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Research on the Application of Artificial Neural Networks for Voltage Stabilization of Synchronous Generators in Power Systems

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ABSTRACT: Currently, a variety of control methods have been employed to enhance voltage stability performance, including logic control circuits, conventional PID controllers, integrated control systems, and advanced control techniques such as fuzzy control, neural control, and adaptive control. Among these, fuzzy control-based on fuzzy logic theory-has demonstrated significant application potential due to its high adaptability, robustness, good stability, ease of design, and straightforward tuning [1].
Artificial neural networks (ANNs), with their powerful learning and adaptive capabilities, are well-suited to managing the dynamic operating conditions of power systems. By adjusting control parameters in real time, ANNs contribute to optimizing voltage stability [2].
In order to improve control performance, reduce voltage oscillations, and enhance the overall stability of the power system, this study proposes the application of artificial neural networks for voltage stabilization of synchronous generators. This research leverages the notable advantages of neural networks-including self-learning, high adaptability, and efficient handling of nonlinear systems-to contribute to improving power quality [3, 4].
KEYWORDS: Power system; Voltage stability; Artificial neural network (ANN); Neural PID control; Power quality improvement.

I. INTRODUCTION

According to IEEE/CIGRE, the concept of voltage stability refers to the power system's ability to maintain acceptable voltage levels at all buses following a disturbance from the initial operating condition. This level of stability depends on the system's capability to supply sufficient power to the load through both generation sources and the transmission network [9].

With the continuous development of society and the improvement in living standards, the demand for modern electrical machines is steadily increasing. The growing scale and rapid expansion of industrial and agricultural sectors require the power industry to make corresponding advancements. In this context, synchronous generators play a vital role in power systems, particularly in ensuring voltage stability. To maintain terminal voltage within acceptable limits, the use of voltage stabilization devices becomes essential for effective voltage regulation and control [5, 6].

The application of neural networks in this study is considered a modern control solution to address the voltage stability problem of generators operating in complex, multi-node power systems. Implementing control techniques based on neural networks not only expands their applicability in the energy sector but also provides a more effective approach for voltage regulation in systems characterized by strong nonlinearity and time-varying loads [7, 8].

A notable feature of this approach lies in the online training of the neural network's weights, which does not rely on traditional optimization techniques such as gradient descent or backpropagation. Instead, weight updates are entirely governed by stability conditions established through the Lyapunov function. This approach is particularly well-suited for highly nonlinear systems with significant uncertainties, offering substantial improvements in the design of adaptive nonlinear controllers.

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II. AUTOMATIC VOLTAGE REGULATOR (AVR)

Nowadays, modern excitation systems are typically composed of an AC generator combined with a rotating rectifier, collectively referred to as a **brushless excitation system**. Variations in active power primarily affect the system frequency, while changes in reactive power are mainly influenced by the voltage amplitude. The interaction between voltage and frequency in control processes is minimal. This allows the two control systems to be analyzed independently of each other [4].

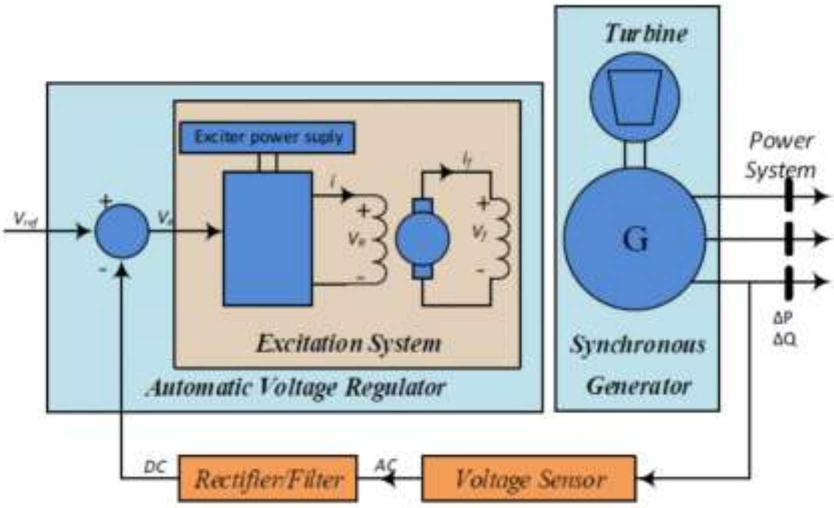

Figure 1. Block diagram of the Automatic Voltage Regulator (AVR) [5].

Reactive power in the power grid is primarily generated by synchronous generators and capacitor banks. In a synchronous generator, reactive power is controlled through the excitation field flux. Voltage in the power network is also supported via transmission system components such as on-load tap changers in transformers, capacitor switching, voltage stabilizers, and static VAR control equipment.

In synchronous generators, reactive power is regulated by the Automatic Voltage Regulator (AVR) system. The fundamental function of the AVR is to maintain the generator terminal voltage at a predefined setpoint. The operating principle of the AVR is illustrated in Figure 1.

The voltage sensing block is also represented by a mathematical model; the measuring device used here is a voltage transformer (TU). The voltage output from the TU is then fed into a bridge rectifier. The simplest transfer function of this block is described as follows: $\frac{V_S(s)}{V_t(s)} = \frac{K_s}{1+\tau_s S}$ (1)

With all the components described, the block diagram of an AVR system is illustrated in Figure 2.

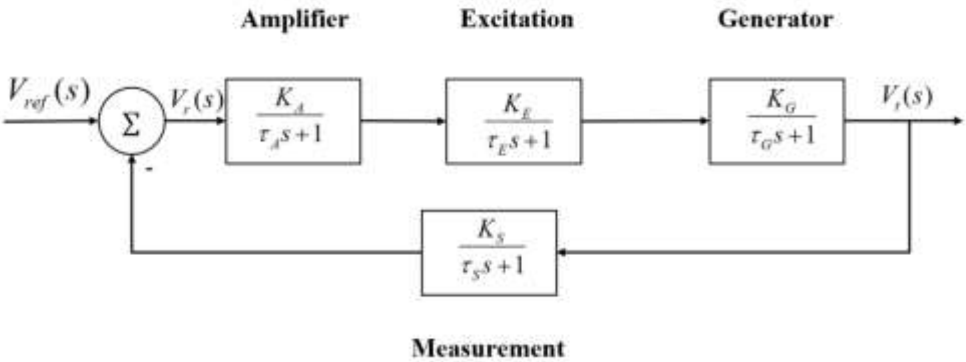

Figure 2. Block diagram of the AVR system

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The open-loop transfer function of the AVR system, derived from the block diagram in Figure 2, is expressed as follows:

$$AG(S)H(S) = \frac{K_A K_E K_G K_S}{(1+\tau_A S)(1+\tau_E S)(1+\tau_G S)(1+\tau_S S)} \quad (2)$$

The closed-loop transfer function, which represents the relationship between the output voltage V_t and the reference voltage Vref, is given by:

$$\frac{V_t(S)}{V_{ref}(S)} = \frac{K_A K_E K_G (1+\tau_S S)}{(1+\tau_A S)(1+\tau_E S)(1+\tau_G S)(1+\tau_S S)+K_A K_E K_G K_S} \quad (3)$$

If the input reference voltage has the form $V_{ref}(S) = \frac{1}{s}$, then the steady-state response of the output voltage is determined as follows:

$$V_{tss} = \lim_{s\to 0} sV_t(S) = \frac{K_A}{1+K_A} \quad (4)$$

Adding a PID Controller to the Excitation System: PID is one of the most widely used controllers today. The PID controller is applied to improve dynamic response and eliminate steady-state error. The transfer function of the PID controller is given by:

$$G_{PID\,(S)} = K_P + \frac{K_i}{s} + K_D s \quad (5)$$

Accordingly, the updated block diagram of the AVR system incorporating the PID controller I shown in Figure 3**.**

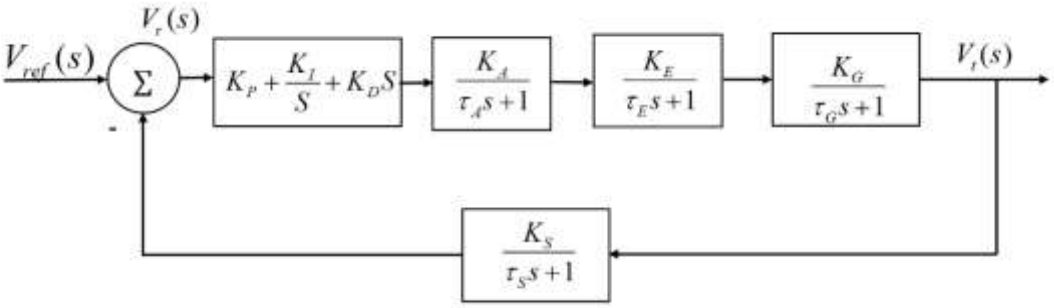

Figure 3. Block diagram of the AVR system with PID controller

Training a neural network to determine the PID (Proportional–Integral–Derivative) parameters for stabilizing the voltage of a synchronous generator is a modern approach in intelligent control. The objective is to identify the optimal PID parameters that ensure the most stable output voltage when the generator is subjected to load variations, disturbances, or other operating conditions.

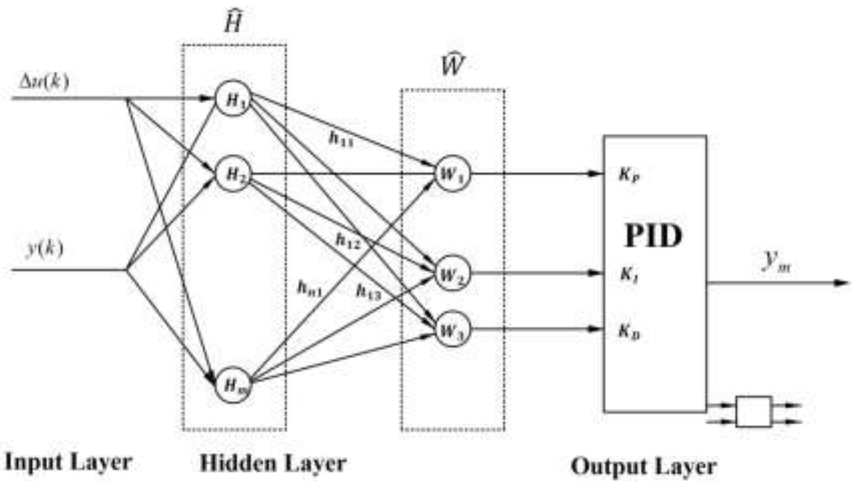

Figure 4. Structure of the RBF neural network

In the Radial Basis Function (RBF) neural network structure, the input vector is $X = [x_1, x_2, \ldots, x_n]^T$ and the RBF vector is assumed to be $H = [h_1, h_2, \ldots, h_m]^T$, where h_j is the Gaussian function, defined by the following mathematical relationship.

$$h_j = exp\left[-\frac{\|x-c_j\|^2}{2b_j^2}\right], j = 1,2,..m \quad (6)$$

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The center of the basis functions at node$j$is $C_j = [c_{j1}, c_{j2}, \ldots, c_{ji}, \ldots . c_{jn}]^T, i = 1,2, \ldots, n,$ where $b_j$is the spread of the basis function for node $j$and $b_j > 0$. The weight vector of the network is $W = [w_1, w_2, \ldots, w_m]^T$. The total weight of the RBF neural network is calculated as follows.

$y_m(k) = W^T h = w_1 h_1 + w_2 h_2 + \ldots + w_m h_m$(7)

The weights of the network are updated based on the least squares error minimization, as presented in Equation (10).

$E(k) = \frac{1}{2}\left(y(k) - y_m(k)\right)^2$ (8)

Here,$y(k)$is the system output at the k-th time step.

Using the Gradient Descent algorithm, the variation in the output weights$\Delta w_j(k)$between the basis function node and the center node, Δc_{ji}, is calculated as follows.

$\Delta w_j(k) = \eta\left(y(k) - y_m(k)\right)h_j$ (9)

$w_j(k) = w_j(k-1) - \Delta w_j(k) + \alpha\left(w_j(k-1) - w_j(k-2)\right)$ (10)

$\Delta b_j(k) = \eta\left(y(k) - y_m(k)\right)w_j h_j \frac{\|X - C_j\|^2}{b_1^3}$(11)

$b_j(k) = b_j(k-1) + \Delta b_j + \alpha\left(b_j(k-1)\right) - b_j(k-2)$ (12)

$\Delta c_{ji}(k) = \eta\left(y(k)\right) - y_m(k) w_j \frac{x_j - c_{ji}}{b_j^2}$ (13)

$c_{ji}(k) = c_{ji}(k-1) + \Delta c_{ji} + \alpha\left(c_{ji}(k-1)\right) - c_{ji}(k-2)$ (14)

Here, $\alpha$is the learning rate, and$\eta$is the momentum coefficient. The Jacobian is calculated based on (15) [6].

$\frac{\partial y(k)}{\partial \Delta u(k)} \approx \frac{\partial y_m(k)}{\partial \Delta u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{ji} - x_i}{b_j^2}$ (15)

Where $x_1 = \Delta u(k)$

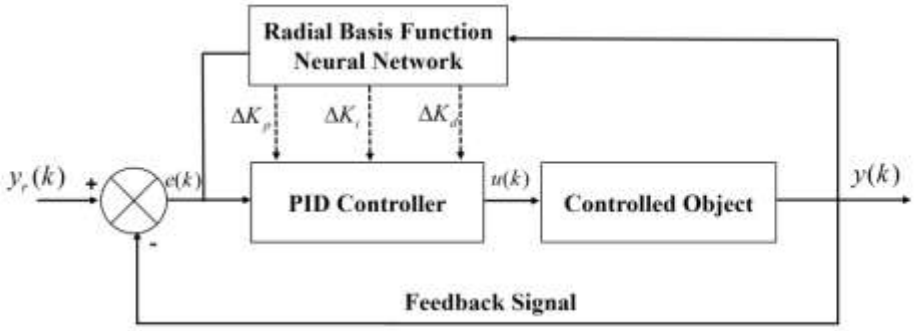

Figure 5. Neural network-based PID controller optimization model

The input error of the PID controller is defined as (16).

$e(k) = y_r(k) - y(k)$ (16)

The three inputs of the PID controller are determined by the following equations.

$xc(1) = e(k) - e(k-1)$ (17)

$xc(2) = e(k)$ (18)

$xc(3) = e(k) - 2e(k-1) + e(k-2)$(19)

The output variation of the PID controller is defined as

$\Delta u(k) = K_p[e(k) - e(k-1)] + K_i e(k) + K_d[e(k) - 2e(k-1) + e(k-2)]$(20)

$E(k) = \frac{1}{2}e(k)^2$ (21)

The PID controller parameters are updated using the Gradient Descent method with the following equations.

$$AK_p = -\eta\frac{\partial E}{\partial K_p} - \eta\frac{\partial E}{\partial y}\frac{\partial y}{\partial \Delta u}\frac{\partial \Delta u}{\partial K_p} = \eta e(k)\frac{\partial y}{\partial \Delta u}xc(1) \quad (22)$$

$$\Delta K_i = -\eta\frac{\partial E}{\partial K_i} = -\eta\frac{\partial E}{\partial y}\frac{\partial y}{\partial \Delta u}\frac{\partial \Delta u}{\partial K_i} = \eta e(k)\frac{\partial y}{\partial \Delta u}xc(2) \quad (23)$$

$$\Delta K_d = -\eta\frac{\partial E}{\partial K_d} = -\eta\frac{\partial E}{\partial y}\frac{\partial y}{\partial \Delta u}\frac{\partial \Delta u}{\partial K_d} = \eta e(k)\frac{\partial y}{\partial \Delta u}xc(3) \quad (24)$$

Here,$\frac{\partial y}{\partial \Delta u}$represents the Jacobian information of the controller, determined by the RBF neural network.

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III. SIMULATION AND EXPERIMENTAL RESULTS

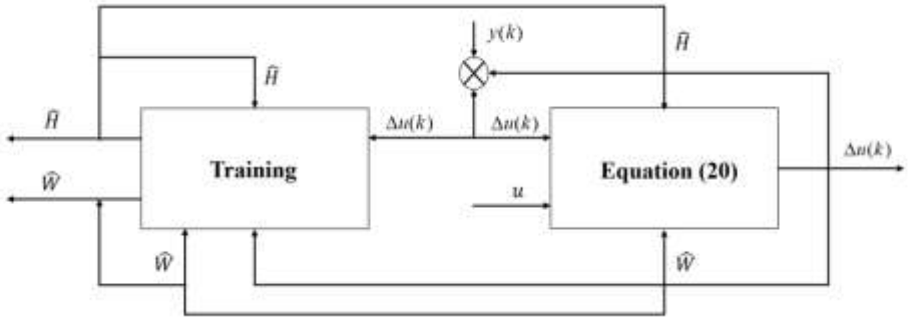

Figure 6. Neural network training structure

The simulation diagram using a conventional PID controller and an RBF neural network-based PID controller is shown in Figure 6. This diagram was designed using MATLAB/Simulink.

The two-layer radial basis neural network employs a large number of output-layer linear neurons to enhance convergence. The input layer consists of K_p, K_i and K_d to estimate parameters and optimize the neural network weights, which are then applied to Equation (3.16) to declare the PID controller parameters as per the structure in Figure 6.

The RBF neural network algorithm was designed using MATLAB's built-in optimization tool. During the simulation, the conventional PID controller model used predefined parameters and . The RBF neural network-based PID controller was trained using the Gradient Descent algorithm to update the parameters . Figure 7 compares the conventional PID controller and the RBF neural network-based PID controller.

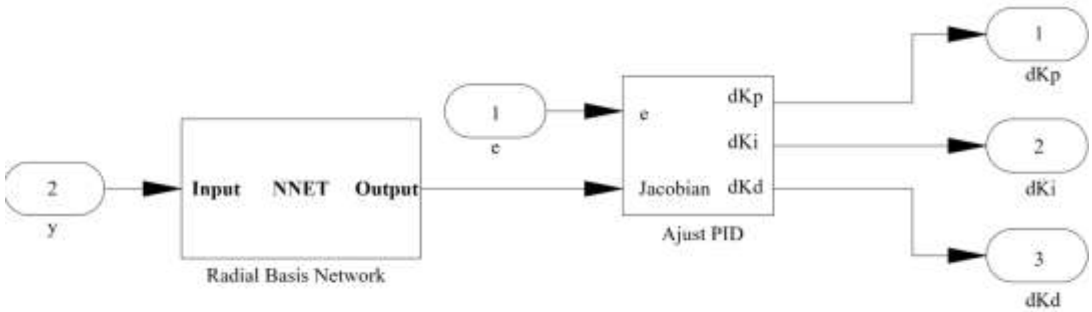

Figure 7. Neural network-based PID parameter structure

The outer control loop was designed as a self-tuning PID voltage controller, utilizing the RBF neural network to enhance adaptability to uncertain load changes and varying system conditions.

Moody and colleagues proposed a two-layer RBF neural network architecture, featuring a single hidden layer, to simulate systematic human decision-making in handling constrained control conditions.

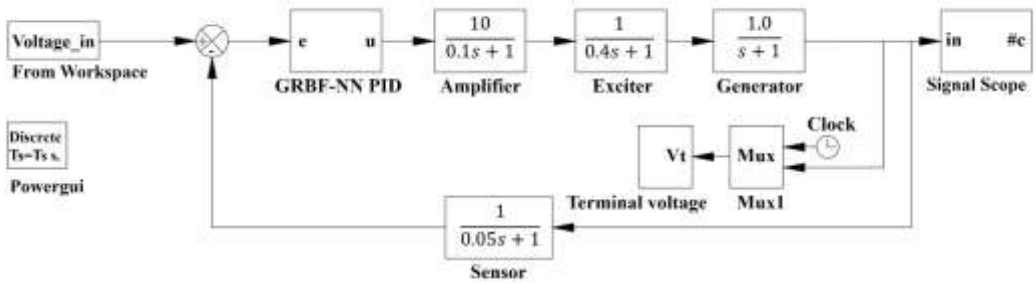

Figure 8. Block diagram of voltage stabilization using a neural network

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The Gaussian kernel function in the RBF neural network allows each node in the hidden layer to act as a local detector in the input data space. This characteristic enables the RBF neural network to serve as a local estimator, making it highly suitable for controlling complex processes.

A notable advantage of the RBF network is that it does not require special input data distributions, ensuring flexibility across diverse applications. Additionally, the RBF network supports online learning and rapid convergence, making it ideal for real-time control systems.

In control applications, the RBF neural network is used to determine optimal controller parameters, minimizing the system's control error.

Simulation Results with the Neural Network Controller

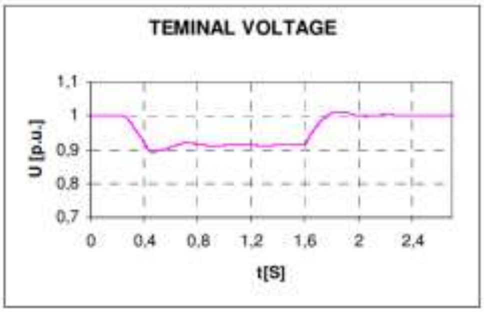

Figure 9. Voltage stabilization of the generator using the neural network controller

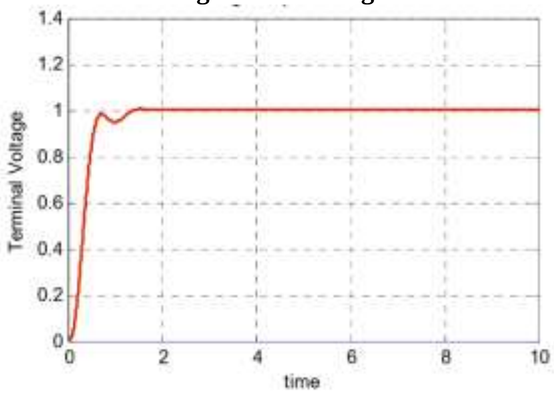

Figure 10. Terminal voltage characteristics of the generator with the neural network controller

Figure 10 illustrates the generator voltage and active power parameters for the neural network control structure, demonstrating stability. The stabilizing effect of the modified error function was simulated, with the generator operating at 0.5 p.u. and 0.8 p.u. active power. The results are shown in Figures 11 and 12

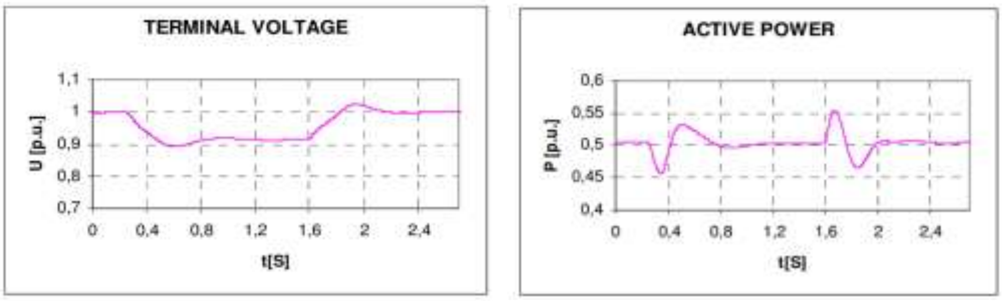

Figure 11. Voltage response under 0.5 p.u. load power variation

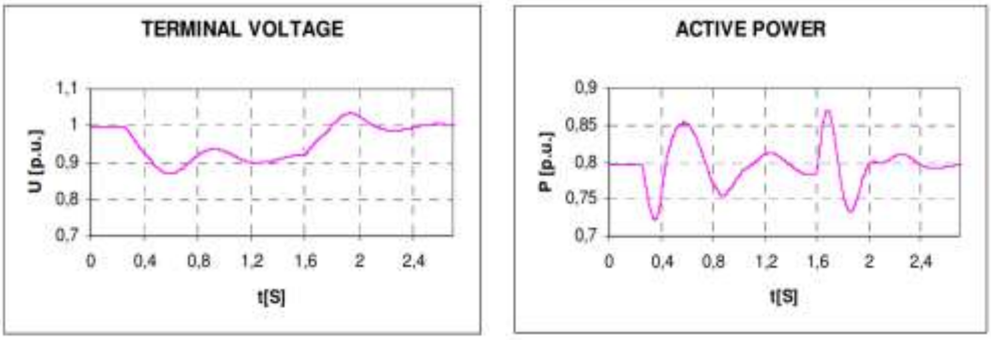

Figure 12. Voltage response under 0.8 p.u. load power variation

The neural network-based excitation control system was implemented for a grid-connected synchronous generator and simulated in MATLAB/Simulink. During online training, a backpropagation algorithm with a modified error function was employed to enhance learning efficiency.

The neural network was trained using sampled input and output data from the synchronous generator, eliminating the need for full system state identification. The simulation results demonstrate that the neural network's stabilizing effect significantly reduces voltage oscillations and improves terminal voltage control quality.

IV. CONCLUSIONS

This paper addresses theoretical aspects of automatic voltage stabilization systems for synchronous generators. The simulations yielded promising results. However, the study was limited to a single grid-connected generator with a standalone artificial neural network controller. In practice, power plants often involve multiple interconnected generators. Therefore, further research is needed to develop controllers suitable for multi-generator systems in power grids. Future work will focus on more accurate modeling of large-scale power systems and applying advanced control methods to enhance stability and operational efficiency.
The preliminary findings open new prospects for intelligent controllers in grid frequency and power management, contributing to the optimization and improvement of modern power system operations.

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