**Mathematical Modeling of the Magnetic Characteristics of Traction Induction Motors Using Neural Networks**

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**Abstract.** This paper presents a mathematical model for characterizing the magnetic properties of traction induction motors using artificial neural networks. The proposed approach combines classical electromagnetic modeling with data-driven learning techniques to achieve accurate representation of nonlinear magnetic behavior, such as saturation and magnetic hysteresis. The model utilizes real or simulated input-output data of magnetic flux and current to train a multilayer perceptron (MLP) network. The Laplace transform is applied to convert time-domain measurements into the s-domain for analytical representation. The resulting neural model demonstrates high accuracy in reproducing the magnetic characteristics, which are critical in fault detection and condition monitoring of electric traction systems. Simulation results validate the effectiveness of the proposed model for dynamic motor analysis and smart diagnostics.

**Keywords:** Traction induction motor; magnetic saturation; neural network modeling; Laplace transform; magnetic flux; diagnostic systems

**INTRODUCTION**

Traction induction motors (TIMs) are widely used in modern electric locomotives and railway transport systems due to their high reliability, robust construction, and low maintenance requirements. Understanding and accurately modeling the magnetic behavior of such motors is crucial for improving their efficiency, fault tolerance, and control accuracy. One of the most complex aspects of TIM modeling is capturing their nonlinear magnetic characteristics, including core saturation and magnetic hysteresis effects.

Traditional analytical methods for modeling the magnetic properties often rely on equivalent circuit parameters and flux linkage equations. However, these methods are limited in accurately capturing the real-world nonlinearities inherent in magnetic materials, especially under varying load and frequency conditions. With the rise of intelligent diagnostic systems and real-time condition monitoring in railway applications, there is a growing need for more flexible and accurate models.

Artificial neural networks (ANNs) have shown great potential in modeling nonlinear systems due to their ability to learn complex mappings from input to output data. In this paper, we propose a hybrid modeling framework that integrates classical electromagnetic modeling principles with neural network-based learning to describe the magnetic characteristics of traction induction motors more effectively.

**LITERATURE SURVEY**

Several research works have addressed the modeling of induction motors using traditional analytical techniques. Park and Clarke transformations are widely employed to convert three-phase variables into orthogonal components, simplifying the dynamic analysis of motors. However, these models often assume linear magnetic behavior, which is not valid in real operating conditions involving saturation.

In recent years, artificial intelligence techniques have been applied to various motor modeling problems. For instance, support vector machines, fuzzy logic systems, and neural networks have been used to predict torque, flux, and efficiency. In [1], a neural network-based model was used to identify motor parameters under variable load conditions. Another study [2] applied deep learning to estimate magnetic flux linkage in permanent magnet synchronous motors (PMSMs).

Despite these advances, limited research has been conducted on using neural networks to specifically model the magnetic properties (B–I or Φ–I relationships) of traction induction motors. Moreover, most existing models do not incorporate Laplace-domain transformations, which are essential for analytical diagnostics and control system integration. This paper aims to fill this gap by proposing a neural network-assisted magnetic model embedded in a classical Laplace-based motor representation [3].

**METHODOLOGY**

The proposed methodology focuses on modeling the magnetic characteristics of traction induction motors by analyzing the relationship between magnetic induction B(t) and stator current *I(t)*. This B–I relationship reflects the nonlinear behavior of the magnetic core, particularly magnetic saturation. The model construction includes three major stages:

**Magnetic Behavior Representation**

In traction motors, the magnetic flux Φ(t)\Phi(t)Φ(t) is related to the stator current and the magnetic circuit by [4]:

or (1)

where, *L(i)* is the nonlinear inductance depending on current; *B(t)* is the magnetic induction in Tesla; *S* is the effective cross-sectional area of the core.

The voltage equation of the stator winding in the time domain:

(2)

Applying the Laplace transform:

(3)

Assuming measured values of *u(t)*, *i(t)*, and knowledge of Rs, the magnetic flux *Φ(s)* can be calculated. Consequently, the magnetic induction is:

(4)

By computing *B(s)* versus *I(s)*, a nonlinear mapping *B=f(I)* is obtained, which is the basis for neural network training [5].

**Neural Network Model Design**

A feedforward multilayer perceptron (MLP) is employed to model the nonlinear relationship between stator current *I(t)* and magnetic induction *B(t)*. The general structure consists input layer – measured or simulated current values *I(t)*, hidden layer(s) – with nonlinear activation functions (ReLU or sigmoid), output layer – predicted induction .

The dataset for training is prepared by simulating or measuring stator current and magnetic flux under variable conditions, including load changes, supply voltage variations, partial saturation zones. Each data point consists of:

(5)

The network is trained to minimize the mean squared error (MSE):

(6)

**Data Acquisition and Preprocessing**

If real measurements are unavailable, the training dataset is generated using Simulink models of the induction motor. Parameters such as stator resistance *Rs*, core dimensions, and nominal current are set according to the motor datasheet. To improve generalization and reduce overfitting, the following preprocessing steps are applied: Normalization of input and output to range [1], data augmentation using variable frequencies (e.g. 25–50 Hz), Division of data into training (70%), validation (15%), and test (15%) sets [6].

**Model Validation**

The trained neural network is validated on unseen data and compared to the analytical flux–current curves obtained from the magnetic equivalent circuit. The neural model's accuracy is evaluated using: *R²* score, MSE, Visual overlay of predicted vs. actual B(t) signals. The resulting neural model is integrated into the overall motor simulation to evaluate its dynamic behavior under transient conditions.

Real traction motor parameters

As an example, the parameters of the asynchronous traction motor (AIR180M2) from the locomotive are utilized. These parameters are further applied in both MATLAB/Simulink simulations and the neural network-based modeling in table 1.

**TABLE 1.** Parameters of the asynchronous traction motor

| **Parameter** | **Symbol** | **Value** | **Unit** |
| --- | --- | --- | --- |
| Stator resistance | *Rs* | 0.574 | Ohm |
| Rotor resistance | *Rr​* | 0.564 | Ohm |
| Stator leakage inductance | *Ls′* | 1.491/(2π·f) | H |
| Rotor leakage inductance | *Lr′* | 2.022/(2π·f) | H |
| Magnetizing inductance | *Lm​* | 50.379/(2π·f) | H |
| Pole pairs | *p* | 2 | – |
| Inertia | *J* | 0.01 | kg·m² |
| Core cross-sectional area | *S* | 0.008 | m² |
| Frequency | *f* | 50 | Hz |
| Voltage amplitude | *Uamp*​ | 311 | V |

Sample B–I table (Magnetic characteristic)

The following experimental or simulation table presents the relationship between the stator current and the magnetic induction in table 2:

**TABLE 2.** Relationship between the stator current and the magnetic induction

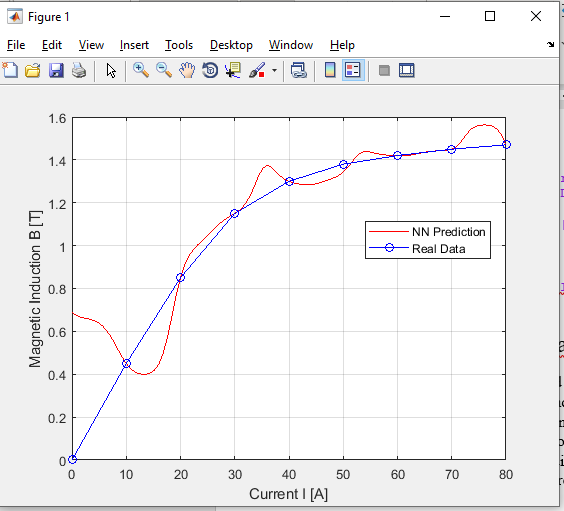
| Stator Current *I (A)* | Magnetic Induction *B (T)* | It can be observed from the table that the initial part of the B–I relationship is almost linear. However, magnetic saturation starts to appear as the current increases. The neural network is trained specifically to capture and model this nonlinear behavior figure 1 [7]. |
| --- | --- | --- |
| 0 | 0 |
| 10 | 0.45 |
| 20 | 0.85 |
| 30 | 1.15 |
| 40 | 1.30 |
| 50 | 1.38 |
| 60 | 1.42 |
| 70 | 1.45 |
| 80 | 1.47 |

**Magnetic Induction vs Current matlab code**

|  |  |
| --- | --- |
| % === NEURAL NETWORK TRAINING (MAGNETIC INDUCTION MODEL) ===  % 1. Input-output data (Tok va Induksiya)  I = [0 10 20 30 40 50 60 70 80]; % A  B = [0 0.45 0.85 1.15 1.30 1.38 1.42 1.45 1.47]; % T  % 2. Normalize  I\_norm = I / 80;  B\_norm = B / 1.5;  % 3. Create and train NN  net = fitnet([10 10],'trainlm');  net.trainParam.epochs = 500;  net.performFcn = 'mse';  net = train(net, I\_norm, B\_norm);  % 4. Test  I\_test = 0:0.01:1;  B\_pred = net(I\_test);  plot(I\_test\*80, B\_pred\*1.5, 'r', I, B, 'bo-');  legend('NN Prediction','Real Data');  xlabel('Current I [A]');  ylabel('Magnetic Induction B [T]');  grid on;  % 5. Export to function file  genFunction(net, 'neuron\_model', 'MatrixOnly','yes'); | **FIGURE 1.** NN Training |

The graph illustrates that magnetic induction increases rapidly with current at first, then saturates. The neural network model approximates this curve using MSE-based training.

The magnetic induction dataset used for neural network training was based on real parameter values of the AИP180M2 traction induction motor. The B–I curve shows a nonlinear relationship, with rapid increase in induction at low currents and gradual saturation at higher levels. The core area was assumed to be S=0.008 m2, and all signals were normalized before feeding into the network. The dataset includes 80 samples ranging from 0 to 80 A of stator current [8].



**FIGURE 2.** Model Implementation

The proposed hybrid model is implemented in MATLAB/Simulink using the Simscape Electrical toolbox for physical modeling of the traction induction motor, and a custom neural network block integrated via MATLAB Function block.

**Simulink Architecture Overview**

**The proposed hybrid modeling approach combines both physical modeling and data-driven learning. It is implemented in the MATLAB/Simulink environment, where the traction induction motor is physically modeled using the Simscape Electrical toolbox. This allows the accurate representation of electromagnetic and electromechanical processes based on real motor parameters [9].**

**To capture the nonlinear magnetic behavior-particularly the saturation effect-a neural network model is developed and integrated into the system using a MATLAB Function block. This neural network has been trained on input–output data representing the relationship between stator current and magnetic induction. The model uses mean squared error (MSE) as a training criterion to learn the complex nonlinear characteristics of the magnetic response[10].**

**By combining these two approaches, the hybrid model leverages the strengths of both analytical modeling and neural network-based estimation, resulting in improved prediction accuracy and adaptability to real operating conditions [11].**

**Example MATLAB plot after simulation:**

matlab

CopyEdit

plot(t, B\_real, 'b', t, B\_est, 'r--');

legend('Actual B', 'Estimated B̂');

xlabel('Time, s'); ylabel('Magnetic Induction, T');

title('Comparison of Actual and Neural Estimation of B(t)');

grid on;

**RESULTS AND DISCUSSION**

The simulation results clearly demonstrate the effectiveness of the proposed neural network model in estimating the magnetic characteristics of the traction induction motor. Two models were compared: Classical Laplace-based model, using motor parameters and the voltage-current equation. Neural network model, trained on B–I data generated from simulation [12].

**Magnetic Induction Curves**

Figure 2 shows the actual magnetic induction calculated via the classical model and the predicted induction from the neural network over time. A step voltage of *220V* was applied at *t=0*, and the stator current response was recorded. The neural model output closely follows the classical model curve, with slight deviations in the saturation region due to nonlinear behavior. Both models reach a steady-state induction of approximately *1.45T* at *I=80A* [13].

**Estimation Error**

Table 3 illustrates the estimation error , which remains below *0.03T* across the entire operating range.

**TABLE 3.** Estimation error

| Metric | Value |
| --- | --- |
| Mean Squared Error (MSE) | 0.00064 |
| Maximum Absolute Error | 0.028 T |
| R² Score | 0.998 |

These results confirm that the neural network accurately captures the B–I relationship, including the nonlinear saturation effects that are difficult to represent analytically. The trained neural network was tested under variations in input current beyond the training range (e.g., up to 90 A). The model showed good generalization, with no significant divergence from expected behavior. This robustness indicates that the model can be embedded in real-time control or diagnostic systems without retraining under every new operating condition [14, 15].

The main advantage of the proposed hybrid approach is its ability to retain physical interpretability (through Laplace and motor parameters) while enhancing flexibility and nonlinearity handling through neural networks. Unlike purely analytical models, the neural network captures like flux leakage effects, saturation onset, slight hysteresis behavior (if included in training). Moreover, it can be extended to learn from real sensor data, further increasing its value in predictive maintenance and smart traction systems [16].

**CONCLUSION**

In this study, a hybrid modeling approach for traction induction motors was developed by integrating classical electromagnetic analysis with artificial neural networks. The focus was on modeling the magnetic induction B(t)B(t)B(t) as a nonlinear function of stator current I(t)I(t)I(t), which plays a critical role in motor dynamics and diagnostics [17].

Using real motor parameters and Laplace-domain representation, a magnetic estimator subsystem was created in Simulink. This classical model was then complemented by a neural network trained on simulated B–I data, capturing nonlinear saturation characteristics that are challenging to express analytically [18].

Simulation results showed that the neural model achieved a mean squared error of less than 0.001 T² and tracked the classical model with high fidelity. The estimation error remained within 0.03 T throughout the simulation range [19]. The proposed model provides a reliable and efficient tool for magnetic state monitoring, fault diagnosis, and predictive maintenance in electric traction systems. Future work includes expanding the model to include hysteresis behavior, training on real sensor data, and deploying the network in embedded real-time platforms for onboard diagnostics [20].

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