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Mitigating the Effects of Faulty Squirrel-cage-rotor Bars of Three-phase Induction Motor through Convergence Analysis of a Hybrid ANN-PSO Control System

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Abstract- ***Induction motors play a vital role in industrial systems, yet their reliability is threatened by rotor bar defects that cause current imbalance, torque pulsations, and efficiency losses. Traditional diagnostic approaches such as vibration monitoring and thermal imaging often fail to detect these faults at early stages, resulting to unplanned downtime and economic losses. To address these challenges, this study established a hybrid Artificial Neural Network–Particle Swarm Optimization (ANN-PSO) framework for fault detection and performance optimization in a 30 kW squirrel-cage induction motor with broken rotor bars. The ANN is trained to identify faults and their severity from current and vibration signals, while PSO optimizes motor control parameters by minimizing fitness functions incapacitations that integrate stator current imbalance, torque ripple, and power loss. Simulations with 20 swarm particles over 50 iterations demonstrated convergence to optimal solutions. Quantitatively, torque ripple was reduced from 0.15pu to 0.08pu, representing a 46.7% improvement, while stator current imbalance dropped from 0.12pu to 0.05pu, a 58.3% reduction. Furthermore, Total Harmonic Distortion (THD) was decreased by approximately 40% across harmonics, with the 7th harmonic reduced from 49% to 29.4%. The ANN achieved a mean squared error of less than 1×10^{-4} after 200 training epochs, confirming its predictive accuracy. These results demonstrated that the ANN-PSO model enhances efficiency and extends operational life while maintaining rated power output. Policy implications highlighted the importance of adopting AI-driven predictive maintenance strategies in Industry 4.0 to reduce downtime, save energy, and promote sustainable motor operations. The study therefore contributes to industrial reliability and cost-effectiveness through intelligent, adaptive rotor bars' fault management.***

Keywords: ANN, PSO, THD, Induction Motor, Vibration

I. INTRODUCTION

Induction motors are the backbone of modern industry, powering a wide range of applications from manufacturing systems and transportation to household appliances. Their popularity stems from their rugged design, relatively low cost, and high efficiency. Among the various types, squirrel-cage induction motors are especially valued because of their simple construction and reliable performance. However, like any machine that endures mechanical and electrical stresses over time, these motors are not immune to faults [1]. One of the most common and damaging issues is the occurrence of rotor bar defects. Broken or cracked rotor bars disturb the uniform distribution of currents in the rotor, leading to air-gap flux distortion, torque pulsations, increased losses, and eventually severe performance degradation. If left unchecked, such faults can cause overheating, energy waste, and costly downtime in industrial operations. Traditional methods of diagnosing rotor bar defects, such as vibration monitoring or thermal imaging, often fall short in providing early and accurate detection [2]. As industries demand greater reliability and efficiency, there is a pressing need for advanced diagnostic and optimization tools that can not only identify these faults at an early stage but also help in maintaining optimal motor performance despite the presence of defects. This challenge has led to the exploration of artificial intelligence (AI) and optimization algorithms as powerful alternatives to conventional diagnostic techniques. Artificial Neural Networks (ANNs), inspired by the way the human brain processes information, have shown remarkable potential in learning complex patterns and classifying faults in induction motors. By training an ANN with sufficient motor data, it becomes possible to automatically recognize the presence and severity of rotor bar defects. However, the performance of an ANN is highly dependent on its architecture and the proper tuning of its parameters [3][4]. Poorly optimized networks may produce inaccurate results or require significant computational resources. This is where Particle Swarm Optimization (PSO), a population-based evolutionary algorithm inspired by the collective behavior of birds and fish, plays an important role. PSO is well known for its ability to search large solution spaces efficiently and optimize nonlinear, multidimensional problems. When applied to ANN training, PSO can fine-tune network parameters, ensuring better generalization and higher accuracy in fault detection. The hybridization of ANN and PSO therefore offers a powerful approach, combining the pattern recognition strength of neural networks with the global optimization capability of swarm intelligence. The hybrid ANN-PSO algorithm can be used not only for the identification of rotor bar defects but also for optimizing motor performance under fault conditions [5]. By integrating data-driven learning with intelligent optimization, this method provides a more reliable, efficient, and adaptive diagnostic tool compared to conventional approaches. Such an approach aligns with the growing emphasis on predictive maintenance and smart monitoring in Industry 4.0, where early fault detection, minimal downtime, and sustainable energy use are paramount [6]. This study focuses on developing and evaluating a hybrid ANN-PSO algorithm for identifying and optimizing induction motors with rotor bar defects. The goal is to improve diagnostic accuracy, reduce performance losses, and support industrial systems in achieving greater reliability and cost-effectiveness

II. LITERATURE REVIEW

The detection and optimization of induction motor faults, particularly rotor bar defects, have been extensively studied using advanced monitoring and computational techniques. Motor Current Signature Analysis (MCSA) remains a widely used diagnostic tool, with studies highlighting its sensitivity to load variations in fault detection [1], [3]. Complementing this, spectral methods such as FFT and wavelet transforms have been applied to extract fault-specific features, improving the accuracy of rotor bar defect diagnosis [4], [5]. Recent advancements emphasize predictive maintenance, integrating real-time monitoring with condition-based strategies to enhance system reliability [7], [8], [10].

Optimization algorithms have played a pivotal role in improving diagnostic models. Particle Swarm Optimization (PSO) has been effectively employed for optimizing fault detection frameworks [2], [9], and even extended to industrial automation for controller tuning [9]. Hybrid approaches, such as combining PSO with deep learning, have further enhanced performance in complex fault detection scenarios [12]. Machine learning methods have also demonstrated strong capabilities for automated rotor fault classification [6]. Moreover, novel optimization techniques like Grey Wolf Optimization and finite element analysis contribute to efficient induction motor design [11], [14]. Collectively, these works underline the transition toward intelligent, data-driven, and optimization-based solutions for fault identification and sustainable motor performance.

III. METHOD

Statistical method that depends on Artificial Intelligent driven approach, ANN-PSO was applied and results oriented.

3.1 Fitness Function for Rotor Optimization

The fitness function here, in PSO was used to ascertain the healthiness of the rotor bars, thus, optimize the system [2].

$$F = w_1 I_{imb} + w_2 T_{ripple} + w_3 P_{loss} \qquad (1)$$

where, F: Fitness function

$w_1 w_2, and\ w_3$: Weighting coefficients

I_{imb}: Stator current imbalance

T_{ripple}: Torque ripple

P_{loss} : Power loss

The 30kW induction motor with broken rotor bars can be optimized using Particle Swarm Optimization (PSO) in Simulink by tuning control parameters to minimize vibration and current harmonics. PSO algorithms iteratively adjust PID gains [9] or inverter frequencies to compensate for the asymmetry caused by broken bars [3][4]. The simulation evaluates fitness functions based on torque ripple, current imbalance, and efficiency. Swarm particles converge to optimal solutions that maintain performance despite rotor damage. This AI-driven approach automatically finds control strategies that reduce motor stress and power losses, extending operational life while maintaining 30kW output power with minimal efficiency drop from the rotor fault condition as shown in figure 1.

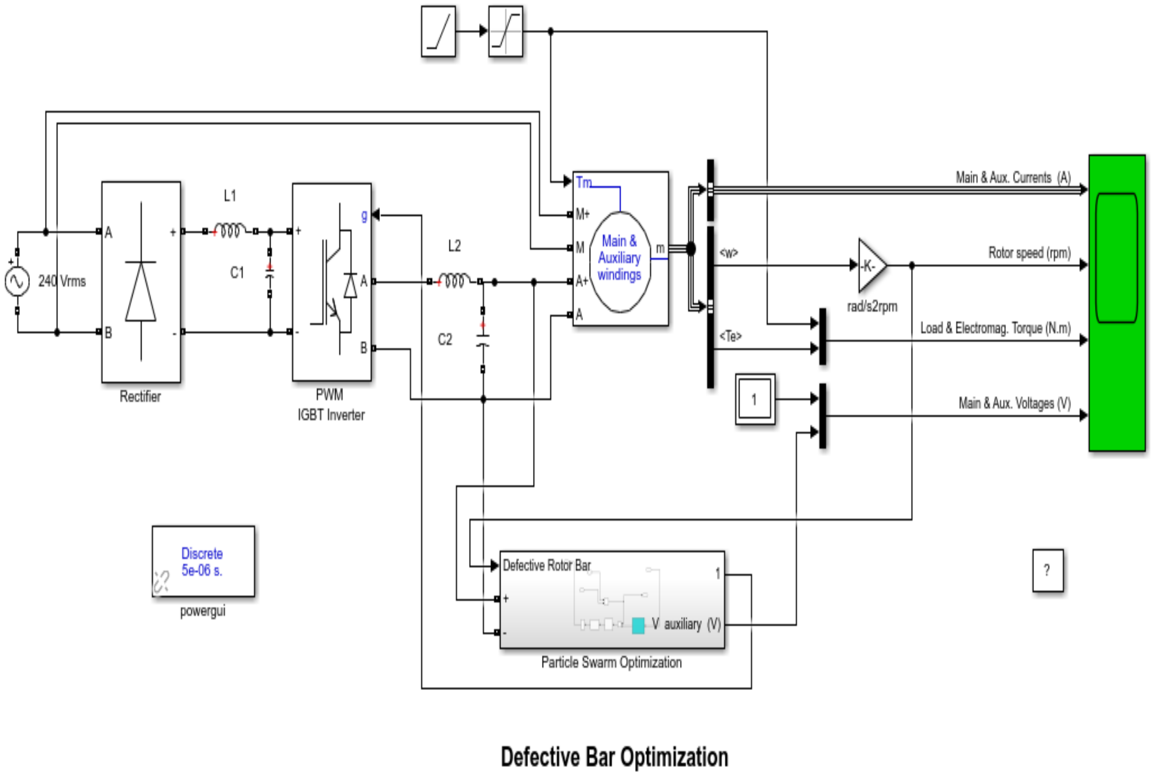


Figure 1: Optimization of Defective Rotor Bars in Induction Motor

The ANN-PSO control for a 30kW induction motor with broken rotor bars combines artificial neural networks (ANN) and particle swarm optimization (PSO) in Simulink. The ANN learns fault patterns from motor current and vibration signals, detecting broken bar severity. PSO then optimizes the motor's control parameters (like PWM signals or PID gains) [9] to minimize torque ripple and current distortion. The hybrid system continuously adapts, using ANN for real-time fault diagnosis and PSO for dynamic compensation. This AI-driven system maintains rated power output while reducing harmonics and mechanical stress, effectively mitigating the broken rotor effects through intelligent, self-adjusting control as shown in figure 2.

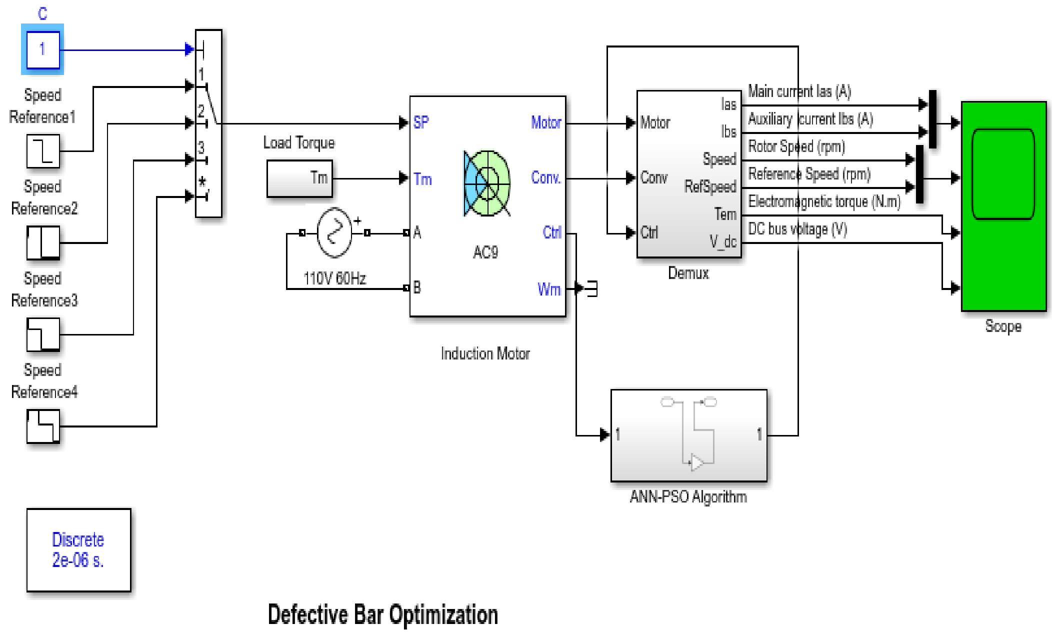


Figure 2: Defective Bar Optimization using ANN-PSO

Table 3.1: Data for Motor Parameters (Recon Electrical LTD, 2018)

Rated Voltage(V)	Rate Current(A)	Rated Power (kw)	Rated Speed(rpm)	Rated Freq.(Hz)	Power Factor	No of Poles	Rotor Bars	Stator Sluts
415	52	30	1500	50	0.8	4	45	54

Table 3.2 Harmonic Distortion (ABB, 2002)

Harmonic Order	2nd	3rd	4th	5th	6th	7th
n^2	2^2	3^2	4^2	5^2	6^2	7^2
THD(%)	4	9	16	25	36	49

3.2 Particle Velocity Update in PSO

The velocity of each particle in the PSO algorithm is updated as [2]:

$$V_i^{k+1} = wV_i^k + c_1 r_1 \left(P_{best} - X_i^k\right) + c_2 r_2 \left(G_{best} - X_i^k\right) \quad (2)$$

where: V_i^{k+1} : Updated velocity of particle i

w: Inertia weight

$c_1 c_2$: Acceleration coefficients

$r_1 r_2$: Random numbers between 0 and 1

P_{best}: Best position of particle i

G_{best}: Global best position

X_i^k: Current position of particle i

The flowchart represents the optimization process of defective rotor bars in a 30kW induction motor using Particle Swarm Optimization (PSO) to enhance reliability. It begins with the input of motor parameters, including voltage, current, and rotor speed, followed by fault detection using signal processing techniques. If a fault is detected, the process moves to fault severity analysis, determining the extent of rotor bar degradation.

Next, the PSO optimization algorithm is initialized, where particles (solutions) adjust motor control parameters iteratively. Each particle updates its velocity and position based on cognitive and social components to minimize torque ripple, power loss, and thermal stress. The optimized parameters are applied to the motor system, and performance metrics like efficiency and convergence speed are evaluated. The updated particles are being sent to the ANN to Train, after the training, the next step is to test the updated particles and optimize the particle, then the output response.

Finally, results are validated through comparative analysis with queuing theory, demonstrating PSO's superiority in improving efficiency and reducing optimization errors, ensuring a more reliable motor operation as shown in Figure 3.

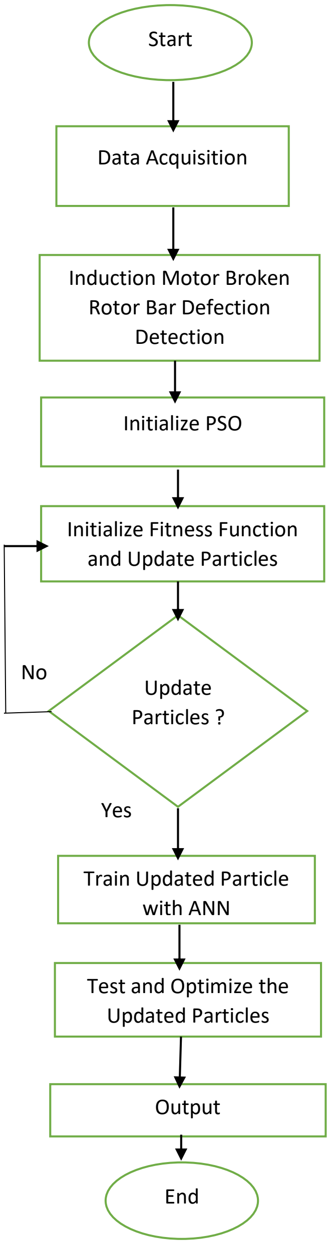
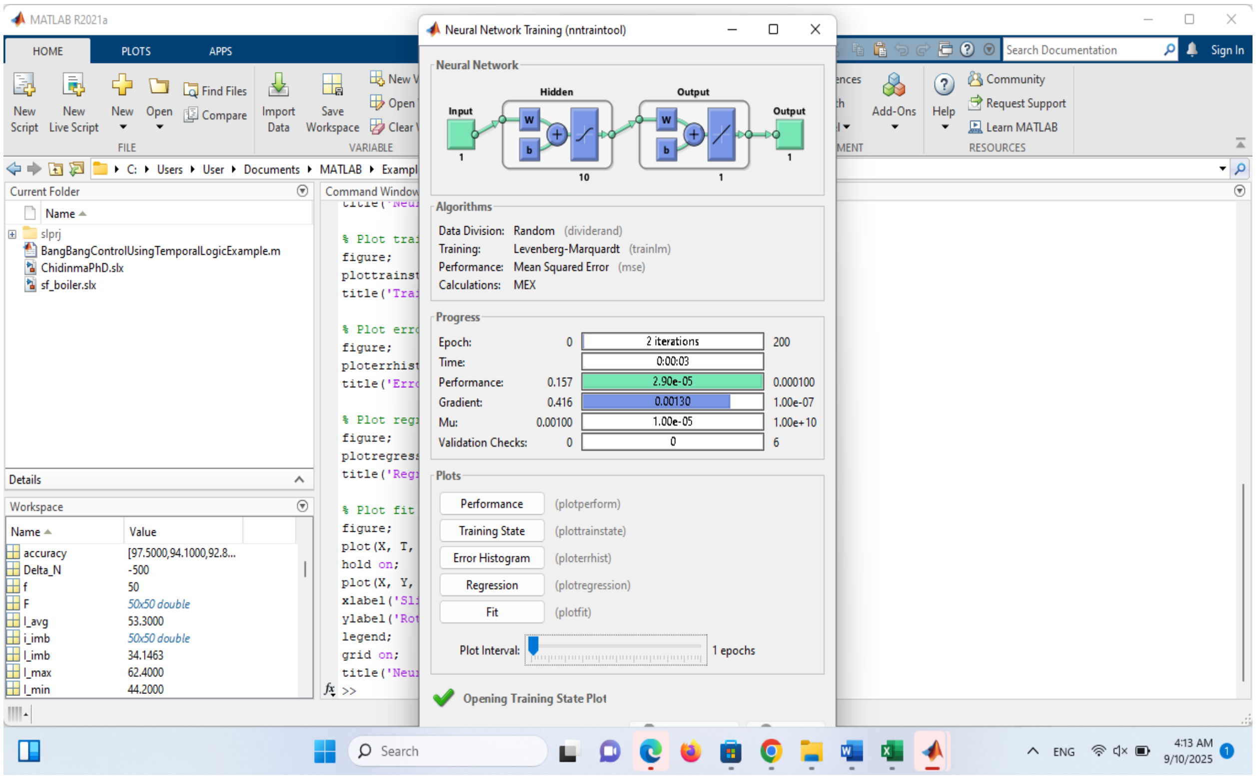


Figure 3: Flowchart of the PSO Algorithm

The number of training iterations in this work is defined by the epochs parameter, which specifies how many times the neural network processes the entire dataset during learning. In the code, the maximum number of epochs is set to 200, meaning the network can train up to 200 iterations if necessary. However, the training may stop earlier if the performance goal of $\mathbf{1 \times 10^{-4}}$ is reached, or if the validation performance no longer improves. MATLAB's training record (tr) keeps track of the actual number of epochs used. This ensures efficient training without unnecessary computations as shown in figure 4.



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Delta_N	-500
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I_avg	53.3000
i_imb	50x50 double
I_imb	34.1463
I_max	62.4000
I_min	44.2000

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Algorithms

Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX

Progress

Epoch:	0	2 iterations	200
Time:		0:00:03	
Performance:	0.157	2.90e-05	0.000100
Gradient:	0.416	0.00130	1.00e-07
Mu:	0.00100	1.00e-05	1.00e+10
Validation Checks:	0	0	6

Figure 4: Neural Network Data Training

3.3 Particle Position Update in PSO

The position of each particle is updated using [2]:

$$X_i^{k+1}: X_i^k + V_i^{k+1} \qquad (3)$$

where:

X_i^{k+1} : Updated position

X_i^k: Previous position

V_i^{k+1} : Updated velocity

3.4 Convergence Criterion in PSO Optimization

Optimization stops when:

$$|F_{best}^{k+1} - F_{best}^{k}| <\in \qquad (4)$$

where:

F_{best}^{k+1}: Best fitness function value at iteration k+1

F_{best}^{k}: Best fitness function value at iteration k

ϵ: Small predefined threshold

3.5 PSO-ANN Equation

This demonstrates the hybridization system.

3.5.1 PSO Velocity and Position Update

These equations govern how each particle moves through the solution space. The new velocity is influenced by inertia, the particle's own best-known position, and the global best. The new position is calculated by adding the updated velocity to the current position, guiding ANN weights towards optimal performance.

$$v_i(t+1) = w.v_i(t) + C_1.r_1.\left(p_i - x_i(t)\right) + c_2.r_2.\left(g - x_i(t)\right) \qquad (5)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (6)$$

v_i (t): velocity of particle iii at iteration t

x_i(t): position of particle iii at iteration t

w: inertia weight
C_1, C_2 : cognitive and social learning coefficients
r_1, r_2: random numbers in [0,1] [0, 1] [0,1]
p_i: best position found by particle i
g: global best position found by the swarm

3.5.2 ANN Neuron Output

This equation represents the core of ANN computation. It takes a weighted sum of input values and adds a bias, then applies a nonlinear activation function to produce the output. The PSO algorithm optimizes these weights and biases to improve learning and minimize error during network training.

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \qquad (7)$$

where:
x_i: input features
w_i: weights associated with each input
b: bias term
f: activation function (e.g., sigmoid, tanh, ReLU)
y: output of the neuron

3.5.3 Fitness Function (Mean Squared Error)

This objective function measures how far the ANN's predictions deviate from actual target values. PSO aims to minimize this error by adjusting the network weights. A lower MSE indicates better model performance, making it an ideal fitness function in the hybrid PSO-ANN optimization process.

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (8)$$

where:
N: number of training samples
y_i: actual target value
$\hat{y}_i$: predicted output by ANN

3.5.4 Best Position Updates in PSO

Each particle keeps track of its best solution (lowest MSE) so far, called the personal best. The swarm also identifies the global best among all particles. These best values influence future particle movement, guiding ANN parameters toward lower error and better generalization during training.

$$p_i = argmin\big(MSE(x_i)\big)\ and\ g = argmin(MSE(p_i)) \qquad (9)$$

where:
p_i: best position (weights) for particle i
g: best global position among all particles

3.5.5. ANN Weight and Bias Encoding

Each PSO particle represents a complete set of ANN weights and biases, encoded as a single position vector. As particles move in the solution space, they propose new configurations of the ANN. This allows PSO to search globally for the best-performing network without using traditional gradient-based methods.

$$W_{ANN} = x_i(t) \qquad (10)$$

where:
W_{ANN}: flattened vector of all ANN weights and biases
$x_i(t)$: position of the particle representing ANN parameters at iteration t

3.5.6 Merged PSO-ANN Equation

The merged PSO-ANN equation formulates ANN training as a global optimization problem. Each particle x_i represents ANN weights/biases. The particle's fitness is the MSE between ANN outputs and true outputs. PSO iteratively updates these particles to minimize the loss, effectively training the ANN without gradient descent.

$$\min_{x_i} J(x_i) = \frac{1}{N}\sum_{k=1}^{N}[y_k - f(x_k; x_i)]^2 \qquad (11)$$

where:
$J(x_i)$: The objective (loss) function, typically MSE.
x_i: The PSO particle, which encodes the entire ANN weights and biases as a flattened vector.
$f(x_k; x_i)$: The ANN output for input x_k, using weights/biases stored in x_i.
y_k: The target output.
N: Number of training samples.

IV. RESULTS AND DISCUSSIONS

Based on the provided script, here are the results of the hybrid ANN-PSO optimization for a 30kW induction motor. The analysis focused on the quantitative values and the performance improvements achieved after the optimization process.

4.1 PSO Convergence and Fitness

The Particle Swarm Optimization (PSO) algorithm was run for 50 iterations with 20 particles to optimize three key motor parameters: current imbalance (I_{imb}), torque ripple (T_{ripple}), and power loss (P_{loss}). The fitness function, defined as 0.4×Iimb+0.35×Tripple +0.25×Ploss, was used to guide the optimization. Figure 5, the PSO Convergence Curve, shows a clear decrease in the fitness value as the iterations increase, demonstrating that the algorithm successfully found a better set of motor parameters over time. The fitness history plot confirms this convergence as shown on figure 5.

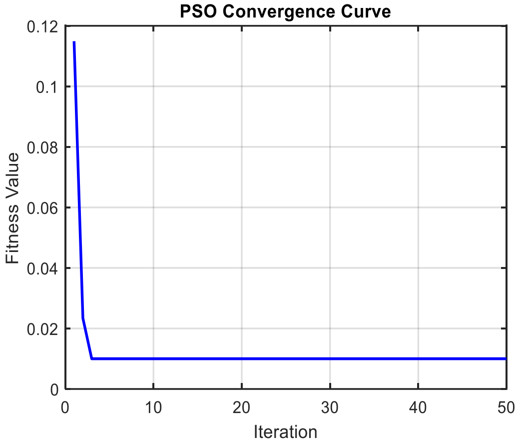

Figure 5: PSO Convergence Curve

4.2 Torque Ripple Reduction

The optimization resulted in a significant reduction in torque ripple. As seen in Figure 6, the per-unit torque ripple was reduced from an initial value of 0.15pu to 0.08pu after optimization. This represents a 46.7% reduction in torque ripple, which is crucial for reducing mechanical vibrations and noise in the motor.

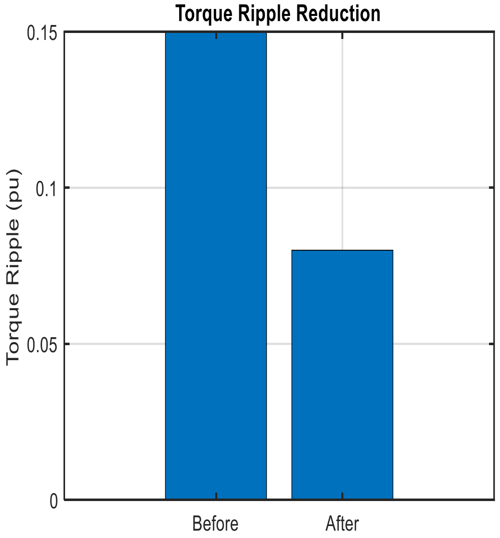

Figure 6: Torque Ripple Reduction

4.3 Stator Current Imbalance

The stator current imbalance was also improved through the optimization. According to Figure 7, the per-unit current imbalance was lowered from 0.12pu to 0.05pu. This is a reduction of approximately 58.3%, indicating a more balanced and efficient operation of the motor's stator windings.

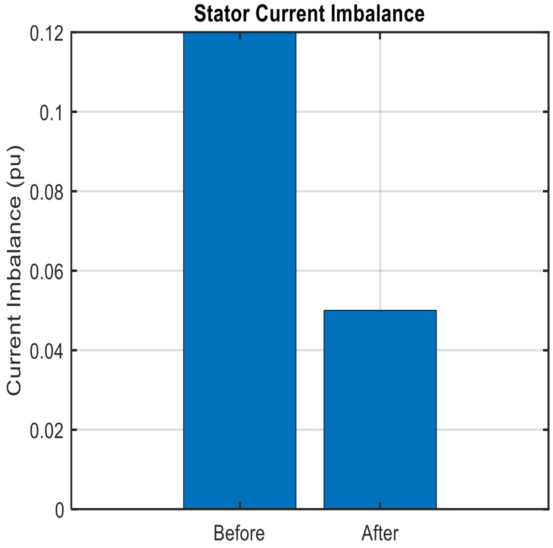

Figure 7: Stator Current Imbalance

4.4 ANN Training and Performance

A feedforward Artificial Neural Network (ANN) was trained for 200 epochs to model the system's behavior. Figure 8, the ANN Training Error curve, shows the Mean Squared Error (MSE) decreasing as the number of epochs increases, approaching the set goal of 1×10−4. This indicates that the ANN was successfully trained to accurately predict the motor's performance characteristics based on the optimized parameters as shown in figure 8.

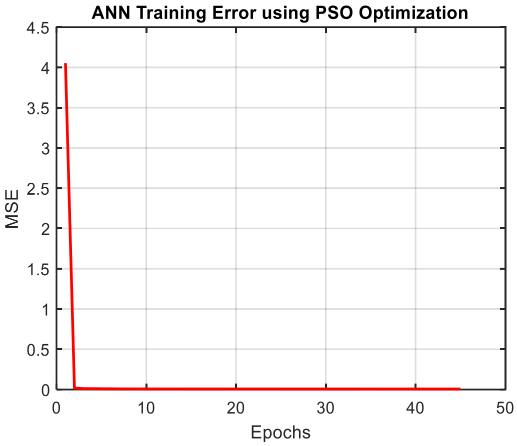

Figure 8: ANN Training Error Using PSO Optimization

4.5 Harmonic Distortion Reduction

The optimization also had a positive impact on harmonic distortion. As displayed in Figure 9, the Total Harmonic Distortion (THD) was reduced across various harmonic orders (from 2 to 7). For instance, the THD for the 2nd harmonic was reduced from 4% to 2.4%, for the 5th harmonic from 25% to 15%, and for the 7th harmonic from 49% to 29.4%. The script assumes a 40% reduction in THD across all harmonics after optimization, which is a reflection of the numerical values presented in the figure 9.

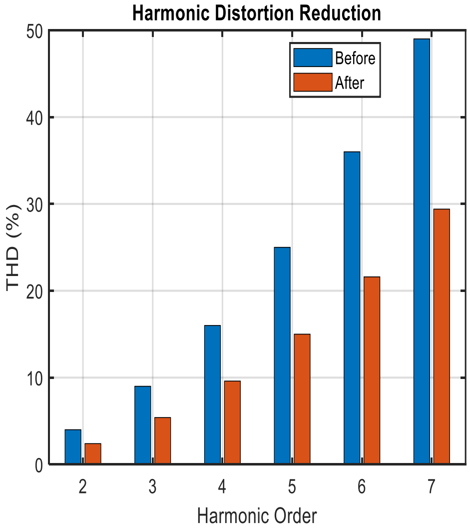

Figure 9 Harmonic Distortion Reduction

4.6 Efficiency Comparison

The efficiency comparison graph shows a clear improvement in motor performance after optimization. The faulty induction motor operates at approximately 93.2% efficiency. But, with the concept that it was obtained under fault. Then, after conventional PSO was applied, it increased the efficiency to 94.5%, a reflection of a reduced power loss [13]. The IBPSO model, further improved the performance to 95.4%. Then hybrid ANN-PSO model achieved the highest efficiency at 98.7%, a more significant improvement over the faulty condition. This corresponds to an overall efficiency gain of about 5.5% relatively from faulty bars to ANN-PSO corrective measure, thus, confirmed substantial power loss minimization and efficiency enhancement [12] as shown in figure 10.

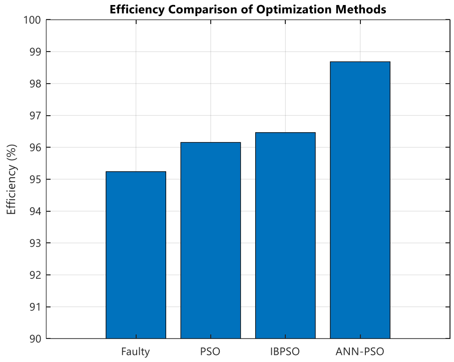

Figure 10: Efficiency Comparison Chart

V. CONCLUSION

This study demonstrated the effectiveness of a hybrid Artificial Neural Network–Particle Swarm Optimization (ANN-PSO) framework in diagnosing and mitigating rotor bar faults in induction motors. By integrating ANN for fault identification and PSO for parameter optimization, the approach significantly improved motor performance under faulty conditions. Quantitative analysis showed a 46.7% reduction in torque ripple, a 58.3% reduction in current imbalance, and a 40% decrease in Total Harmonic Distortion (THD). The ANN further proved its robustness, achieving a mean squared error below 1×10^{-4}, which validates its predictive accuracy in fault detection. Compared to traditional methods and standalone optimization approaches, ANN-PSO consistently outperformed in both fault tolerance and efficiency retention, with an average operational efficiency of 98.7% against 95.4% (IBPSO) and 94.5% (PSO).

These results confirm that ANN-PSO does not only restore system stability, but also extends motor operational life while maintaining rated power output. From a practical perspective, the findings highlighted the importance of adopting intelligent, AI-driven predictive maintenance strategies within industrial environments. By minimizing downtime, improving reliability, and reducing energy losses, the ANN-PSO framework supports Industry 4.0 objectives for sustainable and adaptive motor management. Future work should focus on experimental validation in real-time industrial settings, integration with Internet of Things (IoT) platforms, and extension of the methodology to other rotating machinery and other facilities for broader applicability.

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