of modern power systems, particularly as grid complexity increases with the integration of highly dynamic power sources. Conventional Power System Stabilizers (CPSSs) have been widely adopted to improve damping performance; however, their effectiveness deteriorates when the operating conditions deviate from the design point. Consequently, intelligent adaptive control techniques have attracted significant attention owing to their ability to adjust controller parameters online in response to system dynamics. This paper presents a comprehensive comparative investigation of two intelligent adaptive control strategies, namely the Feedback Error Learning (FEL) controller and the Adaptive Neuron-Proportional-Integral (Neuron-PI) controller, for enhancing the small-signal stability of a Single-Machine Infinite-Bus (SMIB) power system. Unlike previous studies that investigated each controller independently, the proposed work evaluates both controllers under identical operating conditions, using the same SMIB model, disturbances, and simulation parameters to ensure a fair and objective comparison. The performance of both controllers is evaluated using MATLAB-SIMULINK 2025 software for multiple operating conditions. The simulation results demonstrate that the FEL controller exhibits superior adaptive learning characteristics and excellent robustness under varying operating conditions.
Keywords. Small-signal Stability, Single-machine Infinite-bus (SMIB), Heffron-Phillips Model, Feedback Error Learning (FEL), Adaptive Neuron-Pi, ADALINE Neural Network, Robust Control.

Introduction

The continuous expansion of modern electrical power systems, together with the increasing integration of renewable energy resources, power electronic converters, and long-distance transmission networks, has significantly increased the complexity of power system operation. Modern interconnected power systems are expected to operate closer to their stability limits to maximize the utilization of existing transmission infrastructure and satisfy the ever-growing electricity demand. Although operating near these limits improves economic efficiency, it simultaneously reduces system stability margins and increases the likelihood of electromechanical oscillations following small disturbances [1]. Consequently, maintaining adequate damping of low-frequency oscillations has become one of the most important challenges in power system operation and control. The Conventional Power System Stabilizer (CPSS) has traditionally been considered one of the most economical and effective solutions for enhancing damping [2, 3].

Although CPSSs have achieved considerable success in practical applications [4], their performance strongly depends on fixed controller parameters determined around a specific operating point. In practice, however, electrical power systems operate under continuously changing loading conditions, network topologies, and generation schedules. Consequently, a controller designed for one operating condition may exhibit degraded performance or even become ineffective under different operating scenarios. To overcome these limitations, numerous intelligent optimization and adaptive control techniques have been proposed during the last two decades. Artificial Neural Networks (ANNs), Fuzzy Logic Systems, Genetic Algorithms, Particle Swarm Optimization, Differential Evolution, Reinforcement Learning, and Adaptive Dynamic Programming have all been investigated for power system stabilization [5-9]. Among these techniques, ANN-based controllers have attracted considerable attention because of their nonlinear approximation capability, adaptive learning characteristics, and ability to operate without requiring an accurate mathematical model of the plant [10].

One of the earliest ANN-based adaptive approaches applied to control systems is the Feedback Error Learning (FEL) algorithm [11]. FEL combines a conventional feedback controller with a feedforward neural network that gradually learns the inverse dynamics of the controlled plant. During the learning process, the neural network continuously minimizes the feedback error until it becomes capable of generating the required control signal independently. This adaptive mechanism significantly improves transient response, robustness, and disturbance rejection while maintaining closed-loop stability. Recently, another ANN-based adaptive strategy, namely the Adaptive Neuron-Proportional-Derivative-Integral (Neuron-PID) controller, has been proposed for power system stabilization [12]. Instead of learning the inverse dynamics directly, the Neuron-PID controller employs an Adaptive Linear Neuron (ADALINE) network to continuously update the gains of a PID controller according to real-time operating conditions.

Compared with many optimization-based controllers that require extensive offline tuning using evolutionary algorithms, the Adaptive Neuron-PID controller offers a relatively simple implementation with only three adaptive parameters while maintaining excellent damping performance. Although both intelligent controllers have independently demonstrated

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promising performance, the available literature lacks a rigorous comparative evaluation performed under identical simulation conditions. Most existing studies focus on developing a single controller and comparing it only with the conventional PSS.

The primary objective of this paper is therefore to provide the first comprehensive comparative assessment of the Feedback Error Learning and Adaptive Neuron-PI controllers using a unified simulation platform based on the Single-Machine Infinite-Bus (SMIB) system. The Adaptive Neuron-PI approach, proposed by the authors of this article, A. Askir and I. Ali [13], introduces an innovative NEURON-PI controller that replaces the traditional PSS entirely by employing an Adaptive Linear Neuron (ADALINE) network to dynamically tune the Proportional-Integral (PI) controller parameters in real-time. The FEL scheme, presented by S. Nazlibilek, I. Ali, and A. Askir [14], which integrates an Artificial Neural Network (ANN) as a supplementary controller to enhance the existing CPSS. To ensure a fair comparison, both controllers are implemented using identical machine parameters, identical operating conditions, and the same evaluation criteria. The investigation includes dynamic performance analysis under both normal and heavy loading conditions, considering rotor speed deviation, power angle deviation, settling time, maximum overshoot, and steady-state error.

Comparative Overview

This study compared the results obtained in previous research using two different intelligent controllers, namely FEL and NEURON-PI [13, 14]. The intelligent controllers were tested on a Single-Machine Infinite-Bus (SMIB) power system at different operating points. Both controllers rely on the ADALINE network for efficient performance, but the difference lies in the fact that the network in the FEL strategy learns the inverse dynamics to minimize the output error of the entire system, while in NEURON-PI, the network acts as a parameter optimizer for the controller itself. (Figure 1) shows the Heffron-Phillips SMIB power system model used in the comparison process under the MATLAB-SIMULINK 2025 software.

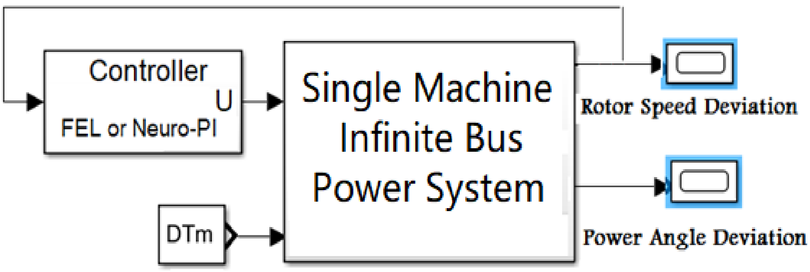

Figure 1. Power system model used in the comparison process

The Heffron-Phillips SMIB power system model remained unchanged throughout the study. Only the supplementary stabilizing controller was replaced to investigate the performance of the Feedback Error Learning (FEL) and Adaptive Neuron-PI controllers. To ensure consistency, the following conditions were maintained throughout all simulation scenarios: identical Heffron-Phillips SMIB model, identical simulation time, identical numerical solver configuration, identical disturbance magnitude, identical operating conditions, and the same controller input signal (rotor speed deviation). All system parameters, as well as the operating points used in the simulation process, are listed in the table provided in Appendix A [13].

The Feedback Error Learning (FEL)

The FEL based control scheme proposed in 2021 [14] operates on the principle of biological motor control, where an inverse model of the plant is learned online. The ANN-based FEL acts as a supplementary stabilizer, as shown in (Figure 2).

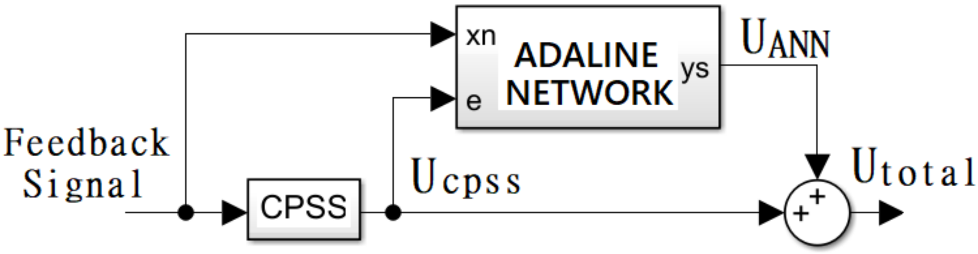

Figure 2. Feedback Error Learning Control

The overall control signal U_{total} is the sum of the fixed-gain CPSS output and the ANN adaptive signal:

$$Utotal(t) = U_{CPSS}(t) + U_{ANN}(t) \quad (1)$$

Unlike optimization-based methods that require offline parameter tuning, the FEL controller performs online learning throughout system operation. Initially, the conventional feedback controller is responsible for maintaining system stability while the neural network gradually learns the required control action. As learning progresses, the neural network

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increasingly compensates for system nonlinearities and disturbances, reducing the control effort required from the feedback controller. More details about the FEL controller can be found in [14].

The NEURON-PI Adaptive Control Framework

In contrast, the NEURON-PI approach introduced in 2026 [13], represents a paradigm shift from augmentation to integration. Instead of adding a supplementary signal, the ADALINE network is employed to modify the internal gains (Kp, Ki) of a standard PI controller as shown in (Figure 3).

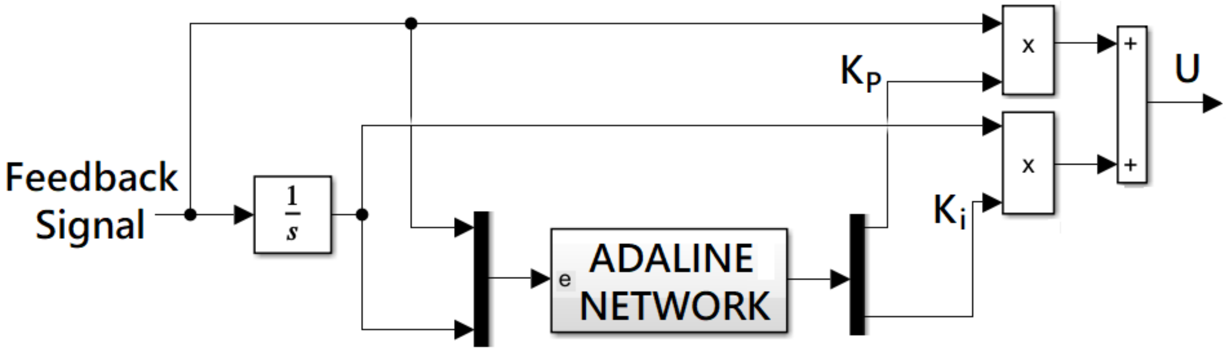

Figure 3. NEURON-PI controller

The control law is defined by:

$$u(t) = Kp(e,t)e(t) + Ki(e,t)\int e(t)dt \qquad (2)$$

By reducing the tunable parameters from six (as in the lead-lag PSS) to only two, this model significantly alleviates the "curse of dimensionality" and enhances computational convergence. The Adaptive Neuron-Proportional-Integral (Neuron-PI) controller combines the simplicity of the classical PI controller with the online adaptation capability of artificial neural networks. Unlike the FEL controller, which attempts to learn the inverse dynamics of the plant, the Adaptive Neuron-PI controller continuously adjusts the proportional and integral gains of a PI controller according to the instantaneous operating condition. More details about the used NEURON-PI control strategy and ADALINE neural network can be found in [13].

Results and Discussion

Performance Analysis under Normal Load Conditions

In this scenario, a +2% step change in mechanical torque (ΔTm) was applied to the SMIB system. Both the FEL and NEURON-PI controllers demonstrated the ability to damp electromechanical oscillations effectively. However, the transient response profiles reveal distinct behavioral patterns whether in rotor speed deviation and power angle deviation. As shown in (Figure 4) and (Figure 5), the FEL controller exhibits a more aggressive damping characteristic.

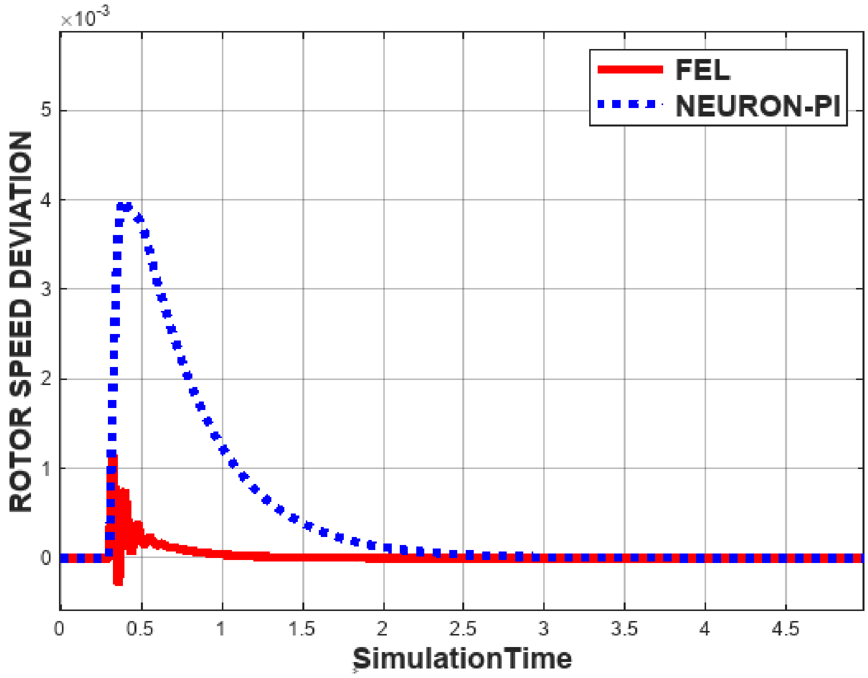

Figure 4. Rotor speed dev. due to a +2% step change in ΔTm for normal load

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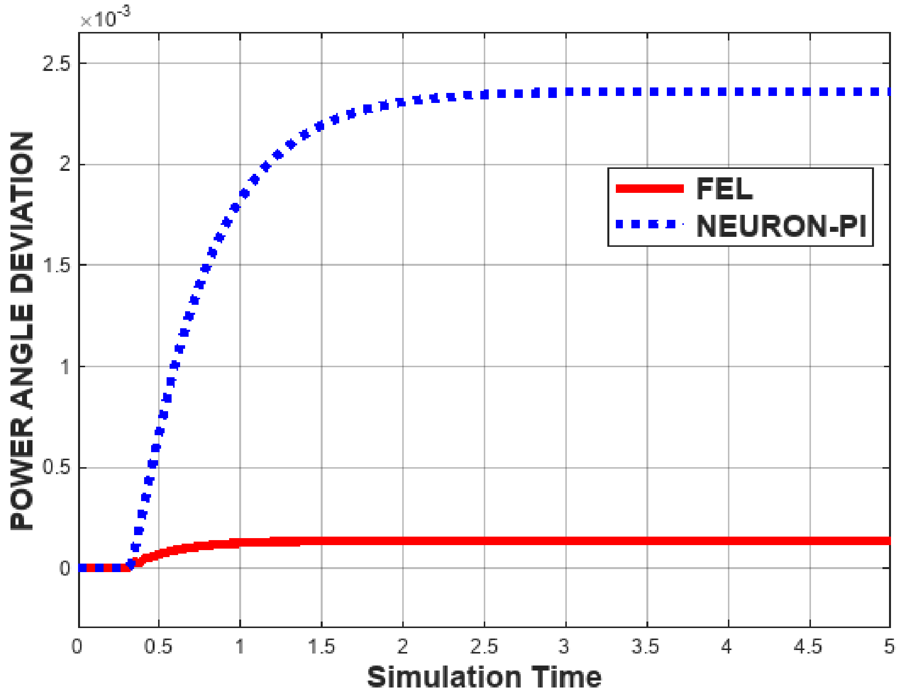

Figure.5. Power angle dev. due to a +2% step change in ΔTm for normal load

The overshoot for the FEL controller was recorded at [1.2 x 10^{-3}] p.u. for rotor speed deviation and [0.2 x 10^{-3}] p.u. for power angle deviation, compared to [3.9 x 10^{-3}] p.u. and [2.4 x 10^{-3}] p.u. for the NEURON-PI controller. This reduction in overshoot indicates that the additive signal approach of the FEL provides a more precise damping torque than the adaptive tuning of the PI parameters. Furthermore, the settling time was improved from [2.6] s for rotor speed dev. and [2.5] s for power angle dev. using (NEURON-PI) to [0.9] s and [1.3] s using (FEL), signifying a faster return to steady-state operations.

Performance Analysis under Heavy Load Conditions

The heavy load condition represents a severe test of controller robustness due to the increased non-linearity of the system's power angle characteristics. Under this condition, the performance gap between the two controllers widens, favoring the augmentative FEL intelligent control. Again, (Figure 6 and Figure 7), demonstrate the superiority of the control FEL controller.

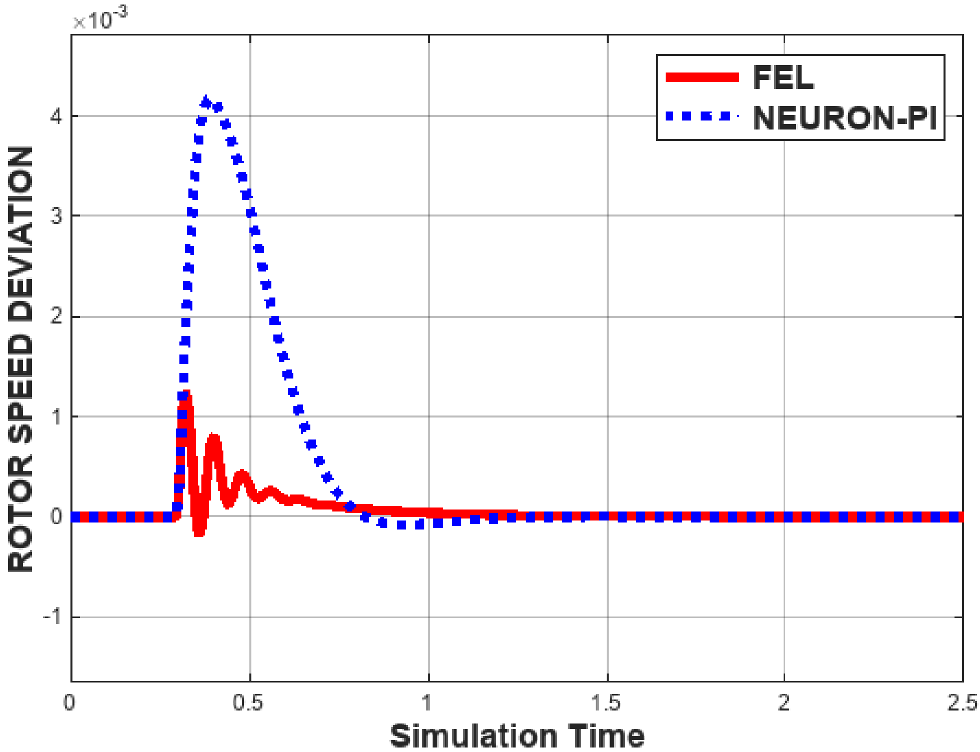

Figure 6. Rotor speed dev. due to a +2% step change in ΔTm for heavy load

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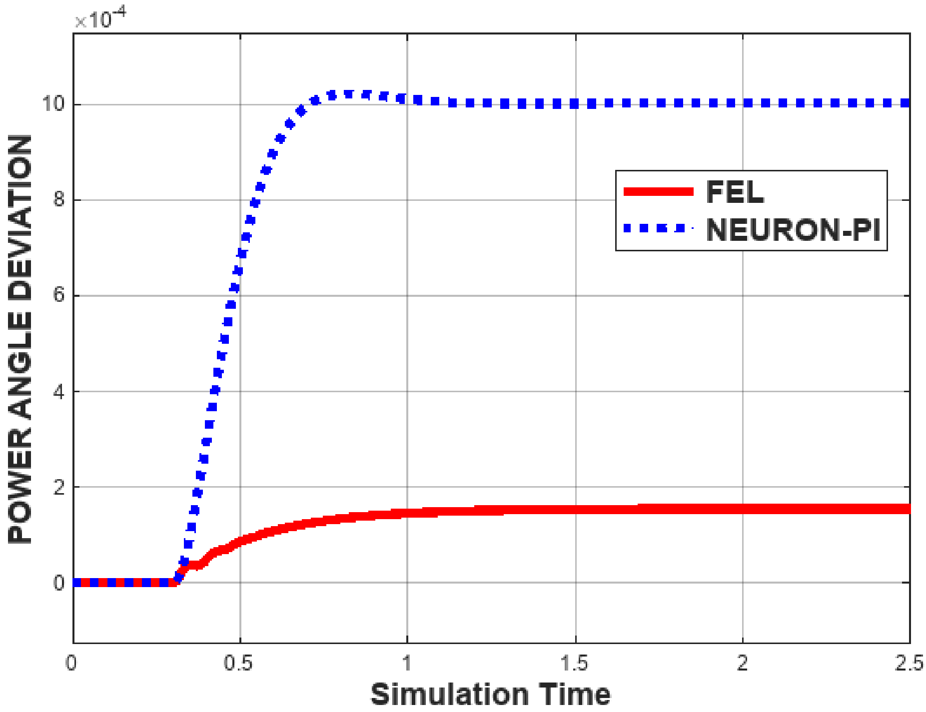

Figure 7. Power angle dev. due to a +2% step change in ΔTm for heavy load

While the NEURON-PI approach maintains stability, the settling process displays higher overshoot. Conversely, the FEL controller maintains a highly stable profile, effectively minimizing the impact of the +2% ΔT_m disturbance. The quantitative analysis depicted in (Table 1) confirms that the FEL controller achieved a [21.4] % reduction in settling time compared to the NEURON-PI approach.

Table 1. Numerical Comparison of Rotor Speed Deviation due to +2% change in ΔT_m

Load Condition	Controller Type	Overshoot (p.u.)	Settling Time (s)
Normal Load	FEL	1.2×10^{-3}	0.9
	NEURON-PI	3.9×10^{-3}	2.6
Heavy Load	FEL	1.25×10^{-3}	1.1
	NEURON-PI	4.2×10^{-3}	1.4

Conclusion

This paper presented a comprehensive comparative evaluation of two adaptive intelligent control strategies, namely the Feedback Error Learning (FEL) controller and the Adaptive Neuron-Proportional-Integral (Neuron-PI) controller, for enhancing the small-signal stability of a Single-Machine Infinite-Bus (SMIB) power system. Unlike previous investigations that evaluated each controller independently, both controllers were implemented within the same simulation environment using identical system parameters, operating conditions, and disturbance scenarios. This unified framework ensured a fair and objective assessment of their dynamic performance. Simulations were conducted under both normal and heavy loading conditions by applying a +2% step increase in the mechanical input torque. The transient responses of rotor speed deviation and power angle deviation were analyzed to evaluate the effectiveness of each controller in suppressing electromechanical oscillations. In addition to the graphical responses, some quantitative performance indices were measured, including maximum overshoot and settling time. The obtained results demonstrate that the adaptive learning mechanisms employed by the FEL and Adaptive Neuron-PI controllers enable continuous adjustment of the control signal according to the instantaneous operating conditions, thereby improving damping performance and reducing transient oscillations under both loading scenarios. The comparative analysis highlights the distinctive characteristics of each controller. The FEL controller provides superior nonlinear learning capability through its adaptive feedforward mechanism, making it particularly suitable for operating conditions characterized by significant parameter variations and nonlinear system behavior. In contrast, the Adaptive Neuron-PI controller achieves comparable damping performance using a simpler control structure with lower computational complexity, making it attractive for practical real-time implementation. From an engineering perspective, the selection of the most appropriate controller depends on the intended application. Systems requiring maximum robustness and adaptive capability may benefit from the FEL controller, whereas applications emphasizing implementation simplicity, computational efficiency, and ease of integration may favor the Adaptive Neuron-PI controller.

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APPENDIX A.

PARAMETERS of SMIB-POWER SYSTEM AND PSS:

Component	Parameters					
Generator & Exciter	H	D	T_{do}	ωe	Ka	Ta
	3.5	0	7.23	314	200	0.2
Loading Point	K1	K2	K3	K4	K5	K6
Normal Load	0.760	0.860	0.320	1.420	0.150	0.420
Heavy Load	1.635	0.842	0.360	1.077	-0.032	0.521
Conventional Stabilizer	Ks	Tw	T1	T2	T3	T4
	9.47	1.53	0.43	0.81	1.01	0.35

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