

Neural Network -Based Control Systems

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Abstract - The rapid evolution of industrial automation and smart grid technology has exposed the inherent limitations of classical control theories. Standard Proportional-Integral-Derivative (PID) and Linear Quadratic Regulator (LQR) controllers rely heavily on precise mathematical modelling and the assumption of linearity. However, most electrical "plants"—including Induction Motors (IM), Permanent Magnet Synchronous Motors (PMSM), and Power Electronic Converters—are characterized by high-degree nonlinearities, magnetic saturation, and time-varying parameters such as temperature-dependent resistance shifts.

This seminar explores the integration of Neurological Network-Based Control Systems (NNBCS) as a robust, data-driven alternative to conventional modelling. By leveraging the universal approximation capabilities of Artificial Neural Networks (ANNs), these systems can identify and compensate for unmodeled dynamics without an explicit transfer function $G(s)$. The report focuses on three primary architectural implementations: Neural System Identification, where the network creates a "digital twin" of the plant; Neuro-Adaptive PID Control, where the NN dynamically tunes controller gains to eliminate overshoot; and Direct Inverse Control, where the network learns the inverse physics of the electrical drive to provide high-precision trajectory tracking.

Specific attention is given to the application of these networks in Power Electronics and Machine Drives. Case studies presented include Sensor less Speed Control of asynchronous machines, where NNs estimate rotor position from stator current/voltage, and Maximum Power Point Tracking (MPPT) in Photovoltaic (PV) systems, where neural algorithms significantly reduce settling time compared to traditional "Perturb and Observe" methods. Furthermore, the abstract addresses the role of NNBCS in improving Power Quality through the real-time estimation and cancellation of Total Harmonic Distortion (THD) using Active Power Filters. Despite the superior performance in handling nonlinearities, the transition to NN-based control faces challenges regarding computational latency and formal stability verification (the "Black Box" problem). The

report concludes by evaluating implementation strategies using high-speed hardware such as Digital Signal Processors (DSPs) and Field Programmable Gate Arrays (FPGAs), highlighting the future shift toward Edge AI in self-optimizing electrical infrastructure and resilient smart grids.

Key Words: Artificial Neural Networks (ANN), Nonlinear Control, Power Electronics, Induction Motor Drives, System Identification, Adaptive Control, Smart Grids.

1.INTRODUCTION

The landscape of modern industrial automation and electrical power systems is undergoing a paradigm shift. For decades, the cornerstone of electrical control has been the **Proportional-Integral-Derivative (PID)** controller, valued for its simplicity and reliability. However, as we push toward higher efficiency in Electric Vehicles (EVs), renewable energy integration, and high-precision robotics, the limitations of these classical methods have become a significant bottleneck.

The Problem: Nonlinearity and Uncertainty

Most electrical "plants"—whether they are induction motors, DC-DC converters, or complex smart grids—are inherently **nonlinear**. In a laboratory setting, we often simplify these systems using linear transfer functions $G(s)$. In the real world, however, these systems are plagued by:

- **Magnetic Saturation:** Where the relationship between current and flux is no longer proportional.
- **Thermal Parameter Drift:** As an induction motor heats up, its internal resistance changes, rendering fixed PID gains inaccurate.
- **Hysteresis and Friction:** Nonlinear losses that are difficult to model mathematically.

The Solution: Neural Network-Based Control Systems (NNBCS)

Neurological Network-Based Control Systems offer a revolutionary alternative by shifting the focus from "modelling" to "learning." Instead of requiring a physicist to write complex differential equations for every component, a Neural Network (NN) acts as a **Universal Approximator**. It observes the input (sensor data) and the output (system response) and "learns" the internal dynamics of the plant through iterative training.

In an electrical context, the NN replaces or augments the classical controller. It can predict potential instabilities and adjust the **Pulse Width Modulation (PWM)** signals in microseconds. This results in "smarter" hardware that adapts to its environment, ensuring that a motor runs efficiently even as its components age or temperatures fluctuate. This seminar explores how we bridge the gap between biological inspiration and electrical execution to create the next generation of resilient power systems

2. Architectural Framework for Electrical Plants

An NN-based controller in an electrical environment function through a synergy of sensing and execution:

- **Perception Layers (Sensing):** Instead of simple feedback, these layers process multi-modal data from Hall-effect current sensors, potential transformers (PTs), and encoders. They use architectures like LSTMs to filter noise and estimate the state of the grid or motor.
- **Control Layers (Processing):** The network generates optimal control signals. In modern drives, this often takes the form of an Adaptive Neuro-Fuzzy Inference System (ANFIS) or a Neural Policy that adjusts the duty cycle of a converter.
- **Execution (Power Stage):** The output of the NN is typically translated into Pulse Width Modulation (PWM) or Space Vector Modulation (SVM) signals to drive Power MOSFETs or IGBTs.

This block diagram is optimized for an electrical engineering seminar on NNBCS. It maps the neural network directly to electrical control hardware, showing how learning updates modify the control of an electrical plant.

Description of the Block Diagram

The diagram depicts a standard closed-loop control architecture, customized with an embedded on-line learning neural controller.

1. **Reference Input:** The system starts with the Desired Reference Input (θ_r), which is the goal value (e.g., a target motor speed or converter voltage). This is compared against the actual measured output from the plant at the initial Summing Junction.
2. **Error Signal $e(t)$:** The difference between the desired and actual output—the error $e(t)$ —is fed into the NNBCS Controller.
3. **NNBCS Controller:** This block is the heart of the system, comprising:
 - o **MLP Neural Network Controller:** It processes the error and generates an Adaptive Control Output. Crucially, it has "Synaptic Weights (W_1, W_2)" that are modified during operation.
 - o **Classical PID Controller (Optional):** In many hybrid designs, a baseline PID controller is included to ensure fundamental stability, while the NN optimizes performance around non-linearities. Their outputs are summed to form the final control signal $u(t)$.
4. **Signal Generation & Conversion:** The control signal $u(t)$ must be translated into electrical power signals. This is handled by:
 - o **PWM Generator:** Translates the continuous control output $u(t)$ into a digital Pulse Width Modulation signal.
 - o **Gate Driver:** Amplifies the PWM signal to the voltage/current levels required to trigger the power switches.
5. **Power Converter / Electrical Plant:** This section is the electrical plant to be controlled. The standard example provided is a full model:
 - o **IGBT Inverter:** Receives Firing Pulses and modulates the DC power source into a controlled variable AC or variable DC power.
 - o **DC Motor:** The schematic shows the physical component being driven by the inverter, featuring an Armature Resistance (R_a), Inductance (L_a), and Field Winding layout.
6. **System Output & Feedback:** The mechanical/electrical System Output (θ, ω) (e.g., position, speed) is measured and converted by the Feedback Sensor / Transducer and fed back to close the loop.
7. **On-Line Learning Mechanism:** The key differentiator: The current Plant Output is compared at a second summing junction with an Identifier Output (an internal estimate) to generate an Identification Error (e_{id}). This error is processed by the On-Line Learning Algorithm (e.g., Backpropagation), which directly updates the Weights (W, b) inside the NN controller block.

This on-line adaptation loop is what allows the neural controller to constantly learn the changing dynamics of the motor (such as R_a changing with temperature), keeping the control optimal without manual retuning.

3. Mathematical Foundation

For an electrical engineer, the artificial neuron is essentially a multi-input, nonlinear summer:

$$y = f\left(\sum_{i=1}^n w_i x_i + b\right)$$

Where w_i (weights) act as adjustable gains, b is the bias, and f is the activation function (mimicking the saturation of an operational amplifier).

4. Electrical Branch Applications

A. Speed Control of Induction Motors (IM)

IMs are highly coupled and nonlinear. A Neural Network can be trained to learn the "Inverse Dynamics" of the motor. It monitors stator current and voltage to provide Sensorless Control, estimating rotor speed accurately without the need for a physical tachometer.

B. Maximum Power Point Tracking (MPPT) in Solar PV
Traditional MPPT methods like "Perturb and Observe" are slow and oscillate around the peak. An NN-based controller can process instantaneous solar irradiance and temperature to jump directly to the optimal operating voltage, significantly increasing efficiency.

C. Power Quality and Active Power Filters (APF)
Nonlinear loads (like VFDs and computers) inject harmonics into the grid. A Neural Network can "learn" the harmonic profile and generate a compensatory current in real-time to cancel out Total Harmonic Distortion (THD), ensuring a pure 50/60 Hz sine wave.

5. Comparison: Classical vs. Neural Control

Feature	Classical Control (PID/LQR)	NN-Based Control
Model Dependency	High (Requires $G(s)$)	Low (Learns from I/O data)
Nonlinearity	Poor (Fixed gains)	Superior (Handles saturation)
Adaptability	Rigid	Real-time weight updates
Hardware	Analog Op-Amps / MCU	DSPs / FPGAs / Edge AI chips

6. Challenges and Future Scope

- The "Black Box" Problem: It is mathematically difficult to guarantee the stability of an NN controller under all fault conditions.

- Computational Latency: High-speed switching (above 20 kHz) requires powerful hardware like FPGAs to process neural layers within microseconds.
- Edge AI: The future involves embedding neural controllers directly into "Smart Power Modules" (SPMs) to predict component failure before it occurs.

7. CONCLUSIONS

Neural network-based control represents the next evolution in electrical engineering. By moving from reactive PID logic to predictive "learned" logic, we can create smarter power grids, more efficient electric vehicles, and resilient industrial automation systems.

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The heading should be treated as a 3rd level heading and should not be assigned a number.

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