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An effective approach for electric motor fault diagnosis using deep learning

***Abstract**. Induction motors have versatile applications across various industries. However, during their integration into different systems, they can be susceptible to a range of failures such as broken bars and interturn faults. To mitigate the risks of unforeseen motor breakdowns, this study introduced an Artificial Neural Network (ANN) based fault detector to assess the severity of fault conditions. The primary goal is to enhance the reliability and longevity of induction motors by promptly identifying potential issues. In this proposed model, Levenberg–Marquardt back-propagation algorithm is utilised for training and the ANN was subjected to testing under both healthy and five distinct fault conditions of the electrical machine.The results obtained from the experimentation phase are promising, revealing that the proposed ANN topology exhibits a noteworthy accuracy level of around 96%. This accuracy surpasses that of the pre-existing topology, indicating a significant advancement in fault detection capability.*

Streszczenie. *Silniki indukcyjne mają wszechstronne zastosowanie w różnych gałęziach przemysłu. Jednakże podczas integracji z różnymi systemami mogą być podatne na szereg awarii, takich jak pęknięte pręty i uszkodzenia międzyzwojowe. Aby ograniczyć ryzyko nieprzewidzianych awarii silnika, w badaniu wprowadzono detektor usterek oparty na sztucznej sieci neuronowej (ANN) w celu oceny powagi warunków awarii. Głównym celem jest zwiększenie niezawodności i trwałości silników indukcyjnych poprzez szybką identyfikację potencjalnych problemów. W proponowanym modelu do uczenia wykorzystano algorytm propagacji wstecznej Levenberga-Marquardta, a sieć SSN poddano testom zarówno w warunkach prawidłowego działania, jak i w pięciu odrębnych stanach usterek maszyny elektrycznej. Wyniki uzyskane w fazie eksperymentów są obiecujące i ujawniają, że zaproponowany model Topologia SSN charakteryzuje się godnym uwagi poziomem dokładności wynoszącym około 96%. Dokładność ta przewyższa dokładność istniejącej topologii, co wskazuje na znaczny postęp w zakresie możliwości wykrywania usterek.* (***Skuteczne podejście do diagnostyki usterek silników elektrycznych z wykorzystaniem głębokiego uczenia się***)

Keywords: ANN, Stator Inter Turn Fault(SITF) Detection, Induction Motor (IM), Accuracy.
Słowa kluczowe: NN, wykrywanie usterek międzyobrotowych stojana (SITF), silnik indukcyjny (IM), dokładność

Introduction

Induction Motors (IMs) are pivotal electromechanical devices for converting electrical energy into mechanical power, boasting a vast spectrum of applications across industries. Their popularity is attributed to their affordability, robustness and extensive speed range. Nevertheless, these motors are susceptible to failure due to diverse factors including mechanical stress, electrical issues and environmental variations. Notably, statistical data on IM failures underscore that approximately 40% of electrical failures can be attributed to faults in the stator winding. These faults often originate with Shorted-Turns in the Stator Winding (SITF), which if left undetected, can progress into more severe fault conditions such as phase-ground or phase-phase faults. In the case of SITF, the substantial voltage differential across the turns can lead to insulation breakdown within the stator windings, necessitating early detection and intervention to ensure the proper operation of IMs. Numerous methodologies have been proposed to detect SITF in IMs, broadly falling into the categories of signal/model-based approaches and those harnessing Artificial Intelligence (AI) techniques [1]. Model-based methods rely on analytical models of the induction motor's behavior, but due to the inherent complexity of the system, these methods tend to suffer from limited accuracy [2]. On the other hand, signal-based techniques can be categorized as either non-invasive or invasive. Approaches like Fast Fourier Transform (FFT), correlation functions, Short-Time Fourier Transform (STF), and Wavelet Transform (WT) are employed to analyze the harmonic components present in the frequency domain [3,4].

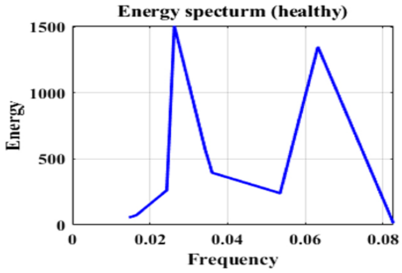
In the field of fault diagnosis, traditional approaches predominantly rely on linear methodologies However, modeling industrial processes can be challenging due to their complexity, and the presence of noise and unreliable sensors often leads to corrupted measurements. Consequently, many researchers have explored the use of artificial intelligence (AI) tools as an alternative approach for encoding knowledge about faults[10]. These AI tools include fuzzy logic, neural networks, and hybrid networks such as neuro-fuzzy networks [5,6]. Thus, this work have opted artificial neural networks (ANNs) to detect the fault. The rationale behind this choice is that ANNs are data-driven models capable of effectively filtering out disturbances and noise in the data. Importantly, they achieve this without requiring the development of complex mathematical models that may necessitate neglecting certain aspects of the system's dynamics for the sake of simplification. Furthermore, ANNs offer the advantage of delivering stable, highly sensitive, and cost-effective fault diagnosis.

Methods

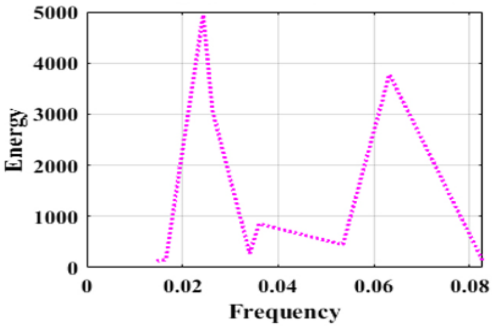
The methodology employed by this system to detect Stator Inter-Turn Faults (SITF) is illustrated in Figure 2. The proposed approach involves the development of a mathematical model for the SITF to facilitate its identification. The initial investigation of the model is conducted under normal operating conditions, maintaining all parameter values unchanged. Subsequently, a deliberate fault is introduced in the phase A winding, leading to a sudden increase in current across phases A, B, and C. This alteration aims to analyze the behavior of the system under faulty conditions.

The variations in current values also exert an impact on the torque and speed of the Induction Motor (IM). Under normal circumstances, the IM exhibits symmetry and generates solely positive sequence currents. However, the introduction of a fault disrupts this symmetry, resulting in the generation of positive, negative, and zero sequence currents within the IM.

As a consequence of the fault, the negative sequence component of the current gradually intensifies with the severity of the fault. This particular attribute is harnessed to quantify the extent of the fault's severity. Thus, Figure 1 depicts energy plot for both healthy and winding fault conditions.



(a) Healthy Condition



(b) Faulty Condition

Fig1. Energy plot for both healthy and winding fault conditions

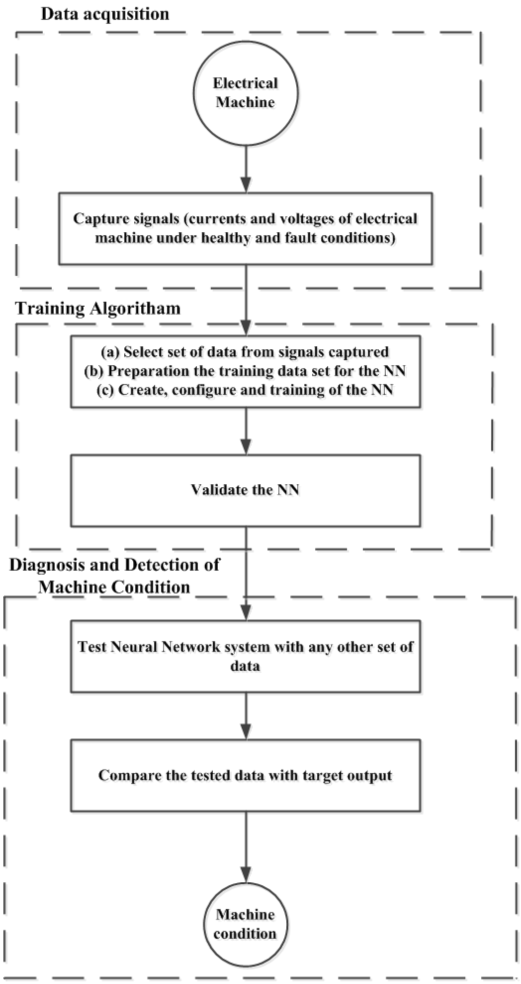


Fig 2. Block Diagram of proposed Model

Mathematical Modelling

Figure 3 illustrates a 3ϕ IM with a turn fault occurring in the stator winding of phase A. The symbol β represents the proportion of shorted turns.

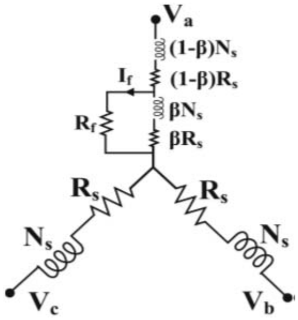


Fig 3. SITF on A-phase ending of a IM.

Thus, the voltage and flux linkage of the shorted turns can be given as

(1) $V_{as2} = \beta R_s(i_{as} - i_f) + \frac{d\lambda_{as2}}{dt} = R_f i_f$)

(2) $\lambda_{as2} = -\beta {A_2}^T {i_s}' - \beta {A_3}^T i_\gamma - \beta\,(L_{is} + \beta L_{ms}) i_f$

Sequence Component Analysis

Any imbalanced system's issues can be identified and resolved using the symmetrical components. Thus, with the use of Fortescue's transformation (equ.6), symmetrical components (I0, IP, IN,) can be obtained from unbalanced phase currents[11,12].

(3) $$\begin{bmatrix} I_P \\ I_N \\ I_0 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1 & 1 & 1 \end{bmatrix}\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix}$$

Where a = operator $e^{j(2\pi/3)}$.

Then , the per unit change in a negative sequence current is utilised to identify the severity of the fault condition and can be calculated using the formula .

(4) $\delta = \frac{(\text{positive sequence current} - \text{negative sequence currect})}{\text{positive sequence current}}$

(5) $$\delta = \frac{(I_P - I_N)}{I_P}$$

The obtained value δ is given as input to the ANN network.

Design of ANN

The implemented process involves the utilization of gradient descent for optimization, backpropagation for training, and an adaptive learning rate. The hyperbolic tangent sigmoid transfer function is integrated to compute the output. Eventually, a setup with 500 samples was chosen, adopting a layer arrangement of 1 input layer, 12 neurons in the hidden layer and 6 neurons in the output layer. For training purposes, a dataset consisting of 320 samples was gathered. The remaining 180 samples were reserved for both testing the model's performance and validation. The output layer is composed of six neurons, each corresponding to a distinct condition: health condition, 5, 10, 15, 20 and 25 turns short circuit.

Results and Discussion

This section presents the performance evaluation of the proposed model in detecting STFT fault in IM. The simulation model assesses short circuit faults ranging from

0% to 25%. The integration of ANN aids in identifying faulty conditions in IM. Figure 4 illustrates the optimal fitting of the ANN across all conditions, including training, validation, and testing.

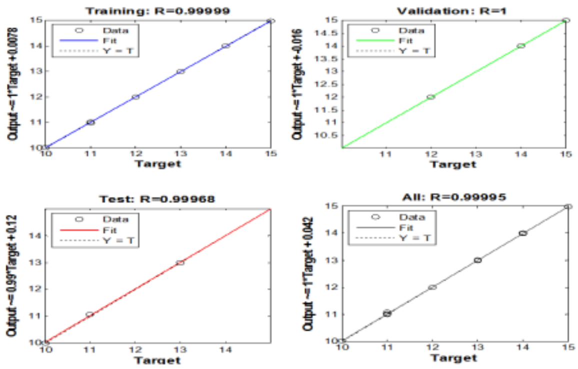


Fig 4. Regression Analysis

The training, validation, and test phases for the neural network (NN) model yield correlation coefficients of R = 0.9999, R = 19, and R = 0.99968, respectively. When these values are combined, the overall regression correlation is R = 0.99995. This indicates that the model exhibits a strong correlation between the predicted outputs and the target values. Consequently, it can be inferred that the model is highly robust and accurate in detecting the condition of the electrical machine.

Figure 5 illustrates the validation performance plot of the neural network. This plot displays the performance function's values over the course of training, with each point on the graph representing an iteration (epoch). It tracks the performance metrics for the training, validation, and test datasets.

The default performance function for feed-forward networks is the Mean Squared Error (MSE), which quantifies the average squared difference between the network's output (y) and the target values (t). Smaller MSE values are indicative of better network performance, with a perfect score of zero denoting no error. In Figure 5, the MSE is reported as 0.0017803, which is considered an excellent result. This low MSE suggests that the network is effectively minimizing the error between its predictions and the actual target values, demonstrating its capability to make accurate predictions and generalize well to new data.

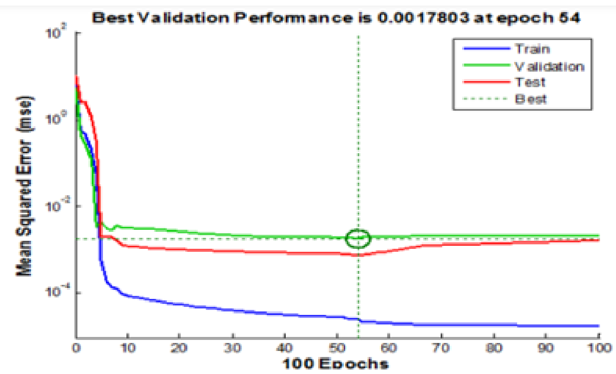


Fig 5. Validation Performance Plot

The preceding assessment substantiates the precise determination capability of the proposed system in identifying the SITF within the IM system. The accuracy of the system with ANN, as depicted in figure 6. In the case of a healthy condition, the accuracy reaches an impressive 100%. Similarly, when subjected to various fault conditions, the accuracy remains high at around 96%. Based on the comprehensive analysis provided, it is reasonable to deduce that the proposed ANN model claims a significantly elevated level of accuracy.

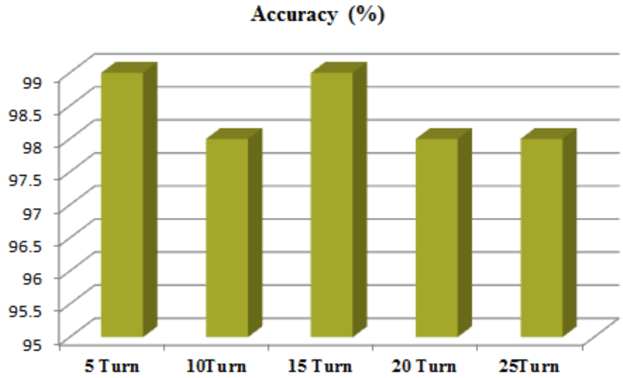


Fig 6. Percentage of accuracy under different percentage of fault turn condition.

In addition, Table 1depicts the comparative analysis of the proposed topology with existing topology.

Table 1. Comparative analysis of the proposed ANN with state of art

Methodology	Accuracy (%)
Instantaneous Frequency [7]	90
Kalman filter [8]	85
Kalman filter based algorithm [9]	94
Proposed ANN	96

In Table 1 of reference [8], the proposed algorithm demonstrates an impressive accuracy of 90%. However, it appears to be somewhat susceptible to Gaussian noise, which might impact its robustness in noisy environments. Conversely, the findings in reference [7] showcase even greater accuracy compared to the previous algorithm, although this improvement comes at the cost of increased delay times.

Turning attention to reference [9], an alternative approach has been embraced, emphasizing low computational complexity while achieving a commendable accuracy level of 94%. Yet, the most promising solution seems to lie in the ANN-based topology proposed herein. This innovative topology not only addresses the limitations observed in the aforementioned methods but also achieves a remarkable accuracy of approximately 96%. This suggests that the ANN-based approach offers a viable avenue for reconciling the shortcomings of prior methods while substantially enhancing overall performance.

Conclusions

This research study showcases the successful identification of Subsynchronous Resonance-Induced Torsional Flutter (SITF) faults within Induction Motor (IM) drive systems. The study introduces an Artificial Neural Network (ANN)-based detection mechanism tailored for SITF identification. Consequently, the primary benefits of the novel approach, in contrast to existing methodologies, encompass heightened precision and resilience in the face of power quality concerns.

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