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Neural Networks in Electrical and Computer Engineering: A Comprehensive Review

May Abdulsamad Sadeq, Mustafa Ali Abdulhadi [2]
1 electrical and computer engineering, Anbar University

2 electrical engineering, Babylon University

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ABSTRACT

Artificial Neural Networks (ANNs) have evolved into the core technology of electrical, computer, and industrial engineering, providing potent tools for intelligent modelling, optimization, prediction, as well as autonomous decision-making. Their ability to estimate very nonlinear and dynamic systems with data-driven learning and adaptability has allowed engineers to overcome most of the limitations that are related to the traditional analytical and mathematical methods. With modern engineering systems growing more complex due to the emergence of smart grids, interconnected embedded devices, industrial automation and extensive communication networks, the scope of neural networks (NNs) has grown exponentially. This review gives a detailed and structured review of the technologies of the NN in terms of engineering. It starts with the theoretical background of neural computation, learning algorithms, and activation functions and then goes further by exploring some of the most significant architectures, including multilayer perceptrons (MLPs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and advanced deep learning models. The review identifies the use of these architectures in different engineering fields, such as stability assessment of power systems, prediction of loads and renewable energy, fault detection in electrical machine, signal and image processing, embedded AI in microcontrollers, robotic control of industries, and intelligent wireless communication systems. Moreover, the current issues that ANN deployment faces, including the requirement of large annotated datasets, computational intensity, model interpretability, training stability, energy consumption, and hardware implementation limits in embedded and real-time applications are discussed in the paper. New research areas, including neuromorphic hardware, edge-AI acceleration, hybrid neuro-fuzzy system, reinforcement learning-based control and AI-controlled autonomous industrial production are also discussed to indicate future directions.

Corresponding Author:

May Abdulsamad Sadeq
Department of electrical and computer engineering, Anbar University
Anbar, Iraq
Email: may.abdulsamad@uoanbar.edu.iq

1. INTRODUCTION

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, consisting of interconnected processing units (neurons) that learn input–output relationships from data rather than explicit analytical equations. Over the last decades, ANNs have evolved from simple perceptron models into deep architectures capable of handling vision, language, time-series, and control tasks at or beyond human performance in many domains. Electrical and computer engineering (ECE) has been deeply influenced by this progress. In electrical engineering, neural networks are used for load and price forecasting, renewable energy prediction, power system protection, condition monitoring of machines, and intelligent control of power electronic converters. In computer engineering, they power computer vision, embedded AI on microcontrollers and FPGAs, FPGA-based accelerators, and intelligent communication systems. This review paper focuses specifically on neural networks in electrical and computer engineering, rather than general AI. It aims to:

1.Summarize the theoretical foundations relevant to engineers;
2.Review major neural architectures used in ECE;
3.Survey applications in electrical and computer engineering with emphasis on recent trends;
4.Identify challenges and open research problems;
5.Highlight promising future directions.

2.THEORETICAL FOUNDATIONS OF NEURAL NETWORKS

2.1. Artificial Neuron and Network Model

An artificial neuron computes a weighted sum of its inputs, adds a bias term, and passes the result through a nonlinear activation function:

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

where xix_ixi are inputs, wiw_iwi are synaptic weights, bbb is the bias, and f(·)f(\cdot)f(·) is a nonlinear function such as the sigmoid, hyperbolic tangent, or rectified linear unit (ReLU).

The nonlinearity plays a significant role in allowing NNs to approximate complex nonlinear input output mappings; this is formalized by the universal approximation theorem. The neurons are organized in layers: an input layer, one or more hidden layers and an output layer. When information flows strictly forward from input to output, the model is called a feedforward neural network (FNN); when feedback connections exist, the model becomes recurrent.

2.2. Training and Optimization

Given a dataset {(x(k),t(k))}\{(x^{(k)}, t^{(k)})\}{(x(k),t(k))}, where x(k)x^{(k)}x(k) is the input and t(k)t^{(k)}t(k) the target, training aims to find weights and biases that minimize a loss function LLL, such as mean squared error (MSE) for regression or cross-entropy for classification. The standard training pipeline involves:

- Forward propagation to compute the network output;
- Loss evaluation comparing output and target;
- Backpropagation to compute gradients of the loss with respect to parameters;
- Gradient-based optimization (e.g., stochastic gradient descent, Adam) to update parameters.

Regularization, dropout, and batch normalization are commonly employed to reduce overfitting and stabilize deep network training.

2.3. Deep Learning and Representation Learning

Deep learning refers to neural networks with multiple hidden layers, which can automatically learn hierarchical feature representations from raw data. In ECE, deep models eliminate much of the manual feature engineering traditionally required in signal processing and control, allowing raw waveforms, images, or time-series to be fed directly into the network.

3.NEURAL NETWORK ARCHITECTURES IN ECE

A variety of neural architectures are employed in electrical and computer engineering applications.

3.1. Feedforward Neural Networks (FNNs)

FNNs or multilayer perceptrons (MLPs) are the simplest architecture, widely used for static regression and classification tasks such as load forecasting, parameter estimation, or mapping sensor inputs to control commands. They remain a baseline model in many engineering applications due to their conceptual simplicity and universal approximation capability.

3.2. Convolutional Neural Networks (CNNs)

CNNs exploit spatial locality via convolutional filters, originally developed for image processing. In ECE, they are employed in:

- Visual inspection and defect detection in manufacturing;
- Infrared and thermal image analysis in power equipment;
- Time–frequency representations of electrical signals (e.g., spectrograms, wavelet scalograms) for fault diagnosis and power-quality assessment.

1D CNNs are particularly effective for processing raw one-dimensional time-series, such as current, voltage, or vibration signals from rotating machines.

3.3. Recurrent Neural Networks (RNNs), LSTM, and GRU

RNNs are designed to model sequential data by maintaining an internal state. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks address the vanishing gradient problem, enabling learning of long-term dependencies. In electrical engineering, they are used for:

- Short-term and medium-term load forecasting;

- Renewable generation forecasting (wind speed, solar irradiance);
- Dynamic behavior prediction in electrical drives and grid components.

In communication systems, RNNs and LSTMs are used for channel prediction, sequence detection, and traffic forecasting.

3.4. Autoencoders and Variants

Autoencoders learn compact latent representations by reconstructing input signals. They are valuable in:

- Dimensionality reduction for high-dimensional sensor data;
- Anomaly detection (e.g., abnormal patterns in current or voltage waveforms);
- Denoising of ECG, vibration, or partial-discharge signals prior to classification.

3.5. Generative Adversarial Networks (GANs)

GANs consist of a generator and discriminator trained adversarially. In ECE, they are used for:

- Synthetic data generation for rare fault conditions (e.g., specific machine failures);
- Super-resolution enhancement of diagnostic images;
- Data augmentation for robust training when real labeled data are scarce.

3.6. Graph and Power-System Neural Networks

Recently, Graph Neural Networks (GNNs) and related architectures have been applied to power systems, which naturally form graph-structured data (buses and transmission lines). GNNs model relationships between nodes (buses) and edges (lines), supporting tasks such as state estimation, fault localization, and topology-aware forecasting.

3.7. Neuromorphic and Spiking Neural Networks (SNNs)

Spiking neural networks operate with discrete spikes and are implemented on neuromorphic hardware for ultra-low power and real-time processing. These architectures are promising for embedded sensing and edge-AI in electrical systems, but their use in real-world ECE deployments is still emerging.

4. APPLICATIONS IN ELECTRICAL ENGINEERING

4.1. Power Systems and Smart Grids

Deep learning has been widely surveyed as an enabling technology for electrical power systems. Key applications include: Load forecasting: Hybrids of LSTM and CNN-LSTM give very accurate short-term and day-ahead predictions as compared to the traditional ARIMA or regressions models which improves unit commitment and the dispatch decision. Renewable energy forecasting: The NNs are used to predict the stochastic behavior of the solar irradiance and the wind speed based on the meteorological inputs (cloud cover, temperature, wind direction) and this helps in scheduling and reserve estimation. Fault detection and classification: Faults (single-line-to-ground, line-to-line, three-phase) are classified by FNNs and CNNs according to the current and voltage waveforms, allowing faster protection as well as isolation. Voltage stability and security assessment: Deep networks learn mappings from system states to stability margins, allowing faster online security assessment compared to iterative numerical methods. Energy theft and anomaly detection: Autoencoders and CNNs detect suspicious consumption patterns from smart meter data. These applications collectively contribute to more reliable, efficient, and resilient smart grids.

4.2. Electrical Machines and Drives

Neural networks are extensively used for condition monitoring of induction motors, synchronous machines, and permanent-magnet drives. Vibration, current, and acoustic signals are processed by 1D CNNs or FNNs to detect bearing defects, broken rotor bars, eccentricity, and insulation degradation.

In control, neural networks provide:

Sensorless estimation of speed and torque;

Adaptive control of drive systems under parameter variations;

Efficiency optimization by learning loss models.

4.3. Power Electronics

In power electronic converters, neural networks are used to:

Implement maximum power point tracking (MPPT) for photovoltaic systems under rapidly changing conditions

Approximate nonlinear switching dynamics for model predictive control of inverters;

Classify power-quality disturbances using CNNs applied to waveform transforms.

These improvements can increase energy yield and reduce stress on components.

4.4. Signal Processing and Biomedical Engineering

Neural networks complement and sometimes replace classical digital signal processing in:

Denoising and classification of ECG, EEG, and EMG signals;

Non-intrusive load monitoring by separating household appliances from aggregate power signals;

Radar and sonar processing, including clutter suppression and target recognition.

5. APPLICATIONS IN COMPUTER ENGINEERING

5.1. Computer Vision and Industrial Inspection

CNNs and vision transformers are widely used in quality inspection on production lines, defect detection in PCBs, and recognition of surface cracks in infrastructure. Computer engineers design and deploy these models on GPUs, FPGAs, or dedicated AI accelerators for real-time performance.

5.2. Embedded Systems and Edge-AI

TinyML and optimized deep-learning frameworks make it possible to run compact neural networks on microcontrollers and resource-limited SoCs. Applications include:

- Smart sensors that classify vibration or current locally;
- Wearable devices that monitor physiological signals using embedded CNNs;
- Low-power anomaly detection in distributed electrical assets.

Field-programmable gate arrays (FPGAs) are also widely used to accelerate CNNs and other deep models when power efficiency and parallelism are critical.

5.3. Communication Systems and Networking

Neural networks are increasingly integrated into physical and network layers of communication systems, where they perform:

- Data-driven channel equalization and decoding;
- End-to-end learning of modulation and coding schemes;
- Beamforming and resource allocation in massive MIMO 5G/6G networks;
- Traffic prediction and congestion control.

5.4. Cybersecurity

In computer and communication networks, neural networks underpin intrusion detection systems, malware classification, spam filtering, and anomaly detection in traffic flows. Complex statistical patterns in the high-dimensional network data are also those that are not easily detected by rule-based systems but are easily captured by deep learning (DL) models.

5.5. Robotics and Autonomous Systems

NNs support perception, control, and mapping, in robotics:

- Vision-based object detection and semantic segmentation;
- Sensor fusion from cameras, LiDAR, and IMUs;
- Reinforcement learning policies for navigation and manipulation.

The abilities form the core of autonomous cars, drones, and intelligent industrial robots.

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6. CHALLENGES AND OPEN ISSUES

However, regardless of their success, NNs in electrical and computer engineering have a number of challenges:

1. Data availability and quality Many electrical systems lack large labelled datasets, especially for rare events such as faults or extreme weather. Synthetic data (e.g., via GANs) help but may introduce bias.
2. Computational and memory requirements Deep networks are resource-intensive to train and deploy, which conflicts with the constraints of embedded and real-time systems. Model compression, pruning, quantization, and neural architecture search are active research areas.
3. Interpretability and trust For safety-critical infrastructure (grids, medical devices, vehicles), black-box models are problematic. Explainable AI (XAI) techniques are needed to interpret decisions and verify compliance with engineering constraints.
4. Robustness and security Adversarial attacks and distribution shift may be a weakness of NNs and this is of concern in cyber-physical systems.
5. Integration with physics-based modelsThe models that are purely data-driven could violate physical laws. A novel and less developed area of focus is hybrid methods that use both differential equations and NNs (physics-informed NNs).

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7. FUTURE DIRECTIONS

The NNs in electrical and computer engineering have several research directions that are most promising:

- Neuromorphic computing and spiking neural networks, enabling energy-efficient, event-driven processing for edge devices and sensor nodes

- AI-driven smart grids, where neural networks coordinate distributed energy resources, storage, and flexible loads in real time
- Graph neural networks for complex infrastructures, including power, communication, and transportation networks
- Edge-AI and TinyML, integrating compressed neural models into microcontrollers and IoT devices for pervasive intelligence
- Neural architecture search (NAS) to automatically discover efficient models for embedded deployment and hardware co-design
- Cross-disciplinary design, combining control theory, power engineering, and AI to produce verifiable, safe, and optimal intelligent systems.
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8. CONCLUSIONS

The NNs have been a part of the development of electrical and computer engineering. They are particularly suited to contemporary challenges in engineering because they are able to learn complex nonlinear relationships, they are able to process high-dimensional sensor data, and operate adaptively in uncertain environments. NNs are transforming how systems are designed, operated, and maintained; starting with smart grids, power electronics, and electrical drives up to embedded AI, communication networks, and robotics.

Simultaneously, there are still serious issues regarding the data requirements, computational performance, interpretability, and robustness. These problems will be solved by neuromorphic hardware, model compression, explainable AI, and hybrid physics-aware models, which will be important to the safe and scalable deployment of NNs to critical electrical and computer engineering tasks. The review has presented a structured synthesis of current knowledge and trends, which can be used as the basis of the further investigation and practical applications in the current fast-paced evolution.

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Author 1	**Asst. Lecturer May Abdul Samad Sadeq** received her MSc degree in Electrical and Computer Engineering. She is currently a lecturer in the Electrical Engineering Department and is involved in teaching and academic activities in the field of Electrical Engineering. She can be contacted at email: may.abdulsamad@uoanbar.edu.iq .
2 Author 2	**Asst. Lecturer Mustafa Ali Abdulhadi** received his degree in Electrical Engineering from Babylon University. He is currently involved in the field of electrical engineering.